Science Arena Publications
Specialty Journal of Geographical and Environmental Science
Available online at www.sciarena.com
2017, Vol, 1(1): 1-11

Comparing The Utilization of Shuffle Frog Leaping Algorithm, Ants Colony Algorithm and Genetic Algorithm in Geometry Optimization of Morning Glory Spillway

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Abstract:*Simulating the natural evolutionary process of living organisms and its result in solving real complex problems and engineering issues has already brought very positive results. In this study, it has been tried to suggest the most appropriate algorithm in solving a single problem that is optimizing the flow volume of morning glory spillway by investigating the efficiency of Shuffle frog leaping algorithm, (based on the theory of Lamarck), Genetics (based on Darwin's theory) and Ants colony algorithm (based on swarm intelligence). The results obtained from ant colony algorithm, genetic algorithm and Shuffle frog leaping algorithm are respectively 0.6093m^3, 0.59285m^3 and 0.59334m^3. There is a little difference between each of the three numbers gained from the test. However, by investigating the performances of these three algorithms in a number of different repetitions and comparing the standard deviation of the objective function values in each run, it was showed that genetic algorithm is sharply sensitive to the local optimum point in small numbers of repetitions. But two other algorithms do not have this problem in small numbers of repetitions; however, as the number of repetitions and the rate of population members in search space increases, genetic algorithm seems to be more efficient than the other two algorithms and acts with a more acceptable speed. Ant's colony algorithm is much better and more efficient than Shuffle frog leaping algorithm.*
Keywords*: Shuffle frog leaping algorithm, Ants colony algorithm, genetic algorithm, optimization, morning glory spillway*

INTRODUCTION

Since 1960 a great desire has been emerged to solve complex optimization problems by imitating the mechanisms of human life and other living organisms. By studying the behavior of living organisms in nature and expressing their behavior mathematically, and the expansion of computer use, the algorithms based on these mathematical equations were defined. For example, the algorithms inspired by the behavior of birds and fishes can be stated which is similar to the algorithm of particles' swarm optimization (PSO), the algorithms based on insects' behavior such as Ant colony optimization (ACO), algorithms based on Darwin's theory such as genetic algorithm or patterns based on Lamarck's theory that stated an algorithm like the Shuffle frog leaping algorithm (SFLA). Morning glory spillway is composed of a circular opening in the lake and a vertical circular convertor and a horizontal (or nearly horizontal) under pressure tunnel that ultimately conveys water from the lake to the downstream. In other words, morning glory spillway consists of a circular crown that guides the flow to a mile or vertical shaft. The flow in low altitudes is a function of circular openings capacity but in higher capacities it follows the channel conditions under horizontal pressure. The diameter of the spillway in the crown must be more than the diameter of the vertical axis and the tunnel; in this case, the stream fountain can easily pass the circular spillway that is designed to match the flow lines. The water flow will have a negative pressure due to the imposing figure of the spillway. The length of the crown is equal to πD minus the length of the occupied part by Piers (if there is any).

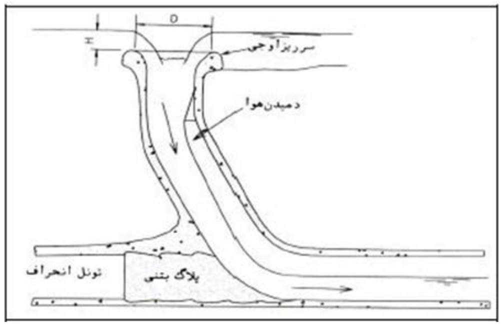

Figure 1: A view of the morning glory spillway

Hong and Jeong (2014) compared two genetic and SCE-UA algorithms in the simulation of rainfall runoff model and suggested that a genetic algorithm should be used in areas where there is no time limit. Borhani Darian et al. (2008) examined the use of annealing simulation in optimal utilization of water resources compared with other methods of exploration (Genetic and Ant colony Algorithm)in the catchment area of Dez reservoir and it was observed that the annealing simulating algorithm is a more stronger method than ant colony and genetic algorithms. Yousefi et al. (2006) compared the ant colony algorithm with genetics and the combination of genetic and ant colony algorithms for planning the simultaneous development of posts and distribution lines.

