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PAPER

Estimation of the hydraulic parameters of leaky aquifers based on pumping tests and coupled simulation/optimization: verification using a layered aquifer in Tianjin, China

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Abstract
Accurate estimates of aquifer parameters are necessary for effective groundwater management and for geotechnical engineering applications. Pumping tests may be employed to estimate the hydraulic conductivity in leaky aquifer/aquitard systems. This work introduces a hybrid algorithm with global search capacity (the Genetic algorithm, GA) and local search capacity—the Levenberg-Marquardt (LM) algorithm—coupled with a modified Neuman-Witherspoon solution for leaky aquifers to estimate the aquifer's hydraulic parameters from pumping-test data. The GA is employed to determine the initial guesses of the aquifer parameter values. The optimal parameter values are then obtained with the LM algorithm, yielding a mixed GA/LM algorithm, herein named GALMA. Results show that the drawdown trends based on the estimated parameters agree well with measured drawdown. The proposed estimation algorithm identifies aquifer parameters with greater reliability than previous approaches. Verification of the GALMA is carried out based on three pumping tests in a layered aquifer in Tianjin, China, and on four historical case studies involving diverse hydrogeological settings. The excellent match between observed drawdown and GALMA-estimated parameters demonstrates the estimation accuracy and superior performance relative to previously reported estimation methods.

Keywords Analytical solutions · Hydraulic properties · Leaky aquifer · Pumping test · Optimization

Introduction

The analysis of groundwater flow using hydrogeological and geotechnical engineering approaches depends on various model parameters, such as hydraulic conductivity K and specific storage S_s. Accurate evaluation of these parameters is key for the correct characterization of groundwater processes and to carry out numerical predictions (Zeng et al. 2018, 2019; Zheng et al. 2019; Ha et al. 2019). In-situ testing produces more representative estimates of aquifer hydrogeologic properties than laboratory testing of disturbed soil samples, especially for permeable coarse-grained soils (Mckay et al. 1993a, b; Shen et al. 2015). Graphical and numerical methods are commonly employed to aid estimation of aquifer parameters from drawdown, measured during pumping tests. These estimation methods may yield results that depend on the analyst's individual judgment (Cooper and Jacob 1946; Çimen 2009; dos Santos et al. 2011). Unreliable results may be obtained when the graphical matching is poor (Samuel and Jha 2003). Alternatively, minimization of norms between measured and calculated groundwater variables (e.g., the sum of square difference between measured and calculated variables) is widely employed in three-dimensional (3D) numerical modeling (see, e.g., Carrera and Neuman 1986; Doherty 2018). The latter approach necessitates initial parameter estimates that may be obtained with approximate equations,

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which may or may not lead to accurate estimates (Bear 1979; Yeh 1984; Wang et al. 2008; Shen et al. 2015; Liu et al. 2017; Zhang et al. 2017). Minimizing the various norms of the difference between measured and calculated pumping-test data may involve a considerable computational effort, and may be hindered by poor convergence and yield inaccurate parameter estimates (Mania and Sucche 1978; McElwee 1980; Johns et al. 1992; Leng and Yeh 2003; Yeh and Huang 2005; Jha et al. 2006; Bateni et al. 2015).

The equations governing groundwater flow are typically nonlinear and nonconvex. Several optimization methods, including traditional nonlinear optimization and meta-heuristic algorithms, have been applied for estimating hydraulic parameters. Analytical solutions have been coupled with parameter-estimation methods such as the radial basis function collocation method (RBFCM; Sahin 2016), extended Kalman filter (EKF; Leng and Yeh 2003), particle swarm optimization (PSO; Şahin 2018), and ant colony optimization (ACO; Bateni et al. 2015). The latter methods yield accurate solutions; however, they require significant computational effort or local hydrogeology knowledge.

This work introduces a hybrid algorithm for estimating hydraulic parameters in leaky aquifer parameters, and demonstrates its superior performance over other estimation methodologies with data sets from several pumping tests. An in-situ aquifer test conducted in Tianjin, China, is described, and the associated data are employed to assess the performance of the proposed estimation method. The efficacy of alternative optimization methods in aquifer parameter estimation is then discussed. Subsequently, an analytical solution for leaky aquifers is combined with the proposed estimation algorithm to obtain aquifer hydraulic parameters from pumping-test data. Validation of the proposed GALMA is carried out with three pumping tests in a layered aquifer in Tianjin, China, and four case studies involving diverse hydrogeological settings. The estimation skill of the proposed GALMA is compared with that of previously reported methods to estimate aquifer parameters.

A brief overview of optimization methods to estimate aquifer parameters

Optimization methods for aquifer parameter estimation can be broadly classified as traditional or nontraditional techniques (James 2004; Zhang et al. 2009). Traditional optimization techniques (e.g., the Levenberg-Marquardt (LM) algorithm, Marquardt 1963), steepest-descent method, Gauss-Newton method) apply algorithms that calculate functional derivatives iteratively in the search for global optimal parameter estimates. Nontraditional optimization techniques, on the other hand, apply algorithms that can solve nonlinear and nondifferentiable estimation problems and converge to near-global parameter estimates. The genetic algorithm (GA) is a popular nontraditional or, more specifically, evolutionary optimization algorithm (see e.g., Holland 1975; Bozorg-Haddad et al. 2017). It has previously been applied in groundwater optimization problems.

Optimization methods

The LM algorithm and the GA have been frequently applied in optimization studies, including the estimation of aquifer parameters relying on pumping-test data.

The Levenberg-Marquardt (LM) algorithm

The LM algorithm is a frequently used optimization method. It performs better than the simple gradient-descent algorithm and other conjugate gradient algorithms in a wide range of problems. The LM algorithm is a hybrid of the gradient-descent and the Gauss-Newton algorithms used to solve nonlinear least-squares minimization problems (Madsen et al. 2004). In the context of pumping-test parameter optimization, the LM algorithm is based on a linear approximation to a function $f(\mathbf{x}, \boldsymbol{\beta})$ employed to calculate drawdown as a function of a vector of independent variables $\mathbf{x}$ (say, elapsed time of pumping, distance to the pumping well, pumping rate) and a vector of parameters. The empirical data from a pumping test yields a vector of paired observed drawdown ($\mathbf{y}$) and elapsed time since pumping starts. The LM algorithm starts with user-provided initial estimates of aquifer parameters, denoted by the vector $\boldsymbol{\beta}_0$. Under suitable conditions, the LM algorithm improves the estimates of the parameters $\boldsymbol{\beta}$ in each iteration until satisfying a convergence criterion. In the k-iteration of the LM algorithm ($k = 1, 2, 3, \ldots$) the current vector of parameters $\boldsymbol{\beta}_k$ is improved by adding to it the descent increment vector $\boldsymbol{\delta}_k$, in which δ_k is obtained by solving the following system of linear equations:

$$\left(\mathbf{J}_k^{\mathrm{T}}\mathbf{J}_k + \mu_k \mathbf{I}\right)\boldsymbol{\delta}_k = \mathbf{J}_k^{\mathrm{T}}[\mathbf{y} - f(\mathbf{x}_k, \boldsymbol{\beta}_k)] \tag{1}$$

where μ_k denotes the (nonnegative) Levenberg damping parameter in iteration k; $\mathbf{I}$ represents the identity matrix; $\mathbf{J}_k^{\mathrm{T}}$ denotes the transpose of the matrix $\mathbf{J}_k$, $\mathbf{x}_k$ denotes the value of the independent variables in the k-th iteration, and $\mathbf{J}_k$ represents the Jacobian matrix in the k-th iteration whose j-th row is given by the gradient (row) vector of the drawdown function evaluated at the current $\boldsymbol{\beta}_k$ and the j-th element of the vector $\mathbf{x}_k$:

$$\mathbf{J}_{kj} = \frac{\partial f\left(x_{kj}, \boldsymbol{\beta}_k\right)}{\partial \boldsymbol{\beta}_k} \tag{2}$$

The improved vector of the parameter is calculated as follows:

$$\boldsymbol{\beta}_{k+1} = \boldsymbol{\beta}_k + \boldsymbol{\delta}_k \tag{3}$$

The LM algorithm's convergence to a (minimum) global solution can be guaranteed only when the function f is convex. In the case of more complex functions the initial guess $\boldsymbol{\beta}_0$ must be close to the solution. Otherwise, the LM algorithm may be trapped in a local optimum.

