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A Comparative Study on QoS-based Web Service Selection using GA, PSO and ACO

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Abstract —**With the increasing number of functionally similar web services, the need for good selection strategy is also increasing. The proper choice of selection strategy makes it possible to choose the matching web service without losing the performance efficiency. To differentiate between different candidate services, some non-functional parameters known as QoS (Quality of Service) are considered. Web Service Selection on the QoS parameters is a NP-Hard problem. Bio inspired algorithms are being used to offer better and near-to optimal solutions to NP-hard problems as compared to other algorithms. In this paper, a comparative study on application of three bio-inspired algorithms (Genetic Algorithm, Particle Swarm Optimization and Ant Colony Optimization) for solving web service selection problem is presented. Further, the state-of-the-art is reviewed and advantages, research gaps, important observations drawn and possible future directions are also discussed. Papers from last thirteen years are used to perform the review.**

Keywords — Web Service Selection(WSSel),Composite Web Service(CWS), Quality of Service(QoS), Genetic Algorithm(GA),Particle Swarm Optimization(PSO),Ant Colony Optimization(ACO).

I. INTRODUCTION

Web services are software that can be universally deployed and invoked over Web. They are platform as well as language independent. Web services uses XML messaging and communicate through Simple Object Access Protocol (SOAP) using Hypertext Transfer Protocol (HTTP) [1]. Different service providers provides services by registering them in UDDI (Universal Description, Discovery, and Integration) along with WSDL (Web Service Description Language) [1] and service consumers can use them from UDDI according to functionality they require. Due to ease of usage and code reusability SOA(Service oriented Architecture)[2] is followed mostly now-a-days. Micro services are another concept of Application Development Architecture is a method that allows parallel computation by breaking large software applications into loosely coupled modules. In micro service architecture each module runs different service as a unique process and communicates through APIs [3]. They differ from web services in a way that in micro service architecture a service performs single task while a web service can perform multiple functions and can call multiple APIs.

There are many web services provided by different service providers that provide similar functionality. To select a web service from a pool of services is known as Web Service Selection. To differentiate among functionally congruent web services, Quality of Service (QoS) parameters like reliability, throughput, availability, cost, response time, etc are useful. Along with functional requirements, service consumers also have some non-functional requirements. These QoS are defined as constraints known as quality constraints that are provided by the end user. The web services offered by various providers, need to meet these quality constraints. Services from different providers can be integrated into a composite service regardless of their locations, platforms, and/or execution speeds to implement complex business processes and transactions. This process of making a service composite service is known as Web Service Composition.

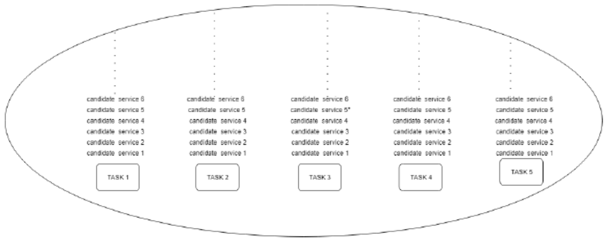

Fig 1. Problem scenario

Selecting combination of web services to perform a composite task is a problem considered in this paper. From the past research it is found that the problem of selection of WSS is a NP-hard problem[6],[7],[12],[14],[26].Various approaches for solving this problem are proposed. These proposed methods either finds best local solution or best global solution, however, experiences some issues like fail in satisfying user needs, less efficient, etc. Many of the past

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researches on web service selection have used Computational Intelligence algorithms which includes Bio inspired algorithms.

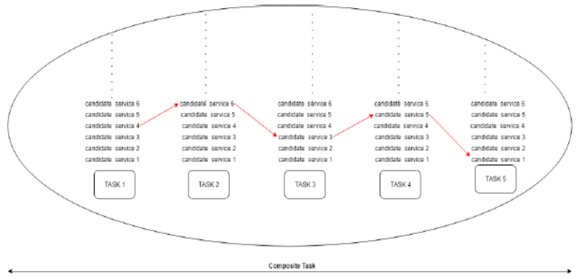

Fig 2. Example of solution

Bio inspired algorithms are based on meta-heuristics for searching near optimum solution for any optimization problem. They evolve through number of iterations and led to find a solution that may be the best solution possible or can be a solution. The existing state-of-the-art related to bio inspired algorithms based web service selection needs to be studied thoroughly to identify the possible research gaps and carry out the improvements in selection strategy. Thus, in this paper we have done a detailed review of three widely used and popular bio inspired algorithms for selection of web services - Genetic Algorithm (GA), Particle Swarm Optimization (PSO) and Ant Colony Optimization (ACO). Also, the comparative analysis of these techniques and combination of them to solve the web service selection problem is presented. Figure 1 show a problem scenario and figure 2 shows example of possible solution which will be on the basis of quality parameters of web services. For this review paper we have considered papers of last 13 years on GA, PSO, and ACO based Web Service Selection.

Rest of the paper is organized as follows: Section-3 presents a detailed review on state-of-the-art. Section-4 highlights the various observations drawn from the survey followed by conclusions drawn from the study in Section-5.

II. Bio inspired algorithms

In this section a brief introduction about the three algorithms is given.

2.1 Genetic Algorithm : A heuristic algorithm for finding the near-to-optimal solution more efficiently rather than exact solutions. It is based on Darwin'sprinciple of natural selection and evolutionary biology. It is an bio inspired algorithm in which at each generation fitness of the individuals are checked and the one with higher fitness has probability of being chosen. At each generation, individuals undergo cross-over and mutation that are genetic operators responsible for convergence and divergence of search space respectively.

