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Simulation optimization model for aquifer parameter estimation using coupled meshfree point collocation method and cat swarm optimization

Alice Thomas, Partha Majumdar, T.I. Eldho*, A.K. Rastogi

Department of Civil Engineering, Indian Institute of Technology Bombay, Mumbai, India

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ABSTRACT

Here we propose a new simulation-optimization model (S-O) for aquifer parameter estimation by coupling radial point collocation meshfree method (RPCM) with cat swarm optimization (CSO). The decision and state variables are zonewise transmissivity values and hydraulic heads at the predefined locations, respectively. The hydraulic head values obtained using RPCM acts as input for the CSO model. The RPCM-CSO model minimize sum of the weighted squared difference of simulated and observed hydraulic heads for different realization of transmissivity values. Further for comparison, RPCM model is coupled with particle swarm optimization (PSO) and elitist-mutated PSO (EMPSO). The RPCM-CSO model has been applied to estimate the zonal transmissivity values of a synthetic aquifer for validation and to a field problem. For synthetic problem, the transmissivity values are compared with available results. The RPCM-CSO model is more accurate than other models based on the genetic algorithm (GA) and PSO. For the field problem, average percentage error in parameter estimation using RPCM-CSO model is 1.555%, for RPCM-PSO is 3.145% and for RPCM-EMPSO is 2.270%. Further a reliability analysis carried out showed that RPCM-CSO model is accurate and efficient to estimate the transmissivity values. This study showed the effectiveness of RPCM-CSO model for aquifer parameter estimation.

1. Introduction

Scientific assessment of aquifer parameters such as transmissivity, hydraulic conductivity, storativity, areal recharge, etc. is of utmost importance for the proper management of groundwater resources. The accuracy of groundwater flow and transport model predictions relies on the ability to accurately and reliably quantify these unknown parameters. Hence parameter estimation in groundwater using inverse modeling is a major component of groundwater flow and contaminant transport modeling [1]. The inverse problem aims at the optimal determination of the aquifer parameters like transmissivity, hydraulic conductivity, storativity and areal recharge by the observation of state variables collected over a period of time and space domain. Inverse modeling has been widely attempted by a number of researchers [2–10]. There is a considered opinion that it improves the quality of groundwater models and yield results that are generally not readily available through non-automated calibration efforts. It is also observed that inverse modeling substantially reduces the time required for obtaining aquifer parameters [11]. Simulation-optimization (S-O) models are extensively used in previous studies to estimate aquifer parameters by inverse modeling approach [3,5–7].

The groundwater flow processes are usually simulated by numerical methods like Finite Element Method (FEM) [12–15], Finite Difference Method (FDM) [13,14,16, and 17], Boundary Element Method (BEM), [18], Analytical Element Method (AEM) [19,20] etc. All these methods have their own advantages as well as disadvantages. The AEM is not suitable to simulate transient flow condition or highly heterogeneous media [20]. The FDM/FEM uses a predefined grid/mesh where the groundwater flow equation is approximated by a set of algebraic equations for the chosen grid/mesh in the system. These methods are computationally expensive for large-scale problems due to the preprocessing effort required. The Meshfree (MFree) methods are relatively new techniques, and recently have been applied to simulate groundwater flow and contaminant transport processes [21–27]. Further, the accuracy and computational efficiency of meshfree models such as RPCM is well established [21,23,26]. The MFree method establishes a system of algebraic equations without the use of a predefined mesh but uses a set of nodes scattered within the problem domain as well as on the boundaries of the domain. The absence of meshing when solving for large-scale problems can save substantial cost and significant reduction in computational time on preprocessing which is one of the main advantages of MFree methods [28,29]. In this study, radial point collocation-based meshfree method (RPCM) is adopted for simulating groundwater flow. Recently the RPCM is widely used for solving many groundwater flow related issues [21,23,24]. The computational benefits of MFree methods over mesh based method (FEM) are discussed by

* Corresponding author.
E-mail address: eldho@civil.iitb.ac.in (T.I. Eldho).

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Thomas et al. [26]. RPCM comes in the category of ideal or true mesh-free methods (strong form) where meshing is not required throughout the process of formulating and solving the governing equations. Further Mesh-Free methods are more accurate and computationally efficient in simulating advection-dominated transport problems than mesh-based method [21]. Hence, MFree-methods are better numerical approach for groundwater flow and transport simulation [21,23,24,26].

In the inverse models to estimate aquifer parameters, the simulation model is usually linked with an optimization model. The optimization model repetitively executes the simulation model in a way to reduce the difference between the simulated and field observed values. In earlier studies, many heuristic optimization algorithms, such as Genetic algorithm (GA) [3,6,7], Simulated Annealing (SA) [30,31], Differential Evolution (DE) [32,33], Particle Swarm Optimization (PSO) [34] and Ant Colony Optimization (ACO) [35,31] have been used for aquifer parameter estimation by inverse modeling. Heuristic optimization methods do not require derivative calculations or initial point to start search processes unlike traditional gradient-based methods, which is a major advantage [19]. Mattot et al. [36] provided a comparative study for groundwater remediation using various optimization algorithms, such as: Genetic algorithm-GA, Conjugate gradient-CG, Particle swarm optimization-PSO, Random search algorithm-RND and claimed the superiority of PSO, [36]. Ketabchi and Ashtiani [37,38,39,40] also compared the application of seven evolutionary algorithms which were Differential evolution (DE), GA, Particle swarm optimization (PSO), Artificial bee colony optimization (ABC), Continuous ant colony optimization (CACO), Simplex simulated annealing (SIMPSA), Shuffled complex evolution (SCE), and Harmony search (HS) for optimal management of coastal groundwater and suggested CACO and PSO based on solution accuracy and computational time for further application in coastal groundwater management problems. It is reported that CACO and PSO based models have better convergence rate when compared to other evolutionary algorithms. However, PSO is prone to premature convergence or stagnation point error [41,42].

