國 立 交 通 大 學
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博 士 論 文

含水層參數檢定與洩降敏感度分析

Aquifer Parameter Estimation and Drawdown Sensitivity Analysis

研 究 生：黃彥禎

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中文摘要

抽水試驗是調查含水層水文地質參數的重要方法，傳統的分析方式，都應用圖解法或數值方法中的梯度法求解，然而，這些方法都有其限制。本研究建立一參數檢定模式，應用模擬退火演算法結合水層抽水洩降的解析模式，推求滲漏及自由含水層的參數。結果顯示此參數檢定模式較傳統圖解法，更能準確求出水層參數值，且與擴展式卡門濾波和牛頓法的結果精度相同。此外，本研究對模擬退火演算法的控制參數進行敏感度分析，結果顯示本方法是可信賴、且穩定的。

一般而言，進行一個抽水試驗需要花費許多人力及資源，包括井的設置、數據的量測及分析等。若洩降數據不足，使用傳統圖解分析方法，往往無法得到正確的答案。長時抽水及人力需求的問題，可透過於現地量測洩降數據的同時，即時檢定含水層的參數。然而，在滲漏及自由水層部分的水文地質特性，需要抽水一段時間後，才會充分的反應於洩降數據上。因此在應用參數檢定模式即時推求參數時，很難決定停止參數檢定

的時間。本研究使用敏感度分析，尋找滲漏與自由水層的參數，在進行抽水試驗時，反應於洩降的影響時程。同時，應用建立的參數檢定模式，即時推求參數值。結果顯示當含水層參數開始影響洩降時，即時參數檢定模式立刻正確的檢定出水層參數值。這個發現可作為停止參數檢定時間的重要參考。此外，本研究透過敏感度分析，進一步分析、探討不同的比出水率，及不同的抽水井與觀測井間的距離，對於試驗停止時間的影響。

關鍵字：地下水、抽水試驗、參數檢定模式、模擬退火演算法、即時檢定、敏感度分析、滲漏含水層、自由含水層

Aquifer Parameter Estimation and Drawdown Sensitivity Analysis

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ABSTRACT

The pumping test is a very important method in investigating the aquifer hydrogeologic characteristics. Conventional graphical or computer methods for identifying aquifer parameters have their own inevitable limitations. This study applies the parameter estimation model (PEM) based on the simulated annealing (SA) and analytical models to estimate the parameters of leaky and unconfined aquifers. The estimated results of proposed method have better accuracy than those of the graphical methods and agree well with those of the computer methods based on the extended Kalman filter and Newton's method. Moreover, the sensitivity analyses for the control parameters of SA indicate that the proposed method is very robust and stable in parameter estimation procedures.

Generally, a pumping test requires a lot of effort and expense to perform the test and the drawdown data are measured and analyzed for determining the aquifer parameters. The estimated aquifer parameters obtained from graphical approaches may not be in good accuracy if the pumping time is too short to give a good visual fit to the type curves. The problems of long pumping time and required efforts can be reduced if the drawdown data are measured and the parameters are simultaneously estimated on-line. However, the drawdown behavior of the leaky and unconfined aquifers in response to the pumping may have a time lag. The time to terminate the estimation may not be easily and quickly to decide when applying a PEM on-line to analyze the parameters. This study employs the sensitivity analysis to analyze the influence period of parameters in response to the pumping in both leaky and unconfined aquifers. In the meanwhile, a PEM based on the SA is used to determine the parameters of these two aquifers on-line. The results indicate that the aquifer parameters can be accurately estimated when they start to influence the drawdown. This finding can be used as a guide in terminating the estimation. Moreover, the sensitivity analysis is also used to study the effects of different values of specific yield S_y and the distance between pumping well and observation well on the influence time of S_y during the pumping.

Key Words: Groundwater; Pumping test; Parameter estimation model; simulated annealing; on-line estimation; sensitivity analysis; leaky aquifer; unconfined aquifer

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NOTATIONS

b	: thickness of aquifer (L)
b'	: thickness of aquitard (L)
B	: leakage factor, $\sqrt{Tb'/K'}$ (L)
D	: random number between zero and one
D_1	: random number between zero and one
d_D	: dimensionless vertical distance between the top of perforation in the pumping well and the initial position of water table, d/b
E	: the system energy
$f(x)$	: objective function
$J_0(\ )$	: zero order Bessel function of the first kind
K	: hydraulic conductivity of main aquifer (LT^{-1})
k	: Boltzmann's constant
K'	: vertical hydraulic conductivity of leaky confining layer (LT^{-1})
K_r	: horizontal hydraulic conductivity of unconfined aquifer
K_z	: vertical hydraulic conductivity of unconfined aquifer
L	: leakage coefficient, r/B
l_D	: dimensionless vertical distance between the bottom of perforation in the pumping well and the initial position of water table, l/b
ME	: mean error between estimated drawdowns and pumping test data
n	: total number of the time step
O_{h_i}	: observed drawdowns at time step i
O	: output function of the system

