A Framework for Ranking of Cloud Services using Non Dominated Sorting

Preeti Sirohi, Amit Agarwal, Piyush Maheshwari

Abstract: ***Cloud computing technology offers variety of cloud services to the users. The cloud user faces the challenge in choosing the service which can meet his requirements. Therefore, selection of an approach which can compare and select the best service according to the requirement is an issue. Several approaches, algorithms and frameworks have been proposed and designed which provide solutions to its user in choosing the best services. This paper proposed a framework which will use both subjective and objective parameter and is based on non-dominated sorting approach for ranking of cloud services. Various genetic algorithm are studied, analyzed and compared with each other find out their limitations.***

Index Terms: Cloud computing, Genetic Algorithm, Multi-Objective Optimization

I. INTRODUCTION

The decision making problem having multiple objectives are often conflicting with each other and in real world are known as multi-objective optimization problem (MOOP) [2] . Here the decision problems are based on several objectives which have to be simultaneously optimized for finding optimal solution for multi-objective problem. The optimization problem for single objective differs from that of bi-objectives and multi-objectives. In case of single objective optimization the solution of the problem is obtained by finding the best solution of the problem and for that the optimization problem is taken as either maximization or minimization objective problem. In case of multi-objective optimization finding one best solution will not be sufficient as different objectives have different requirements which need to be optimized simultaneously for getting optimal solution for the problem [28]. In multi-objective optimization problems, there are conflicting objectives which prevents the simultaneous optimization of every objective. The solutions offer better result in some objectives as compared to others. These solutions are known as non dominated solutions d other solution in as these solutions dominate other solution in at least one objective. The solutions which are dominated by other solution are known as dominated solutions.

The non-dominated solutions are also known as pareto optimal solutions that are conflicting with respect to each other. The first set of solution in pareto optimal solution set occupies the decision space in first pareto optimal front. Now the remaining solutions are again compared with each other and the better solution among them and the non dominated solution this time will occupy the second pareto front. This comparison among the solutions will continue until all the solutions are assigned till the last pareto front. The size of pareto optimal set increases or decreases according to the size of the objectives.

There are various techniques, approaches and algorithms which are designed for resolving complex multi-objective optimization problem [29]. The approaches are meta heuristic and assists in solving the multi- objective optimization problem [1]. There are existing approaches, techniques, algorithms and frameworks which are proposed by various authors and researchers for solving the problem with multiple objectives. These techniques includes Particle swarm optimization technique (PSO) [14], Vector evaluated genetic algorithm (VEGA) [30], Weight based genetic algorithm (WBGA) [24], Multiple objective genetic algorithm (MOGA) [16], Non dominated sorting genetic algorithm (NSGA) [26], Fast non dominated sorting genetic algorithm (NSGA-II) [9].

The paper gives a brief about the fundamental concepts of multi objective optimization problem in 2nd section. Brief descriptions of different evolutionary algorithm are discussed in section 3. Existing approaches which use genetic algorithm is studied in section 4. Cloud service ranking framework using NSGA approach is proposed in section 5. In the last section 6 conclusion and the future work is discussed.

II. MULTI-OBJECTIVE OPTIMIZATION

A multi-objective optimization problem optimizes two or more objectives while satisfying constraints defined within the problem [3,10]. In the real life application the objective defined are often conflicting which means that optimized solution obtained with one objective may not give best result with other objective which lead to a conflicting situation. The definition of multi-objective optimization problem is as follows [4]:

Let us consider there are n set decision variables, let there be k be the set of defined objective functions and the total number of constraints associated with objectives is defined by m. The decision vector a is defined in A decision space and the objective vector b is defined in the B objective space.

The objective of optimization approach is to provide optimized solution [5].

Maximization/ Minimization = $b=f(a) = (f_1(a), f_1(a), \ldots f_k(a))$

Subject to $e(a) = (e_1(a), e_1(a), \ldots e_m(a)) \leq 0$

Where $b = (b_1, b_2, b_3 \ldots\ldots\ldots b_n) \in B$

$a = (a_1, a_2, a_3 \ldots\ldots\ldots a_n) \in A$

Revised Manuscript Received on December 22, 2018.