The genetic algorithm (GA)

The GA is a stochastic search procedure (i.e., evolutionary algorithm) that searches the optimal solution by mimicking the processes of natural selection and genetic evolution (Holland 1975; Abdel-Gawad and El-Hadi 2009; Cavazzuti 2013). It begins by initializing a population of candidate solutions randomly sampled from a feasible solution space. The GA improves the initial randomly generated population of solutions, and continues to improve subsequent populations as it advances through the iterative search until a convergence criterion is satisfied (Bozorg-Haddad et al. 2017). The population of solutions in the k-th iteration is called the k-th generation. Each generation is improved by the application of mutation and cross-over techniques (see e.g., Bozorg-Haddad et al. 2017) in each iteration.

Criteria for iterative solution of optimization problems

The object function

An objective function defines a measure of the agreement between the observed data and estimated data. The standard error of estimates (SEE) is often employed to evaluate the error (Leng and Yeh 2003; Yeh and Huang 2005), in which case the objective function is expressed as follows:

$$\mathrm{SEE} = \sqrt{\frac{1}{\nu}\sum_{i=1}^{n} e_i^2} \tag{4}$$

where e_i represents the i-th difference between the value of the observed drawdown and the estimated drawdown; ν denotes the degrees of freedom, which equals the number of data points in the drawdown test minus the number of estimated parameters.

Termination criterion

uitable termination criterion is required to terminate the calculation during the computational process (Johns et al. 1992; Jha et al. 2006). The mean square error (MSE) is frequently relied upon to evaluate the difference between the observed and estimated drawdowns, or estimation errors (Yeh and Huang 2005; Leng and Yeh 2003); it is calculated as follows:

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n} e_i^2 \tag{5}$$

The parameter estimation search is commonly terminated when the MSE equals or is less than 10^{-3}, or when a maximum number of iterations in the optimization search is reached.

Pumping tests

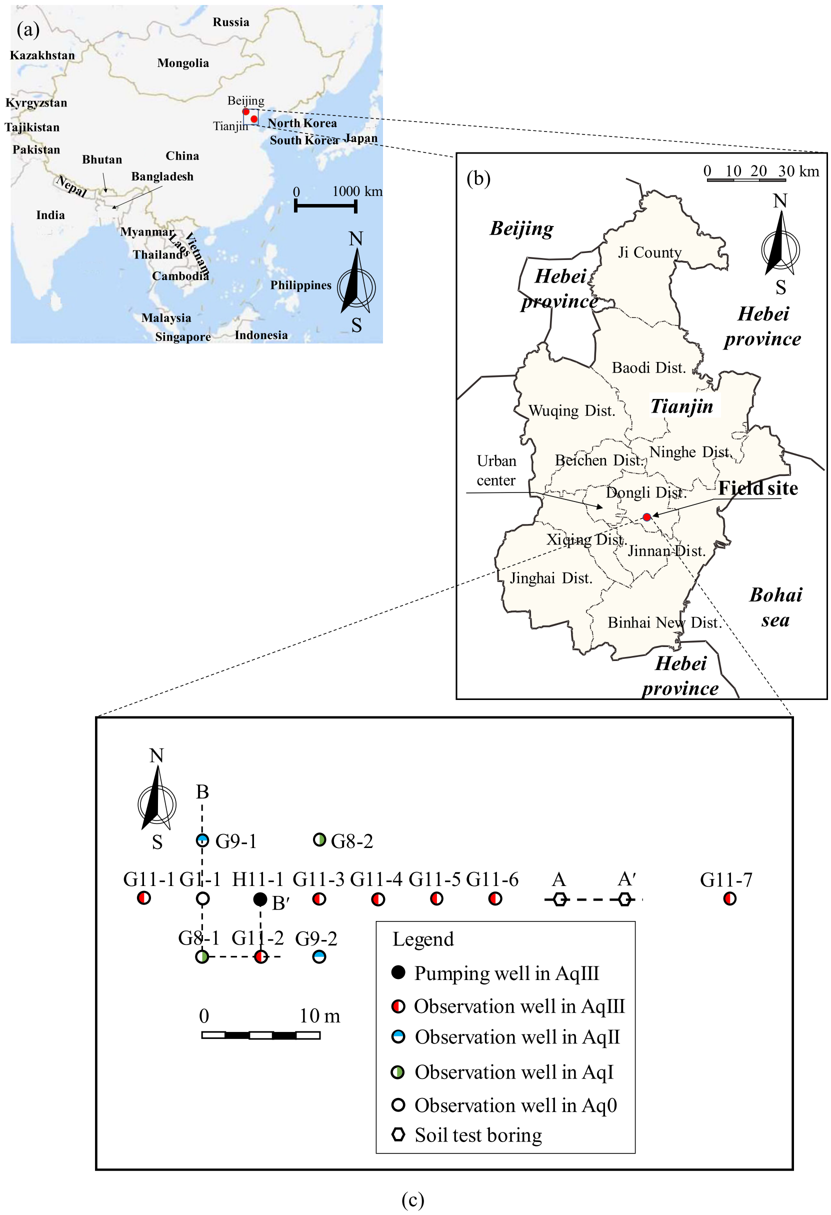
Site description

The field site chosen for the experiments is the suburban area of Tianjin, China, situated about 90 km southeast of Beijing, China's capital. The Quaternary deposits at the experimental site reach a thickness of 500 m. These Quaternary coastal deposits consist of saturated clayey soils and silty soils characterized by a stratified distribution (Chai et al. 2004; Yang et al. 2008; Shen and Xu 2011; Zheng et al. 2014, 2015a, b). The multi-layer aquitard-aquifer system (MAAS) prevailing at the study site contains several aquifers separated by aquitards. Above a depth of approximately 80 m the MAAS comprises one phreatic aquifer and several semiconfined layers.

Pumping tests were conducted to assess the response of an aquifer to groundwater withdrawal. Groundwater flowed under natural conditions at the study site and was not influenced by underground infrastructures (Ma et al. 2014) commonly found in the subsurface of Chinese urban areas. Figure 1 depicts the location of the test site and wells installed, which included one pumping well (labeled H11-1) and 11 observation wells (labeled G8-1 through G11-7).

The soil in the experimental site comprises artificial fill, silt, and silty clay. The experimental site stratigraphic profile features, from top to bottom, one phreatic layer (Aq0), two shallow semiconfined silty layers (AqI, AqII), and a deep semiconfined silty-clay aquifer (AqIII) recharged mainly through overlying layers (Wang 2013). Ground elevation ranges from 2.1 to 2.3 m above mean sea level (amsl) at the study site. A uniform ground elevation was chosen as the reference datum for measured water level at the experimental site. Figure 2 displays two cross-sectional views of the soil profile (labeled A–A′ in Fig. 1) and details about observation wells (labeled B–B′ in Fig. 1). Layer Aq0 consists of the topmost shallow soil, layer AqI, mainly composed of silt with an average thickness of 2.9 m, is situated beneath the overlying aquitard AdI and its initial piezometric head was −8.6 m amsl. Layer AqII, with an initial piezometric head of −13.6 m amsl, consists mainly of silt with an average thickness equal to 1.8 m. Aquifer AqIII has an average thickness equal to 7.8 m and is mainly composed of silty sand, with initial piezometric head equal to −15.1 m amsl. The three semiconfined layers were separated by several aquitards (referred to as AdI, AdII,

