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A Comparative Study of Different Optimization Algorithms for Optimal Allocation of Water Resources

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Abstract—The objective of water resources allocation is to find a symmetry for different water allocation methods among diverse water use sectors, like domestic, agricultural and industrial water so that it helps in the sustainable development of the society. Optimal allocation of water resources plays a significant role in planning of water resources. Genetic algorithm and differential evolution algorithm are the two optimization algorithms used extensively in optimal allocation of water resources. Genetic algorithms are frequently used in water resource allocation optimization problems due to its easy implementation and suitable performance. Differential evolution algorithms are an alternative of genetic algorithm because search performance is very good in differential algorithm and is robust compared to genetic algorithm. Particle swarm optimization algorithm is a population-based stochastic optimization technique based on bird flocking and fish schooling. This paper aims at comparing the performance of these three algorithms based on accuracy of the optimal solution, their robustness to the size of population, convergence speed, and the number of generations and efficiency of computation. The experimental results show that differential evolution algorithm significantly outperforms and has timely advantages over the genetic algorithm and particle swarm optimization algorithm and efficiently improves the speed of convergence and quality of optimal solution, thereby showing excellent characteristics in the optimal water allocation problem.

Keywords—Optimal allocation of water resources, Evolutionary algorithms, Genetic algorithm, Differential evolution algorithm, Particle swarm optimization

I. INTRODUCTION

People use water for different purposes therefore water from different sources has to be collected and shared among different types of users to meet there basic demand. Optimal water allocation is a necessity of time in order to preserve the most precious natural resource that is water and to utilize it effectively so that water is not wasted. The main aim of water allocation systems is to rightfully allocate water resources among different users, guard existing water users from having their supplies narrowed by new users; administer the sharing of inadequate water during droughts when supplies are insufficient to meet all needs; help well- organized usage of water by depending on different sources of water. Optimal water allocation is significant as water demands surpass reliable supplies. Therefore water allocation systems must be extended and advanced so that it can meet the increasing water demands with population and economic growth. The strategic initiatives of the water allocation model are depicted in “Fig. 1”.

Evolutionary algorithms (EAs) are powerful and reliable methods widely used in the water distribution systems and water resource allocation systems optimization methods.

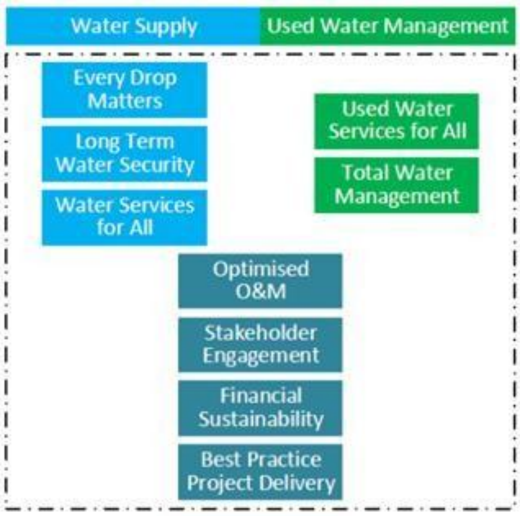

Fig.1.Strategic initiatives of the water allocation model

Compared to deterministic optimization techniques like linear and nonlinear programming in evolutionary algorithms the search space is found using the evolution of stochastic methods instead of gradient information. The advantages of evolutionary algorithms are applicability to wide range of problems, conceptual simplicity, performs better on real problems compared to classic methods, use of knowledge representation, parallelism, able to solve problems that have no known solution methods, capable of handling dynamic changes, self-optimization capability, capable of self-adapting the search to find the optimal solutions, discrete search spaces are handled directly, chances of getting trapped at local optima is minimal and capable of providing many similar cost solutions for different designs [1].

Some of the evolutionary algorithms used in the optimization of water allocation systems are genetic algorithm, ant colony optimization, shuffled frog leaping algorithm, particle swarm optimization, tabu search, harmony search, simulated annealing , ANN meta models, scatter search, cross-entropy algorithm, differential evolution and honey-bee mating optimization [1, 2]. The performance of each method varies based on the case studies and each method has its own advantages and disadvantages [3]. Each method can produce diverse outcome for the equivalent optimization problems. Be that as it may, no correct outcome is delivered since random function is normally connected in evolutionary algorithms. The execution possibly is influenced by the parameter setting or activities inside every strategy. Hence, the inspiration of this paper is to think about the execution of GA, DE and PSO by utilizing similar parameters setting and streamlining issues. Among these methods the most popular one is genetic algorithm (GA) and recently differential evolution algorithm (DE) has gained popularity for continuous optimization problems. These algorithms use a population of solutions rather than one solution which is denominated by Pareto optimal front [4].

