International Journal of Computer Sciences and Engineering Open Access
Research Paper Volume-5, Issue-10 E-ISSN: 2347-2693

Groundwater Pollution Source Identification Using Genetic Algorithm Based Optimization Model

Md. Ayaz

Civil Engineering Section, University Polytechnic, Aligarh Muslim University, Aligarh, India

Corresponding Author: ayaz.math@gmail.com

Available online at: www.ijcseonline.org

Received: 26/Sep/2017, Revised: 11/Oct/2017, Accepted: 21/Oct/2017, Published: 30/Oct/2017

Abstract- Groundwater is an important natural resource available on the earth. Contamination of groundwater resources has become a major problem today due to some artificial and natural activities. Identification of groundwater pollution sources is a major step in groundwater pollution remediation. A pollution source is said to be known only when its source characteristics (location, strength and duration of pollution activity) are known. Identification of unknown groundwater pollution source is an inverse problem, which is generally ill posed due to existence of local minima. This problem becomes more complex for real field conditions, when the lag time (defined as the time difference between the first reading at the observation well and the time when source becomes active) is not known. Genetic Algorithm (GA) based simulation optimization methodology has been used in this study for complete identification of unknown groundwater pollution source. GA is non-gradient based search technique and it is capable of finding the global optimum. A contaminant transport model, which can simulate the concentrations at the observation well location, is combined with the GA based optimization simulation model. The performance of the developed methodology is evaluated for one and two dimensional cases with error free and erroneous concentration measurement data. Performance results show the capability and practical applicability of proposed methodology. Main advantage of the proposed methodology is that complete identification of unknown groundwater pollution source is possible with the help of only one observation well when the lag time is also not known.

Keywords- Groundwater Pollution, Genetic Algorithm, Inverse Problem, Optimization, Pollution source identification

I. INTRODUCTION

Groundwater has always been a precious natural resource for human life. It is a major source of drinking water and also an important source for agricultural and industrial sectors. Groundwater is found in geological formations called aquifers (confined and unconfined). Due to expanding population, extraction of groundwater is increasing day by day, which results in the depletion of water table as well as deterioration of water quality. Contamination of groundwater resources has become a major problem today. Human activities including industrial and agricultural activities are generally responsible for this contamination. Some of the common activities which cause contamination of groundwater are: leakage from underground storage tank and pipelines, injection of polluted water into the aquifer, direct disposal of wastes on land surface, application of fertilizers and pesticides in agricultural field. Identification of groundwater pollution sources is a major step in groundwater pollution remediation. A pollution source is said to be completely identified when its location, magnitude and disposal periods are known. Only after knowing the exact locations of pollution sources, the appropriate remedial actions can be adopted. Identification of unknown pollution sources in terms of location, magnitude and disposal period is a very complex inverse problem. It becomes more complex in the absence of concentration data, presence of multiple pollution sources, spatial and temporal variation of source flux, absence of well defined initial and boundary conditions and uncertainty associated with estimation of flow and transport parameters.

Unknown groundwater pollution sources can be identified with the help of observed responses at different observation wells. These responses consist of observed concentrations of pollutant with respect to time. Several methodologies have been developed to solve this complex problem with different limitations. Authors of [4] introduced the response matrix approach to solve the identification problem. This method was based on the principle of superposition of unit responses, due to which it was only applicable for linear or approximately linear groundwater systems. The main objective of this study is to identify the groundwater pollution sources with the help of observed responses. The identification problem is an inverse problem which is generally ill posed. It means that the solution may be unstable to small change in the input data and it may not be unique. Due to this nature, the solution of groundwater identification problem becomes more complex and challenging. Existence of more than one observation wells, heterogeneity of the aquifer, uncertainty in parameter estimation, uncertainties in initial and boundary conditions, unavailability of observed concentration data increases the complexity of identification problem. This problem becomes more complex for real field conditions, when the lag time (defined as the time difference between the first reading at the observation well and the time when source becomes active) is not known. Over the years, optimization techniques have been used by researchers for identification of unknown groundwater pollution sources. Gradient based search techniques may not be able to solve this problem due to the existence of local minima. In this present study, Genetic Algorithm (GA) based simulation optimization methodologies are developed for complete identification of unknown groundwater pollution source. Since GA is a non gradient based search technique, it is able to overcome the shortcomings of gradient based search methods by finding the global optimal solution.

The paper has been presented in eight sections. The current section is the introduction giving a brief overview of the topic. Second section contains the literature review, which presents some of the important works in the field of groundwater pollution source identification. Third section briefly describes the working principle of Genetic Algorithm. In section four, the governing partial differential equations along with initial and boundary conditions for one and two-dimensional cases have been discussed. Section five deals with the formulation of objective function for GA based optimization model. Section six and seven present the performance results of developed optimization models for error-free and erroneous data respectively. Finally the conclusions of this study are summarized in section eight.