Fig. 1 **a** Map of China. **b** Locations of field pumping tests. **c** Plan of the pumping and observation wells



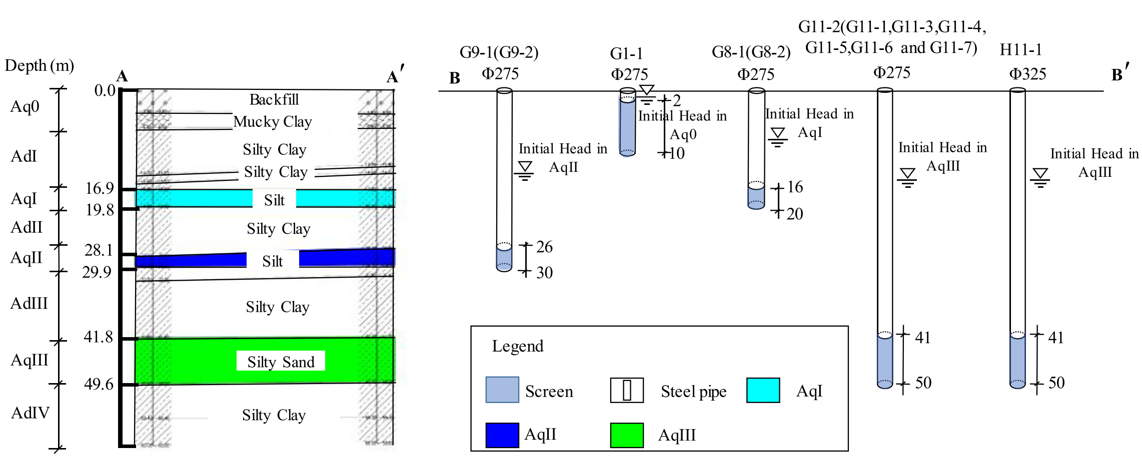


Fig. 2 Cross-sectional views of the soil profile (A–A′) and wells (B–B′)

and AdIII). The internal radii of the single-pumping well and eleven observation wells were 325 and 275 mm, respectively. The pumping well (H11–1) and the observation wells G11–1 through G11–7 were installed within AqIII to a depth of 50 m, and the screens of the seven wells in AqIII were 9 m long.

Table 1 lists the experimental site's soils properties obtained from geological investigation and laboratory tests. The specific storage S_s for a saturated soil is related to the compression index C_c (Leake 1991) according to the following formula:

$$S_s = \frac{0.434 C_c \gamma_w}{\sigma'(1+e_0)} \tag{6}$$

where e_0 is the initial void ratio, σ' is the pre-consolidation stress, and γ_w denotes the unit weight of water.

Experimental scheme

Pumping tests were performed in aquifer AqIII between January 9, 2016, and January 18, 2016. Table 2 lists details pertaining to the three pumping tests, which featured pumping rates averaging 2.1, 3.0, and 3.5 m^3/h, and durations of pumping respectively equal to 24.5, 24.0, and 25.0 h.

Pumping was maintained approximately constant through the tests until the water level in the observation wells stabilized. Figure 3 displays a slight variation of the pumping rates during the three tests due to transient conditions developed in the pumped aquifer and measures taken with the controlling equipment to reach steady pumping rates.

The small drawdown test (with 148 measured data) was selected for parameter estimation because it conforms best with the theoretical solutions for leaky aquifers used in this project, which assume small drawdown. The estimated parameters were used for drawdown prediction. Comparison between measured and predicted drawdown was carried out with the intermediate-drawdown test (with 150 measured drawdown data) and the large-drawdown test (with 152 measured drawdown data).

Figure 4 presents the variation in the measured water levels within the observation wells during the pumping and recovery phases. Only the pumping tests were analyzed herein; the analysis of the recharge tests is beyond the scope of this study. It is seen in Fig. 4 that the hydraulic head in the observation wells G11-4, G11-5 and G11-7 tapping AqIII decreased rapidly in the early stage of testing in the intermediate drawdown test; thereafter, the groundwater level approached steady state. The groundwater level recovered rapidly after the pump was shut down and regained its initial value after 12 h. The groundwater levels in the observation wells G11-4, G11-5, and G11-7 tapping AqIII corresponding to the three scales of drawdown followed a similar pattern. Additionally, the observed water level in observation wells G9-1 and G9-2 tapping AqII was only slightly affected by groundwater extraction, exhibiting drawdowns less than 0.3 m during three pumping tests. The hydraulic head in the AqI measured in observation wells G8–1 and G8–2 was nearly constant during the three pumping tests.

Influence of wellbore storage

The wellbore storage may influence the accuracy of estimated parameters in the early stage of pumping in the presence of low hydraulic conductivity and clogged granular material in the annular space outside the well casing. The wellbore-storage effect generally becomes negligible after a period of pumping, at which time the observed drawdown data become well approximated by the analytical solution. Therefore, a critical time t_a is commonly introduced to account for the wellbore storage effect (Shen et al. 2015; Chapuis and Chenaf 2003). The critical time t_a is estimated by the following formula (Schafer 1978)

Table 1 Summary of soil properties at the experimental site

Hydrogeology profile	Soil strata	Unit weight (kN/m^3)	Depth (m)	e_0	C_c	S_s	K (m/day)
Aq0	Backfill	17.8	6.5	1.182	0.16	0.00628	–
Aq0	Fat clay	19.3	14.2	0.791	0.0811	0.00161	0.0004
AdI	Silty clay	19.9	16.9	0.713	0.0745	0.00127	0.022
AqI	Silt	19.4	19.8	0.721	0.0418	0.000598	1.2
AdII	Silty clay	19.3	28.1	0.832	0.0872	0.000814	0.0036
AqII	Silt	20	29.9	0.628	0.0295	0.00029	2.2
AdIII	Silty clay	19.3	41.8	0.801	0.038	0.00024	0.0026
AqIII	Silty sand	20.1	49.6	0.597	0.027	0.000158	4
AdIV	Silty clay	19.9	60	0.652	0.0368	0.000171	0.00001

Notes: e_0 initial void ratio; C_c compression index; S_s specific storage; K hydraulic conductivity; the values in the table represent mean values

Table 2 Details of the pumping tests

Drawdown scale	Aquifer	Pumping well	t_p (h)	Q (m^3/h)	s_w (m)	t_0	t_e
Intermediate drawdown test	AqIII	H11–1	25	3	3.59	13:00 10th Jan	14:00 10th Jan
Large drawdown test	AqIII	H11–1	24.2	3.5	4.21	10:00 15th Jan	10:10 16th Jan
Small drawdown test	AqIII	H11–1	24.5	2.1	2.67	10:00 17th Jan	10:30 18th Jan

t_p duration of pumping time; Q pumping rate; t_0 starting time; t_e ending time; s_w drawdown in the pumping well; h hour

$$t_a = 0.017\left(d_c^2 - d_p^2\right)/(Q/s) \tag{7}$$

where d_c denotes the internal diameter of the well casing (in mm); d_p denotes the outer diameter of the pump rising pipe (in mm); Q/s represents the well specific capacity (in (m^3/day)/m) at time t_a. The values of d_c and d_p in this work equal 325 and 100 mm, respectively. The estimated critical times t_a are listed in Table 3, which imply that the wellbore storage effect can be ignored after 90 min of elapsed time of pumping during the tests.

Application of the proposed optimization method

This section evaluates the effectiveness of the LM and GA methods based on the pumping tests results.