Materials and Methods

Shuffle frog leaping algorithm [5]

Shuffle frog leaping algorithm is a mixture of those behavioral algorithms that have the same structure as the Shuffled complex evolution (SCE-UA). In the following, this algorithm will be discussed, and then, the utilization of this algorithm in Shuffle frog leaping algorithm will be considered.

Shuffled complex evolution algorithm [4]

The algorithm was introduced by researchers at the University of Arizona (Downs, 1993). This algorithm has not been inspired by nature, but it used the classical and evolutionary optimization approach. In fact, this hybrid algorithm has benefited from Control random search(CRS)algorithms and genetic algorithm in the competitive and evolutionary phase. Another algorithm that is inspired is a method in classic optimization known as Nelder-Mead algorithm. This algorithm is based on the geometric mapping that a series of its elements is used in the evolution of mixed aggregations

How to implement the steps of SCE-UA algorithm

1. Determining the values of parameters: parameters involved in the calculation of this algorithm are: 1. the number of complexes (P),2- The size of the complex (m), 3- Dimensions of Search space (n), 4- Size of the total population (S), the requirements that these parameters should have are as follows:

1- $P > 1$
2- $m > n + 2$
3- $S = P \times m$

2. Producing the initial population of answer (S) in a random order

3.Sorting answers in terms of competence

4. Dividing the population members by complex Peach with size m

5. Improvement of each of the complexes by the improver algorithm under the population

6. Mixing the improved complexes and sorting larger population

7. In case of not meeting the termination conditions, go back to step 4 and repeat the steps, otherwise end the cycle.

Competitive Complex Evolution (CCE)

As can be seen from Figure 1, each complex is given to a subpopulation algorithm which is known as the competitive complex evolution algorithm. This algorithm uses the Nelder-Mead algorithm and improves the complexes. The improved complexes will re-merge with each other to satisfy the termination conditions. The performance of CCE algorithm 1- Determination of the required parameters:

1 .Parents (q) $2 \leq q \leq m$

2. Determining the probability of selecting i_{th} member:

$$i = 1, 2, ..., m \quad Pi = \frac{2(m+1-i)}{m(m+1)} \quad (4) \qquad \sum Pi = 1,$$

3. By considering the possibility of Pi, q members of the complex is selected as a parent.

4. Creating new children.

5. The new produced members in case of being answers in the optimal range will be replaced with the original population (complex). Then, new members are arranged.

6. Steps 1 to 5 will be repeated for the number of btimes

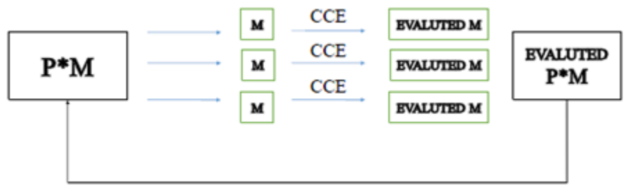

Figure 2: the overview of the algorithm's performance

Theoretical foundations of the shuffle frog leaping algorithm

In Lamarck's theory that forms this algorithm, it is believed that behaviors like biological properties will change over time. Although, shuffle frog leaping is an evolutionary algorithm, it is placed in a particular class of evolutionary algorithms (Memetic Algorithm). In this algorithm, frogs imitate each other and are trying to locally improve their behavior and become a model for others to imitate them. This is not a mere imitation and at the same time, they imitate consciously and their imitation is in line with improving that behavior. SFLA is similar to SCE algorithm, only with this difference that Frog leaping algorithm is used instead of internal improving with CCE algorithm that was described. In this algorithm, Memeplexe is used instead of applying the word of complex. Implementation steps for Frog leaping algorithm are:

1. Preparation and initialization of parameters

m = number of memeplex $\geq$ 1
n= memeplex size $\geq$ d+1
F= m $\times$ n :Population Size

2.Creating the initial population of frogs

3. Sorting and ranking of frogs

4. Building complexes (in this algorithm the word Memeplexe is used that reflects the complexes containing characteristics or Meme) by dividing the population members

5. Improving the members of each Memeplexe by using FLA algorithm

6. Mergers and acquisitions of improved Memeplexes to create new populations and sorting them

7. Investigating the termination conditions and repeating from step 4 if needed

The steps of FLA algorithm:

1. Preparation and initialization of m and n parameters

2. Production of a sub-memplex or weighted random sampling such as the CCE method and without replacement from the population. Probability function is considered as a triangle.

