A Trust Model and Quality of Service Based Heuristic Scheduling in Cloud Using Firefly Algorithm

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Abstract
The cloud computing technology is almost ubiquitous, wherein computing services are provided to the user by means of flexible, highly scalable and conducive IT resources. Security and trust are the two key issues in cloud. The applications on cloud are mostly modelled as workflows, wherein, the completion of a task requires many sub tasks to be executed in a certain manner .The management of various tasks is the main role in cloud computing and the most important part is workflow scheduling. This is because, it decides on implementation duration, expense and other performances, based on various factors. A new methodology for dimensionality based on the Firefly algorithm (FA) is presented by this work. The biochemical and social characteristics of real flies are the basis for FA. This flashing behaviour of the fireflies is formulated with the problem's (to be optimized) objective function. Better performance is achieved by empirical outcomes compared to the suggested method.

Keywords: Cloud Computing, Scheduling, Security, Trust, Genetic Algorithm (GA) and Firefly Algorithm (FA).

Introduction
As it delivers highly efficient computing resources over the internet for solving huge scientific applications, cloud computing has become an increasingly popular paradigm .Hence , there is a need for adopting a novel approach for harnessing the opportunities and the challenges of this technology to obtain a cost optimum schedule[1]. Also, as a utility service, the cloud provides computing . The cloud services can be categorized as Infrastructure as a Service (IaaS), Platform as a Service (PaaS), and Software as a Service (SaaS). The current work focuses on IaaS . These are proven to give efficient performances and optimal cost benefits compared to cluster and grid computing.

Resources are allocated based on the requirement and are controlled by service consumers by IaaS.An end user is facilitated to obtain and release the computer resources according to the demand by the Cloud Service Provider [2]. Thus the resource pool can be scaled up or down depending on the demand. While decreasing the total expenditure, the cloud assigns only the needed computing resources from the resource pool. In this manner, the overall utilization of resources can be enhanced. The price model that is adopted by the CSP is pay –per-use, wherein the users only pay for the computing resources utilized, whereas the other service providers charge the users for the entire duration even if the resource has been used only for a fraction of the last time duration.

One of the main hindrances for the increased demand of cloud computing is the security. Because of the security issue , many of the individuals and organizations do not concur to deploy the applications and data over the cloud environment. The data that is hosted on the cloud environment by the service providers is not under their control any longer which may lead to security issues. The shared infrastructure services provided by the cloud technology have increase the susceptibility to illicit access of information . Thus, there is an issue of privacy of data, management of user identity, authorization, complying , maintaining data confidentiality, providing data integrity , ensuring availability, encryption , susceptibility of the Internet Protocol (IP) (The IP cases are mostly not trustworthy and this enables a person in the middle attack), physical and network security[3].

A complicated issue to be dealt with in the area of cloud computing is Trust. Trust management system that ensure confidentiality have been incorporated by tech giants like Google and Amazon. This enables the users to employ trustworthy resource providers for carrying out e-business transactions in a secure environment, with confidence[4]. Data integrity, availability, turnaround efficiency and reliability are the parameters on which the trust value is computed .A critical part of forming and maintaining a successful and symbiotic relationship between business stakeholders in the cloud environment is referred to as Trust Management. It is slightly difficult for the users , in a very vast and competitive environment to detect dependable cloud service providers. Because of these restrictions, it is tough for potential cloud users to believe in the cloud service providers who offe reliable services [5].

It is computationally expensive and involves communication expenditure to schedule the tasks. Areas like astronomy and biology can use the cloud services for executing their workflows .Scheduling refers to mapping the inter dependent tasks to resources that are available in such a manner that workflow application can complete its task implementation within the constraints specified under Quality Of Service(QoS). Not taking into account the expense of accessing the resources, the grid workflow management systems have workflow scheduling algorithms that try minimizing the duration of implementation. In cloud computing cases, the faster resources cost more than the slower ones . Hence, there are both time and cost constraints that are specified by the user, in cloud workflow scheduling. While restrictions in duration make sure that the workflow is executed within the given deadline, the cost constraint makes sure that the expenses do not exceed the allocated budget. An optimal algorithm achieves balance between the two [6].

