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Optimization Algorithms based Task Scheduling Method for Cloud Computing Environment

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***Abstract:** There are various enhancements in the world of technology. Among that Cloud computing delivers numerous amenities over the Internet. It employs data centers which comprise hardware and software provision for loading, servers, and systems. The primary reason for the popularity of Cloud computing is consistent performance, economical operation, prompt accessibility, rapid scaling and much more. The chief cause for concern in cloud computing are the errors that happen either in the software or the hardware and energy consumption on a large scale. The clients pay only for resources utilized by them and assets which are accessible during the computing in a cloud setting. In the environment of cloud computing, Task scheduling is significant concepts which can be used to minimize the energy and time spent. The algorithms in Task scheduling might employ various measures toward dispense preference to subtasks that may generate many schedules to the divergent computing structure. Moreover, consumption of energy could be dissimilar for every source which is allocated to a job. This present research explores that the PSO-CA based energy aware task scheduling method can predict with the aim to enhance the resource distribution.*

***Keywords :** Cloud computing, Particle Swarm Optimization, Cultural Algorithm, Task Scheduling, Energy-aware.*

I. INTRODUCTION

As stated in the National Institute of Standards and Technology (NIST), USA, “The term ‘Cloud Computing’ is perfect for allowing the on-demand, appropriate network permission to a mutual collection of configurable computing assets (e.g., applications, networks, storage, servers, and services) that can be promptly provisioned and rapidly provisioned and released with minimal management effort or service provider interaction”. The benefits of cloud computing comprise of scalability, reliability, elasticity, low cost, and great availability to the end users. The esteemed organizations like Google, Microsoft, IBM, Salesforce, and Amazon are consuming cloud to distribute their services. Among that Google has a protected cloud for transporting dissimilar facilities comprising of statistics, text translations, analytics and more; created on big data analytics [1]. There are thousands of servers internally associated with each other in contemporary data centers. The various applications are accommodated on these cloud servers. In addition, there are numerous computing resources accessible to the end users over the internet in the system of configurable Virtual Machines (VMs) [2]. Most of the huge data centers are cybernetic, not real. Figure 1 exhibits the virtualization system method in cloud computing.

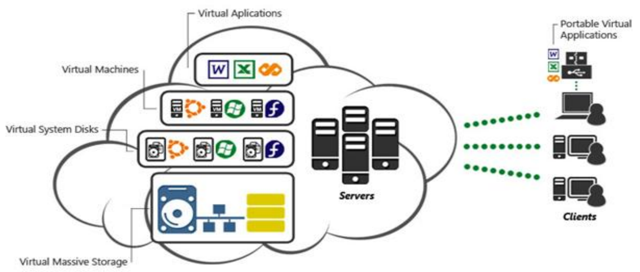

Fig.1: Virtualization in Cloud Computing [3]

Cloud computing is an emerging commercial set-up that uses the internet and is also an economical model in which information can be retrieved from an online browser by customers based on their requirements. It's a paradigm of calculating usage of resources by deploying on-demand availability of assets in a dynamic and accessible manner, wherein the support is accustomed to represent structures, application, facilities, or storage. It stretches the computing bases for the pool of clients via the internet. Moreover, it provides vital environment for software application development. It has feasible setup, assigns or reassign the computing resources dynamically and is available all the time. Consequently, the cloud computing model makes feasible for the client to take part in a few services with particular operations on their specific systems. As many resources like servers, storage, network are used, electricity consumed by these resources is also huge. Cloud computing is often categorized based on the services delivered. They are significantly classified as Infrastructure as a Service (IaaS), Platform as a Service (PaaS), and Software as a Service (SaaS), and so on. The cloud computing can be characterized into four ranges like public, private, community, and hybrid cloud.

II. RELATED WORKS

Kaur, Kamaljit, Navdeep Kaur, and Kuljit Kaur [4] intended to exhibit a setting and load alert procedure for competent task scheduling by altered genetic algorithm branded as a family genetic algorithm.