3. Sorting the members of sub-memplexso that the first member is the best, PB (the worst member is also shown by Pw)

4. Process of improving the worst member:

Firstly, choose a random number called S between the best and worst members and value of the worse member will increase. If U_q^{new} is in the search space, the objective function value will be used for it, otherwise, it should be taken to step 5and if U_q^{new} is better than Pw, it will be replaced by it.

$$u_q^{new} = P_w + S$$
$$S = rand(P_B - P_w) \qquad (5)$$

5. If step 4 is not successfully conducted, instead of using the best local member, the best answers of the whole population will be used for population improvement and it should be carried out like stage 4.

6. If the two previous stages are not successfully performed, censorship will be used and the member will be prevented from being release.

7. Steps (1) to 6 are repeated in specified numbers.

Ant Colony Algorithm

This algorithm is classified as the method of computational or swarm intelligence.

The main factors in swarm intelligence are: 1. Population 2. Cooperation between members of the population (this algorithm, in contrast to genetic algorithms, does not have swarm intelligence because there is no cooperation between the population members) 3. Connection, cooperation needs the contact between members of the population. 4.Exchange of information. 5. The flow of information. 6. The members of the population should abide the regulations. Initially, Ants' behavior was studied by a scientist named Gauss using Argentine ants. In this experiment, different paths that an ant travels to reach the bait were examined and they have solved engineering problems through mathematical expressions. In this experiment, ants are in the nest and one of the two paths is shorter than another. Initially, Ants do not know the environment.Ants secrete a substance on their path called pheromones. The concentration of pheromones is more in shorter routes because more ants are moving in shorter paths. Naturally, Ants tend to pheromones. After a while, Ants will reach their stable system and are attracted to the shorter path. Note that the ability to choose the shortest path will arise due to being together and not their individual impact.

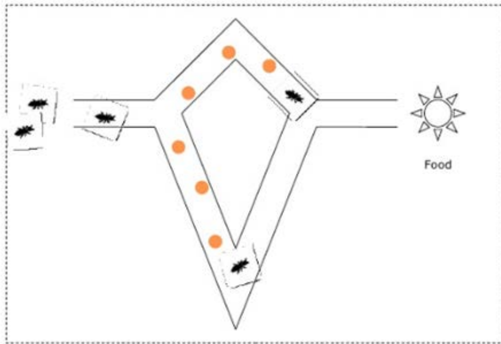

Figure 3: Gus tests on ants

The effect of pheromone on ants' colony acts as the numerical data that have been distributed in the space of solutions and ants use them in implementing the algorithms to show their own experiences to others. Artificial ants that are used in the ant colony can procedure random solutions by manufacturing procedures so that by adding the components of a solution to the partial obtained answers it would be possible to alternatively produce answers. Ants use the heuristic information of the problem, effects of artificial pheromones that change during the process of solving the problem and experiences gained by research agents (the ants) to build answers.

0. Starting the meta-heuristic procedures

1. Regulating the activity of ants

2. Placing every ant on the point of a graph

3.The placement of pheromone initial value and calculating heuristic values

4. Calculating the probability of Ants' movement to the points in the neighborhood

5.Continuous moving of Ants until the completion of a return for each ant

6. End of setting the activities

7. Upgrading pheromones

8. Placing pheromone based on the quality of the answer

9. Evaporation of pheromones

10. End of the pheromones' upgrading

11. The end of meta-heuristic procedures

Genetic algorithm

The natural basis of genetic algorithm is based on this principle that the competition between living organisms for owning limited natural resources leads to their evolution. The authority of victorious species is due to their unique physical and natural features. After victory, they know themselves as the owners of what they have fought for. As a result, the possibility to use more resources will be provided for them. Since powerful creatures are more likely to survive than others, they will be more effective in producing their next generation than others. Therefore, most of the new generations will be powerful creatures that are victorious in their natural competition. On the other hand, the members of the new generation will get their parents 'unique features by receiving their genes. The factors mentioned above cause most of the new generation to have power equal to or more than their parents. Competitions among the new generation will bring victory for stronger members.