Length of Chromosome of GA for WSS_{el} is equal to number of tasks and a gene corresponds to web service corresponding to a task.

For solving WSS_{el} problem, The genetic algorithm as mentioned in [4] is as follows :

Algorithm 1 : Genetic Algorithm

```
{
  Initialize population randomly;
  Evaluate fitness of each individual in the population;
  While stopping condition not achieved
  {
    Perform selection;
    Perform crossover and mutation;
    Evaluate fitness of each individual in the population;
  }
}
```

2.2 Particle Swarm Optimization : A biologically inspired algorithm that follows the pattern of swarm of real birds for their technique to search food source. A bird nearest to food source give direction to all other birds in swarm. Similarly artificial birds called particles are assigned a position(x) and velocity(v) which is improved at each iteration. Each solution has a value calculated using a fitness function which determines how convenient that solution is. Particles move in the search space based on their previous direction, best position found (local best), and the best position in the swarm (global best). Particle of PSO are all web services participating in selection. Pseudo code for PSO is discussed below.

Algorithm 2:

```
For each particle
    Initialize particle
END
Do
    For each particle
        Calculate fitness value
            If the fitness value is better than the best fitness value (pBest)
            in history
                set current value as the new pBest
        End
  Choose the particle with the best fitness value of all the particles as the
gBest
  For each particle
    Calculate particle velocity according equation:
  v[] = v[] + c1 * rand() * (pbest[] - present[]) + c2 * rand() * (gbest[]
- present[])
 Update particle position according equation
  present[] = persent[] + v[] (b)
  End
```

v[] is the particle velocity, persent[] is the current particle (solution). pbest[] and gbest[] are defined as stated before. rand () is a random number between (0,1). c1, c2 are learning factors. usually c1 = c2 = 2.

2.3 Ant Colony Optimization :

ACO is a meta-heuristic which relies on a set of artificial ants which communicate with each other to solve optimization problems. This algorithm is inspired from real ants, which search for food and find the shortest route to the food source. Some ants starts searching in different directions by different routes and lay pheromone trails so that other ants can follow them. This pheromone evaporates after certain time and the path on which pheromone deposition is maximum, that path is chosen as best solution. Algorithm consists of three steps which are repeated until a stopping condition is fulfilled .Before these steps are iteratively performed, ants are initialized by setting them in a position in search space. Then, each artificial ant builds a

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solution by deciding to add a new solution component to its partial solution probabilistically in step one ,in the second step, a local search is performed optionally by each ant aiming to improve their associated solutions, in the third step, based on the quality of each solution which is evaluated with a fitness function, the pheromone level of each solution is updated (increased or decreased) [5].

Algorithm3 :Basic ACO algorithm

Set parameters and Initialize pheromone trails

```
Begin
 bestA = {};
 repeat
  for each ant k do
   construct an assignment Ak;
    if fit(Ak) < fit(bestA) then
      bestA= Ak;
  endfor;
 update pheromone trails;
  until the maximum evaluation number is arrived or the other
  termination condition is satisfied;
return bestA;
End
```

III. LITERATURE SURVEY

The Web Service selection (WSS_{el}) is an important research area for past decade. Many solutions are suggested by the researchers to deal with the problem of WSS_{el}. In the following section, the review of existing techniques on WSS_{el} is done in brief. The WSS_{el} can be done in many ways.

3.1 Genetic Algorithm : In [6] Genetic Algorithm is used for solving QoS aware WSS_{el} problem in which both static and dynamic fitness functions are considered. In dynamic fitness function penalty factor and number of maximum generations can be changed dynamically within iterations. In [7] GA is improved by making changes in fitness function and mutation policy and applying relational matrix as encoding scheme. Three objective functions and four mutation policies are proposed and are compared with both one dimensional coding scheme as well as relational matrix coding scheme. Results shows which objective function and mutation policy is better and even encoding scheme performs well. A self-adaptive GA is proposed in [4] in which parameters like population size (based on best individual), number of cross over points and mutation rate are adaptively fixed which results in more explorative search. It groups the population in which individual of same group reproduce and that of different group compete to perform better and uses previously discovered knowledge for focused search [4]. Michigan style was used to built classifier and machine learning techniques are used to test the system. The solution for problem of prematurity and convergence was proposed in [8] as population diversity handling mechanism and relational matrix coding scheme. Expectation value(e) is calculated (on the basis of fitness of population) for population and the one having lower value of e is replaced by the one with higher value, hence the population with lower diversity is promoted thus population diversity is handled and for improving convergence initial population is such selected that every gene have higher value of fitness and number of chromosomes depends on number of paths of chromosomes. Genetic operators can generate invalid chromosomes therefore the children are checked and if found lower in case of either fitness value or genetic factors then it is replaced by mother.

Another solution is proposed in [9] in which filtering mechanism is used along with selection mechanism. After filtering out the web services, candidate services go for filtering for optimal quality checking and workflow management engine so that QoS of overall workflow is checked.GA is applied for selection on the basis of QoS of workflow, solution is given. In [18] a top-down approach is proposed in which global quality constraints are decomposed into local constraints using GA and then linear search is performed to obtain optimal solution at atomic level. The utility degree is calculated for each QoS property and accordingly quality degrees are set and then selected locally through linear search strategy. In [11] a comparative review on premature convergence of GA is proposed. Different researchers presented different solutions for premature convergence of GA. Changes are made in genetic operators crossover and mutation) and their effects are discussed in [18].