II. LITERATURE REVIEW

Identification of groundwater pollution source using GA based simulation optimization technique requires two models. The first one is groundwater pollutant transport model and second is optimization model. Groundwater flow and pollutant transport model is highly complicated because of changing boundary conditions and uncertainties involved in aquifer parameters. In recent years groundwater flow and transport model is widely used for groundwater management model. This is done by incorporating the flow and transport model into the desired management objective. In 1988, authors of [10] classified groundwater models as: identification or evaluation models, prediction models and management models. Groundwater identification model deals with the source identification, aquifer parameter estimation or sometimes both simultaneously. Groundwater prediction model deals with the prediction of aquifer responses. Groundwater management model deals with a flow and transport model combined with an optimization model to achieve the optimal management strategy. Authors of [4] presented an optimization approach for identification of unknown groundwater pollution source. They used linear programming as well as least square regression. They used response matrix approach to incorporate the groundwater solute transport model into the optimization model. Authors of [6] developed a methodology for optimal monitoring network and groundwater pollution source identification. In this methodology they combined the optimal groundwater quality monitoring network design with a source identification model. Authors of [4, 13] reported that embedding technique has numerical difficulties with large scale real world groundwater heterogeneous systems. Due to this reason they have taken 1.04 square kilometers as the largest size of aquifer for performance evaluation. Authors of [7] developed a methodology using nonlinear optimization model for estimation of unknown groundwater pollution sources. They considered transient flow and transport conditions. The governing equation of flow and solute transport was incorporated in the optimization model as binding equality constraints. Limitation of this methodology was that it requires large computer storage and computational time. Authors of [8] developed an optimization based methodology for optimal identification of groundwater pollution sources and parameter estimation. This methodology utilizes an optimization model in which the flow and transport equations were embedded as constraints. They also incorporated errors in the measurement data. Authors of [11] developed a methodology to identify the unknown groundwater pollution source using artificial neural network (ANN). They trained a feed forward multilayered back propagation ANN based on the simulated concentration measurement data observed at specified observation well. Authors of [12] developed GA based linked simulation optimization model to identify the unknown groundwater pollution sources. They externally linked a flow and transport simulation model to a GA-based optimization model. Authors of [9] developed an analytical solution to Advection-Dispersion equation for one dimensional solute transport in semi infinite porous medium with no provision of sorption and degradation process. Authors of [1] developed a general analytical solution for two dimensional solute transport subjected to a third type input boundary condition. Specific solutions are also derived for a single strip source. They considered a unidirectional flow field containing strip solute sources. They assumed that the medium is homogeneous and isotropic. Authors of [4] presented two primary techniques to incorporate the simulation model into the management model: Embedding approach and Response matrix approach. This technique is not applicable for large scale groundwater systems. This technique requires large computational time and storage. Authors of [3, 5] used response matrix approach to incorporate the simulation model into the optimization model. This approach is based on the principle of superposition. Its performance was poor for highly non linear system.

It is evident from the literature review that several attempts have been taken to identify the optimal groundwater pollution source. Some of them were based on classical optimization technique and the latest works are based on non gradient based search techniques using GA as a linked simulation approach. Each of the methodology has its own merits and limitations. The methodology proposed in this study is based on GA based optimization technique in which a simulation model is linked for optimal identification of unknown pollution source in terms of distance, source concentration, duration of activity of the source. The main advantage of the proposed methodology is that it is cost effective as it requires only one observation well for the complete identification of pollution source.

III. GENETIC ALGORITHM

The genetic algorithm is a method for solving both constrained and unconstrained optimization problems. It is based on natural selection, the process that drives biological evolution. A detail description on Genetic Algorithm is available in [2]. Following are the steps involved in the working principle of Genetic Algorithm:

Initial Population: A population is an array of individuals. The algorithm begins by creating a random initial population. The number of individuals in the initial population is known as population size. All the individuals in the initial populations lie between the initial ranges. If it is approximately known, where the minimal point of the function lies, then the initial range can be set in such a way that the point lies near the middle of that range.

Creating of Next Generation: At each step, GA creates next generation by using the population in the current generation. Algorithm computes fitness values of each member of the current population. Based on the fitness value, algorithm selects a group of individuals in the current population, which are known as parents. The algorithm usually selects individuals which have better fitness value as parents. There are three types of children which are created by GA for the next generation (Figure 1):

1. ***Elite Children*****:** The individuals in the current population which have best fitness value are chosen for elite children. These individuals are passed to the next population.
2. ***Crossover Children*****:** These children are created by the combining the vector entries of a pair of parents. The crossover function randomly selects a gene from one of the two parents and assigns it to child.
3. ***Mutation Children*****:** These children are created by introducing some random changes or mutations to a single parent. For this, algorithm adds a random vector for a mutation function to the parent.