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The decision space in multi-objective problems comprised of the various of candidate solutions. The objective space where the candidate solutions are matched with the objective functions. The fitness function for candidate solution is calculated after checking the position of the solution in the objective space. The calculation of the optimized solution in single objective is comparatively easier. Finding optimal result in case of multiple objectives various approaches and frameworks were designed. Non dominated or pareto-optimal solution are those solutions which are not being dominated by other solution at least in one objective [13]. The following is the definitions of pareto optimal solutions [19, 26] which are defined in the Pareto set (PS) [21].

Definition 1. A solution $x = (x_1, . . . , x_m)$ is said to dominate another solution $y = (y_1, . . . , y_m)$, denoted as $x < y$, iff $\forall$ $i \in \{1, . . . ,m\}$, $x_i \leq y_i$ and $x_i \neq y_i$.

Definition 2. A feasible solution $x \in \Omega$ of multi objective problem is called a Pareto optimal solution, iff $y \in \Omega$ such that $F(y) < F(x)$.

III. EVOLUTIONARY ALGORITHM

Evolutionary algorithms are the optimization methods which work on the population and helps in dealing with multiple-objective problem. Traditional algorithm uses genetic operators for solving conflicting multi-objective problems. Researchers are continuously working for multi-objective optimization problem and have also proposed several approaches, algorithms and framework [28]. The evolutionary approaches discussed in the paper are compared on the basis of their technology, functionalities and limitations. The algorithm are (VEGA) [20], (MOGA)[14],NPGA)[17], (SPGA)[15], (NSGA)[31], (NSGA-II) [22] .

IV. GENETIC ALGORITHM

A term genetic algorithm was given by J.H Holland in 1975 [18] and the algorithm is based on the biological evolution of nature i.e the solution which have better fitness value will have more chances of survival and will move to the next generation . The algorithm is based on genetic operators known as selection of the fittest individuals, crossover and mutation involves creation of new individuals. The general flow diagram of genetic algorithm is shown in figure 1.

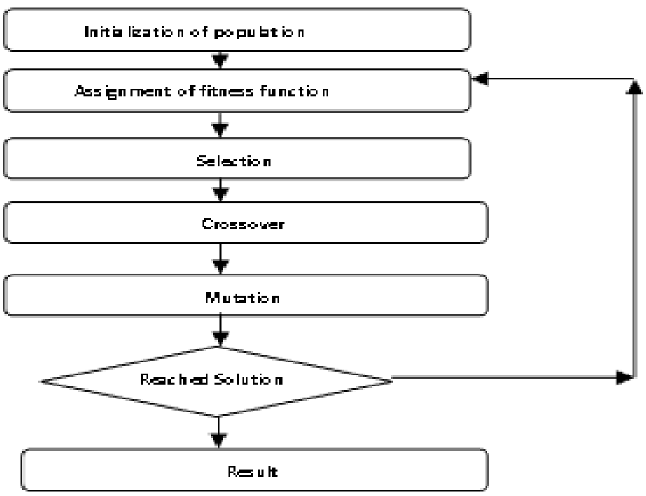

Fig 1: General framework of Genetic Algorithm [8]

The structure of genetic algorithm starts with the initialization of the population. There are two operators crossover and mutation which helps in maintaining diversity and convergence. Genetic algorithm is based on biological theory of natural selection which states that strong individual will survive and the weak individuals will extinct from the process of selection in next generation. In genetics the individual solutions are known as chromosomes and these chromosomes are made of genes which represents the attributes.