Analytical model for analyzing pumping tests

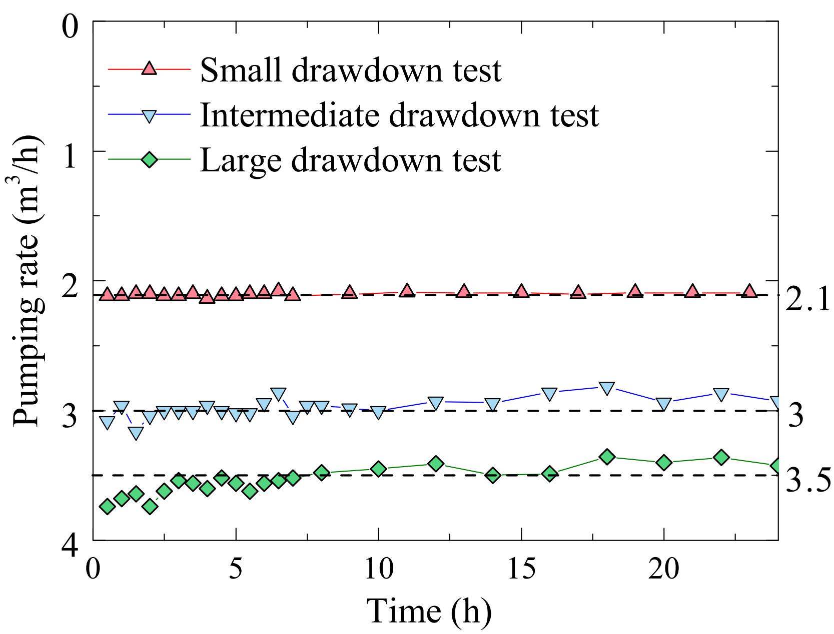
The aquifer AqIII is recharged from above through the overlaying layers. The thickness of the aquitard AdII overlying the aquifer AqIII is about 12 m. The hydraulic head in AqIII was nearly constant during the pumping tests (i.e., the drawdown was less than 0.3 m, as shown in Fig. 4).

A modified version of the Neuman and Witherspoon (1969) solution for drawdown developed by Yeh and Huang (2005) is considered appropriate for the semiconfined or leaky aquifer AqIII:

$$s(r,t) = \frac{Q}{2\pi T}\int_0^\infty \frac{1}{y}\left[1 - exp\left(-y^2 t_D\right)\right] J_0[w(y)]dy \tag{8}$$

where $s(r, t)$ represents the drawdown a distance r from the pumping well and elapsed time t since the beginning of pumping; Q denotes the constant pumping rate; t_D equals Tt/r^2S; t_D denotes the dimensionless time equal to $t_D L^2/16\psi^2$; B denotes the leakage factor defined by $\sqrt{T/(K'/M')}$; $L = r/B$; $\psi = \beta/L$; $\beta = r\sqrt{S'}/4B\sqrt{S}$; $w^2(y) = (L^2y^2/16\psi^2) - L^2 y \cot y$; J_0 denotes the Bessel function which must be set equal to zero when $w^2(y) < 0$; K denotes the hydraulic conductivity of the semiconfined aquifer; K' represents the vertical conductivity of the aquitard; M is the thickness of the semiconfined aquifer; M' is the thickness of the aquitard; T denotes the transmissivity, which equals KM; S denotes the storage coefficient of the semiconfined aquifer; S' denotes the storage coefficient of the aquitard overlying the semiconfined aquifer AqIII.

Fig. 3 Pumping rates of the three tests



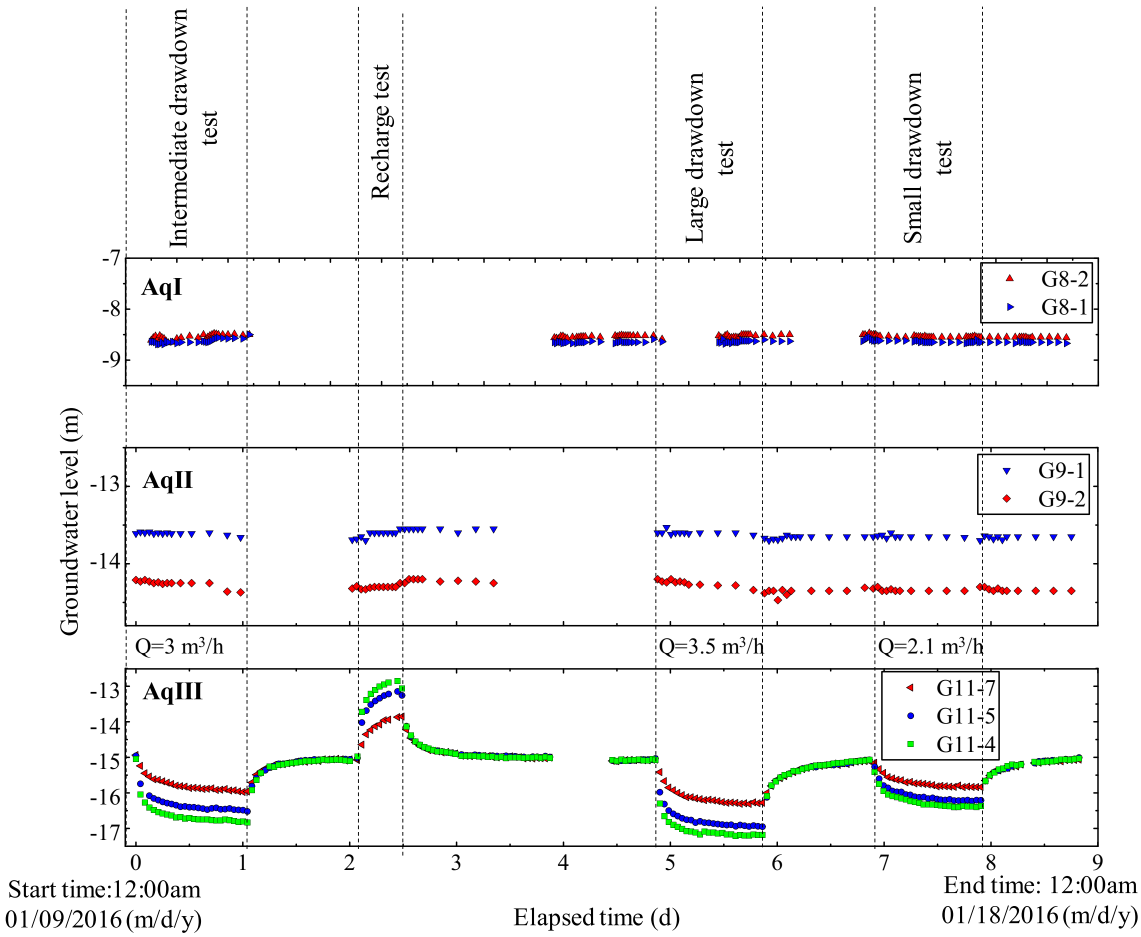


Fig. 4 Measured variation of groundwater level in the observation wells

The integral of Eq. (8) was accurately calculated with the Gauss-Kronrod quadrature in MATLAB, which achieves a relative error tolerance equal to 0.001. The LM algorithm and the GA are implemented in conjunction with the analytical solution (Eq. 8) in a simulation-optimization (SOM) approach: (1) the analytical solution is evaluated with generated initial estimates of the hydraulic parameters, (2) the algorithms improve the initial guess; (3) the analytical solution is re-evaluated with the improved solution, and the algorithms generate a newly improved solution, and (4) the simulation-optimization iterations are repeated until a termination criterion is satisfied.

Performance of selected optimization methods

This section illustrates how the LM algorithm and the GA are coupled with the modified solution (Eq. 8) to estimate hydraulic parameters. Thereafter, the results obtained from these algorithms are compared.

Effectiveness of the LM algorithm

The LM algorithm is a modified Gauss-Newton optimization approach in which the parameter vector is updated iteratively. The parameters T, S, S' and B are considered time-invariant during the pumping tests. A maximum number of 100 iterations of the LM algorithm was adopted in this study as the termination criterion; an initial damping parameter μ_0 is set equal to 10^{-3} (Madsen et al. 2004).