A multi-population genetic algorithm (MGA) is proposed in [12] which tries to find feasible solution set and if not found it aims to minimize the violations of QoS by relax constraints. The difference between quality constraints and quality values are calculated and the one having larger value than constraint are denoted as d_i^+ and one with lower value as d_i^- where i denotes i^{th} quality parameter. Also it divides the population with large number of individuals into sub population and solves it in parallel. In [13] solution is proposed using GA as Multi-objective Bio inspired algorithm (MEO) in which different parameters are considered as multiple objectives rather than combining them as single objective. Ranking of individuals is done the basis of feasibility of solution which is defined by comparing the dominance of two individuals. Reputation is considered as fuzzy values and then converted to crisp values. Feasibility of the solution is shown using Travel Service as example.

In [14] a transactional mechanism is proposed to get reliable solution for QoS-aware WSS_{el}. Transactional properties are introduced for single web service as well as composite web service and then transactional rules were proposed. On the basis of workflow, performance of CWS is evaluated with the help of a method called TCA proposed previously is used to find the probability of successful execution. It aims at satisfying transactional rules and maximizing QoS. Population initially is generated randomly but it is judged whether it is TCWS or not. It contains three sub-algorithm: IG(for creating initial group), TCAC for performance evaluation on the basis of workflow and GA for selecting TCWS(GAST).Proposed algorithm is compared with exhaustive algorithm and

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found GAST to be better in aspects of execution time and QoS values selected.

3.2 Particle Swarm Optimization : PSO algorithm for solving WSS_{sel} problem is applied in[15] and the problem of lower fitness value of PSO is considered and solved by introducing hybrid-PSO in which PSO is combined with Munkres algorithm which results in higher scalability and good fitness value.The velocity and displacement modes are slightly changed and improvement in search ,convergence rate and execution time can be observed in [16].Integers generated by uniform distribution are added to the velocity model which controls the evolutionary search inside the integer search space. The bird's communication mechanism is modified in [17] ; the entire community is divided into colonies (after arranging the birds in descending order of their fitness) and from each colony local best is selected and velocity is changed accordingly.

The solution to the problem is designed as Fuzzy expert system in [18] to adapt dynamically to respond with dynamic nature of QoS. Fuzzy Expert System works on rules and fuzzy membership function[18] and these rules are generated automatically through training set data by Fuzzy Clustering and PSO. An improved discrete immune optimization algorithm based on particle swarm optimization (IDIPSO) is proposed in [19] which uses clone proliferation and hypermutation of immune optimization algorithm and considering particle as antibody , the problem is solved effectively by adding changes in local selection strategy of PSO. In[20] Skyline algorithm is used for pruning redundant services and then PSO is applied for cloud based CWS Selection. With the help of skyline operator dominating services are selected from each service group and then they are provided to PSO algorithm for finding optimal combination.

An approach is proposed for finding solution for WSS_{el} problem in lesser time in [21] hence decreases time cost. They proposed to design a coding scheme to get optimal quality control line therefore integer array coding scheme is used and then PSO is applied. Experimental results shows that execution time is actually very less (that is less than 1 second for services below 500). In [22] PSO is applied for solving the selection problem by formulating it as optimizing problem and solved it using more number of QoS parameters. in [23] an intelligent optimization algorithm is proposed by combining Shuffled Frog Leaping Algorithm(SFLA) and PSO, which overcomes the shortcomings of both algorithms like SFLA is unable to find optimized result and PSO can't keep stability of optimization. the particles or candidate services are represented as frog and updating rule of SFLA and PSO are redesigned. If maximum allowed updation in frog's position is exceeded then frogs can be replaced for obtaining the position of local best. The position of particle is updated according to its previous best position as well as the fitness function. Initial population is initialized with the help of SFLA because it finds optimal regimen and if any frog violates, it is replaced. An improved Discrete PSO is proposed in [24] that uses search operator of Artificial Bee Colony(ABC) to prevent PSO falling into local optima and to maintain balance between selection space and global convergence. The diversity parameter of PSO is used to control execution time of ABC search operator. Addition operator of PSO can create new position, subtraction operator can create new velocity. When particle diversity is less than diversity parameter (that is a constant), then ABC search operator is used to produce diversity.

Multi Objective PSO(MOPSO) is introduced in [25] which differs from PSO in three aspects that are :

- If new position and local optima of any particle are non-dominating solutions, then a mechanism is needed for this particle to be chosen as new local optimum.
- A mechanism is needed to select global optimum from a set of non-dominating local optima.
- The size of set of non-dominated local optima in all iterations can exceed the external archive size, so the update of external archive should scatter it evenly in objective space.

Algorithm is tested on the basis of Generational Distance (GD) that is calculated using Euclidean distance, Spacing, Maximum Spread (MS) for calculating approximation, uniformity and coverage respectively.

Multi Colony-PSO is proposed in [26] in which interacting swarm model is combined with PSO. Particles are sorted in descending order of their fitness and then divided into certain number of colonies. By using multi-–swarm cooperative approach, provides optimal result and provides diversity. Colonies work coordinately and cooperatively with each other and compete with the particles from another colony which helps in achieving global best. Worst particle from any colony is improved using some formula upto a certain limit and after that it is eliminated and replaced by some random particle. In [26] local search is done by applying availability and reliability for fitness evaluation and for global fitness evaluation overall response time and cost are considered.