P_i	: ith input parameter of the system
P_{h_i}	: estimated drawdowns at time step i
$P(E)$	: occurrence probability
P_{SA}	: acceptance probability
Q	: the discharge of the well (L^3T^{-1})
r	: radial distant from pumping well (L)
R_t	: temperature reduction factor
r_w	: outside radius of the pumped well screen
S	: storage coefficient the aquifer
S'	: storage coefficient of the aquitard
s	: drawdown
$S_{i,t}$	: normalized sensitivity
S_{pi}	: parametric sensitivity
S_s	: specific storage
S_y	: specific yield of unconfined aquifer
SEE	: standard error of estimate for the estimated drawdowns
T	: transmissivity (L^2T^{-1})
Te	: temperature of the system
t_s	: Tt/Sr^2
t_D	: dimensionless time for pumping aquifer, $t_D = Tt/r^2S$
$\bar{t}_D$	: $t_D L^2/16\psi^2$
u	: dimensionless parameter, $r^2S/4Tt$
VM	: step length vector
w_i	: weighting factor

$W(u, r/B)$	: leaky well function without considering the storage effect in aquitard
$\overline{x}_i$	: corresponding to zero of the n^{th} order Laguerre polynomials
z_D	: dimensionless elevation of observation point, z/b
β	: $K_z r^2 / K_r b^2$ in unconfined aquifer system
$\overline{\beta}$	: $r\sqrt{S'/S} / 4B$ in leaky aquifer system
σ	: S/S_y
ψ	: $\overline{\beta}/L$

CHAPTER 1 INTRODUCTION

1.1 Background

Groundwater is an important source of water supply for drinking, agriculture, and industry. It represents 98% of freshwater readily available to humans [Schwartz and Zhang, 2002]. Groundwater is found in aquifers, which have the capability of both storing and transmitting groundwater. Recently, the groundwater problems, such as industrial wastewater injected into groundwater system and seawater intrusion, have been attracted public attention. The hydraulic properties of the aquifer systems have to be determined prior to characterizing or investigating the pollutant and its plume. Groundwater hydrologists often conduct aquifer tests to determine the in situ hydraulic properties of the soil formation, such as hydraulic conductivity and storage coefficient. These parameters are necessary information for quantitative and/or qualitative groundwater studies.

The pumping test is a very reliable method for estimating aquifer parameters. Figures 1 (a) and (b) display the sketch of the pumping tests in leaky and unconfined aquifers, respectively. Typically, a pumping test consists of a pumping well and one or more observation wells. The observation wells are located at varying distances from the pumping well. The water levels at observation well are measured periodically after starting of pumping. The term drawdown (s in Figures 1 (a) and (b)) shows the change in water levels through the test. The drawdown curve which describes a conical shape is cone of depression.

In the past, the pumping test data was usually analyzed using a graphical procedure with type curves to estimate the aquifer parameters. In addition, the parameters can also be obtained by computer methods, which usually estimate parameters using the least-square approach by taking the derivative of the sum of square errors between the observed and estimated drawdowns with respect to the parameters. The gradient-type methods are then utilized to solve the nonlinear least-square equations to determine the best-fit parameters. However, two disadvantages might be occurred when the gradient-type methods were used to solve the nonlinear least-square equations to obtain the parameters. First, those methods may yield divergent results if the initial guesses of parameters are not close enough to the target parameter values. Second, those methods may give poor results if improper increments were made when applying finite difference formula to approximate the derivative terms appeared in the least-square equations.

Recently, the computer-based parameter estimation models (PEM) were developed promptly. The models of aquifer parameter estimation usually combine a suitable solution for describing the pumping test with an optimization approach such as simulated annealing (SA) or a recursive approach, such as extended Kalman filter (EKF). Some commercial softwares, like AQTESOLV [Duffield, 2002], use nonlinear weighted least-squares approach to fit the time-displacement data obtained from an aquifer test to the type curve.

A pumping test was usually required to perform for a long period of time if a graphical approach is chosen to analyze the measurement data. Otherwise, the estimated result may not be in good accuracy if the data is too short and the data points are too sparse to give a good visual fit to the type curve. However, such a test would spend a lot of time, money, and groundwater resources. These problems were aggravated when analyzing the data from the leaky and unconfined aquifers.