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Based on investigations of the user features, user requests are rewarded by the accurate form of resource. Such an organization supports to attain competent scheduling and amended load balancing and will substantiate the value for the forthcoming of the cloud.

Dong, Ziqian, Ning Liu, and Roberto Rojas-Cessa [5] proposed an ideal of task scheduling for a cloud-computing data center to examine energy-efficient task scheduling. The researchers articulate the tasks of tasks to servers as a number based integer-programming problem with the objective of decreasing the energy disbursed by the servers of the data center. The authors evidenced that the practice of a greedy task scheduler limits the control service time whilst lessening the number of active servers.

Wang, Xiaoli, Yuping Wang, and Yue Cui [6] proposed a new energy-aware multi-job scheduling model based on MapReduce. In the recommended model, first, the discrepancy of energy consumption with the performance of servers is taken into account; second, meanwhile network bandwidth is a comparatively restricted source in cloud computing, 100%data vicinities is guaranteed; last but not least, in view of that task-scheduling approaches be subject to unswervingly on data placement policies, It express the problem as a digit bi-level programming method.

Salimian, Leili, Faramarz Safi Esfahani, and Mohammad-Hossein Nadimi-Shahraki [7] proposed an adaptive fuzzy threshold-based algorithm to identify overloaded and under-loaded hosts. The recommended algorithm creates procedures vigorously and apprises affiliation tasks to acclimatize the modifications in workload. It is authenticated with real-world PlanetLab workload.

Sundararaj, Vinu [8] proposed a hybrid Queue Ant Colony-Artificial Bee Colony Optimization (Ant-Bee) algorithm for the optimal task of tasks in MCC environment. The anticipated algorithm functions on a two-way MCC model with the discharging system, that reflects both the ‘cloudlets’ and the public ‘cloud’. The ‘cloud’ and the ‘cloudlets’ are calculated on the source of the queue method for the approximation of customers waiting time in the restriction of resources.

Kumar, Sunil, and Mala Kalra [9] dedicated an emerging eco-friendly and energy-efficient scheduling algorithm. Various techniques for energy efficient task scheduling have already been recommended, however, there are numerous rooms for enhancements. The researchers exhibited a mixture of Genetic Algorithm and Artificial Bee Colony-based approach along with DVFS to complete energy-efficient task scheduling.

III. PARTICLE SWARM OPTIMIZATION

00000000Metaheuristic techniques discover near best results in a legitimately respectable time and are categorized into single-solution and population metaheuristics. Single-solution metaheuristic techniques reflect a particular solution at a time. Despite the fact that population metaheuristic techniques execute by numerous solutions simultaneously [10]. Metaheuristic strategies/approximate techniques can discover results with an advanced feature than deterministic approaches and regulate estimated outcomes in lower calculation time than conventional exhaustive approaches [11]. Particle Swarm Optimization (PSO) is a population-based stochastic optimization for explaining multimodal uninterrupted complications [12]. PSO is competent and strong stochastic optimization method for probing the problem space [13]. In addition, PSO is based on the notion of social interaction and does not relate the incline the problem being elevated, therefore it does not need the optimization problem to be variance, as is required by typical optimization approaches. An additional property of PSO has its capacity for optimization of asymmetrical problems that are blaring and transformation over time [14]. The classification is casually modified with the swarm of particles and each solution is depicted by the position of a particle. These particles are stimulated nearby the search-space and everyone has an appropriateness value and velocity to postulate the speed and its direction. As a result, all particles are directed by their own new position and velocity to discover a healthier result [15]. The method is repetitive and by doing so particle swarm steadily depicts the optimal location and solution.

Searching direction of each particle are iteratively modernized by earlier velocity ($v_i(t)$), personal best ($p_{id}(t)$) and the global best ($p_{gd}(t)$). Personal best (pbest) displays the finest probing skill of the individual so far. Global best (gbest) designates the finest recognized result of the complete swarm.