Another method for optimistic WSS_{el} is proposed in [27] in which a graph-based approach and a greedy -based approach is proposed and compared. A master graph is constructed first that contains all possible inputs and outputs and then solution is found along with considering sequential and parallel workflows. Graph-based algorithm chooses next node on the basis of maximum value of edge score which is calculated at the time of creating master graph, while greedy- approach chooses next node randomly keeping in mind functional property required. Observations concluded that if high fitness value is required and execution time could be high then graph-based algorithm can be applied, and if inverse is required then greedy – approach can be applied. Accurate sub-swarm PSO (ASPSO) is introduced in [28] in which

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premature convergence problem of PSO is solved by niching technique (An extension of bio inspired algorithm: EA technique that is used where target is multiple optima or where EAs tends to converge fast). The particles are divided into sub groups called sub swarm and their grid cells are stored in separate file. Grid represents the maximum solution space for a sub swarm and the most feasible solution of the solution is also stored in a separate file. Sub-swarms are constructed in the areas where density of solution is higher and clusters are constructed using simple clustering. Main swarm and sub swarms are separated using niching technique and size of particles is maintained throughout hence providing better search and avoids particle falling into local optima.

By modifying inertia coefficient and dynamic particle modification, premature convergence problem of PSO is tried to be resolved in [29]. Higher the value of inertia weights results in more global search and lower the value of inertia weights results in more local search. To improve efficiency, inertia coefficient adjustment function is introduced which first assigns higher value for global search and then decreases its value gradually after number of iterations. Constantly increase or decrease in inertia weight will give negative impact on searching therefore any change in inertia weight is performed with some probability. Particle modification function is also introduce which selects particles that have best evaluation function value and then extract the properties that are restricting them to become optimal solution. Services satisfying those parameters are found from remaining service set and then replaced; hence better solution with higher efficiency is achieved.

3.3 Ant Colony Optimization:

[30] proposed a model of WSS_{el} with global QoS optimization and convert it into a multi-objective problem solution.ACO is applied first time in this model for solving multi objective problem in which problem is designed as a graph and dominance of different paths are calculated on the basis of QoS parameters. Paths are chosen randomly. Pheromone matrix for each path is stored and updated when required. Another solution to multi objective optimization problem is given in [31] in which slight changes are done in pheromone updation and transition probability in which learnt desirability of a node is to be selected is done on the basis of its predecessor, thus changes are done in pheromone laying phenomenon. In [32] optimized path is found with the help of ACO and then ranking is done on the basis of performance index calculated with the help of QoS parameters.

All the previous researches uses static graph but graph construction is done dynamically in[33] using unsupervised clustering process thus increases exploration. The path of graphs are exploited using dynamic expanding process and to reduce problem space for ant based clustering, Multicriteria Dominance Relation are introduced to reduce the problem space for which skyline filtering is used and after that unsupervised clustering process is applied to partition the skyline set and construct a graph. Min-Max of pheromone is set explicitly to confine the search exploration. Ant based clustering process is used for clustering defined in [34]. A method for dynamic changing QoS in different cases is proposed in [35]. On the context of number of invocations for service three cases are considered they are :

- Number of invocations exceeds upper threshold or less than lower threshold, then service provider rejects the requests.
- Number of invocation is between upper and lower threshold then QoS of service is degraded.
- Number of invocations is between upper and lower threshold and QoS of service remains unchanged (for example provider somehow increases the number of physical resources).

Different paths are found by ACO and distance for them are calculated on the basis of QoS which should be minimum. Different possible cases of value of distance and their solutions are:

If all QoS are equal and Distance are equal then randomly choose one

- If at least two QoS differ but Distance are equal then leave choice to user for which value of QOS is required.
- If neither Distance nor QoS are same, choose the one with minimum distance value.

For AND/OR cases(AND means parallel and OR means fork), best QoS of their successors are calculated and then weight of edges between them are calculated(using QoS). In case of OR, choose best one from all its successors and for AND case choose one from every successor. Different changes are done in local and global pheromone updating rules for all three cases. For case 1 no change is , for case2 a factor U^{Th} is introduced that is a parameter controlling pheromone evaporation and the is number of invocations from service.

In [5] Enhanced Planning Graph is constructed dynamically according to each user by some Web Service Composition method after that 1-OPT heuristic is defined which controls the expansion of search space so as to avoid local optima and stagnation. The heuristics used in probabilistic function is inversely proportional to weighted sum of QoS parameter values. Generalized MOACO (Multi-objective ACO) is proposed in [36] and is compared to MOGA (Multi –objective GA) in non-dominating solutions are included in a set and pheromones are updated accordingly.

In [37] ACO is applied for solving cloud based WSC problem. Two algorithms were proposed Greedy_WSC and ACO_WSC, in which a set of minimum clouds of higher quality and time efficient is to be found that can satisfy user constraints. Problem is modeled as digraph to be solved using ACO. Changes are made in selection probability of ACO by using [$\theta^{i}_{j}(t)$], which is gain parameter that shows gain by ant by selecting i^{th} path,

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which works as positive feedback for that path. As compared to many existing algorithms this algorithm works well in case of efficiency and running time. A heuristic function, global and local pheromone updation and combined state transition rules are proposed in [38]. A heuristic function is defined that covers objective for all parameters and different objective functions are not needed. Global and local pheromones are updated using min-max values and concept of re-initialization is also used that is if optimal solution is found the pheromone matrix is reinitialized for next iteration.

3.4 Combination: A very few of the solutions for solving the selection problem in the context of web service also includes combinations of GA, PSO and ACO. In this sub-section, review of state-of-the-art on combination of GA, PSO, ACO is presented.