The physical model of morning glory spillway: [1]

In this study, a physical model has been selected that is similar to the spillway of San Luis dam located in the Central Valley of California, America.

This model is prepared with some changes in its size and scale, with a ratio of 1:50 to carry out new experiments. For the considered physical model, the crossing section is the spillways mouth that has a small curvature radius (10.6cm) and the large curvature radius of the spillway is 20.3cm. The height of each spillway is 28.20 cm.

The highest part of this model is the reservoir of the dam that is composed of a trapezoidal channel along with the spillway's inlet. This channel guides water to the opening of the spillway's crest. The dimensions of this cube-shaped reservoir are $1.20x1.05x0.911m^3$. The next part of model is the body of the morning glory spillway that is capable of being separated. The desired spillway with more than 1.46 meters length, crest diameter of 35.00cm, guttural diameter of 7.00cm, bending diameter of 10.16cm and downstream tunnel diameter of 7.62cm performs the action of discharging the dam's reservoir. In the downstream tunnel of the dam, a tank of 2000 liters of water has been considered. In this model, water will be transmitted by a three inches pump from the downstream reservoir to the trapezoidal channel of the dam's reservoir. After a while, the upstream reservoir which is filled with water flows from the spillway's crest. After passing the spillway's distance, bends and tunnels, water will move into the downstream reservoir of the dam.

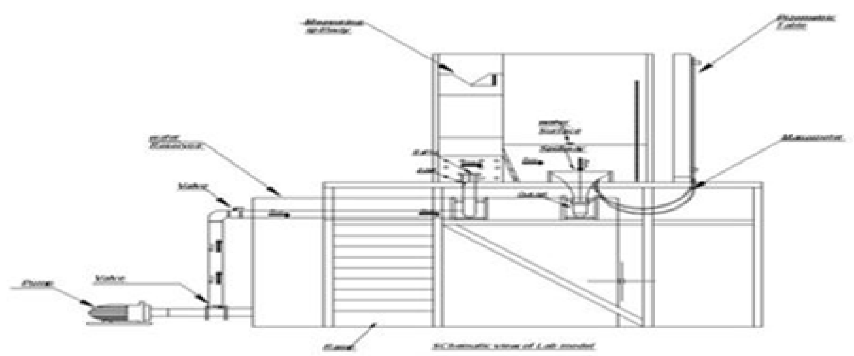

Figure 4: Cross section of the dam and spillway's physical model (Reference 1)

Results and Analysis

Firstly, we define the objective function of Equation (6) that calculates the volume of morning glory spillway and its constraint function shave been applied in the related parameters with regard to the point that flow is free in the duct. The equation is the volume of the hollow truncated cone and cylinder (tunnel). The objective function consists of the spillway's crest Rs, spillway crest height Ht, ninety-degree bend radius Rv, tunnel radius Rt, and T as the thickness. Initially, the optimal value will be examined in 10 times of implementation by using a binary genetic algorithm with numbers of 50, 150, 300, 500, 1,000, 5,000, 10,000, 20,000 as the repeating times, 20 as the number of population,8 percent for reproduction,0.3 percent mutation and 0.02 as the mutation rate. The result of using genetic algorithms shows that 0.59285m³ is the suggested optimized volume by the genetic algorithm.

$$Z(Rs, Ht, Rt, Rv, Lt) = (\pi \times (Rs + r + T) \times (Sqrt((Ht).^2)$$

$$2) \times (Rs - r + T).^2)) + (\pi \times Lt \times ((Rt + T) \times 2)$$

$$\longrightarrow +(\pi \times ((Rv + T).^2) \qquad (6)$$

Table 1 - the objective function value in binary coded genetic algorithm

The number of repetitions See	Minimum value of the objective function	Maximum value of the objective function	Average of the objective function	Standard Deviation	Execution time
50	0.60594	0.6566	0.6227	0.0104	1.79
150	0.5961	0.6331	0.6157	0.0139	2.141
300	0.5898	0.6175	0.6024	0.0076	3.769
500	0.592	0.6079	0.6013	0.0069	4.724
1000	0.5911	0.6047	0.6015	0.0042	7.887
5000	0.5897	0.597	0.59	0.0022	33.864
10000	0.5896	0.5923	0.5906	0.0009	60.709
20000	0.588	0.5914	0.5904	0.0009	1333.389