On the basis of various requirements that may serve functional or non-functional purposes, the workflow tasks are mapped to the Virtual machines (VMs), by workflow scheduling algorithms. A workflow refers to a set of tasks. These depend on one another and are held together by means of functional or data dependencies . While scheduling, these dependencies must be factored .However, in cloud computing, workflow scheduling is a NP hard optimization problem and to achieve an optimal schedule is not easy. Several user tasks may have to be scheduled by taking into account various goals and factors involved in scheduling, as there exist many VMs on the cloud. Minimizing the makespan by efficient allocation of virtual resources to tasks os the common goal of the workflow scheduling methods[7].

No algorithm so far has been able to formulate an optimal solution within the polynomial time , for scheduling problems. Hence, for solving scheduling problems using random variables, stochastic optimization methods have to be applied[8]. Simulated Annealing (SA), swarm algorithms and evolutionary algorithms are some of these methods. The cost and performance are attempted to be optimized by applying the GA and the FA for workflow . The remainder of the investigation is arranged as follows- The related work in literature is discussed in the second section. The various methods used in the work are discussed in the third section. The fourth section delineates experimental results while the conclusion of the work is given in the fifth section.

Related Works

The trust computing techniques in cloud computing have been discussed by Chiregi & Navimipour [9]. They have been classified into two chief groups – centralized mechanism and distributed mechanism. The author, in addition to trust applications like tracking and monitoring , he has also defined trust characteristics like availability, security, integrity, reliability, safety, scalability, confidentiality, dependability and dynamicity. The differences between the methods discussed regarding availability, security, integrity, reliability, safety, scalability, confidentiality, dependability and dynamicity and the directions for research in future has been discussed in this work.

Trust Com is a new framework for assessing trust and Rough Set-based Hypergraph Technique (RSHT) for the detecting the optimal Trust Measure Parameters (TMP) subset was discussed by Somu et al., [10]. The prominence of RSHT compared to the other methods of feature selection have been shown by experiments using Cloud Armor and synthetic trust feedback datasets. Using the Weka tool and the hypergraph based computational model, the RSHT's performance has been analyzed with regard to reduction of size, time, complexity and service ranking.

The Dynamic Power-saving Resource Allocation (DPRA) mechanism based on a Particle Swarm Optimization (PSO) algorithm was suggested by Chou et al., [11] for increasing the efficiency of energy. The DPRA mechanism taken into account both the energy consumption of Physical Machine (PM) and VM , and the takes care of the energy efficiency ratio in an air conditioner. Also, to predict the resource usage of PM , the least square regression method is used . This allocates the Virtual machines and removes the virtual machines migrations. It has been shown by the results of simulation that, the DRPA performs better than the traditional schemes , when VM number exists, and the chosen objective performance metrics include the prior solutions in terms of the energy consumption including that of the ACs and the PMs, Total electric bill, Number of shutdown PMs, VM migration.

A multiple goal problem that involves task scheduling with required consumers' expectations regarding the Quality of Service and a scheduling model in relation to the problem was suggested by Gabi et al., [12]. For solving the model, a Dynamic Multi-Objective Orthogonal Taguchi Based-Cat (dMOOTC) algorithm is then proposed. For executing the proposed algorithm, CloudSim tool is sued. It is evaluated with the execution time metrics and that of the execution cost and the quality of service. It was shown by the throughput that when compared to the standard Multi-Objective Particle Swarm Optimization (MOPSO), Cat Swarm Optimization (CSO), Orthogonal Taguchi Based-Cat Algorithm (OTB-CSO) and Enhanced Parallel CSO (EPCSO), the solution that was suggested has better performance by meeting with the Quality of Service expectation from the consumer.

An Augmented Shuffled Frog Leaping Algorithm (ASFLA) based method to provide the necessary computing resources and workflow scheduling in the Infrastructure as a Service (IaaS) cloud environment was presented by Kaur & Mehta [13]. The cutting edge PSO and SFLA algorithms' efficiency has been compared with that of ASFLA, and also using a custom simulator that was based on Java, its efficiency was evaluated over some popular scientific workflows. A sharp increase in the performance of achieving the target within deadline and within the given budget has been shown by the simulation outcomes.