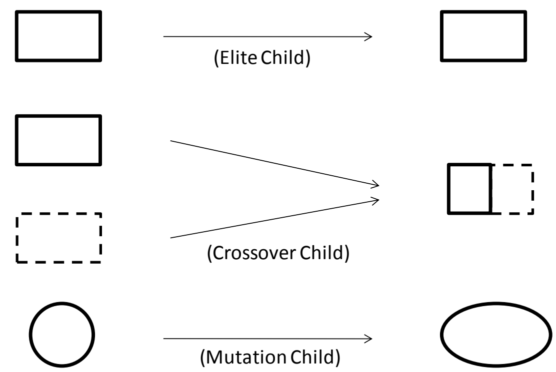

Figure 1: Types of children created by GA

IV. MATHEMATICAL MODEL FOR GROUNDWATER CONTAMINANT TRANSPORT

Mathematical model is a model which can simulate the physical process. Groundwater contaminant transport is governed by the advection-dispersion equation. To find the unique solution of the governing partial differential equation, initial and boundary conditions are required.

Governing Partial Differential Equations:

One-Dimensional Case:

$$\frac{\partial C}{\partial t} = \frac{D}{R_d}\frac{\partial^2 C}{\partial x^2} - \frac{U}{R_d}\frac{\partial C}{\partial x} - \nu C \qquad (1)$$

Two-Dimensional Case:

$$\frac{\partial C}{\partial t} = \frac{D_x}{R_d}\frac{\partial^2 C}{\partial x^2} + \frac{D_z}{R_d}\frac{\partial^2 C}{\partial z^2} - \frac{U}{R_d}\frac{\partial C}{\partial x} - \nu C \qquad (2)$$

where,

t = time
C = Concentration of the dissolved pollutant
D_x = Coefficient of hydrodynamic dispersion in x- direction
D_y = Coefficient of hydrodynamic dispersion in y- direction
U = Groundwater velocity in x- direction
R_d = Retardation factor
ν = Decay constant

Initial and Boundary Conditions

Generally there are two types of problems exist in nature: Steady state problem which is not a function of time and unsteady state problem which depends on time. For the unique solution of steady state problem, only boundary condition is required while for the unique solution of unsteady state problem, both initial and boundary conditions are required. The above mentioned governing partial differential equations require both initial and boundary conditions. Initial and boundary conditions for one and two-dimensional cases are given below.

One-Dimensional Case:

$C(x,0) = 0$ (3)
$C(0, t) = C_0$ for $0 \le t \le T_0$ (4)
$C(0, t) = 0$ for $t > T_0$ (5)
$C(\infty, t) = 0$ (6)

where
T_o = Duration of disposal period
C_0 = Pollution source strength

Two-Dimensional Case:

$C(0,z,t) = C_0$ for $-B \le z \le B$ and $0 \le t \le T_0$ (7)
$C(0,z,t) = 0$ otherwise (8)
$C(x,z,0) = 0$ (9)
$\lim_{r\to\infty} C(x,z,t) = 0$ (10)
$r = (x^2 + y^2)^{1/2}$ (11)
where, B = Half of the width of the strip source

V. GA BASED OPTIMIZATION MODEL OBJECTIVE FUNCTION FORMULATION

Identification of unknown groundwater pollution source is an inverse problem which is generally ill posed. Objective function formulated for such type of problems is not unimodal and it might contain some local minima. Due to the above reasons, gradient based search techniques which are also known as classical optimization techniques, are not able to handle such type of problems effectively. To overcome the problem of existence of local minima, non gradient based optimization technique is required. Genetic Algorithm (GA) is a non gradient based optimization technique which is able to find the optimal solution. In this study a GA based optimization simulation methodology is developed for the complete identification of unknown groundwater pollution source.