3.4.1 GA and PSO :

In [39] two approaches were proposed using GA and DGC-PSO. Service Selection problem is considered as finding match between service consumer and service provider and match score is considered as fitness function for algorithm. Experiments are done using DGC-PSO ,GA and Munkres algorithm and results are compared. Munkres algorithm is an Hungarian algorithm used for combinatorial problem. Results were found that Munkres algorithm provides best match score as compared to both the bio inspired algorithms but fails in terms of scalability.In case when selection result for large problem is needed in less time and scaling factor is needed to be raised to higher power in this case DGC-PSO shows better result than both of the other algorithms.

3.4.2 GA and ACO :

In [40] a combination of GA and ACO is proposed as solution to WSS_{el} problem. GA is used to set the key parameters of ACO like population generation, the times for selecting path, fitness computation etc. that can overcome the shortcomings to ACO algorithm. Hence by getting optimal parameters for ACO , we will get an optimal result .Experimental results concluded that speed and probability of getting optimal result increases and average number of iteration for obtaining optimal (or near to optimal results) increases. For finding initial pheromone trails, GA is used in [41]. GA is vulnerable to partial optimum, has slow convergence and weak partial searching while ACO results in slower start and stagnation because of initial pheromone distribution. These disadvantages of both these algorithms are resolved here by combining both of them. Global and random search ability of GA is used for initial pheromone formation which will be optimized already in accordance with user requirements and then from n number of solution sets obtained, final result is obtained by applying ACO and using positive feedback mechanism and parallelism of ACO. In [42] improved ACO and improved GA are combined in a manner opposite to that in [41]. ACO is used for generating initial population for GA. Disadvantages of ACO like lack of global search ability and stagnation is resolved using GA as GA has characteristic of high global search ability. Similarly characteristics like positive feedback and high convergence speed of ACO are used by GA for improved results. ACO is improved by introducing partial pheromone updation that is done including pheromone decay coefficient responsible for pheromone evaporation. Maximum and minimum value of pheromone deposition is fixed to avoid algorithm converge to local optimal solution too quickly. Non-Dominated Solution Set (NDSS) is derived from ACO and is given as initial population to GA. After GA process, if optimal solution is not obtained, then again the population is passed through ACO until optimal solution is not obtained.

3.4.3 PSO and ACO :

In [43] a combination of PSO and ACO is proposed so as to overcome shortcomings of ACO. The rapid global convergence characteristic of PSO is used to find several optimal paths and set the initial pheromone values of those paths, then by using ACO's feedback mechanism and parallelism, further optimal solution is found. Concept of elimination is also introduced as if any particle even after number of some fixed iterations does not reach any extreme point that means it had stuck in local optima so it is eliminated.

3.4.4 GA, PSO and ACO :

In [44] Lijuan Wang, Jun Shenl and Jianming Yong discussed about different bio-inspired algorithms(Ant Colony Optimization(ACO), Genetic Algorithm(GA), Particle Swam Optimization(PSO) and Bio inspired algorithm(EA)) used for web service selection and concluded that GA,EA and PSO suffer from problem of premature convergence while ACO is less efficient. Some researchers performed combination of these algorithms and found different merits and demerits of them. Lijuan Wang, Jun Shen in [45] categorized bio inspired algorithms into optimal, suboptimal and meta-heuristics and gave observations of different researches on the basis of four factors: cost, availability, reliability and time. They summarized the result on applying ACO, PCO GA and their combinations and discussed about some remaining problems to be researched. They concluded that mostly local optimization approach cannot satisfy global QoS constraints and meta-heuristics find near-optimal solutions while sub-optimal algorithms have good scalability as well as less computational complexity as compared to optimal algorithms.

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TABLE 1. Following table shows different parameters of GA and their values used in different methods

Reference	Selection technique used	Mutation point	Cross over point	Mutation probability	Cross over probability
[41]	Roulette Wheel	NM*	NM	NM	NM
[42]	Bubbling up	Single point	Single point	NM	NM
[6]	Roulette Wheel	Single point	Two-point	0.01	0.7
[7]	Roulette wheel	Single point	NM	0.1	0.7
[4]	Elitist scheme	NM	Adaptive(non-uniform)	0.01	1
[8]	Roulette Wheel	Single Point	Single point	0.1	0.7
[9]	NM	Single point	Single point	NM	NM
[40]	NM	Single point	Single point	0.05	0.6
[18]	Roulette wheel	Single point	Single point	0.10	0.80
[12]	Roulette wheel	Single point	Single point	0.05	0.7
[13]	Tournament Selection	Single point	Single point	0.5	0.9
[31]	Roulette wheel	Single point	Single point	0.10	0.9

TABLE 2. Following table shows advantages and disadvantages of different algorithms proposed