With the objective of increasing the accuracy and the efficiency of cloud computing industry alliance, the improved PSO algorithm was put forth by Gao et al., [14], for conducting knowledge research. Firstly, for particle grouping process, the author made use of the Map function of MapReduce model. Next, for shortening the particle search result list and the search duration, the author employed the reduce function. Lastly, the average value of the optimal position within each group was decided by the interaction of information of the particles. This avoided premature convergence using the local optimal time. Three rounds of simulation were employed by this work, for comparing it with other standard methods and it was found that both in terms of efficiency and accuracy, PSO was better.

A Balanced and file Reuse-Replication Scheduling (BaRRS) algorithm for cloud computing environments was presented by Casas et al., [15]. This was specifically for optimally scheduling scientific application workflows. For balancing system utilization via parallelization, the scientific workflows were split by the BaRRS into multiple sub-workflows . This could also optimize the quantity of data that needed to be propagated between different tasks at the run time , by employing reuse of data and replication methods. For this, the key application features like file sizes, dependency patterns and task execution times were analyzed by the BaRRS. Two optimization constraints- Execution time and monetary cost of running scientific workflows were selected after performing a trade off analysis by the BaRRS for selecting an optimal solution. After having been compared with popular scheduling approach, BaRRS has proven to be more efficient.

Adaptive penalty function for the strict constraints compared with other GAs was suggested by Liu et al., [16]. Also, for adjusting crossover and likelihood of mutation, co-evolution approach is employed ; This can not only prevent prematurity but also accelerate convergence. Baselines such as random, PSO, HEFT, and GA in a WorkflowSim simulator on four representative scientific workflows were used for algorithm comparison. In terms of both meeting the deadlines and the execution cost, it has shown to perform better than the other cutting edge algorithms.

The PSO algorithm for increasing the efficiency of the Neural Network (NN) was introduced by Mao et al., [17], by means of initial settings optimization. PSO is employed for looking for appropriate parameters for neural networks , in the proposed hybrid prediction algorithm named PSO-NN. This is to realize accurate test trust forecast of the cloud services. Several experiments were carried out on the basis of the public QoS data set and also in depth comparison analysis, for finding out the PSO-NN effectiveness. It has been shown by the results that, in terms of the accuracy of forecast, the suggested method has a much better performance compared to the basic classification methods and also shows better stability when compared to the basic neural network.

However, optimal solution cannot be met for some basic principles of cloud like heterogeneity and elasticity, by this work. Hence, the focus of this work is the scheduling strategies for scientific workflow on IaaS cloud. An algorithm that was formed on the basis of meta heuristic optimization method was proposed by Goyal & Aggarwal [18]. Here, the ant colony optimization (ACO) and PSO are combined for both local and global optimization that reduces the makespan or the overall workflow execution time , thereby bringing down the expenses. CloudSim and many other popular scientific workflows of varying sizes have been evaluated by the heuristic and it has been shown that it compares better than the PSO algorithm.

Methodology

For NP hard problems many heuristic and evolutionary methods have been suggested and each of them concentrates on restricted number of constraints and chief goals like the makespan, min-min, min-max or suffrage[19]. Also, list based techniques like Heterogeneous Earliest Finish Time (HEFT) or critical path utilized in simple model systems fail to accurately represent the real systems are what some traditional solution scheduling algorithms rely on. PSO, Tabu Search (TS), SA, GA etc are some of the meta heuristic based methods that have been shown for solving the NP problems. For giving superior outcomes in several optimization domains and for providing strong seeking methods that generate efficient outcomes, GA and FA are known to be better, especially for large spaces and for searching in parallel in polynomial time by making use of the evolution principles. For evaluating efficient parameters, it could present many solutions.