The framework starts with initializing the population by producing random solutions and then fitness value is assigned to these solutions. The fitness value of the solution will be the deciding factor that which solutions will pass on to the next level for mutation and crossover. The output of the above operators leads to the some optimal solution. If the generated solution satisfies the termination condition then the final optimized solution is said to be found otherwise the process is repeated again. After few generations the convergence will occur leading to the final optimized solution. There are two main operator in genetic algorithm are crossover and mutation. In crossover operator the two parent chromosomes combines together to form two new child chromosomes which is supposed carry the best characteristics of both the parents. The crossover operator helps in convergence to the good solution. Mutation operator allows random change of the attribute at the gene level of the chromosome. The mutation operator facilities by introducing diversity in the population and slows down the process of convergence to the optimal solution. The selection of the individual for next generation will depend on the fitness value assigned to the solution.

A. Multi Objective Genetic Algorithms

For solving the multi-objective optimization problems, genetic algorithm is widely used for finding the optimal solution. The algorithm evaluates and compares different set of solutions available and then find the optimal result for the problem. The genetic algorithm are efficient algorithms for handling situation where the problem is complex, non convex and discontinuous. The algorithm finds the solutions which are non dominated and are explored further using crossover and mutation operator. Genetic algorithm does not involve human intervention like involvement of user in prioritizing weights and this feature makes the algorithm a famous heuristic approach for providing solution to handle the issue related with multi-objective optimization problem.

a. Vector Evaluated Genetic Algorithm (VEGA)

Schaffer [28] proposed VEGA approach for dealing with multi-objective problems which is also an extension of simple genetic algorithm. The algorithm used the proportional selection method for identifying the sub population. Suppose the total population is 'N' and the number of objectives is 'K', the sum of sub population generated is t= N/K. The total population N is divided into the sub-population on the basis of individual objective . Suppose there are three objectives f1,f2 and f3 therefore the population N is divided into three sub-population on the basis of these three objectives only. The number of solutions in sub-population is not always equal in number it can either be equal or can vary in number. Once the sub-population is identified for each objective functions then all the sub-population are combined together.

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The sub population t is then shuffled and the new population of size 'N' is produced after that crossover and mutation operators are applied. The number of generation for finding optimal solution is completely based on the different objectives and the number of solution for finding the optimal result. The local dominated solutions are generated each time for the current population. The dominance relationship among solutions is identified and the solutions which are dominated are taken for next generation for finding optimal solutions.

Advantages:- The algorithm is uncomplicated and straight forward genetic algorithm which is used for finding optimal solution to multi-objective optimization problem. As the number of objectives are identified in the initial steps and the sub-population is identified on the basis of these individual objective function therefore the algorithm is useful for solving individual objectives.

Disadvantages:- The algorithm is less efficient in converging to the optimal solution while having a superiority only in one objective and are not good in other objectives.

The framework below shows the complete working of the vector evaluated genetic algorithm. The flow shows how the sub-population is identified from the total population.

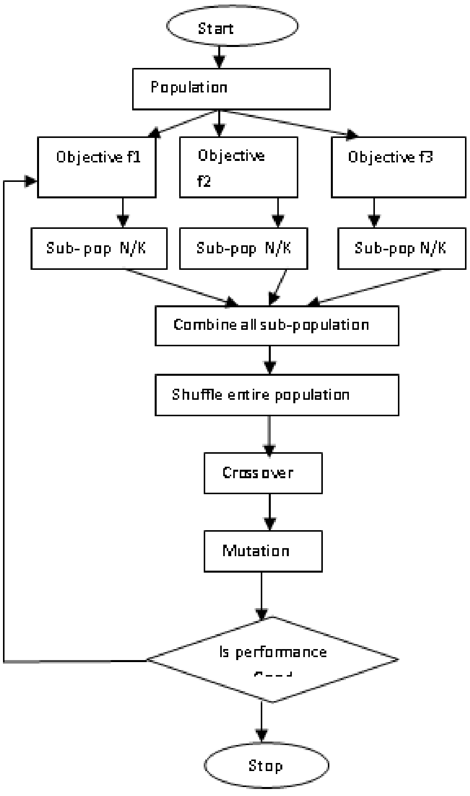

Fig 2: Framework of VEGA [27]

b. *Strength Pareto Evolutionary Algorithm (SPEA)*

The algorithm [7] uses methods from existing and new techniques for finding pareto-optimal set. The approach is based on finding non-dominated solution set. The approach starts with initialization of population and later creating temporary pareto optimal set where all the non dominated individuals are transferred. Weakly dominated individuals are removed by using clustering method thereby reducing number of individuals stored externally. The dominating solutions are taken into a separate set which are later evaluated on the basis of their fitness function value which is then assigned to the individuals . Once the fitness function is assigned to individuals then other genetic operators such as selection, crossover and mutation are performed on the individuals. The process is repeated for several generations till the optimal solution is not achieved.