Genetic algorithm is one of the most widely used and popular optimization technique used in water allocation system. It is an adaptive stochastic algorithm based on natural selection process that mimics the evolution of biological events. Genetic algorithms are computationally expensive, when applied to large-scale water allocation systems. Storn and Price (1995) proposed differential evolutionary algorithm as a population-based stochastic search method for global optimization [5]. Particle Swarm Optimization (PSO) was proposed by Kennedy and Eberhart in 1995. It is a population based stochastic optimization strategy which depends on bird flocking and fish schooling. Based on the case studies particles (potential solution) which are present in a set of population are initialized like GE and DE.

Differential Evolution algorithm is widely gaining popularity because of its robustness and simplicity. Fanuelet al.(2017) used evolutionary algorithms like DE and GA in agricultural water management [6]. DE variants NLP-differential evolution algorithm and self-adaptive differential evolution algorithm was projected by Zhenget al., (2011) for water distribution systems optimization [7, 8]. DE was applied to water distribution system by Vasan, Simonovic andSuribabu (2010). A comparative study of different optimization algorithms like genetic algorithms, particle swarm optimization and differential evolution algorithm was carried on by Vesterstrom and Thomsen (2004).All these studies concluded that DE outperformed GA in terms of its efficiency.

A performance comparison on optimal allocation of water between the newly emerged differential evolution algorithm, the most popular genetic algorithm, and the particle swarm optimization algorithms are carried out in this paper. The solution quality and time are the two key performance indicators commonly used in this comparison process.

This paper discusses how evolutionary algorithms like GA, DE and PSO can be used to optimally allocate water to different users based on demand based model. As opposed to supply based model approach a demand based model approach uses calculated or forecasted demands data, while a supply based model uses actual supply data obtained from equipment's measuring the hydraulics of the systems like flow meters, valves and pressure gauges. The domestic water demand is calculated using "(1)".

$$WD = \sum_{w=1}(P_w(1 + R_w)^t K_w) \qquad (1)$$

Where WD is the study areas domestic water demand for the forecast year; w represents a sub division; P_w represents the present population in one sub-division; R_w represent natural population growth rate; t is the time interval between forecast base year and the forecast year; K_w is the per capita water use quota of one sub-division for the forecast year [9]. The water demand calculated for the projected population of Bengaluru city for the years 2020, 2035 and 2050 is given in table 1.

TABLE I. WATER DEMAND PROJECTION (SOURCE BWSSB)

Year	Projected Population (Million)	Projected Water Demand (MLD)
2020	11.08	1795
2035	15.38	2492
2050	20.96	3396