Genetic Algorithms (GA)

Evolutionary biology forms a basis for the GAs that is a special class of evolutionary algorithms. The exploitations of the best solutions from the previous searches are merged with the search of new regions of the solution space. An individual or a chromosome represents shows any solution in the search space of the algorithm. When genetic operators like the selection, mutation and crossover are iteratively applied, a GA will be enabled to maintain a population of individuals that evolves over generations so that the solutions become better. The fitness function determines the quality of individual and also indicates its quality in terms of the others present in the population [20].

The GA algorithm process is discussed as follows:

Initial Population: The solutions to the problems are provided by the initial population when GA is used for problem solving.The set of possible solutions form the original population and this is regarded as chromosome. Using symbol, the chromosome in the initial population are randomly generated and for solving the particular problem, these are chosen[21]. Transformation of the problem to a two dimensional solution space is performed by the initial population and each chromosome is regarded as a string of bits.

Fitness function: For successful GA, it is important to select a suitable fitness function and it also represents the way in which the selected function meets the problem objectives. Every chromosome is evaluated by a fitness function in GA.As per a given objective, , the effectiveness of the solution is measured by the fitness function. Delay in process can result in an incorrect fitness function. The fitness function determines which of the chromosomes can be retained in the population. When the fitness function is larger it meets the task's required Quality Of Service in equation (1).

$$F = \min \{\max \{ck\} + \sum f(di)\} \quad (1)$$

Selection: This is used for the selection of chromosomes in the current population for fitting in the consecutive population, for finding the best individual. Every chromosome has a similar likelihood to its score by the sum of all other chromosome probability [22].These are used for creation of next generation and range selection is utilized. A rank is allocated to every individual based on the fitness function. Using this technique, the individuals will spawn the forthcoming generation. The individual that is the fittest will gain preference using this technique.

Step 1: Choose some chromosomes arbitrarily.

Step 2: After comparing the values with other chromosomes, choose the chromosomes for the successive generation.

The fitness function value is not directly proportional and avaoids stagnating beforehand.

Crossover: All chromosomes are paired using crossover operator and also used to merge two chromosome for producing the ones of the next generation. It mixes the chromosomes of the parents for forming the new generation. As only 1 crossover point exists [23], Single point crossover is used. At the locus, the remaining alleles from parents are swapped to the others, In this single crossover point. The new generation has semblance to the parents if the crossover operation is skipped. C1 represents bad chromosomes while C2 represents good chromosomes.

Mutation: This does the permutation of the chromosomes that are present and is used for maintaining genetic diversity from one generation to another. New gene values are augmented to the existing genes. This process makes small changes at every individual and is used for determining new points in search space so that the variation in population is maintained[24]. They also facilitate chromosomal functions that have been generated by crossover. They help in overcoming the local maxima trapping. Good chromosomes are represented by M2 and the bad ones by M1.

Termination Algorithm: The chromosome in the given population is copied by the selection process and this is repeated for twenty generations. It helps obtaining the highest fit value. The size of the sorted chromosome determines the termination.

Proposed Firefly Algorithm (FA)

Small winged nocturnal beetles , that produce bio luminescent light during mating by virtue of some chemicals in their abdominal region are referred to as fireflies. The FA is a metaheuristic algorithm. Flashing of light, absorption in media and the mutual attractive behaviour among the fireflies is the basis of this algorithm [25].

At first, the FA was developed for solving optimization issues. Later, it was employed for solving discrete problem and widely utilized in the areas of digital image processing , clustering and compression. Presented by Xin-She Yang in late 2007 at Cambridge University, the FA is inspired by the fireflies' flashing behaviour. The three idealized rules , for describing the FA in simple form are [26]:

- Irrespective of the gender, all fireflies are attracted to one another; they are unisex.
- Attractiveness are brightness are proportional in that, for any two fireflies that flash light, the one that is less brighter moves towards the more brighter one ; attraction and brightness reduce as the distance between the fireflies becomes grater.A firefly moves arbitrarily if no other firefly exists in the vicinity.
- The landscape of the objective function determines the brightness of the fireflies.The brightness can be proportional to the objective function's value and in a manner that is similar to the fitness function in the GAs, the other forms of brightness can be defined.