IV. CULTURAL ALGORITHM

Reynolds presented Cultural Algorithms (CA) as an evolutionary method that is imitative from the cultural evolution process in nature [16]. It comprises of certainty and population spaces and a set of communication channels between these spaces to regulate the excellence of the pooled knowledge and its nature. The figure displays how the key periods of CA are implemented in each generation. In the population space, the individuals are produced by the *Obj*() function and the *Accept*() function picks the best individuals that are used to impart the belief space knowledge by the function *Update*(). The *Influence*() function practices the roulette wheel selection to select one knowledge source to accomplish the development of the next generation.

A CA is a knowledge-based evolutionary computational system. Its elementary indication is to integrate information modules into old-fashioned evolutionary computational classifications [17]. Its simulations are divided by the two stages of evolution: the population space level evolution and the belief space level evolution. The two spaces are linked together by a categorical communication protocol poised of an acceptance and an influence functions, which are implied at this juncture as Accept () and Influence (), separately. The acceptance function is used to to assemble the skill of selected individuals from the population; then the belief space can be modified by an update function, selected at this juncture as the update(); next, to monitor the development of the population component, the influence function can create the problem-solving knowledge in the belief space. In the population space, like old-fashioned evolutionary population models, individuals are chiefly appraised by a generation function objective().

The generate() function used to produce the new individuals. Then a selection function select(), is cast-off to choose the population for the next generation.

Cultural algorithm has the features:

(1) Dual evolutionary inheritance: In the population space and belief space are innate parent information.

(2) Sustenance the population space and belief space hierarchy.

(3) Population space evolution is protected by the belief space knowledge to monitor.

(4) Provision the adaptive evolution of two spaces.

(5) Dissimilar space evolution can be passed out at various speeds.

(6) "Cultural" change can be pronounced in altered simulations within a model.

(7) Support a fusion of diverse algorithms to explain the issue.

V. PROPOSED PSO-CA BASED ENERGY AWARE TASK SCHEDULING ALGORITHM

A task scheduling (TS) algorithm in the cloud environment is established which proceeds the benefits of PSO and cultural algorithm. In this research paper, the application method in the cloud takes a customary of *P* different mainframes which are copiously interrelated through a high-speed set-up. The communication among inter-processor are executed by a similar speed upon associates toward streamline the model for TS identical to process in [18]. In this classification, each subtask can be a track only through one processor, and all of them must be programmed. The relationship of Time dependency should be measured when two dependent subtasks, and it can allocated to different computers. A static computational model is measured in this technique and the relation and implementation precedence are programmed and it doesn't change during the task scheduling or presentation. Directed Acyclic Graph (DAG) is used to present the task scheduling to signify the dependencies of the tasks. In the representation of DAG, the vertices characterize the boundaries and tasks epitomize the implementation preference amongst the tasks.

The common principle of PSO is that the velocity data imitates the effects of the pronouncement which have been made by previous particles to detect respectable solutions. Initially, the particles stroll casually. As soon as the particle discovers a source of food, it passes toward the swarm with the velocity that displays the route of the result. Shorter routes are more perspective to be robust, therefore the solution is augmented. In this technique, the PSO is pooled through a CA for cracking the TS discrepancy, which could fundamentally enhance the performance of the procedure and condensed with stretched local convergence and looping time discrepancies. Both algorithms are established on population and they part the data among the population. PSO procedure acquires the gains of the twofold legacy of a CA.

The CA is a portion of evolutionary computation that has double modules: the evolutionary procedure from the skills and information attained is called belief space; and the collection of individuals from the specific space is known as population space [19]. These two modules link with each other over a backup communication protocol. The twofold legacy tool brands the CA a self-adaptation structure which empowers the universal evolutionary data occur additional completely operated. Through a fitness function that governs the presentation of each individual in the population on every iteration by the finest individuals then the belief space is modernized.