Advantages: SPEA approach uses the best features of existing approaches and new approaches thereby increasing efficiency of the algorithm. Moreover this approach introduced the concept of elitism which gives preference to the non dominated solutions by maintaining their elitist class.

Disadvantages: If the external population size increases then the pressure for selecting elites also increases and the algorithm will become less efficient in converging to the pareto optimal front. If the population size is small then the effect of elitism decreases and the convergence to the optimal solution gets fast and elitist individual is not efficiently achieved.

The framework below shows the complete working of the Strength pareto genetic algorithm. The approach shows how the elitism is preserved in each generation till optimal result is reached.

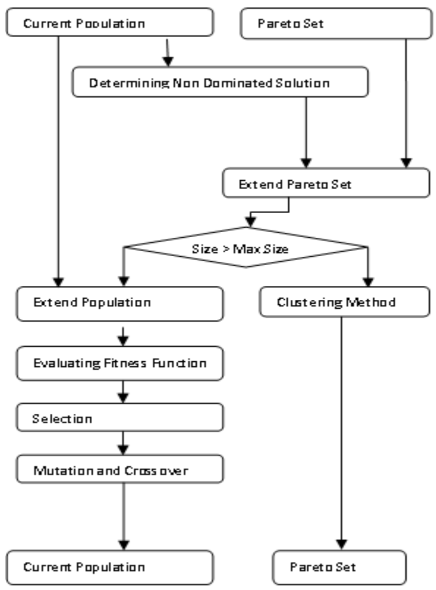

Fig 3: Framework of SPEA [29]

c. *Non Dominated Sorting Genetic Algorithm(NSGA)*

The algorithm [25] works on non-dominated sorting approach for identifying non dominated solutions which later be assigned the fitness value. The dominance comparisons between the solution is done and the solutions which are dominating are taken into consideration for the next generation and the non-dominating solutions are ignored. The first non dominated solutions are assigned the first pareto front and these solutions are then removed from the solution set.

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In order to assign the other solutions in second pareto front then the solutions which already are in first pareto front are ignored and the dominance comparison is done in between other solutions. The above process is repeated till all the solutions are assigned their respective pareto front as per their dominance in the solution set. Dominated individuals are found through crowded comparison approach which maintains diversity among the population. Once the solutions are assigned the pareto fronts then mutations and crossover is operated on the solutions. This process is repeated many generations till optimal solution is achieved.

Advantages : The algorithm helps in persevering diversity of the individuals in the population. It also reduces the complexity as compared to already existing approaches. Elitism helps in preserving already identified pareto optimal solution.

Disadvantages: The crowded comparison operator used for finding the solution can confine the convergence to the optimal solution. The complexity of non dominated sorting increases when the population size increases.

The framework below shows the complete working of the non dominated sorting genetic algorithm. The non-dominated approach for sorting the solutions if done so that they can be assigned respective pareto front. The framework shows the ranking of cloud services by using non dominated sorting approach.