The objective of source identification model is to determine the unknown groundwater pollution source characteristics in term of its magnitude, location and duration of activity. For this purpose objective function is formulated by minimizing the sum of the square of differences between the observed and estimated concentrations. The unknowns for which the objective function is minimized are source characteristics in terms of location, strength and disposal period. The optimization model can be formulated as in terms of objective function:

$$Minimize: f = \sum_{i=1}^{n}\left(C_{est}^{i} - C_{obs}^{i}\right)^2 \quad (12)$$

subject to:

$\mathbf{C} = h(\mathbf{q})$ (13)
$\mathbf{q^l} \le \mathbf{q} \le \mathbf{q^u}$ (14)
$\mathbf{C}, \mathbf{q} \ge \mathbf{0}$ (15)
where,
n = Total number of concentration observation reading at an observation well
C_{obs}^{i} = Observed concentration at the observation well at i^{th} reading
C_{est}^{i} = Estimated concentration corresponding to the observation well at i^{th} reading
$\mathbf{q}$ = Vector of model parameters (source location and release period)
$\mathbf{C}$ = Vector of simulated concentrations
$h(\mathbf{q})$ = Simulation model which transform $\mathbf{q}$ into $\mathbf{C}$
$\mathbf{q^l}$ = Lower bound on vector $\mathbf{q}$
$\mathbf{q^u}$ = Upper bound on vector $\mathbf{q}$
In this formulation $h(\mathbf{q})$ represents the advection-dispersion simulation model and $\mathbf{q}$ represents the explicit decision variables in the optimization model.

VI. PERFORMANCE EVALUATION OF OPTIMIZATION MODEL

GA based simulation optimization methodology was developed to identify the unknown groundwater pollution source. The performance of developed methodology has been evaluated by considering two different cases: one dimensional and two-dimensional. In first case, the unknown source is considered to be a point source and in the second case, the unknown source is considered to be a nonpoint source (single strip source). The pollutant considered is a typical conservative and non reactive pollutant. The strength of the source is assumed to be constant throughout the disposal period. It is also assumed that before the disposal of contaminant, the aquifer was uncontaminated. Strength and the disposal period of the source are not known in this study.

One-Dimensional Case

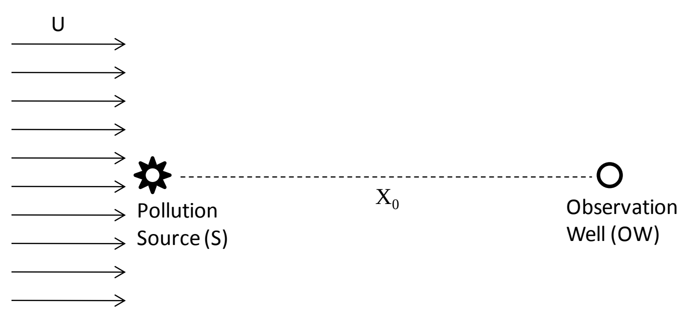

Figure 2: Schematic representation of a single point source with observation well

Figure 2 represents the one-dimensional pollutant transport case. There is a point source (S) at any unknown location which has to be found out. It is assumed that the pollutant is conservative and non-reactive. Water samples have been collected at the observation well "OW" which is located at any arbitrary distance (X_0) from the pollution source. Water samples have been collected at different time steps (known interval of time) and their corresponding concentrations were measured in laboratory. Therefore, the concentration of pollutant at different time steps is the only known data set with which the unknown pollution source characteristics has to be identified (Figure 3).

Following are the four unknown source characteristics in this case.

1. Strength of the pollution source (C_0)
2. The distance between the source and the observation well (X_0)
3. The lag time (T_L)
4. The duration of disposal period of the source (T_0)

MATLAB (R2008a) toolbox for Genetic Algorithm has been used to solve the unknown groundwater pollution source identification problem. Objective function developed in equation 12, which has four independent variables, has been minimized to find the values of four unknown pollution source parameters for which the error between the simulated concentration and measured concentration is minimum. Performance results for error free concentration data are shown in figures 4 and 5 for one-dimensional case and in figures 8 and 9 for two-dimensional case. Actual and predicted values of different source parameters are summarized in Tables 3 and 6 for one and two-dimensional cases respectively. Values of different GA parameters used in optimization models are given in Tables 2 and 5. Flow and transport parameters considered for one and two-dimensional cases are summarized in Tables 1 and 4 respectively.

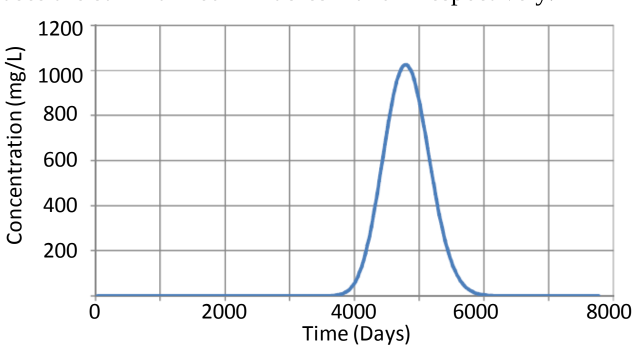

Figure 3: Breakthrough curve observed at location (X_0) for error free data

Table 1: Values of flow and transport parameter for 1-D Case

Parameter	Value
Groundwater Velocity	0.1 ms^{-1}
Coefficient of hydrodynamic dispersion	0.1 m^2day^{-1}