Influence and acceptance are measured by the chief processes of the CA. Further processes are implemented within the population or belief space autonomously. As a result, which is potential toward establish extra procedures into CA structure by totalling explicit rationalities into population and belief spaces and achieving influence and acceptance processes among them [20]. In the projected technique, PSO is cast-off for the selection of processor and the CA has employed to pick the top result and evade deteriorating into confined best result by their workers.

A. Selection of Processor

In the recommended process, particles choose a processor established by its particle and heuristic information. Each particle elects a CPU used for the principal job unsystematically. Particle k picks a job in order then allocates job j to CPU C conferring to the possible data.

$$ct_j = \frac{[par(j,k)]\,[heu(j,k)]^{\beta}}{\sum_{k=1}^{n}[par(j,k)]\,[heu(j,k)]^{\beta}}$$

Where par(j,k) depicts the particle data and C_j gives the processor last completion time. The heuristic data is represented by $heu(j,k)$. For job T_j is the initial start time on the C_j. Heuristic information is acquired from the Earliest Finish Time (EFT) approach of task T_i on processor P_k. A job can solitary be nominated when all preceding jobs are programmed.

$$par(j,k) = (1-\rho)\, par(j,k) + q, \text{ fitness}$$

In the above equation, q is the particle inertia proportion that is among 1 & 0. Fitness is then premeditated Griekwang Function. The outcome of velocity updating rule is marked by the selecting of putting T_j on the processor C_j less desirable for other particles to accomplish modification since particle have a tendency to congregate into a mutual route. The persistence about the velocity updating instruction which is to boost that particles to examine the CPU with consumption of implementation time and low energy.

B. Heuristic Information

Heuristic data in the CPU allocating possibility calculation is accomplished after heuristic based Heuristic Earliest Finish Time (H-HEFT) method. This method is recommended to reduce the duration deprived of impious precedence limitations. The H-HEFT method picks the sub job with the maximum increasing rank rate by every stage & apportions a designated task toward the CPU that lessens their initial surface period through an insertion-based method. Estimated Start Time (EST) of the tasks T_j on a processor C_i is represented as $EST\ (T_j, C_i)$:

$$EST\,(T_j,C_i) = \begin{cases} 0\,, if\ T_j = T_{entry} \\ \max\limits_{T_j\,\epsilon Pred(T_j)} AFT\,(T_j,C_m), & if\ C_i = C_m \\ \max\limits_{T_j\,\epsilon Pred(T_j)} AFT\,((T_j,C_m) + c(T_k,T_j)), & if\ C_i \neq C_m \end{cases}$$

The actual start time (AST) of task T_j on CPU C_i is represented by AST(T_j, C_i)

$$AST\ (T_i, C_k) = \max(EST\ (T_i, C_k), Avail\ (C_k))$$

The $Avail\ (C_i)$ is represented as the initial period at which the processed C_j is ready for the task execution. The EFT of job T_j on processor C_i is represented as $EFT\ (T_j, C_i)$:

$$EFT\ (T_j, C_i) = AST\ (T_j, C_i) + W(T_j, C_i)$$

The actual finish time (AFT) of a task T_j over all processors is represented as $AFT\ (T_j, C_i)$, P_k is the fittest processed for the task T_j.

$$AFT\ (T_j, C_i) = \min_{1 \le l \le m} EFT(T_j, C_j)$$

C. Fitness Function (FF)

The fitness function can unswervingly disturb the method junction and to examine for an optimum result. Through this investigation, the objective function for the scheduling of job is measured the least span then the deepest energy as the objective. The standardization procedure is directed with the intention to form a steadiness of ratio to consumption of energy and makespan. The make span is imitative as of the following equation:

$$makespan(j) = \frac{1}{makespan(j) + energyconsumption\ (j)}$$

Where j is the particle solution with the intention to confirm the eminence of the solution, to evade failing into resident optimum and to attain the best result to the extent that is probable. A FF is deployed to appraise the excellence of concrete results.