Reference	Advantage	Disadvantage
[4]	Self adaptive GA parameters.Better performance and convergence rate as compared to other techniques.It helps in overcoming GA deception better.High classification rates.	Performance varies application to application.
[5]	Search space is controlled using 1-OPT heuristic method that control local optima and stagnation.Number of ants scaled exponentially so that graph size is independent of algorithm time.	NM
[6]	GA permits to deal with non-linear aggregation function of QoS.Good Scalability.As observed performance time is almost constant with increasing number of tasks.Both static and dynamic fitness functions are considered.	Static fitness function outperforms dynamic fitness function.Less significant difference in results when compared to Integer Programming.When workflow size and number of concrete services are limited,Integer Programming outperforms GA.
[7]	Relational matrix encoding scheme is used as one dimensional encoding scheme cannot represent all possible paths.Different fitness functions which deals with negative and positive QoS parameters in different manner. Convergence speed of GA is improved.	Average fitness from the fitness function which is found best, decreases with increasing number of tasks.
[8]	Initial population is selected with high fitness value so further generations come up with higher fitness values.Evolution policy increases search range of composition plans and convergence of GA is enhanced.Population diversity handling mechanism help in obtaining more optimal solution. With the increasing number of tasks, fitness value improves.	Execution time is longer.Suffer with slow convergence. Does not bring better fitness.Suitable for large composite size only.
[9]	Filtering before selection decreases the time and cost required for execution. QoS are calculate on the basis of workflow.Local optimization results in good genetic components.Size of population does not affect the performance.	Wastage of time and cost to check different workflows when number of tasks are very less.
[10]	Top-down approach in which local optimization approach followed along with satisfying global constraints every time.It is efficient and effective.Lifetime is assigned to each and every chromosome on the basis of fitness so that the one having low fitness value is not directly discarded can be the best after going through genetic operators.Local selection is done by linear searching having complexity O(n).A utility value is calculated for each service and binding to expected utility for task is done accordingly.Stabile fitness and convergence is achieved faster as compared to general GA solution.Running time is less.	A good fitness value is achieved only when population size is large.Computation time strongly depends on initial population size.
[12]	By using the concept of relaxing constraint it minimizes the gap between user requirements and Web service composition.Faster convergence as each sub-population evolved independently.Lower fitness value is considered as better performance.Better efficiency and scalability.	More resistant to premature convergence.
[13]	With the use of concept of dominance best feasible individual is selected. Number of non-dominated sets increases with increase in size of population.	The behavior of algorithm is anonymous. Number of objective functions equal to number of quality parameters.
[14]	Reliable results are achieved.Results obtained are more optimal.Execution time is almost constant with increasing number of concrete services.Considers transactional properties and rules as fitness function.	It may result in CWS that is not satisfiable for user. It may give nil result.
[15]	Balance between fitness value and execution time is maintained.Better scalability than Munkres algorithm.	Fitness value first increases then the graph flattens with increasing number of iterations. Execution time is larger as compared to PSO as more time is needed for local search.
[16]	Time complexity is improved as compared to GODOSS algorithm. Better search because of improved velocity and displacement modes. Fuzzy values of QoS parameters are coverted to numerical values for evaluation and quatized by Cauchy distribution membership function. Experimental analysis showed that convergence rate is faster and computation time is lesser as compared to GODOSS.	NM
[17]	Solves the problem of premature convergence.Provides better and more optimal results than PSO.Provides bi-directional information sharing ; both pbest and gbest can exchange information to others.	NM
[18]	It is adaptive in nature as rank of Web Service is changed dynamically with any	

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	change in QoS of it.Output feedback is considered which is used to decrease the number of rules which fastens the processing.	The response time of the algorithm is large.
[19]	Operations of artificial immunology are combined along with PSO operations so as to get more optimized and refined result.Improved local best first strategy results in improvement in local fitness as well as composite fitness.Dynamic self adaptive rule is proposed.Convergence speed as well as swarm divergence is enhanced.Experimental results are better as compared to CoDiGA and PSO in terms of search ability,convergence property and stability.	Fitness value first increases with a number of iterations and becomes constant after some number of iterations.User should have sound knowledge of immunology to use this algorithm without confusion.This algorithm takes more time for less number of tasks.
[20]	Time cost reduces to upto 80 %.Pruning with skyline results in decreased size of search space and better convergence.Achieved about 96% optimality in dynamic cloud based environment.	Less stable.Only selects the best as a result of local selection.
[21]	Very short amount of time is required for finding best results.	Not scalable.
[22]	Convergence of PSO is improved.	Execution time is higher. Navigation plan of particles in search space did not give best results.
[23]	High accuracy and good stability of optimization.With increase in number of services, the optimal solution is still smaller.Algorithm provides high precision.	**NM**
[24]	Search ability and convergence is enhanced.Convergence speed is better than that of GA.Results produced are better than DPSO.	**NM**
[25]	GD value of MOPSO is smaller than GA that means MOPSO is better in approximation.MS value is also better that means Optimal solution obtained covers more areas in solution space.	Algorithm fails when tested for uniformity that means it does not scatter well.
[26]	Cooperation and coordination of different colonies help in achieving diversity and globally optimized solution.Bird can jump from local optimum to neighborhood of possible global optimum.Premature convergence is resolved by balancing global and local search.Performance is improved.New solution is randomly generated if no updation is possible.	Execution time required is more.Mean price is high.
[27]	Solution set calculated gives higher fitness values.Graph-based algorithm converges less faster than greedy-based approach.On the basis of edge score, maximum values of quality parameters selected always.By calculating longest path, maximum cost can be calculated.This approach does not require user with domain expertise.	Execution time required by graph- based algorithm is quite higher than greedy- approach.Does not include preventive measures for forming cycles while traversing the graph.
[28]	ASPSO provides resistance to local optima.Performance is steadier than other algorithms.Accuracy of PSO is improved.Exploration and exploitation capabilities are balanced properly.	Ideal for swarm size below 40 as accuracy is not much improved after that.Execution time is higher.ASPSO is computationally complex.
[29]	Efficiency of PSO is enhanced.Reliability of particles is either improved or in worst case remains constant.Global to local search is improved by adjusting inertia weight.Success running rate is significantly improved.	Running time of algorithm is still high.
[30]	Everytime the value of dominating path is changed, pheromone matrix is re-initialized so as to improve exploration, and otherwise global update is made to improve exploitation.For less number of iterations , performance is better than MOGA(Multi-objective GA).On Increasing number of web service type performance increases and larger number of solutions are obtained. Running time is less than MOGA.Good feasibility and efficiency.	**NM**
[31]	Pheromone trail is optimized.Selection of next done is done on the basis of learning of predecessor node.Pheromone update strategy and transition probability are adjusted to slow down the convergence speed.	On decreasing the number of iterations, response time and price also decreases but less number of iterations cannot give more optimal results.
[32]	Robust and have high tolerance.Provides advantages like service reusability and loose coupling.	**NM**
[33]	Exploration is increased by construction of digraph.For improving exploitation dynamic expanding process is used.Min-Max value of pheromone is set explicitly to confine search exploration.Best convergent point as compared to some variants of GA and PSO.Does not converge faster neither trapped in local optima.	Slower for smaller test instances.
[35]	Weight of edges can be changed dynamically and can deal with dynamic changes of QoS.Result obtained is of high quality.	Time taken for execution is higher.Cost required for execution is high.Minimum distance is either same or increased after transforming from mixed to meta-control logic, execution time is also increased.
[36]	Outperformes GA when number of iterations are less.For large number of web services and web service type, it out performs GA.Time astringency is better.	**NM**
[37]	Gain parameter helps in choosing better result set. Gives results in less amount of time. Execution time is also less. Quality of result is good.	Cannot work in dynamic environment.
[38]	Using min-max pheromone value, search is confined. Exploration and exploitation are improved.	Converges after fitness number bigger than $1*10^5$.
[39]	Both DGC-PSO and GA are scalable as compared to Munkres algorithm. DGC-PSO performs well in case of higher power of scaling factor	Munkres algorithm provides better fitness value than both bio inspired algorithms. Execution time is high.
[40]	Setting initial parameters through GA results in more optimal(near to) final results.The speed of selection increased.Good results obtained in less number of iterations.Convergence is improved.	**NM**
[41]	Min-Max ant system is used to confine the updation of pheromone trails. Execution time required is less compared to GA and ACO individually.Success rate is higher.It quickly gets better solution because of better initial pheromone distribution.	**NM**
[42]	Optimization is performed on non-dominated set of user defined constraints. Advantages of ACO and GA are used to overcome disadvantages of them.	Computation time is high.
[43]	Advantages of PSO and ACO are combined.Idea of elimination helps in minimizing population size and obtaining better result.Slow convergence and falling in local optima of PSO overcome.	Practically not feasible.