II. FLOWCHARTS OF ALGORITHMS

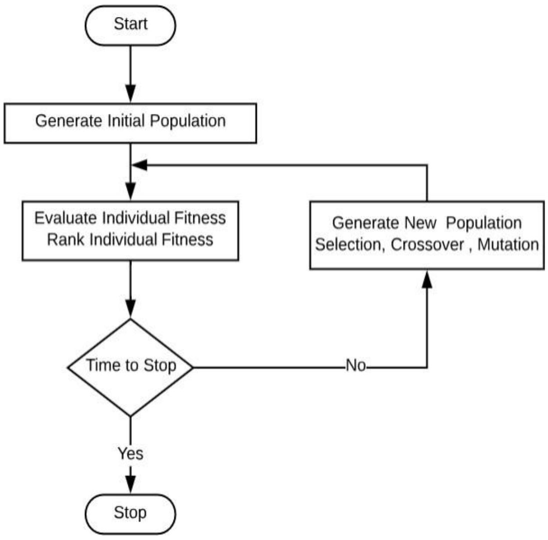

Fig 2 . Genetic Algorithm Flowchart

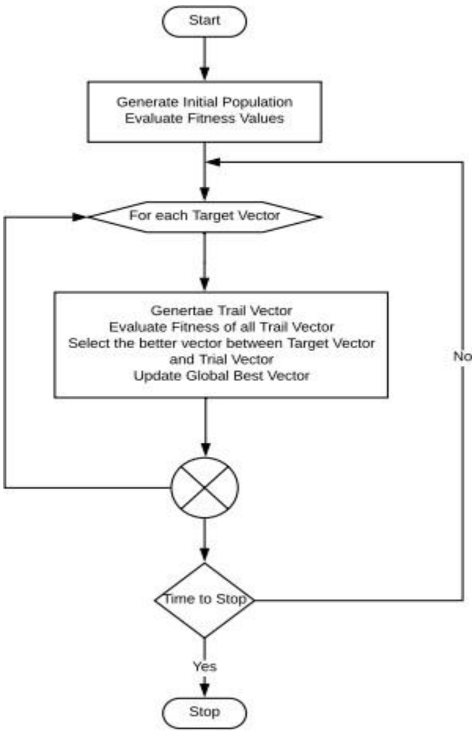

Fig 3 : Differential Evolution Algorithm Flowchart

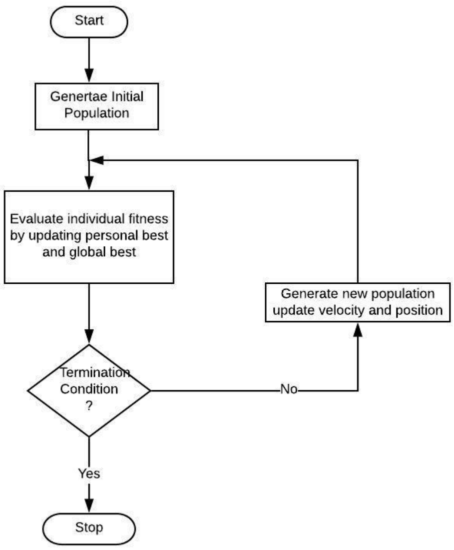

Fig 4 : Particle Swarm Optimization Algorithm Flowchart

III. PARAMETER VALUES FOR EACH ALGORITHM

Both GA and DE uses genetic operators but all the parameters used are not the same. In GA crossover is the main operation whereas in DE it is not. In GA mutation is applied to less than two percentage of the population. Where as in DE the mutation operation is applied to each individual while moving them to the next generation. During the mutation operation a mutant individual is generated by selecting three more individuals for each individual from the population and its fitness value is computed. The fitness value is the deciding factor which chooses the first individual to be replaced [10].

A. *Genetic Algorithm parameters*

Chromosomes are used to represent the solutions in GA. The chromosomes are assessed for fitness values and they are positioned from best to most noticeably awful dependent on fitness value. The parameters used in genetic algorithm are integer coding method, uniform crossover operators and identical parameters; population size, maximum number of allowable evaluations; crossover probability and mutation probability.

B. *Differential Evolution Algorithm Parameters*

The most important parameters of DE are the population, mutation, and cross over. The convergence of this algorithm depends on the values of these parameters. In DE trial vectors were developed using DE/rand/1/bin strategy. Population size, maximum number of allowable evaluations, mutation operator, and crossover operator where the identical parameters used [2, 11].

A initial sensitivity analysis was performed to decide the parameter values of the algorithms for the case study [2]. Table 2 lists the parameter values used by GA and DE algorithms in this study.

TABLE II. GA AND DE PARAMETERS

Parameter	GA Values	DE Values
Population Size	100, 120,140,160	50, 100,150,200
No of Generations	500, 750, 1000	1000, 2000, 3000
Crossover Rate	0.5	0.5, 0.6,0.7
Mutation Operator		0.5, 0.6,0.7
Crossover Probability / Mutation Probability	0.6 / 0.05	
Maximum Number of Allowable Evaluations	55000	25000

C. *Particle Swarm Optimization Algorithm Parameters*

In the population each particles fitness value is assessed using objective function. The global best particle is the one that contains the best fitness value. Each particle will recall its best position and velocity will be resolved after the situation of the particles has been refreshed. V_{max} is the most extreme speed which holds the swarm under control. After particles were refreshed, they will be assessed utilizing a similar fitness function. Best particle will be refreshed and global best particle will be supplanted by different particles that contain better fitness value contrasted with it after refreshing procedure was performed. The refreshing procedure will be ended after end criteria were satisfied. The two key activities in PSO are the refresh of velocity and the refresh of position. The velocity is refreshed dependent on the old speed (inactivity or force term), involvement of an individual particle (subjective or self-learning term), also, experience of the entire swarm (gathering or social learning term). Each term has a load consistent related with it. Table 3 lists out the parameters used in PSO.