D. Belief Space

The main processes of the cultural algorithm are acceptance and influence. An acceptance function regulates which individuals from the existing population will be employed to figure the principles of the whole population. In this function, static approaches use an entire level on the values of fitness to choose the best n percent of individuals. Then energetic techniques do not have a static number of individuals that regulate the belief space, as an alternative, the amount of individuals might vary from generation to generation [22]. On the other hand, the number of individuals is determined as:

$$\eta\beta(t) = \frac{n_s\gamma}{t}$$

Where n_s is the size of the population, $\gamma \in [0,1]$ and t is the iterations counter. With this methodology, the amount of individuals who are accustomed to modifying the belief space is primarily enormous by lessening the overtime.

E. Operators of CA

There are three operators of CA which comprising mutation, crossover and selection worker are offered in this unit. The selection operator is Rolette wheel, which is practiced toward choose that key through the particular operation of point crossover and maximum fitness and particular point crossover operator of a GA for operation of crossover. In conclusion, operator of mutation of the GA is employed to preserve multiplicity.

Selection Operator

Several selection operators are declared as an imperative fragment of a genetic algorithm. Selection operator desires to elect the healthier results and improved entities with great prospect of its existence and reproducing. Rolette wheel technique is used for this worker. This technique adopts that the prospect of the collection is comparative to the appropriateness of a result. A result has a sophisticated value of fitness would take a prominent opportunity to be picked. As consider the PopSize is the population size, each categorized by its fitness $fitness_i > 0(i = 1,2, \dots, PopSize)$. The probability p_i of each solution to be selected can be premeditated along with the possibility demarcated by the equations:

$$q_j = \frac{fitness_i}{\sum_{k=1}^{PopSize} fitness_k}$$

And

$$r_j = \sum_{k=1}^{j} q_k$$

Where r_j depicts the summation from 1 to j of q_j. Therefore, a more filter approach will be nominated with prominent probability and it will become additional offsprings. The normal should hold back and the worst will die off.

Operation of Crossover

The crossover is a GA operator toward a variant the encoding of a chromosome. A crossover is accustomed as a process of substituting certain genes in one parent by other analogous genes. For the TS problem, the operation of crossover is linking two legal parents, where subtasks are well-organized topologically to produce two offsprings which will also be effective.

Mutation Operator

The operation of mutation is a GA operator to preserve variety. This operator alters the genes of a chromosome and transmutes it the population from one to another generation and aids the quest method to evade from dropping to nearby best results by thwarting the population after flattering also parallel to one another or collaborates with operator of crossover to reach a greater result.

VI. RESULT AND DISCUSSION

The performance evaluation of the recommended PSO-CA method by energy consumption and also makespan with the other prevailing method known as PSO. The probability of Mutation and Crossover is measured as 0.7 and 0.3. Similarly, the velocity of the PSO algorithm is set as 0.5. Table 1 represents the reproduction structure deployed to assessing the recommended technique.

A. Simulation Setup

The following are considered for the simulation. The probability of mutation and crossover is set as 0.7 and 0.3. The condition for termination is 50 iterations. The processors consumption energy is marked from 0.001 to 0.004. The size of the population is set as 150, 100. The processors count is given as 6,3. The tasks count is set as 20,10. The DAGs count is 50 and the particle velocity is considered as 0.5.

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Figure 2 depicts the graphical representation of the makespan for the count of 50 DAG randomly generated with number of resources, population and tasks of the existing TS with Particle Swarm Optimization and proposed energy aware TS with PSO-CA method. From the figure 2, it is clear that the makespan of PSO takes maximum time than proposed PSO-CA.