TABLE 3. Some details about working technique of Web Service Selection techniques

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Reference	Optimization mode/Search Strategy	Method Proposed	User-defined Weight of QoS considered	Bio inspired algorithm used	Workflow Considered
[4]	Global as well local	SAMGA	No	GA	Sequential
[5]	Local	**NM**	No	ACO	Sequential
[6]	Global	**NM**	Yes	GA	Sequential, Switch, Flow, Loop.
[7]	Global	Improved GA	Yes	GA	All
[8]	Global	CoDiGA	Yes	GA	All
[9]	Local	**NM**	Yes	GA	All
[10]	Local	QCD	Yes	GA	Sequential, Parallel, Choice, Loop
[12]	Local	MGA	No	GA	Sequential, Switch, Parallel, Loop.
[13]	Local	**NM**	No	GA	Sequential
[14]	Global as well as local	GAST	No	GA	Sequential, Parallel, Selectable, Loop
[15]	Global as well as local	Hybrid-PSO	Yes	PSO	Sequential
[16]	Global as well as local	PSO-GODOSS	Yes	PSO	Sequential, Parallel, Conditional, Loop
[17]	Global as well as local	Modified PSO(MPSO)	Yes	PSO	Sequential
[18]	Global as well as local	**NM**	No	PSO	Sequential
[19]	Local	IDIPSO	No	PSO	Sequential
[20]	Local	Skyline + PSO	No	PSO	Sequential
[22]	Global as well local	**NM**	No	PSO	Sequential, XOR, AND
[23]	Global as well local	**NM**	No	PSO	Sequential
[24]	Global as well local	**NM**	Yes	PSO	Sequential
[25]	Global as well local	MOPSO	No	PSO	Sequential
[26]	Global as well local	MC-PSO	No	PSO	Sequential
[27]	Global as well local	Graph based PSO	No	PSO	Sequential, Parallel
[28]	Global as well local	ASPSO	No	PSO	Sequential, Selective, Parallel, Loop
[29]	Global as well local	**NM**	No	PSO	Sequential, Parallel, Loop, Conditional
[30]	Local	**NM**	No	ACO	Sequential
[31]	Local	**NM**	No	ACO	Sequential
[32]	Local	**NM**	No	ACO	Sequential
[33]	Local	Novel ACO	No	ACO	Sequential
[35]	Local	**NM**	No	ACO	Sequential, iteration, parallel fork
[36]	Local	**NM**	No	ACO	Sequential
[37]	Local	ACO_WSC	No	ACO	Sequential
[38]	Local	MOACS	NO	ACO	Sequential
[39]	Global as well as local	GA with elitism and DGC-PSO	Yes	PSO and GA	Sequential
[40]	Local	ACAGA_WSC	Yes	GA and ACO	Sequential
[41]	Global as well local	MGAACA	No	GA+ACO	Sequential
[42]	Global as well local	**NM**	Yes	ACO+GA	Sequential

*NM=Not Mentioned in reference paper

IV. OBSERVATIONS

In this paper, we have discussed existing work related to three such algorithms- Genetic Algorithm (GA), Particle Swarm Optimization (PSO) and Ant Colony Optimization (ACO). Each of these three algorithms have their advantages and limitations. GA has advantage of good global search ability, ACO gives advantage of positive feedback and low convergence speed but have limitations of low global search ability and stagnation. PSO gives advantage of easy implementation, low CPU and memory requirements, good local search and robustness but have main drawback of premature convergence.