The parameter vector β has four elements, namely:

$$\boldsymbol{\beta}^{\mathrm{T}} = \left[T, S, S', B\right] \tag{9}$$

The value of the parameter vector in the k-th iteration of the LM algorithm is denoted by $\boldsymbol{\beta}_k$.

The Jacobian matrix $\mathbf{J}_k$ in the k-th algorithmic LM iteration reduces to a 4-D vector of derivatives of the drawdown function with respect to the aquifer parameters evaluated in the k-th iteration—with $f_k = f(\mathbf{x}_k, \boldsymbol{\beta}_k)$:

$$\mathbf{J}_k = \left[\frac{\partial f_k}{\partial T} \;\; \frac{\partial f_k}{\partial S} \;\; \frac{\partial f_k}{\partial S'} \;\; \frac{\partial f_k}{\partial B}\right]^T \tag{10}$$

$\frac{\partial f_k}{\partial T}, \frac{\partial f_k}{\partial S}, \frac{\partial f_k}{\partial S'}, \frac{\partial f_k}{\partial B}$ are approximated with the difference equations introduced by Yeh and Huang (2005) as follows:

Table 3 Wellbore storage effect for pumping tests (estimates of t_a from Eq. 7)

Scale	Q (m^3/h)	s (m)	d_c (mm)	d_p (mm)	t_a (min)
Small drawdown test	2.14	2.67	325	100	86
Intermediate drawdown test	3.00	3.6	325	100	81
Large drawdown test	3.50	4.21	325	100	81

$$\frac{\partial f_k}{\partial T} = -\frac{Q}{2\pi T^2}G + \frac{Q}{2\pi T}\frac{G(T+\varDelta T, S, S', B) - G(T, S, S', B)}{\varDelta T} \quad (11)$$

$$\frac{\partial f_k}{\partial S} = \frac{Q}{2\pi T}\frac{G(T, S+\varDelta S, S', B) - G(T, S, S', B)}{\varDelta S} \quad (12)$$

$$\frac{\partial f_k}{\partial S'} = \frac{Q}{2\pi T}\frac{G(T, S, S'+\varDelta S', B) - G(T, S, S', B)}{\varDelta S'} \quad (13)$$

$$\frac{\partial f_k}{\partial B} = \frac{Q}{2\pi T}\frac{G(T, S, S', B+\varDelta B) - G(T, S, S', B)}{\varDelta B} \quad (14)$$

in which G represents the integral on the right-hand side of Eq. (8).

Notice that the increments in the denominators of Eqs. (11–14) are approximated by the parameter value times a factor of 10^{-3} (Leng and Yeh 2003), i.e., $\Delta T = 10^{-3}\ T$. Reasonable initial estimates of T, S, S' and B must be specified to initiate the LM search. The specific storage ranges from 1.02×10^{-3} to 1.6×10^{-5} in sandy and clayey soils, respectively (Domenico and Mifflin 1965; Batu 1998). A wide range from 1×10^{-3} to 1×10^{-5} was assigned to S_s. AqIII consists of silt and silty sand. The representative hydraulic conductivity of sand (ranging from silty sand to sand) ranges from 0.5 to 50 m/day (Lin 2005). By multiplying these values by the layer thickness, the ranges of transmissivity and storage coefficients are respectively 3.9–390 m^2/day and $7.8 \times 10^{-3} - 7.8 \times 10^{-5}$. The ratio between the hydraulic conductivity of the semiconfined aquifer AqIII and the aquitard AdIII ranges from 10 to 10^5. The adopted leakage factor B ranges from 30.5 to 3,050. Eighteen sets of initial guesses of T, S, S' and B covering the range of parameters were generated to assess LM search convergence. The initial sets are summarized in Table 4, which also lists convergence or nonconvergence of the LM method corresponding to each initial set of parameter estimates.

It is evident from Table 4 that the method is sensitive to the initial estimates. Convergence before the maximum number of allowed iterations occurred only for initial estimates 8, 13, and 14, whereas nonconvergence occurred with the other initial estimates. These convergence anomalies can be explained primarily with the following two reasons:

1. The Jacobian matrix elements in Eqs. (11)–(14) are small when the initial guess of the transmissibility coefficient T is large. As a result, the increments of the four parameters (i.e., T, S, S' and B) are too small for convergence.
2. The Yeh and Huang (2005) Eq. (8) is typically nonconvex and nonlinear. This means the LM algorithm is frequently trapped within local optima when the initial parameter estimates are substantially different from the true values (Trinchero et al. 2008; Bateni et al. 2015).

The LM method's success hinges on having a priori knowledge about the approximate values; otherwise, initial guesses far from the optimal solution commonly fail to converge to the correct solution.

Effectiveness of the GA

The initial population of solutions is generated randomly by the GA. A wide range of storage coefficients may be generated far from an optimal solution and cause slow convergence. Therefore, the specific storage is shifted to exponential format to reduce the range of the storage coefficient. Specifically, this

Table 4 Initial guesses of the parameters in the LM algorithm

Guess No.	Initial guesses				Convergence?
	T	$S \times 10^{-5}$	$S' \times 10^{-5}$	B	
1	3.9	780	780	30.5	No
2	3.9	7.8	7.8	30.5	No
3	39	780	780	30.5	No
4	39	7.8	7.8	30.5	No
5	390	780	780	30.5	No
6	390	7.8	7.8	30.5	No
7	3.9	780	780	305	No
8	3.9	7.8	7.8	305	Yes
9	39	780	780	305	No
10	39	7.8	7.8	305	No
11	390	780	780	305	No
12	390	7.8	7.8	305	No
13	3.9	780	780	3,050	Yes
14	3.9	7.8	7.8	3,050	Yes
15	39	780	780	3,050	No
16	39	7.8	7.8	3,050	No
17	390	780	780	3,050	No
18	390	7.8	7.8	3,050	No

T transmissivity of the semiconfined aquifer, S storage coefficient of the semiconfined aquifer, S' storage coefficient of the aquitard, B leakage factor

Table 5 Ranges of the parameters used with the GA

	Hydraulic parameters				
	T (m^2/day)	S	S'	K/K'	B
Upper bound	390	7.8×10^{-3}	7.8×10^{-3}	1×10^5	3,050
Lower bound	3.9	7.8×10^{-5}	7.8×10^{-5}	10	30.5

K hydraulic conductivity of the semiconfined aquifer, K' hydraulic conductivity of the aquitard, S coefficient of storage of the semiconfined aquifer; S' storage coefficient of the aquitard, B leakage factor

work specifies the parameters S and S' as the product of two random numbers, as follows:

$$S = A \times 10^{-\mathrm{INT}(B)} \times M \tag{15}$$

where A is a random number in the range ≥1 to <10, and B is a random number in the range >3 to <6, M is the thickness.

The upper and lower bound of the hydraulic parameters used with the GA are listed in Table 5. The upper and lower bounds of the hydraulic parameters are considered sufficiently broad to assess the global optimization capabilities of the hybrid algorithms. Additionally, the crossover rate P_c and mutation rate P_m are set equal to 0.8 and 0.005, respectively (Goldberg and Holland 1988; Reed et al. 2000). The number of populations of solutions in each GA iteration was set equal to 300 (Samuel and Jha 2003). The maximum number of generations or algorithmic iterations equals 50.

Because of the randomness of the GA, ten runs (labeled runs 1–10) were implemented to search for the optimal parameters. It is seen in Fig. 5 that all 10 runs of the GA exhibit a rapid decline in the objective function and reach a constant value that differs across runs after 10 iterations or generations (Andre et al. 2001). The objective function is the standard error of estimate. It is customary to express solutions obtained from the GA as averages of values obtained from multiple runs (Kapelan et al. 2003; Wan and Birch 2013), aided by calculation of the standard deviation of the values from the runs to measure dispersion about the average value (Bozorg-Haddad et al. 2017). Yet, the dispersion of values about the average may be too high, in which case a hybrid solution method exhibiting the best properties of the LM method and the GA may prove advantageous, as the following sections demonstrate.