Table 2: Values of GA parameters used for optimization for 1-D case

Sl. No	Parameter	Value
1	Population size	20
2	Elite count	2
3	Crossover fraction	0.8
4	Mutation fraction	0.1

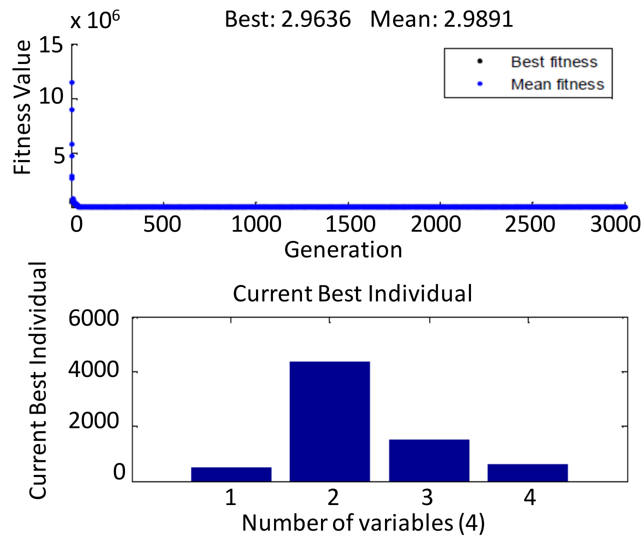

Figure 4: Plot of Objective function value with number of generations

Table 3: Values of actual and predicted parameters for 1-D Case

Parameter	Actual Value	Predicted Value
X_0 (m)	450	450.919
T_L (days)	4380	4387.530
C_0 (mg/l)	1500	1507.472
T_0 (days)	600	596.760

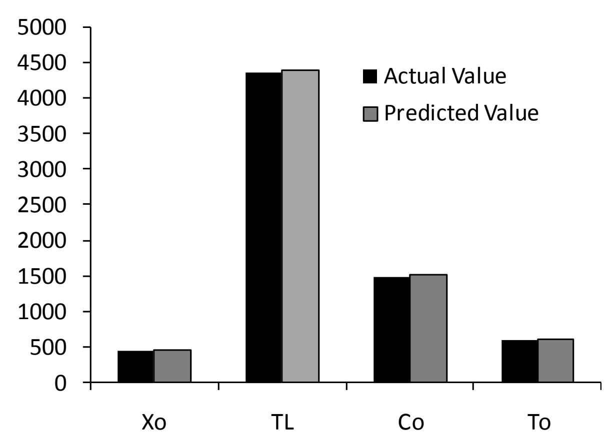

Figure 5: Comparison of actual value with predicted value

Two-Dimensional Case

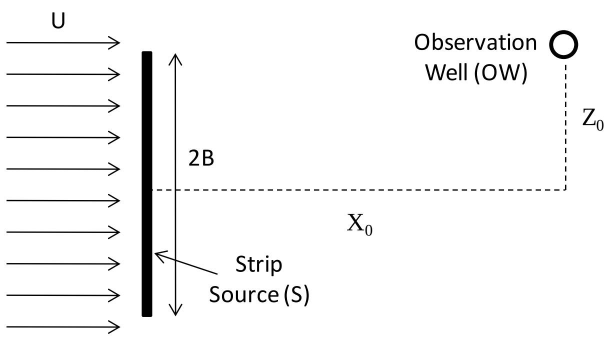

Figure 6: Schematic representation of single strip source with observation well

Figure 6 represents the two-dimensional case in with single strip pollution source. The porous medium is semi infinite in x- direction ($0 \leq x < \infty$) and infinite in z-direction ($-\infty < z < \infty$). The source concentration is uniform throughout the cross section and it is independent of y-axis. There is a strip source (S) of width 2B, situated at any unknown location which has to be found out in terms of its location, width (B), strength (C_0) and disposal period (T_0). It is assumed that the pollutant is conservative and non reactive. Water samples have been collected at the observation well (OW) which is located at any arbitrary distance (X_0) in longitudinal direction and (Z_0) in transverse direction from the centre of the pollution source. Water samples have been collected at different time steps and their corresponding concentrations were measured in laboratory.

Following are the six unknown source characteristics in this case.

