An Overview of the Applications of Particle Swarm in Water Resources Optimization

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Abstract: Optimization methods have evolved over the years to solve many water resources engineering problems of varying complexity. Today researchers are working on soft computing based meta heuristics for optimization as these are able to overcome several limitations of conventional optimization methods. Particle Swarm is one such swarm intelligence based optimization algorithm which has shown a great potential to solve practical water resources management problems. This paper examines the basic concepts of Particle Swarm Optimization (PSO) and its successful application in the different areas of water resources optimization.

Keywords: Water Resources Engineering, Particle Swarm Optimization, Swarm Intelligence

1 Introduction

Planning, development and management of water resources falls within the domain of water resources engineering. Freshwater demand for domestic, irrigational, industrial and recreational purposes already exceeds supply in many parts of the world and continues to rise due to rapid urbanization and population growth. Proper management of the available ground water and surface water resources in all user sectors is of utmost importance for any nation for the best utilization of the available sources of water.

One of the areas where this is more important than others is irrigation sector since over 80% of water in India is diverted towards agriculture. An entire spectrum of activities involving reservoir releases, groundwater withdrawals,

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use of new irrigation techniques call for optimal solutions to obtain maximum benefits from the available water while also meeting all the demands timely. Similarly, to minimize floods and droughts, to ensure water quality considerations and for well field installations water resources management is necessary to meet the competing demands. In this context, the importance of optimization in certain specific areas of water resources is considered in this paper.

2 Optimization

Optimization tools are utilized to facilitate optimal decision making in the planning, design and operation of especially large water resources systems. The entire gamut of operations involved with large water resources projects are complex and directly influence the people. The application of optimization techniques is therefore necessary and also challenging in water projects, due to the large number of decision variables involved. This is further demanded by the stochastic nature of the inputs and multiple objectives such as irrigation, hydropower generation, flood control, industrial and drinking water demands which a project has to meet simultaneously. Presently certain specific cases where optimization practices have been used successfully are considered as follows:

- Reservoir planning, design and operation
- River water pollution control using optimal operation policy
- Regional scale groundwater pollution and utilization management
- Identification of unknown groundwater pollution sources
- Estimation of unknown aquifer parameters in groundwater flow through inverse modelling
- Optimal design of water distribution and waste water systems

Fundamentally, optimization involves systematically choosing solutions from an allowed set of decision variables for maximizing the benefits and minimizing the losses. The conventional numerical optimization methods (viz. linear, nonlinear and dynamic programming) which were used in the past have limited scope in problems of water resources management where objective functions are often non convex, nonlinear, not continuous and non-differentiable with respect to the decision variables. Nonlinear programming methods have rather slow rate of convergence and often result in local optimal solutions since they depend upon initial estimations of variables, whereas the dynamic programming approach suffers from the curse of dimensionality [13]. Thus the conventional methods which utilize gradients or higher order derivatives of objective functions are not suitable for many real world problems in water resources management. For the last two decades non-conventional, metaheuristic techniques have been used successfully for obtaining optimal solutions. Although metaheuristic techniques do not have a rigorous mathematical proof like the conventional numerical methods, they follow a certain logical procedure that allows them to deliver a near global optimum solution.

3 Particle Swarm Optimization

Evolutionary Computation is the general term for several computational techniques which are based to some degree on the evolution of biological life in the natural world. Particle swarm optimization (PSO) is an evolutionary computation technique based upon the behaviour of a flock of birds or a school of fish [24]. When a swarm looks for food, the individuals will spread in the environment and move around independently. Each individual has a degree of freedom and randomness in its movements which enables it to find food deposits. Sooner or later, one of them will find something digestible and being social, announce this to its neighbours. These can then approach the source of food too.