Development of the hybrid algorithm

Due to the limitations of the LM method and the GA for global optimization of the hydraulic aquifer parameters this work introduces a hybrid algorithm combining the advantages of the GA and the LM method, herein named GALMA. Figure 6 describes a computational diagram of the hybrid algorithm. The GA is implemented to find a near-optimal solution. The best solution obtained by the GA serves as an initial guess with which to launch the LM algorithm whenever the GA does not achieve a near-global solution during the allowed maximum number of iterations.

The hydraulic parameters are identified according to the following steps of the GALMA:

Step 1. The initial generation is produced randomly with the GA. The selection, evaluation, crossover, and mutation processes are repeated until the termination

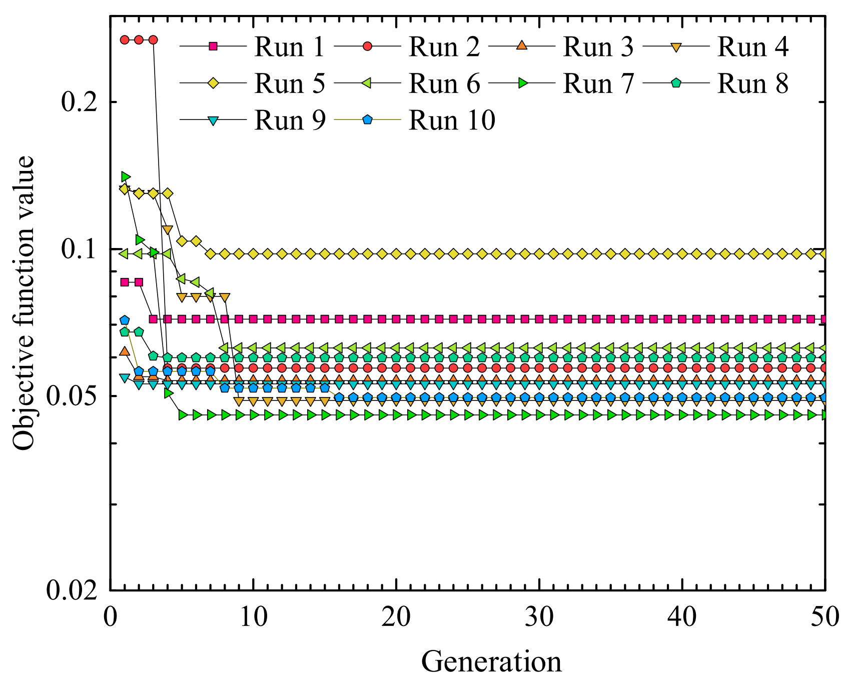


Fig. 5 Convergence histories of the GA for 10 runs

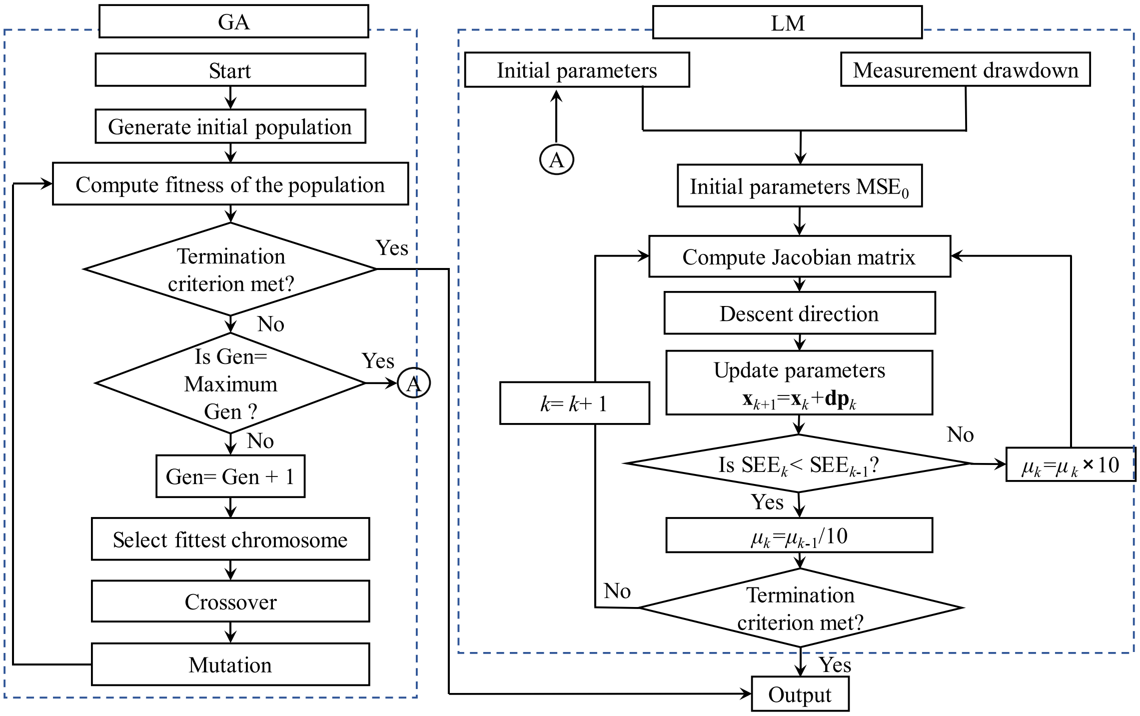


Fig. 6 Flow diagram of the hybrid algorithm

criterion is satisfied, in which case the algorithm proceeds to step 3. Otherwise, upon reaching the maximum number of generations, the best-fitting solution calculated with the GA is used as the initial parameters in the LM algorithm.

Step 2. The trial solution and the SEE are updated along the steepest descent direction **dp** calculated with the LM algorithm.

Step 3. The optimal solution is obtained when the calculated and measured drawdowns satisfy a convergence criterion.

Ten runs (labeled runs 1–10) were solved in search of the optimal results with the GALMA. The 50th generation of solutions calculated with the GA was specified as the initial solution of the LM algorithm. Figure 7 displays the results

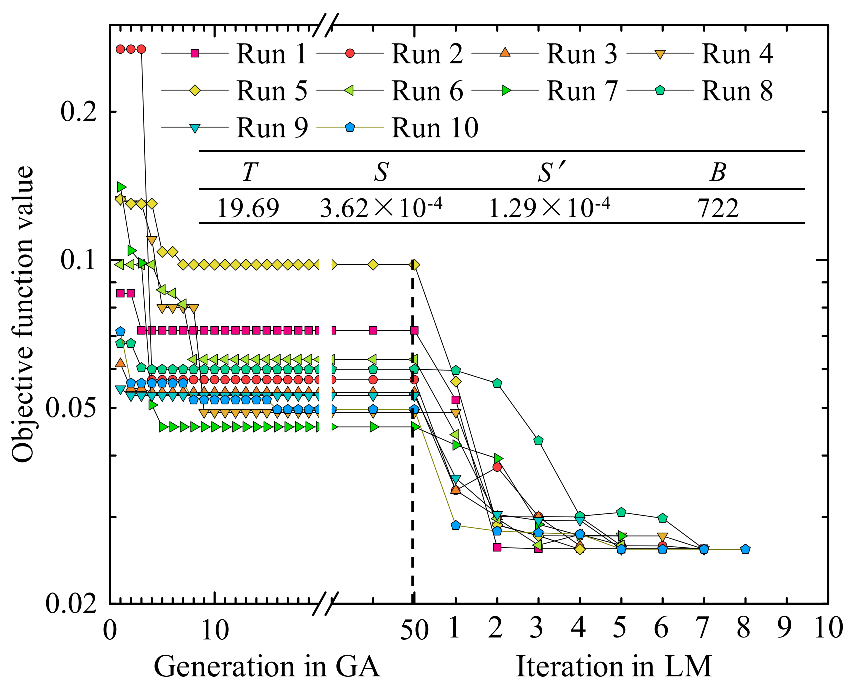


Fig. 7 Convergence history of the GALMA corresponding to the small drawdown pumping test

obtained with the GALMA. A sub-optimal result is first attained with the GA; the LM starts its search with the 50th generation of solutions calculated with the GA. A remarkably improved SEE is achieved with the GALMA which converges to a unique global optimum in all 10 runs. The global optimum was reached in 8 LM iterations.