1. Concentration at the source (C_0)
2. The longitudinal distance (X_0) between the source and the observation well
3. The transverse distance (Z_0) between the source and the observation well
4. The lag time (T_L)
5. The duration of disposal period of the source (T_0)
6. Width of the strip source (B)

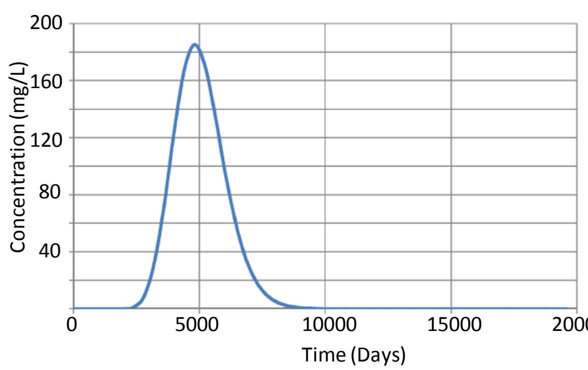

Figure 7: Breakthrough curve observed at location (X_0, Z_0) for error free data

Table 4: Values of flow and transport parameter for 2-D Case

Parameters	Value
Groundwater Velocity (U)	0.1 ms^{-1}
Hydrodynamic dispersion (D_x)	1 $m^2 day^{-1}$
Hydrodynamic dispersion (D_z)	0.1 $m^2 day^{-1}$
Solute retardation factor (R_d)	1.0
First order decay coefficient (v)	0 day^{-1}

Table 5: Values of GA parameters used for optimization for 2-D case

Sl. No	Parameter	Value
1	Population size	20
2	Elite count	2
3	Crossover fraction	0.8
4	Mutation fraction	0.1

MATLAB (R2008a) toolbox for Genetic Algorithm has been used to solve the unknown groundwater pollution source identification problem. Objective function developed in equation 12 which has six independent variables has been minimized to find the values of six unknowns for which the error between the simulated concentration and measured concentration is minimum.

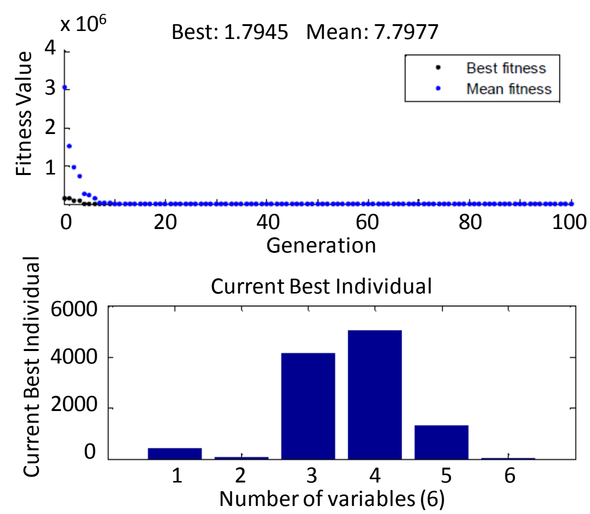

Figure 8: Plot of Objective function value with number of generations

Table 6: Values of actual and predicted parameters for 2-D Case

Parameter	Actual Value	Predicted Value
X_0 (m)	400	425.685
Z_0 (m)	50	50.098
T_L (days)	4000	4105.181
C_0 (mg/l)	5000	5007.889
T_0 (days)	1500	1262.830
B (m)	10	11.123

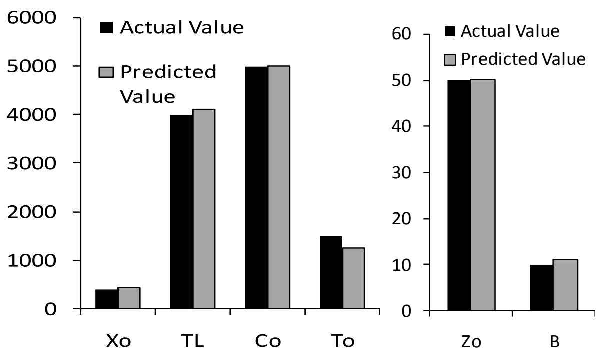

Figure 9: Comparison of actual value with predicted value

VII. PERFORMANCE EVALUATION OF OPTIMIZATION MODEL WITH ERRONEOUS DATA

Observed concentration data generally contains measurement error or noise due to field measurement or laboratory test. To incorporate such errors, uniformly distributed random errors within the range of ±10% of the actual computed values have been added to the observed concentrations. By doing this, it can also be determined that up to what extent the developed model can sustain the random measurement errors.

New Concentration = Observed concentration + error

Performance results for erroneous concentration data are shown in figures 10 and 11 for one-dimensional case and in figures 12 and 13 for two-dimensional case. Actual and predicted values of different source parameters are summarized in Tables 7 and 8 for one and two-dimensional cases respectively.