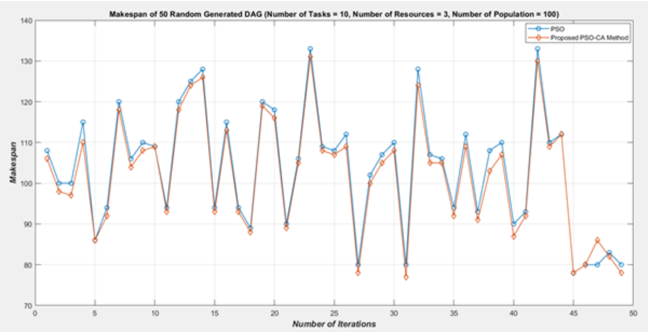

Fig.2: Graphical Representation of Makespan against number of iterations using PSO and proposed PSO-CA method

Figure 3 represents the graphical representation of the energy consumption of the DAG with number of resources, population and tasks using PSO and proposed PSO-CA. From the figure 3, it is clear that the proposed PSO-CA tasks scheduling method consumes less energy than the task scheduling with PSO.

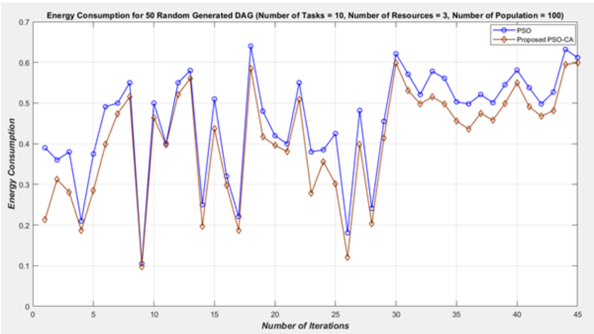

Figure 3: Graphical Representation of the Energy Consumption against number of iterations using PSO and proposed PSO-CA method

Figure 4 depicts the graphical representation of the makespan of the DAG with number of resources, population and tasks. From the figure 4, it is clear that the proposed PSO-CA tasks scheduling takes less time for makespan for random generated DAG than PSO.

Figure 5 depicts the graphical representation of the energy consumption of the DAG with number of resources, population and tasks. From the figure 5, it is clear that the proposed PSO-CA task scheduling method consumes less energy than the PSO tasks scheduling method.

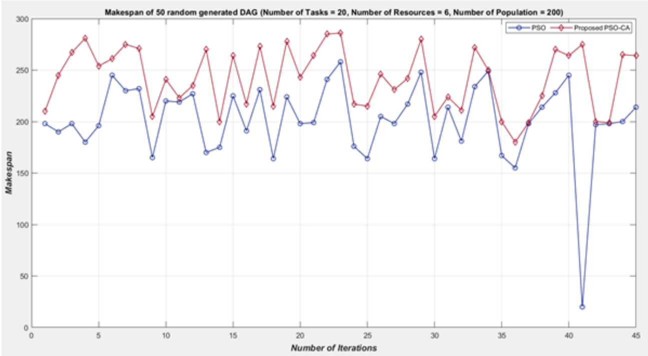

Figure 4: Graphical Representation of the Makespan with number of iterations using PSO and proposed PSO-CA method

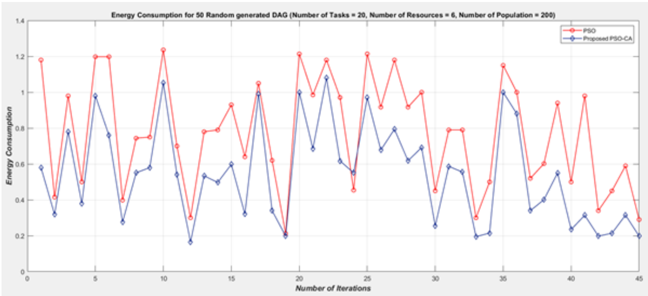

Figure 5: Graphical representation of the energy consumption with number of iterations using PSO and Proposed PSO-CA methods

VII. CONCLUSION

Through this research paper, the TS issue with precedence restriction is depicted. The following two factors like Energy consumption and total time taken for execution are considered for evaluating the proposed method. Thinking about the significance of these two factors, another technique is displayed that consolidates CA and PSO for TS and needs in the environment of cloud computing. The results depicted that the proposed technique beats PSO regarding makespan and consumption of energy.

The overhead of frequency/voltage switching and communication and other questionable parameters in the real situation of a heterogeneous domain will be talked about later on research.

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