Like the other evolutionary computation techniques, PSO is a population-based search algorithm and is initialized with a population of random solutions, called particles. Unlike in the other evolutionary computation techniques, each particle in PSO is also associated with a velocity. This velocity connotes an improvement in the solution which gets added to the initially assumed solution to make it move towards the optimum solution. Particles fly through the search space with velocities which are dynamically adjusted according to their historical behaviours. Therefore, the particles have a tendency to fly towards the better and better search area over the course of search process. Since its introduction by Eberhart and Kennedy [4], PSO has attracted considerable attention from the researchers around the world and seen gradual improvements with the passage of time.

3.1 Original PSO Algorithm

The basic concept of the PSO can be technically summarized in the following steps:

1. Initialize a population of random solutions on D dimensions in the search space. In the D dimensional search space the i^{th} individual (assumed solution or a particle having a position equal to the assumed solution) of the population can be represented by a D dimensional vector

$$X_i = (x_{i1}, x_{i2} \ldots\ldots x_{id})^T \quad (1)$$

2. Each of the above elements of the assumed solution set is modified in each iteration in a probabilistic manner. The improvement made to each of them in each iteration is referred to as velocity. Thus the velocity (position change or change in solution) of the particle can be represented by another D dimensional vector which is also initialized with some random values.

$$Vi = (v_{i1}, v_{i2} \ldots v_{id}) \quad (2)$$

3. For each particle (position or assumed solution) evaluate the desired optimization fitness function in D variables.

4. The best previously obtained fitness value of each particle and the corresponding value of the particle is noted. They are stored in a D dimensional vector

$$p_{id} = (p_{i1}, p_{i2} \ldots p_{id})^T \quad (3)$$

5. The best fitness value obtained so far by any particle in the population space is noted and the value of the particle is stored as p_{gd}

6. Each of the initially assumed solutions (particles) is improved upon in each iteration through the following equation. The improvement in solution is denoted by v_{id} (velocity).

$$v_{id}^{m+1} = v_{id}^{m} + c_1 rand1(p_{id} - x_{id}^{m}) + c_2 rand2(p_{gd} - x_{id}^{m}) \quad (4)$$

$$x_{id}^{m+1} = x_{id}^{m} + v_{id}^{m+1} \quad (5)$$

Where c_1 and c_2 are positive constants, and rand1and rand2 are two random functions in the range [0, 1], m is the number of iterations;

7. Loop to step (2) until a criterion is met, which is either a sufficiently good fitness or depends upon maximum number of iterations. At the end of n iterations the modified $x_{id}$for which the best fitness value has been obtained in all these iterations is denoted by p_{gd} (global best) and in the n^{th} iteration the value of x_{id} in the solution set which gives the best fitness value is denoted by $p_{id.}$ Thus in each iteration initially assumed solution is updated with respect to the best fitness value obtained among all the other members of the population set and its own previous best. Like other evolutionary algorithms, PSO algorithms is a population based search algorithm with random initialization, and interactions among population members. However, unlike the other evolutionary algorithms, in PSO, each particle flies through the solution space, and has the ability to remember its previous best position, and survives from generation to generation [8].

3.2 Parameters of PSO

The first new parameter added into the original PSO algorithm is the inertia weight (Eberhart and Shi 1998a, 1998b).They modified dynamic equation (4) of PSO as:

$$v_{id}^{m+1} = \omega v_{id}^{m} + c_1 rand1(p_{id} - x_{id}^{m}) + c_2 rand2\left(p_{gd} - x_{id}^{m}\right) \qquad (6)$$

where a new parameter, inertia weight ω is introduced. Equation (5), however remains unchanged. The inertia weight is introduced to balance between the global and local search abilities. The large inertia weight facilitates global search while the small inertia weight facilitates local search. A value of 0.1 – 0.9 is recommended in many of the research papers. The introduction of the inertia weight also eliminates the requirement of carefully setting the maximum velocity $V_{\max}$each time the PSO algorithm is used. The $V_{\max}$can be simply set to the value of the dynamic range of each variable and the PSO algorithm still performs satisfactorily.