One-Dimensional Case

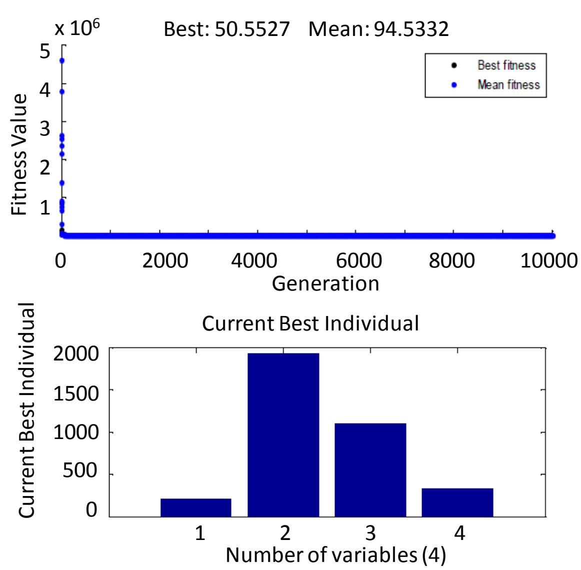

Figure 10: Plot of Objective function value with number of generations

Table 7: Values of actual and predicted parameters for 1-D Case (Erroneous data)

Parameter	Actual Value	Predicted Value
X_0 (m)	200	208.907
T_L (days)	1860	1931.646
C_0 (mg/l)	1000	1099.604
T_0 (days)	360	327.233

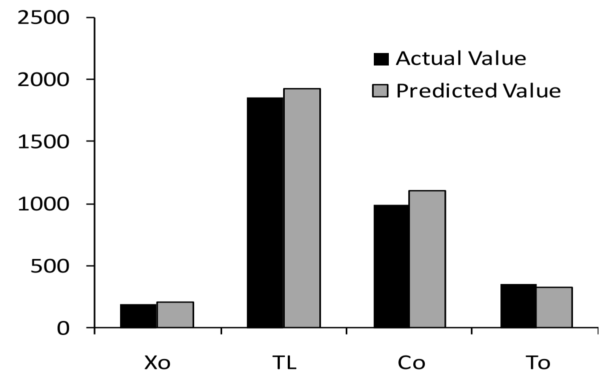

Figure 11: Comparison of actual value with predicted value

Two-Dimensional Case

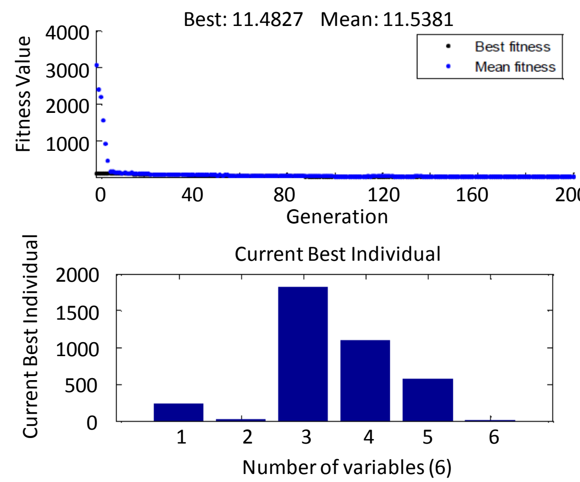

Figure 12: Plot of Objective function value with number of generations

Table 8: Values of actual and predicted parameters for 2-D Case (Erroneous data)

Parameter	Actual Value	Predicted Value
X_0 (m)	200	229.537
Z_0 (m)	20	28.077
T_L (days)	1500	1818.183
C_0 (mg/l)	1000	1088.462
T_0 (days)	600	573.045
B (m)	10	8.571