In a leaky aquifer, the semi-pervious bed (also shown as the aquitard in Figure 1 (a)), although of very low permeability, may yield significant amounts of water to the adjacent pumped aquifer. As time increased, leakage across the semi-pervious bed may become appreciable and flow is not restricted to the pumped aquifer alone. The additional water may be derived from storage of the aquitard and adjacent unpumped aquifers. During the pumping, the water is immediately withdrawn from the aquifer and then the head difference between two aquifers induces a flow across the aquitard. Therefore, the parameters of the confining bed (aquitard) may not be accurately estimated if only first few drawdown data points are used. Two approaches have been developed for dealing with leaky aquifers, one considers the aquitard storage while the other does not consider.

Physically, the drawdown in an unconfined aquifer can be divided into three segments

[Charbeneau, 2000]. In the first stage, water is immediately released from storage due to the compaction of the aquifer and the expansion of the water. In the second stage, the vertical gradient near the water table causes drainage of the porous matrix. The vertical hydraulic conductivity K_z begins to contribute to the pumping and the rate of descent in the hydraulic head slows or stops after a period of time. Finally, the flow is horizontal and most of the pumping is supplied by the specific yield, S_y. Therefore, the analysis of S_y requires sufficient long drawdown data fallen at the third section. In some cases, the effect of well bore storage needs to be considered since the diameter of pumping well is large. The water is withdrawn first from the casing at the beginning of pumping. Then the groundwater flow into the well because the head difference between the well and the adjacent formation.

Most physical systems can be viewed as input-output models that relate the output information to the proper input parameters. Unfortunately, the input parameters can not be known perfectly in the real world. Hence, the basic concept of sensitivity analysis is to investigate how the errors in the input parameters influence the outputs, or, in particular, to study if a small perturbation in the input parameters causes a large change in the output. Now the sensitivity analysis is being wildly applied in all sciences.

1.2 Objectives

The objectives of this dissertation can be categorized into two parts:

First part:

(1) To develop a PEM based on the SA combined with Hantush and Jacob's model [1955] or Neuman and Witherspoon's model [1969] to estimate the parameters of leaky aquifer with or without considering the aquitard storage in the field;

(2) To propose a PEM based on SA coupled with the Neuman's model [1975] for unconfined aquifers to automatically determine the best-fit aquifer parameters.

(3) To test the robustness and stability of the SA with different control parameters;

In the first part, three sets of field pumping test data are chosen, two for the leaky aquifer and one for the unconfined aquifer. The first one is reported in Cooper [1963], the second is select from Sridharan et al. [1987], and the last is obtained from Batu [1998].

Second part:

(1) To investigate the influence period of leaky and unconfined parameters using sensitivity analyses;

(2) To apply a PEM based on SA algorithm to on-line estimate the parameters in both leaky and unconfined aquifers using the synthetic and real field time-drawdown data sets;

(3) To employ the software AQTESOLV to estimate the parameters of unconfined aquifer with considering the effect of well bore storage using the synthetic data set;

(4) To provide a decision support using sensitivity analysis in terminating the test when

applying the on-line PEM in determining the aquifer parameters;

(5) To study the influence period of the S_y in the cases of different S_y values and different distance between pumping well and observation well via sensitivity analysis.

In the second part, three synthetic drawdown data sets, one for leaky aquifer (generated based on Hantush and Jacob's model, 1955), and two for unconfined aquifer (generated based on Neuman's model, 1974; and Moench's model, 1997), are analyzed using the sensitivity analysis and on-line PEM. Moreover, the field data set of an unconfined aquifer obtained from Cape Cod, Massachusetts [Moench et al., 2000] is also analyzed by on-line PEM.

CHAPTER 2 LITERATURE REVIEW

2.1 Theoretical Development and Analysis

Hantush and Jacob [1955] described a mathematical model for non-steady radial flow to a well in a fully penetrated leaky aquifer under a constant pumping rate. In this model, the aquitard is overlain by an unconfined aquifer, and the main aquifer is underlain by an impermeable bed. Their analytical solution for the mathematical model is referred to as the three-parameter model in this dissertation. Hantush [1960] also presented a modified approach to include the effect of the aquitard storage. Neuman and Witherspoon [1969] gave a model describing the drawdown of the lower and pumped aquifer in a hydrogeologic system which is composed of two confined aquifers and one aquitard. Their solution, which considers the effect of aquitard storage and neglects the drawdown in the unpumped aquifer, is called the four-parameter model. Both the three-parameter and four-parameter models are also mentioned in several books, for example, Dawson and Istok [1991] and Batu [1998]. In the three-parameter model, the graphical method based on Hantush's or Walton's type curves [Batu 1998] requires data plotting work and individual judgment during the curve fitting procedure. Therefore, errors may be introduced during the fitting process. In the four-parameter model, the use of the graphical matching method based on the Neuman and

Witherspoon's model is practically impossible since there will be several families of type curves.