Another parameter - constriction coefficient was introduced to accelerate PSO convergence [1][2]. A simplified method of incorporating it appears in Equation (7), where k is a function of c_1 and c_2 as seen in Equation (8).

$$v_{id}^{m+1} = k[v_{id}^{m} + c_1 rand1(p_{id} - x_{id}^{m}) + c_2 rand2\left(p_{gd} - x_{id}^{m}\right)] \qquad (7)$$

$$\mathrm{k} = \frac{2}{\left|2 - \varphi - \sqrt{\varphi^2 - 4\varphi}\right|} \qquad (8)$$

where $\varphi = c_1 + c_2$, $\varphi > 4$

Mathematically, Equation (6) and (7) are equivalent by setting inertia weight ω to be k, and c_1 and c_2 meet the condition $\varphi = c_1 + c_2$,$\varphi > 4$. The PSO algorithm with the constriction factor can be considered as a special case of the PSO algorithm with inertia weight while the three parameters are connected through Equation (8). As a rule of thumb a better approach is to utilize the PSO with constriction factor while limiting *Vmax*to *Xmax*, the dynamic range of each variable on each dimension, or utilize the PSO with inertia weight while selecting ω, $c1$ and $c2$ according to Equation (8)[6].

When Clerc's constriction method is used, φ is commonly set equal to 4.1 and the constant multiplier kis approximately 0.729. This is equivalent to the PSO with inertia weight when $\omega \approx 0.729$ and $c_1 = c_2 = 1.49445$. Since the search process of a PSO algorithm is nonlinear and complicated, a PSO with well-selected parameter set can have good performance, but much better performance could be obtained if a dynamically changing parameter is well designed. Intuitively, the PSO should favour global search ability at the beginning of PSO while it should favour local search ability at the end of PSO.

Shi and Eberhart [5] first introduced a linearly decreasing inertia weight to the PSO over the course of PSO, then they further designed fuzzy systems to nonlinearly change the inertia weight [7][8]. The fuzzy systems have some measurements of the PSO performance as the input and the new inertia weight as the output of the fuzzy systems. In a more recent study, an inertia weight with a random component [0.5 + (*rand*/2.0)] rather than time decreasing is utilized. This produces a randomly varying number between 0.5 and 1.0, with a mean of 0.75 which is similar to Clerc's constriction factor described above [8].

4 Applications of PSO in Water Resources Engineering

Researchers have attempted a wide range of problems in water resources engineering using PSO. Certain problems where particle swarm techniques have been successfully applied in water resources are examined as follows:

4.1 Reservoir Planning Design and Operation

Reservoir Operation optimization involves determining the optimum amount of water that should be released for flood control, irrigation, hydropower generation, navigation and municipal water supply. Being a complex problem it involves many decision variables, multiple objectives as well as considerable risk and uncertainty [14].

Kumar and Reddy [13] discussed the implementation of Particle Swarm Optimization in multipurpose reservoir operation. They considered Bhadra reservoir system in India which serves irrigation and hydropower generation. It was required to obtain the optimum releases to the left and right bank canals (utilized for irrigation and hydropower generation) and to the river bed turbine (for hydropower generation). To handle multiple objectives of the problem, a weighted approach was adopted. The objective function dealt with minimizing the annual irrigation deficits and maximizing the annual hydropower generation with greater weightage for minimizing irrigation deficits. The decision variables were the monthly releases that should be made to the left and right bank canal and the river bed turbine in a year. The optimization was carried out under a set of constraints which included mass balance, storage, canal capacity, power production and water quality requirements.

The performance of the standard PSO algorithm was improved by incorporating an Elitist Mutated PSO (EMPSO) in which a certain number of the best performing solutions (elites) were retained with mutation during each successive iteration to increase population diversity and enhance the quality of the population. The results obtained demonstrated that EMPSO consistently performed better than the standard PSO and genetic algorithm techniques. They concluded that EMPSO is yielding better quality solutions with less number of function evaluations.