In the next step, the objective function was defined in the real genetic algorithms such as binary coded conditions and in similar numbers of repetitions and10 times of implementation that the results are as follows:

Table 2 - The objective function value in real coded genetic algorithm

The number of repetitions See	Minimum value of the objective function	Maximum value of the objective function	Average of the objective function	Standard Deviation	Execution time
50	0.6059	0.6566	0.6227	0.0127	1.95
150	0.5961	0.6331	0.6157	0.0098	2.206
300	0.5898	0.6175	0.6024	0.0098	3.19
500	0.59205	0.60138	0.60792	0.00592	4.51
1000	0.5901	0.60472	0.6015	0.0046	7.532
5000	0.5898	0.5962	0.5908	0.00199	33.291
10000	0.5896	0.5954	0.5907	0.00156	62.494
20000	0.5889	0.59369	0.5905	0.00132	128.29

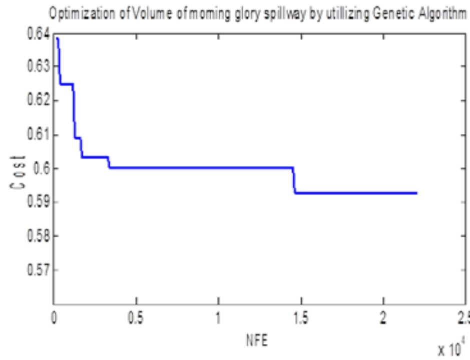

Figure 5: The result of optimization by Genetic Algorithm

With the same repeating conditions with the genetic algorithm and the same community's size as the previous two stages, the shuffle frog leaping algorithm was implemented and the results are as follows:

Table 3 - the objective function value in the SFL algorithm

The number of repetitions See	Minimum value of the objective function	Maximum value of the objective function	Average of the objective function	Standard Deviation	Execution time
50	0.5956	0.6212	0.6059	0.006	2.541
150	0.5886	0.6057	0.5935	0.0053	7.801
300	0.5893	0.6024	0.5912	0.004	16.62
500	0.59342	0.59493	0.59479	0.00083	25.87
1000	0.5904	0.59216	0.591	0.000962	52.347
5000	0.5897	0.59024	0.59	0.00052	256.7
10000	0.5903	0.59978	0.593	0.0004	500.37
20000	0.589	0.59	0.58843	0.0005	1075.4

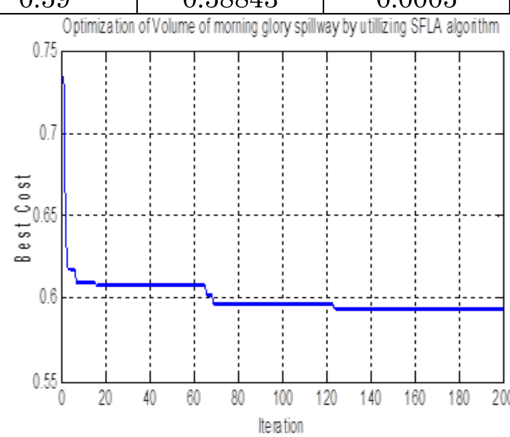

Figure 6 - The result of the shuffle frog leaping algorithm

The other step of using objective function was in the ant colony algorithm that in terms of times of repetition; number of implementations, number of initial population and with 50 primary samples was investigated like the third condition of the previous step and the results are as follows:

Table 4 - the objective function value in the Ants colony algorithm

The number of repetitions See	Minimum value of the objective function	Maximum value of the objective function	Average of the objective function	Standard Deviation	Execution time
50	0.5966	0.6177	0.609	0.0076	1.042
150	0.5897	0.6096	0.5998	0.0068	2.345
300	0.5959	0.61	0.603	0.0048	4.468
500	0.5929	0.6002	0.5981	0.0025	7.466
1000	0.589	0.5993	0.5931	0.0031	14.56
5000	0.5886	0.6007	0.5905	0.003	71.78
10000	0.5583	0.5916	0.5893	0.001	161.10
20000	0.5892	0.5896	0.5894	0.00019	307.7

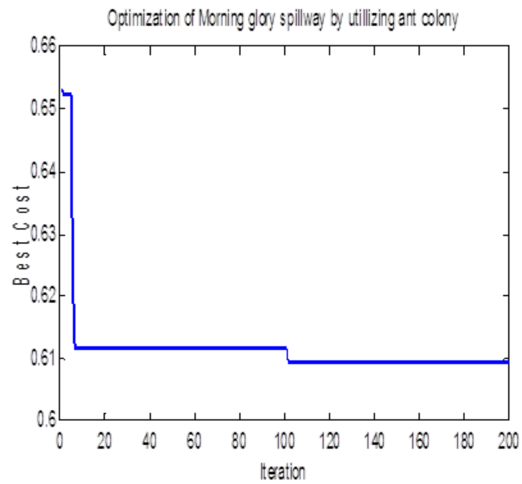

Figure (7): Results of optimization by using ant colony algorithm

By examining the obtained results from Table 1 to 3 and comparing the values of objective function in each algorithm, it can be seen that genetic algorithm is highly sensitive to the local optimum point in small numbers of repetition (less than thousand times) and solutions have convergence towards the global optimum point only in large number of repetitions, (over one thousand times). By considering the standard deviation as the criterion and obtaining objective function values and compering them, it can be seen that the highest level of standard deviation belongs to under 1,000 times of repetitions. The local optimum point refers to the point that can select the algorithm in the search space despite the absolute maximum or minimum value that has the highest or lowest value in the search space.

The difference between the global and local optimum points were compared in Figure (8). By comparing the obtained results it can be seen that, in all repetitions, ants and frogs algorithm have a lower standard deviation than genetic algorithm and do not face local optimal choice even in small numbers of repetitions. If these three algorithms be compared with each other in terms of their speed in responding, according to the same population, it can be seen that the performance of ant colony algorithm is much better than genetic and Frog algorithm in small repetitions and populations. But as the number of data incense, while increasing, the number of repetitions in genetic algorithm converges to the optimal point more efficiently and with much higher speed. Also, despite of its accuracy in calculation and not falling into the trap of local optimal responses, the speed of the shuffle frog leaping algorithm sharply decline with an increase in the number of population and repetitions. Therefore, it is suggested to use genetic algorithm in issues with no time limit and with changes in the number and rate of data.

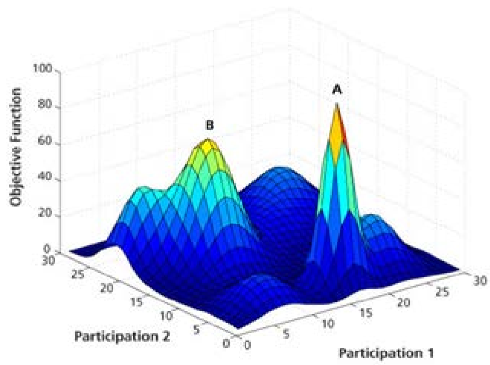

Figure 8 comparing the global and local optimum point

Conclusion

By investigating the genetic algorithm, shuffle frog leaping algorithm and ants' colony algorithm to solve an identical problem at the same conditions, the results indicate that the genetic algorithm is intensity sensitive to the local optimum point in fewer than 1000 repetitions and the responses of objective functions do not end to the global optimum point. But this defect will be fixed by increasing the number of repetitions and the genetic algorithm will be more efficient than the other two algorithms. Although ant colony algorithm and shuffle frog leaping algorithm have good accuracy in global optimum solution but they operate severely poor in large numbers of repetition and too much data. But the ant algorithm is more efficient than the shuffle frog leaping algorithm.

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