The drawdown was assessed based on the hydraulic parameters estimated with the GALMA. Figure 8a depicts a comparison between the measured and estimated drawdown corresponding to the small drawdown test. The corresponding coefficient of determination (R^2) is 0.9762. The time-drawdown curve based on the hydraulic parameters identified by GALMA is reasonably close to the observed time-drawdown curve. The identified parameters are employed to estimate the drawdown corresponding to the characteristics of the intermediate drawdown and the large drawdown tests, as shown in Fig. 8b,c. The estimated drawdown calculated with the calculated analytical solution is relatively larger than the observed drawdown in the early stages of pumping. This behavior stems from the influence of the wellbore storage; however, the calculated results generally coincide with the measured values, and the R^2 for intermediate drawdown and the large drawdown tests equal 0.9510 and 0.9742, respectively. The results demonstrate that the identified parameters are suitable estimates of the hydraulic properties of the aquifer.

Assessment of the proposed approach

Further evaluation of the optimization capacity of the GALMA was pursued with four case histories of pumping tests gathered from the literature. The presented pumping tests were conducted in diverse hydrogeological conditions which allowed for testing of the applicability of the GALMA based on the modified Neuman and Witherspoon's (1969) solution by Yeh and Huang (2005) and Hantush and Jacob's (1955) solution. There was no available information about the local hydrogeology

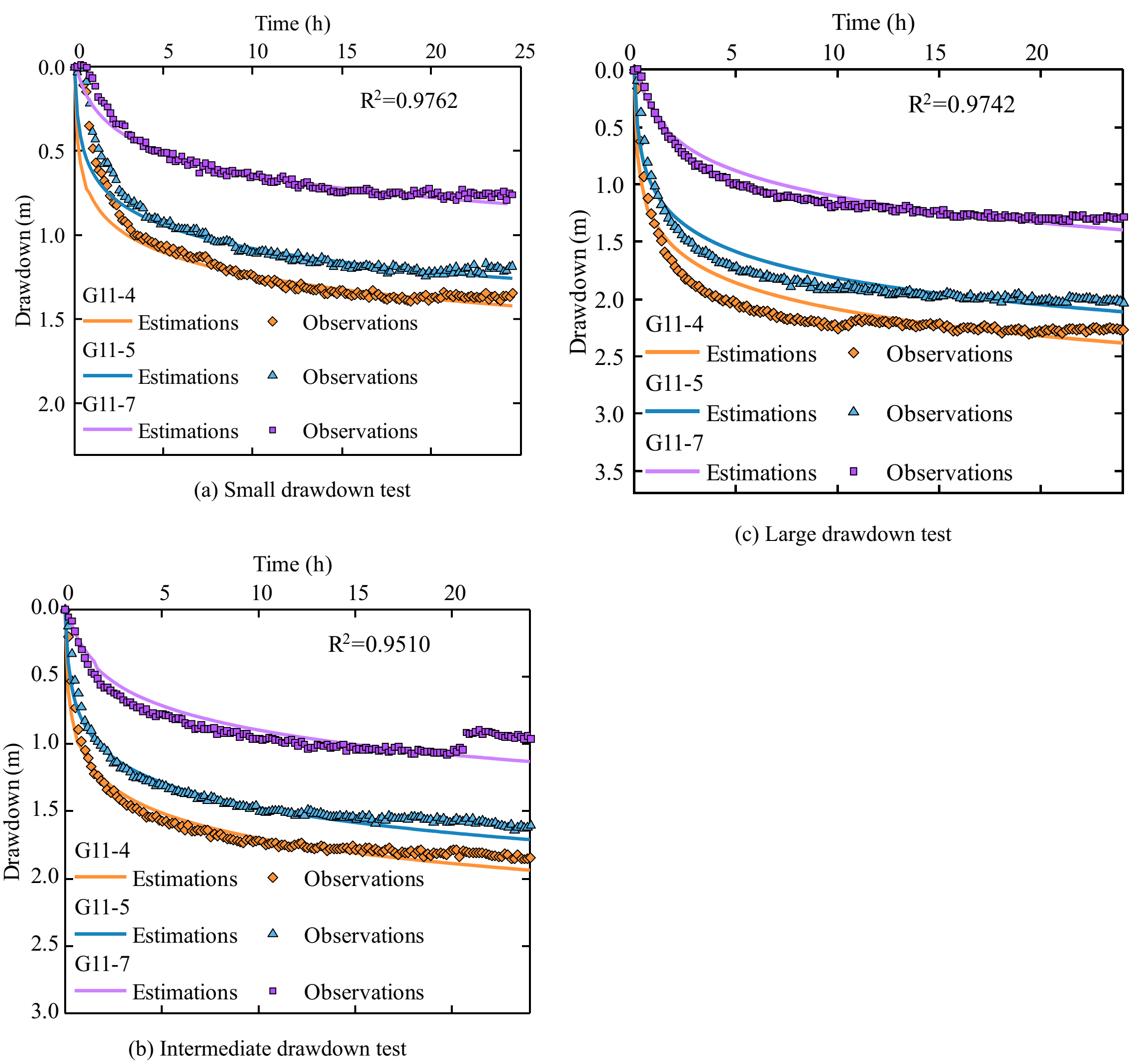


Fig. 8 Comparison between the observed and estimated drawdown in three pumping tests

Table 6 Comparison of estimated hydraulic parameters of the leaky confined aquifer considering the storage effect in an aquitard. Italics shows smaller mean error (ME) and standard error estimate (SEE) of GALMA as opposed to other optimization methods

Resource	Method	Estimated parameters				Errors	
		T (m^2/day)	S	B (m)	S'	ME (×10^{-3})	SEE (×10^{-3})
Sridharan et al. (1987)	SA	23.4	1.64×10^{-4}	218.045	2.59×10^{-9}	−1.81	1.02
	GA	23.9	1.59×10^{-4}	228.346	2.59×10^{-9}	−2.67	1.18
	EKF	22.6	1.73×10^{-4}	204.225	2.76×10^{-9}	1.49	1.36
	NLN	23.3	1.65×10^{-4}	216.418	1.3×10^{-9}	−1.78	1
	GALMA	21.1	1.51×10^{-4}	205.415	1.24×10^{-4}	*0.081*	*0.97*
Cooper (1963)	EKF	1,242.7	1.16×10^{-4}	596.871	3.4×10^{-7}	−1.81	57.9
	GALMA	1,237.8	1.06×10^{-4}	692.871	2.95×10^{-9}	*1.56*	*17.8*

T transmissivity of the semiconfined aquifer, S storage coefficient of the semiconfined aquifer; S' storage coefficient of the aquitard, B leakage factor

associated with the case histories or the pre-assumed upper and lower bound of the storage coefficient. Therefore, the transmissivity coefficient of the semiconfined aquifer, and the leakage factor were allowed to range from 10^{-3} to 10^{-5}, from 0.5 to 3,000 m^2/day, and from 0 to 10,000, respectively. These are reasonable ranges for T, S, S' and B in most field settings. These ranges were obtained from Yeh and Huang (2005), Yeh et al. (2007) and Bateni et al. (2015).