4.2 Groundwater utilization

Gaur et.al.[9] used Analytic Element Method and Particle Swarm Optimization based simulation optimization model for the solution of a groundwater management problem. The AEM-PSO model developed was applied to the Dore river basin, France to solve two groundwater hydraulic management problems: (1) maximum pumping from an aquifer, and (2) minimize the cost to develop the new pumping well system. Discharge as well as location of the pumping wells were taken as the decision variables. The influence of the piping length was examined in the total development cost for new wells. The optimal number of wells was also calculated by applying the model to different sets of wells. The constraints of the problem were identified with the help of water authority, stakeholders and officials which included maximum and minimum discharge limits for the well pumping, minimum allowable groundwater drawdown and water demand.

The AEM flow model was developed to facilitate the management model in particular, as in each iteration optimization model calls a simulation model to calculate the values of groundwater heads. The AEM-PSO model was found to be efficient in identifying the optimal location and discharge of the pumping wells. A penalty function approach was used to penalize constraint violations and this was found to be valuable in PSO and also acceptable for groundwater hydraulic management problems.

4.3 Groundwater Pollution Control

In many parts of our country and in the world ground water is excessively contaminated due to various anthropogenic and industry related activities. Pollution of groundwater happens due to the leachate from animal and human waste dumped on the land, fertilizer application, industrial effluents and municipal waste dumped into surface water bodies. Mategaonkar and Eldho[15] presented a simulation optimization (SO) model for the remediation of contaminated groundwater using a PAT system. They developed a simulation model using Mesh Free Point Collocation Method (PCM) for unconfined groundwater flow and contaminant transport and an optimization model based upon PSO. These models are coupled to get an effective SO model for the groundwater remediation design using pump and treat mechanism. In groundwater pollution remediation using PAT, optimization is aimed at identification of cost-effective remediation designs, while satisfying the constraints on total dissolved solids concentration and hydraulic head values at all nodal points. Also, pumping rates at the pumping wells should not be more than a given specified rate. Only minimization of the remediation cost is considered as the objective function in this remediation design. The decision variables were the pumping or injection rates for the wells considered and the purpose of the design process is to identify the best combination of those decision variables. The cost function includes both the capital and operational costs of extraction and treatment. The PCM PSO model is tested for a field unconfined aquifer near Vadodara, Gujarat, India.

4.4 Estimation of unknown aquifer parameters in groundwater flow through inverse modeling

Jianqing and Hongfei[11] applied the PSO algorithm to the function optimization problem of analyzing pumping test data to estimate aquifer parameters of transmissivity and storage coefficient. The objective function was to minimize the difference between simulated and observed groundwater head values with transmissivity and storage coefficient as the decision variables. The results showed that 1) PSO algorithm may be effectively applied to solve the function optimization problem of analyzing pumping test data in aquifer to estimate transmissivity and storage coefficient, 2) the convergence of PSO algorithm and the computation time are influenced by the number of particles and that fewer iterations are needed in computation with the larger number of particles and 3) the ranges of initial guessed values of transmissivity may also bring some effect on the convergence of PSO algorithm and the computation time. They found that larger the ranges are, the more number of iterations and longer computation time are needed for a guaranteed convergence of PSO algorithm.

A few other applications of PSO are listed below in Table1.