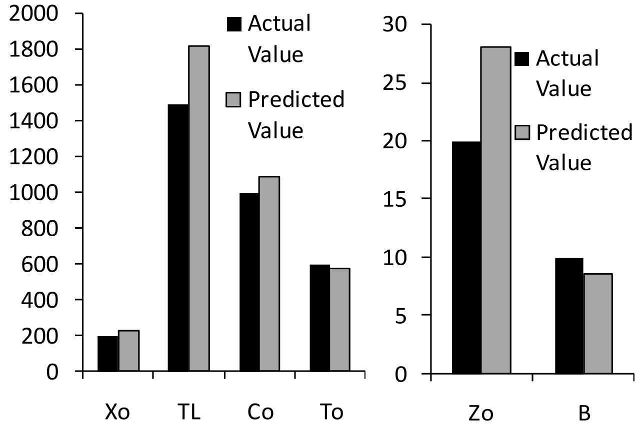

Figure 13: Comparison of actual value with predicted value

Performances of developed GA based optimization models have been evaluated for error-free and erroneous concentration data. In case of error free data, best fitness values were found to be 2.2936 and 1.7945 for one and two-dimensional cases respectively. Estimated source parameters were quite close to the actual values for both the cases. In case of erroneous concentration data, best fitness values were found to be 50.5527 and 11.4827 for one and two-dimensional cases respectively. It can be observed that the prediction error in source parameters has been increased. However, they stay within acceptable ranges. Performance evaluation results demonstrate the potential applicability of proposed GA based optimization model. Therefore it can be concluded that the proposed optimization model is an effective and robust tool in identification of unknown groundwater pollution sources.

VIII. CONCLUSIONS

1. GA based simulation optimization model searches for an optimal set of potential source characteristic in terms of location, magnitude and disposal period for complete identification of unknown pollution source.
2. The performance of the methodology is encouraging even for two dimensional cases where six unknown parameters were successfully determined.
3. Developed GA based simulation optimization model can also incorporate concentration measurement error up to ±10% of noise level.
4. This methodology requires only one observation well for complete identification of pollution source.
5. Developed optimization model is capable of finding the pollution source characteristics when the lag time is not known.

REFERENCES

[1] V. Batu, M.T. van Genuchten, *"First and third type boundary conditions in two dimensional solute transport modeling"*, Water Resourc. Res., Vol. 26, Issue.2, pp. 339-350, 1990.

[2] K. Deb, *"Optimization for engineering design: Algorithms and examples"*, Prentice-Hall Publisher, Delhi, 1995.

[3] R.A. Deninger, *"System analysis of water supply systems"*, Water Resourc. Bull., Vol. 6, Issue.4, pp. 573-579, 1970.

[4] S.M. Gorelick, *"A review of distributed parameter groundwater modeling methods"*, Water Resour. Res., Vol. 19, Issue.2, pp. 305-319, 1983.

[5] T. Maddock III, *"Algebraic technological function from a simulation model"*, Water Resourc. Res., Vol. 8, Issue.1, pp. 129-134, 1972.

[6] P.S. Mahar, B. Datta, *"Optimal monitoring network and ground-water pollution source identification"*, J. Water Resour. Plng. And Mgmt., ASCE, Vol. 123, Issue.4, pp. 199-207, 1997.

[7] P.S. Mahar, B. Datta, *"Identification of pollution sources in transient groundwater systems"*, Water Resour. Mgmt., Vol. 14, Issue.3, pp. 209-227, 2000.

[8] P.S. Mahar, B. Datta, *"Optimal Identification of groundwater pollution sources and parameter estimation*", J. Water Resour. Plng. And Mgmt., ASCE, Vol. 127, Issue.1, pp. 20-29, 2001.

[9] A. Ogata, R.B. Banks, *"A solution of the differential equation of longitudinal dispersion in porous media"*, U.S. Geol. Surv., Prof. Pap. No. 411-A, 1961.

[10] A. Peck, S.M. Gorelick, G. de Marsily, V. Kovalevsky, *"Consequences of spatial variability in aquifer properties and data limitation for groundwater modeling practice"*, J. Water Resour. Plng. And Mgmt., ASCE, Vol. 116, Issue.5, pp. 676-692, 1988.

[11] R.M. Singh, B. Datta, A. Jain, *"Identification of unknown groundwater pollution sources using artificial neural networks"*, J. Water Resour. Plng. & Mgmt, ASCE, Vol. 130, Issue.6, pp. 506-514, 2004.

[12] R.M. Singh, B. Datta, *"Identification of groundwater pollution sources using GA-based linked simulation optimization model"*, Journal of Hydrologic Engineering, ASCE, Vol. 11, Issue.2, pp. 101-109, 2006.

[13] Y. K. Tung, C. E. Kolterman, *"Some computational experiments using embedding technique for groundwater management"*, Groundwater, Vol. 23, Issue.4, pp. 455-464, 1985.

AuthorProfile

Dr. Md. Ayaz is presently working as Assistant Professor in Civil Engineering Section, University Polytechnic, Aligarh Muslim University, Aligarh. He has done M.Tech and PhD in Civil Engineering from Indian Institute of Technology (IIT) Kanpur. He was awarded the "DAAD-IIT Master Sandwich Scholarship" in 2008 to conduct M.Tech research work at University of Stuttgart, Germany. He was also awarded the "Established Scientist Travel Award" in 2014 by European Geosciences Union (EGU) to attend EGU General Assembly-2014 at Vienna, Austria. His research work involves the application of soft computing skills in water resources engineering.