Unsteady flow in leaky confined aquifers with storage effect in an aquitard

A pumping test scheme with an observation well reported by Sridharan et al. (1987) was chosen for GALMA evaluation. The distance between the pumping well and the observation well was 29 m, and the pumping rate Q equaled 136.26 m^3/day. The parameters identified by the proposed hybrid algorithm and the identified parameters from GA, SA (simulated annealing algorithm), Newton's method (NLN), EKF (extend Kalman filter) are compared in Table 6. It is seen in Table 6 that the GALMA produced a smaller mean error (ME) and standard error estimate (SEE) than the other optimization methods.

The second case-history data were taken from Cooper (1963). There were three observation wells, and the distances between the pumping well and the observation wells were 30.48 m, 152.4 m, and 304.8 m. The pumping rate equaled 5,450.98 m^3/day, and the duration of pumping was 1,000 min. It is evident from Table 6 that the ME and SEE of the proposed hybrid algorithm are smaller than those of other approaches, demonstrating the superior optimization capacity of the GALMA in estimating the aquifer parameters.

Unsteady flow in leaky confined aquifers without storage effect in an aquitard

Two pumping test data sets associated with leaky confined aquifers were chosen for GALMA evaluation. The first data set is from Batu (1998). The uniform pumping rate equaled 625 m^3/day, the thicknesses of the aquifer and aquitard were 80 and 28 m, respectively, the distance between the pumping well and the observation well was 105 m, while the test duration was approximately 881.28 min. The second data set is from Fetter (2001), whereby the uniform pumping rate equaled 135.92 m^3/day, the distance between the pumping well and the observation well was 29.26 m and the test duration was approximately 1,185 min.

The assumed bounds of the hydraulic conductivity and specific storage are similar to last section. The ME and SEE

Table 7 Comparison of estimated hydraulic parameters for leaky confined aquifer without considering storage effect in an aquitard. GALMA ME and SEE values are italicized for comparison with other methods

Resource	Method	Hydraulic parameters			Errors	
		T (m^2/day)	S	B	ME (×10^{-3})	SEE (×10^{-3})
Batu (1998)	EKF	907	3.5×10^{-3}	312.5	−2.68	4.97
	GALMA	1,329.61	2.5×10^{-3}	795.3	*0.219*	*2.4*
Fetter (2001)	Graphical	26.4	1.7×10^{-3}	292.1	−15.7	67
	NLP	31.5	8.4×10^{-4}	457.2	13.4	96.1
	GA	22.1	1.32×10^{-3}	221.3	142.2	174
	ACO	25.4	1.27×10^{-3}	256.1	26.2	63.8
	GALMA	21.9	1.7×10^{-4}	180.9	*5.6*	*45.8*

T transmissivity of the semiconfined aquifer, S storage coefficient of the semiconfined aquifer, B leakage factor

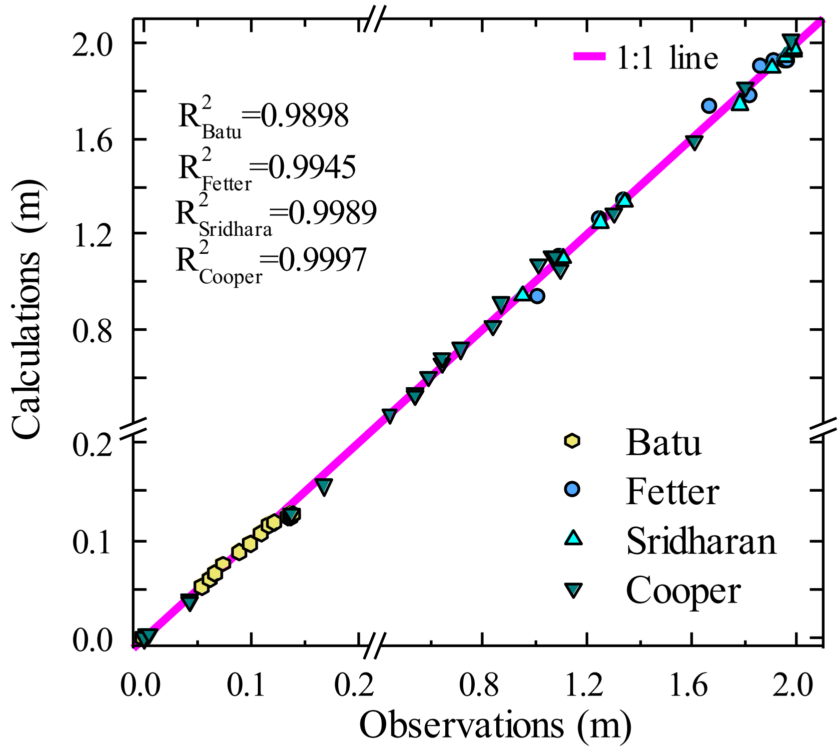


Fig. 9 Drawdown estimates using the identified parameters

of GALMA were compared with those obtained from graphical, nonlinear programming (NLP), ant colony optimization (ACO), and the GA, as shown in Table 7.

In the first case (data from Batu 1998) the GALMA reduced the SEE of drawdown by 52% compared with the EKF. A significant decrease of ME was also obtained from -2.68×10^{-3} to 2.19×10^{-4}. Concerning the second case (Fetter 2001) the GA yields the largest errors. The ME and SEE for graphical, NLP, and ACO range from -1.57×10^{-2} to 2.62×10^{-2}, and 6.38×10^{-2} to 9.61×10^{-2}, respectively. The ME and SEE for GALMA equal 5.6×10^{-3} and 4.58×10^{-2}, respectively, which are lower than those of the other approaches. These results demonstrate the superiority of the proposed hybrid algorithm.

Figure 9 shows a comparison between the observed and calculated drawdown for each pumping test using the developed hybrid algorithm. All of the data points were near to the 1:1 line and the calculated drawdown yielded high goodness of fit (R^2), which equaled 0.9898, 0.9945, 0.9989 and 0.9997 for the four pumping-test case histories. The performance of the proposed approach in identifying the hydraulic parameters in the leaky aquifer is satisfactory.

Conclusion

Three pumping tests were performed in Tianjin, China. A hybrid algorithm for identifying hydraulic parameters was introduced. The applicability of the hybrid algorithm was also tested using four sets of time-drawdown data for two different aquifer systems. The following conclusions are drawn:

1. Analytical solutions of drawdown are typically nonconvex and nonlinear. The LM algorithm may be trapped in a local optimal solution rather than a global optimal solution. Nonconvergence may be encountered during the iterative search process for a global optimum. Successful convergence of the LM algorithm depends on the choice of an initial solution guess. The GA, on the other hand, exhibits premature convergence to a suboptimal solution.
2. GALMA features robust global and a local searching capacity. The GA is implemented to find a suitable initial solution with which to start the LM algorithm to obtain the optimal global solution by local searching. The results of this study demonstrate that the proposed hybrid algorithm outperforms the GA and the LM algorithm concerning the global and the local capacity to search for an optimal solution of the aquifer parameter-estimation problem.
3. The accuracy of the proposed approach was evaluated with case histories from previous studies. The precision and efficiency of the GALMA are superior to those of other optimization approaches employing analytical solutions, i.e., the Neuman and Witherspoon (1969) solution modified by Yeh and Huang (2005), and the Hantush and Jacob (1955) model.

The proposed GALMA for aquifer parameter estimation can be generalized to more complex conditions, where, for example, heterogenous and anisotropic aquifer characteristics preclude the application of analytic solutions. In this instance predictions of drawdown must be carried out with a numerical groundwater model (say, MODFLOW). The GALMA is applied in a simulation/optimization modeling (SOM) approach whereby (1) aquifer parameters are generated within realistic ranges; (2) drawdowns are simulated (i.e., predicted) at observation locations with the numerical model; (3) the GALMA improves the aquifer parameters based on a suitable objective function involving measured and predicted drawdowns; (4) the numerical model simulates anew the drawdown at observation locations with the improved aquifer parameters; (5) steps 2–4 are repeated until a termination criterion is met. This extension of GALMA constitutes research in progress by the authors.

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