Table 1. Applications of PSO

Author/s	Application	Decision variable	Empirical constants Chosen
Mattot et.al [17]	PSO is used for the cost minimization of a pump and treat optimization problem.	Extraction and Injection Rates of the wells and Number of wells required	
Zhou et.al. [25]	Training of Artificial Networks by PSO to classify and predict water quality	Weights of the input and hidden layers of ANN	1) ω = .9-.4 2) No of particles - 80 3) c1 = c2 = 2 4) k is not used5) Termination - 1000 iterations
Gill et.al [10]	Multi Objective PSO (MOPSO) to calibrate the (i) Sacramento soil moisture accounting model model and (ii) a support vector machine model for soil moisture prediction	Parameters of both the models (16+3)	1) ω(linearly varying) - 0.9 - 0.01 2) No of particles - (i) 100 (ii) 50 3) c1 = c2 = 0.5
Izquierdo et.al [12]	design of (i) 2 water distribution networks, the Hanoi new water distribution network and the New York tunnel water supply system (ii) the design of a waste water network and (iii) the calibration and identification of leaks in a water distribution network	pipe diameters and slopes	1). ω= 0.5 + 1/(2(ln(k) +1)) ;k -iteration no 2). No of particles - (i) 100 (ii) 100 (iii) 300 3). c1 = 3 ; c2 = 2 4). Termination after no of iterations - (i) 200 (ii) 800 (iii) 200
Mathur et al [16]	optimal schedule of irrigation from lateral canals	no of minor canals(21) and no of days (120)	1)ω(0.9-0.4) 2) particles - 200 3) c1=c2=1.5 4)Stop after 200steps

5 Conclusions and further Scope

Particle Swarm Optimization has been successfully used in various complex water resources engineering problems to decide water management policies.
Some of the advantages of PSO are as follows:
1. In comparison to other evolutionary algorithms PSO is simpler to understand and implement.
2. The method does not depend on the nature of the function it maximizes or minimizes. Thus approximations made in conventional techniques are avoided.
3. It uses objective function information to guide the search in problem space. Therefore it can easily deal with non differentiable and non convex objective functions.
4. Non Linear Programming solutions are dependent upon the initial estimation of solutions. Therefore different initial estimates of parameters give different suboptimal solutions. PSO method is not affected by the initial searching points, thus ensuring a quality solution with high probability of obtaining the global optimum for any initial solution.
5. In PSO particle movement uses randomness in its search. Hence, it is a kind of stochastic optimization algorithm that can search a complicated and uncertain area. Thus it is more flexible and robust than conventional methods.
6. The convergence is not affected by the inclusion of more constraints.
7. It also has the flexibility to control the balance between the global and local exploration in search space. This property enhances the search capabilities of the PSO technique and yields better quality solutions with fewer function evaluations.
8. The algorithm of PSO, demands fewer adjusted key parameters of the algorithm and its arithmetic process is convenient and programmable. It can be easily implemented, and is computationally inexpensive, since memory and CPU speed requirements are low.

PSO has been highly successful and within little more than a decade hundreds of papers have reported successful applications of PSO. As it is a technique of recent origin, the number of applications of PSO in water resources engineering is relatively less and there is still a lot of scope for a wider application of PSO to solve water related problems. Therefore there is a possibility that it may emerge as a powerful optimization tool in water resources research. Some of the possible areas in water resources where further research may be done is as follows

- Ground water – utilization management, detection of unknown groundwater pollution sources, contaminant remediation, estimation of unknown aquifer parameters, estimation of water table by geo physical methods, optimization for design of multi layered sorptive systems, management of salt water intrusion in coastal aquifers.

The decision variables are specific to the problem under study. It can include the location, number and discharge of pumping wells, unknown aquifer parameters, depth of water table etc

- Reservoir – planning, design and operation.
  The decision variables may include the optimum discharge values for each time period such that the all the demands are met.
- Hydrology – Calibration of hydrological and ecological models , Time Series Modelling, stream flow forecasting,
  The calibration of various models involve the estimation of the various parameters associated with them. It may not be possible to obtain them from physical observations. Hence optimization methods have a definite advantage.
- Irrigation – scheduling of irrigation canals, Canal design
- River Stage forecasting , River Water Quality Control and Prediction
- Design of Water Distribution Networks, Calibration and improvement of urban drainage systems, Detection of leaks and its rectification
- Climate Variability and Change, Calibration of climate models

There are efforts by many researchers to develop better variations of PSO to increase population diversity and ensure global convergence of the algorithm. These researches may make it more suitable for large scale complex combinatorial optimization problems.

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