Genetic algorithm (Algorithm1) evolutes through different generations in which genetic operators (selection, cross-over and mutation) are applied for maintaining convergence and divergence.Convergence of GA is maintained by cross-over operator and mutation operator is responsible for diversity of algorithm. Selection can be done using many techniques but here for WSS_{el} we found that almost in all cases Roulette Wheel selection is used which works on probabilistic principle. The more fit the chromosome is, the higher will be its chance to get selected. Crossover and mutation could be single point or multi-point. Here from Table1. we observed that single point cross over and mutation are used and probability of these operators is observed to be above 0.6 for cross over operator and between 0.01 and 0.1 for mutation operator. GA carries a characteristic of better global search which can also be observed through Table 3. All the variations of GA follow global optimization technique for finding the optimal result. GA evolving solution requires high execution times, slow convergence, vulnerable to partial optimum.

Particle Swarm optimization works in the way as swarm of birds search for the path to their food. It is observed that PSO basically works for continuous data. However, for optimization purpose, it has to deal with discrete data for which different formulas are given. Particles local best as well as global best are updated with each iteration. Hence, this technique finds the solution that is best globally as well as locally. PSO suffers from the problem of premature convergence. To resolve the premature convergence problem, different strategies are proposed (as mentioned in Table 2, along with their advantages and disadvantage). From Table 2, it is observed that PSO has limitation of high execution time for solving web service selection problem.

ACO generally uses local search strategy, changes are done in pheromone updation formula and transition probability.

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Every ant deposit some pheromone trails which gets evaporated at each iteration and the path with maximum amount of pheromone is considered as optimal and required solution. Pheromone update and transition probability considers quality parameters of web services. From Table 3, it can be observed that ACO follows local search strategy hence provides local optimum solution. Also none of the ACO based technique allows user defined weight of QoS parameters. From Table 2, it is further observed that the ACO when applied to WSS_{el} has advantage of high exploration and exploitation. Min-max pheromone value provides an upper and lower bound for pheromone updation and evaporation. Hence, the search should not go beyond any limit. The initial pheromone deposition is very slow process which causes high computation time and imposes limitation of lack of global search ability. ACO is generally applied for sequential workflows (from Table 3).

To utilize the advantages of these three algorithms combination of them is also proposed by different researchers. From Table 2 it is observed that GA does not works well for less number of services.ACO overcomes problem of GA of bad performance when number of web services or number of iterations are less. Also GA has advantage of high global search ability but low local search ability and characteristics of ACO includes high local search ability and positive feedback but low global search ability. Hence both of them forms a good combination and provides good results. In [27] and [42], global as well as local search strategy is followed , solution obtained is good but execution time required is higher.

GA and PSO both suffers from premature convergence and slow convergence respectively hence they are not comparable. PSO outperforms GA in case of ease of implementation and less number of parameters. This combination provides high scalability but still problem of premature convergence is not resolved. This results in less optimal result and high execution time. Combination of PSO and ACO is able to avoid search direction fall into local optima. Practical implementation is not guaranteed. From Table 3 it can be seen that generally all algorithms proposed considered sequential workflow, reason behind which is any other workflow

Application of PSO in solving Web Service Selection problem is mainly observed which results in efficient and optimal solution. Different QoS parameters were considered in different papers along with formulas of finding their aggregated values. The QoS parameters considered in all the referenced papers are presented in the pie chart below :

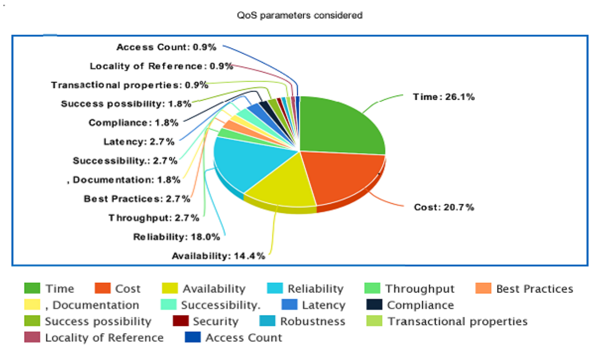

Fig 3. QoS parameters considered for Web Service Selection

Most of the researchers considered time and cost parameter as user generally have issue and constraints related to these two parameters. In Fig. 3, time includes both execution time and response time and cost includes any type of cost required for web service usage and composition.

V. CONCLUSION AND FUTURE WORK

Bio inspired algorithm have performed well in providing solution for web service selection problem. In this paper, we have presented a comparative review of Genetic Algorithm, Particle Swarm Optimization and Ant Colony Optimization applied for selection of web services. Each of these three algorithms performs well and has their own advantages as well as disadvantages. Each of them is used in different ways and different modifications by researchers for solution of web service selection problem. Combinations are used to resolve disadvantage of one with advantage of other, like ACO suffers from lack of global search ability which in turn is a characteristic of GA.

GA works on the basis of genetic operators. Generally convergence is the main problem faced by PSO and GA that can be future work in most of the methods discussed in the paper. PSO is mostly used because of its low complexity. GA does not take network feedback information as ACO but has strong and robust global search. Improve dense area identification method to reduce complexity and multi-objective optimization in ASPSO. Future work can also include overcoming the disadvantages mentioned in Table 2 and extending techniques for workflows other than sequential in Table 3.

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