A relatively new heuristic optimization algorithm viz., Cat Swarm Optimization (CSO) introduced by Chu and Tsai [43] is found to be better than GA, SA and PSO [43–45, and 19]. Application of CSO is found in various engineering fields such as deployment of wireless sensor, clustering, linear phase filter design, infinite impulse response system identification, parameter identification of solar cell models, groundwater quantity and capture zone management analysis [19]. However, to the authors' best knowledge, any application of CSO for aquifer parameter estimation is not yet reported.

In this study, the main objective is to develop a simulation-optimization model for aquifer parameter estimation by combining Meshfree RPCM with cat swarm optimization (CSO). The groundwater flow processes have been simulated by radial point collocation method (RPCM). The RPCM model was also coupled with PSO and EMPSO to develop RPCM PSO and RPCM EMPSO models. The RPCM-CSO model is applied to estimate zonal transmissivity values of a hypothetical and a field aquifer. The performance of RPCM-CSO model is also compared with the results of RPCM-PSO and RPCM-EMPSO model. Further a reliability analysis is done to check the accuracy of the developed model. The use of meshfree RPCM method coupled with cat swarm optimization (CSO) for aquifer parameter estimation has been found to be effective and innovative in the field of groundwater inverse modeling.

2. Methodology

In this study, the groundwater flow processes have been simulated using radial point collocation-meshfree method (RPCM). The RPCM is further coupled with cat swarm optimization (CSO) and Particle optimization (PSO) to develop simulation-optimization models for aquifer parameter estimation. Brief descriptions of the groundwater flow equation, meshfree based radial point collocation method, cat swarm optimization and particle swarm optimization are given in the following sub-sections.

2.1. Groundwater flow equations and boundary conditions

The groundwater flow equation in a two-dimensional inhomogeneous confined aquifer can be expressed as [3]

$$\frac{\partial}{\partial x}\left[T_x\frac{\partial h}{\partial x}\right]+\frac{\partial}{\partial y}\left[T_y\frac{\partial h}{\partial y}\right]=S\frac{\partial h}{\partial t}+Q_w\delta\left(x-x_i\right)\left(y-y_i\right)-q \tag{1a}$$

The initial condition used for transient flow analysis is given as

$$h(x,y,0)=h_o(x,y);\ x,\ y\in\Omega \tag{1b}$$

There are two kinds of boundary condition (BC): prescribed head and prescribed flux boundary

$$\text{Prescribed head (Dirichlet BC)}:\ h(x,y,t)=h_1(x,y,t);\ x,y\in\Omega_1 \tag{1c}$$

$$\text{Prescribed flux(Neumann BC)}:\ T\frac{\partial h}{\partial n}=q_1(x,y,t);\ x,\ y\in\Omega_2 \tag{1d}$$

Where $h\ (x,\ y,\ t)$ is the piezometric head; T_x and T_y are the transmissivity in x and y direction; S is the storage coefficient; Q_w is the source or sink; $\frac{\partial h}{\partial n}$ is the normal derivative to the boundary; h_o (x, y) is the initial head in the flow domain; h_1 (x, y, t) is the hydraulic head value; $q_1\ (x,\ y,\ t)$ is the known inflow rate; q is the recharge rate; Ω is the flow domain.

2.2. Meshfree point collocation method

The Mfree method is used to establish a system of algebraic equations for the whole problem domain without any predefined mesh for the domain discretization [28]. Field nodes are scattered on the boundaries and within the problem domain not for discretizing but only for representing the study area. They do not form a mesh, which means any prior information on the relationship between the nodes for the interpolation or approximation of the unknown functions of field variable is not required [29]. Here, point collocation method (PCM) with standard multi quadratic radial basis function is used for developing the groundwater flow model.

The approximation of a function $h(x)$ within the local support domain is constructed as a linear combination of n radial basis function [29]. Here no polynomial basis function is considered. By considering pure RBF function, the nodal hydraulic head can be expressed as,

$$h(x)=\sum_{i=1}^{n}R_i(x)a_i=R^T(x)a=\Phi^T(x)h_s \tag{2}$$

where $R_i\ (x)$ is the radial basis function (RBF); n is the number of nodes in the support domain; and a_i is the unknown coefficient to be determined;

Multi-quadratics radial basis function (MQ-RBF) is used to develop shape functions here, i.e.

$$R_i(x,y)=\left(r_i^2+\left(\alpha_c d_c\right)^2\right)^q \tag{3}$$

$$r_i=\sqrt{\left(x-x_i\right)^2+\left(y-y_i\right)^2} \tag{4}$$

where, d_c is the average nodal spacing for all the nodes in local support domain;$(x,\ y)$ are the coordinates of the point of interest (data site); $(x_i,\ y_i)$ are the coordinates of any node in the support domain of the point of interest (center point); q and α_c are the shape parameters. The MFree model with a q value of 0.98 gives accurate results [21,26].

The unknown coefficients a_i in Eq. (2) are determined by enforcing the interpolation function to pass through all n nodes within the support domain [29].