It assumed that there are n fireflies x_i, i=1,2,........,n initially positioned randomly in the space and intensity i of each firefly is associated with the objective function in (2).

$$f(x),\ i.e.\ I = \alpha f(x) \quad (2)$$

Only firefly with higher flash intensity attracts the other one i.e. Ii>Ij, j=1, 2…n, j≠i. The brightness of firefly changes with the distance between firefly i and firefly j i.e. $r_{ij} = d(x_i, x_j)$.Additionally, as the light is absorbed in the media, its intensity decreases with the distance. Hence, only from short distances are most fireflies seen.

Thus, we can say that the intensity of the light is inversely proportional to the distance r from the source of light.Thus, the attractiveness also decreases with the increase in distance (3).

$$I(r) = I_0 e^{-\gamma r^2} \quad (3)$$

Where, I=light intensity, I_0=light intensity at initial or original light intensity, γ =the light absorption coefficient, r=distance between firefly i and j;

Attractiveness is proportionally to the light intensity seen by the another fireflies, thus attractiveness is β in (4):

$$\beta = \beta_0 e^{-\gamma r^2} \quad (4)$$

Where β_0 =Attractiveness at r is 0

The distance between two fireflies can define using Cartesian distance in (5)

$$r_{ij} = | x_i - x_j | = \sqrt{\sum_{k=1}^{d} (x_{i,k} - x_{j,k})^2} \quad (5)$$

Firefly i is attracted toward the more attractive firefly j, the measure is defined as (6):

$$\Delta x_i = \beta_0 e^{-\gamma r_{ij}^2} (x_j^t - x_i^t) + \alpha \varepsilon_i, \quad x_i^{t+1} + \Delta x_i \quad (6)$$

In Δx_i equation, the first term represents attraction, is the limitation when the value is tend to zero or too large. If γ approaching zero ($\gamma \to 0$, the attractiveness and brightness become constant $\beta = \beta_0$. In another word, a firefly can be seen in any position, easy to complete global search. If γ the is nearing infinity or too large ($\gamma \to \infty$, the attractiveness and brightness become decrease. The movement of the firefly becomes arbitrary. The implementation of FA can be done in these two asymptotic behaviours. While the second the term is for randomization, as is the randomize parameter.

The ε_i can be replace by ran -1/2 which is ran is random number generated from 0 to 1.

The flow chart of FA as shown in figure 1.

Results and Discussion

In this section, the GA without trust, GA with trust, FA without trust and FA with trust methods are used. The table 1 figure 2 shows the average schedule length.

Table 1
Average Schedule Length

Number of jobs	GA without trust	GA with trust	FA without trust	FA with trust
300	739	716	699	684
600	1563	1531	1478	1437
900	2320	2231	2185	2105
1200	3059	2992	2919	2845
1500	3875	3774	3681	3591

From the figure 2, it can be observed that the GA without trust has higher average schedule length by 3.16%, 5.56% & 7.73% for 300 number of jobs, by 2.06%, 5.59% & 8.4% for 600 number of jobs, by 3.91%, 5.99% & 9.71% for 900 number of jobs, by 2.21%, 4.68% & 7.24% for 1200 number of jobs and by 2.64%, 5.13% & 7.6% for 1500 number of jobs when compared with GA with trust, FA without trust and FA with trust.