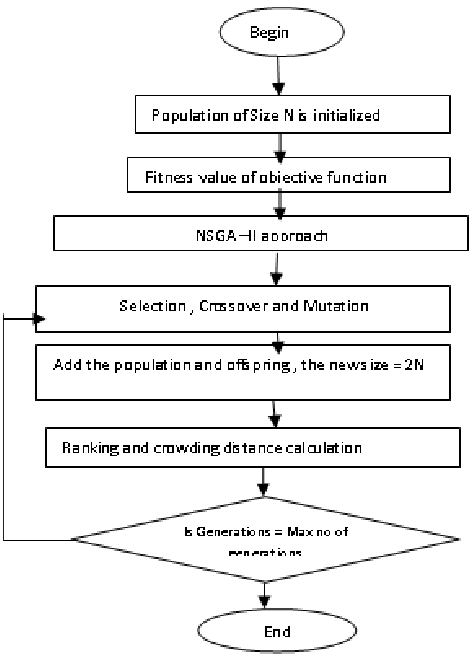

Fig 4 : Framework of NSGA –II [21]

V. PROPOSED FRAMEWORK FOR CLOUD SERVICE RANKING

The proposed framework for selection and ranking of cloud service use non dominated sorting genetic algorithm. The framework proposed can be used for ranking of cloud services for multi objective optimization problems. The framework starts with a solutions Steps of the proposed framework are discussed below:

Step 1. *Sieving step* helps in identifying cloud services which can meet the desired requirement of consumer and such services are names as candidate service. The identified services are known as the initial population required for further process.

Step 2 *Non Dominated Sorting* step involves sorting of population in ascending order for each objective function. The sorting approach used here is bucket sort.

Step 3 *Ranking step* involves ranking of all the sorted services and assignment of same ranked services to same pareto fronts.

Step 4 *Dominance Comparisons* step involves comparing the services in same pareto front for their dominance comparison.

Advantages : The sieving step will filter out the services according to the requirements of the customers therefore the non dominated sorting approach will have to sort lesser individuals and the ranking to the services will also occur for less individuals. The proposed framework will improve the efficiency by maintaining diversity and elitism. The overall time taken in sorting of the population will decrease as now the sorting method has to be applied only on the candidate solutions.

Disadvantages: The proposed approach will increase the overall time as two methods sieving step and local search are applied in NSGA algorithm. Also some of the services might not be covered which can be essential for user but not covered under his requirement list.

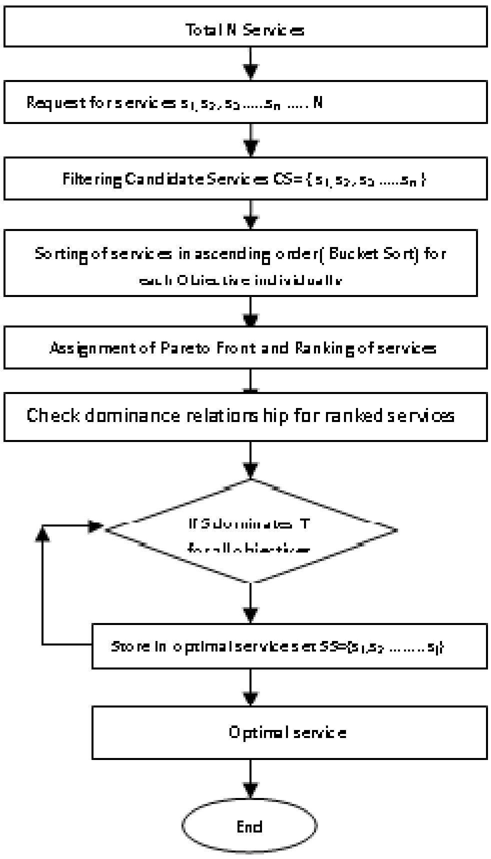

Fig 5: Proposed framework for Cloud Service Ranking

VI. CONCLUSION

The existing approaches generally takes into consideration the objective parameters and therefore subjective parameters are ignored which are also important when the cloud services are ranked. The proposed model considers both the parameters and the future algorithm can cover both of them. Although there exists various service selection techniques, algorithms and frameworks still there are chance of improvement. In future the proposed framework can be used for designing of an efficient algorithm for improving the efficiency for ranking the cloud services for multi-objective optimization problem. The algorithm designed using proposed framework will not only overcome the limitations of the existing approaches but will also improve the efficiency and accuracy of the ranking of cloud services. The proposed framework can also be extended for other evolutionary algorithms.

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