TABLE III. PSO PARAMETERS

Parameter	PSO Values
Number of particles	100
Maximum number of iterations	100
Maximum Velocity	2
Learning factors C_1 and C_2	2
Inertia weight	0.7

IV. RESULTS AND DISCUSSIONS

Table 4 lists out the qualitative parameters used in the comparison of genetic and differential evolution algorithm [12].

The results of the comparison by implementing the algorithms for the particular problem are discussed in this section. GA and DE algorithms were applied to the case study with different values of crossover and mutation rates and the best module ranges for each method were obtained. Both the algorithms are executed for a fixed generation values and at the end of the last generation the best individuals are considered for the evaluation phase. All the algorithms result statistics were recorded. The statistical indicators used for the comparisons were the best solution, percentage of trials for the current best solution and the average number of evaluations conducted to obtain the best solution based on different runs.

TABLE IV. QUALITATIVE COMPARISON OF DE AND GA

	DE	GA
Ranking of Solutions	No	Yes
Effect of population size on population time	Linear	Exponential
Effect of best solution on population	Less	Medium
Average fitness cannot get worse	True	False
Inclination for premature convergence	Low	Medium
Continuity of search space	More	Less
Good solution without local search	More	Less
Improvement of convergence by homogeneous grouping	NA	Yes

"Fig5" represents a performance of the convergence comparison of the two algorithms applied to the case study. Initial random number seeds where the same for both the algorithms and 100 different runs were performed for each case. The maximum numbers of allowable evaluations for DE and GA were 25000 and 55000 respectively. From the result it is clear that DE achieves the results with faster convergence and less evaluation.

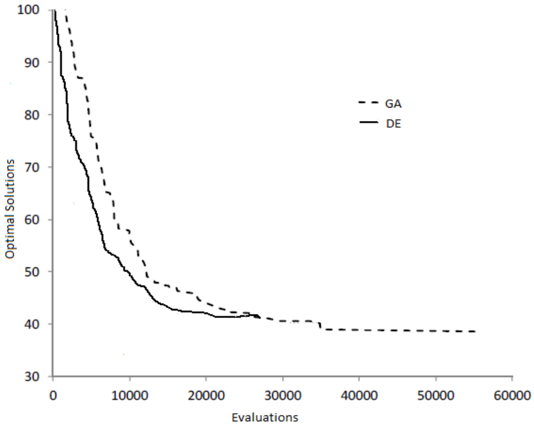

Fig.

Likewise, normal time in creating the outcome has been taken as another examination so as to demonstrate the speed of every strategy. In this way, the strategy that ready to create the most little and normal qualities with quickest speed is considered as the best technique with astounding execution.

Some of the advantages of these methods are; GA ends quicker and shows good performance. By utilizing suitable rearing tasks the diversity of chromosomes can be increased. DE performs better contrasted with GA and it utilizes blend of the equivalent population chromosome in shaping new generations. In PSO Speed and position value can be constrained by utilizing velocity clamping parameter. Number of parameters to be tuned is less and implementation is also easy in PSO compared to other algorithms. Some of the limitations of these algorithms are; In GA the entire population will be supplanted with straightaway age chromosomes. And the results were not steady because the results were based on the global optimum. At the most only two new chromosomes can be presented in every generation. No any new genetic qualities can be acquainted with the population, even though new chromosome structure can be framed using crossover and mutation. In DE presumably none of past age chromosomes are conveyed forward to the next generation even though better outcome can be created. Here crossover and mutation were executed as one process. In PSO based on the global best position different particles will trap in nearby optimum. Past speed and best position were alluded will make the particle position esteem expanding and moving far from the global best solution and ideal outcome.

V. CONCLUSIONS

The experimental results conclude that the performances of the algorithms are problem specific, depends on the selection of the parameters and number of function evaluations. One of the major advantages of these algorithms on optimal water allocation problem is that variants of these algorithms can produce different results [13]. The analysis of the results of this comparative study shows that with respect to the quality and efficiency DE out performed GA. Optimal solutions could be obtained faster in DE. Average number of evaluations required is less in DE compared to GA [14]. While using DE it is possible to produce the same result over different trials, where as in GA it depends on how the initial parameters are initialized. So we can conclude that DE is more robust compared to GA. The performance PSO is slightly better than that of DE but it is slower than DE. PSO is extremely engaging as a result of the straightforward calculated system and the relationship of of birds flocking encouraged calculated perception of the pursuit procedure. Based on this study, it is concluded that the differential evolution algorithms are more suitable for optimal water allocation problem when compared with genetic algorithms because of its simplicity, robustness, fast convergence, and the ability to find the optimal solution in most trial runs.

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