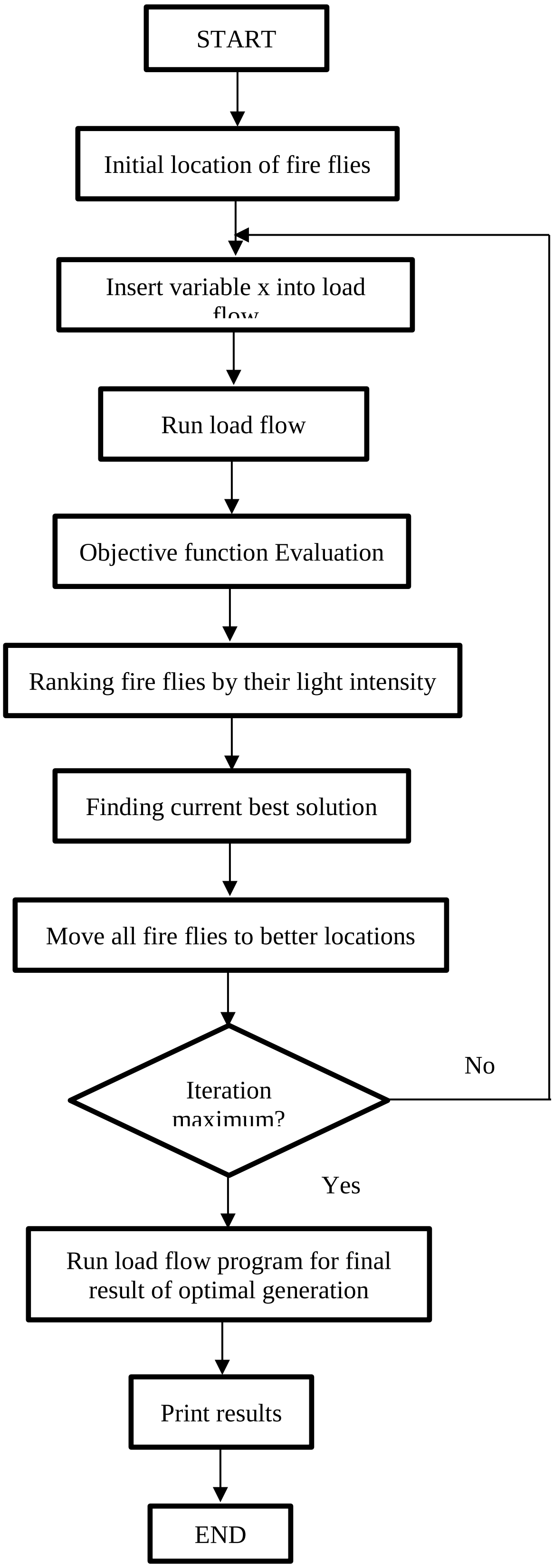

Figure 1: Flowchart for the Firefly Algorithm (FA)

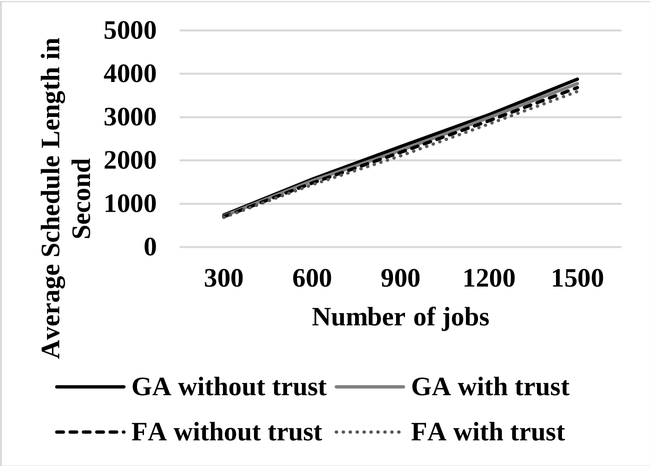

Figure 2: Average Schedule Length

Conclusion

As the cloud technology is progressing, the cloud infrastructure can be used for supporting large scale businesses. This property can be provided by workflow systems. Scheduling and managing the resources is very complicated in a cloud environment, for which sophisticated tools are required to analyze various scheduling algorithms so that, this can be applied in the real environments. In the current work, the genetic algorithm, a meta heuristic algorithm, that is inspired by natural selection and genetics , and , the firefly algorithm , that searches for an optimal solution set by employing randomization, inspired by the flashing of the fireflies have been discussed. It has been shown by the results that, without trust, the GA has higher average schedule length by 3.16%, 5.56% & 7.73% for 300 number of jobs, by 2.06%, 5.59% & 8.4% for 600 number of jobs, by 3.91%, 5.99% & 9.71% for 900 number of jobs, by 2.21%, 4.68% & 7.24% for 1200 number of jobs and by 2.64%, 5.13% & 7.6% for 1500 number of jobs when compared with GA with trust, FA without trust and FA with trust.

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