Boulton [1954, 1963] developed an analytical solution by introducing the concept of delayed yield for unconfined formations. Prickett [1965] presented a systematic approach to estimate the parameters using a graphical procedure based on Boulton's type curves. Cooley and Case [1973] displayed that Boulton's equation yields an exact solution where it describes a flow system with a rigid phreatic aquitard on top of the main aquifer, and the unsaturated flow above the water surface is neglected. Neuman [1972, 1974] developed a solution that considers the effects of elastic storage and anisotropy of aquifers on drawdown behavior. Neuman's model treated the unconfined aquifer as a compressible system and the water surface as a moving boundary. His theory was also extended to account for the effect of a partially penetrating pumping well or/and an observation well in a homogeneous anisotropic unconfined aquifer. Neuman [1975] also gave a graphical type curve solution process to estimate the aquifer parameters. Moench [1995] combined the Boulton and Neuman models for flow toward a well in an unconfined aquifer. McElwee [1980] proposed a least-squares fitting technique and sensitivity analysis to analyze the time-drawdown data for the aquifer parameters. Saleem [1970] proposed a nonlinear programming technique, minimizing the sum of squares of the differences between observed and estimated drawdowns. Mania and Sucche [1978] employed the least-squares approach to analyze parameters in unconfined aquifers, based on Boulton's solution for large-time data. Sridharan et al. [1985] used sensitivity analysis technique based on Neuman's model for the condition of a fully penetrating well for identifying parameters in an unconfined aquifer. Yeh [1987] employed the nonlinear least-squares and finite-difference Newton's method (NLN) for estimating the parameters of the confined aquifer. Yeh and Han [1989] subsequently applied NLN to determine the parameters of the leaky aquifers. Huang [1996] used NLN to identify the unconfined aquifer parameters. The NLN approach has the advantage of high accuracy and quick convergence for reasonable initial guesses. However, those methods may yield divergent results if the initial guess parameter values are not close enough to the target values. In addition, they may obtain poor results if improper increments were made when applying finite difference formula to approximate the derivative terms appeared in the least-square equations. Recently, the Kalman filter has been successfully applied to the aquifer parameter and water table related estimations. Chander et al. [1981] estimated the parameters for both nonleaky and leaky aquifers by the iterated extended Kalman filter. Leng and Yeh [2003] employed EKF to identify the aquifer parameters in confined and unconfined aquifer systems. Yeh and Huang [2005] utilized the EKF to estimate the aquifer parameters in leaky aquifer systems with and without considering the storage effect in the aquitard. The results indicate that the EKF can be applied to analyze the measurement drawdown data even with white noise or temporally correlated noise.

2.2 Simulated Annealing

The theory of SA was developed by Metropolis et al. [1953]. They introduced a simple algorithm to incorporate the idea of the behavior of a particle system in thermal equilibrium into numerical calculations of an equation state. SA is a random search algorithm that allows, at least in theory or in probability, to obtain the global optimum of a function in any given domain. SA is an evolution from descent search method. The major difference between SA and conventional descent method is that the SA used Metropolis mechanism, or called the Boltzmann's mechanism, to control which ascent moves could be accepted. In other words, the SA uses descent strategy but allows random ascent moves to avoid possible trap in a local optimum. This property prevents the SA from having the same problem as those of the descent method. SA was successfully applied in wide range of optimization applications. Kirkpatrick et al. [1983] applied it to solve large-scale combinatorial optimization problems. Goffe et al. [1994] employed SA to solve four econometric problems and compared the results obtained from the conventional algorithms. Their solutions obtained from SA were superior to those obtained from the conventional algorithm. Subsequently, utilization of SA in optimization problems has been applied in hydrological engineering. Dougherty and Marryott [1991] and Marryott et al. [1993] employed the SA to design the strategies of groundwater remediation. Zheng and Wang [1996] used the tabu search and SA to estimate the parameter structure using preliminary results from one-dimensional examples. Cunha and Sousa [1999] used SA to minimize the capacity extension cost of the water distribution network. The solution set obtained from SA and nonlinear programming (NLP) techniques for several medium size networks showed that SA did provide a better solution in general, in comparison with that obtained by the NLP techniques. Kuo et al. [2001] applied SA to agricultural water resource planning and management. Tsai et al. [2003] developed two global-local optimization methods for identifying the parameter structure in groundwater modeling. Tung et al. [2003] developed an optimal zoning procedure by applying simulated annealing (SA) and the shortest distance method with MODFLOW to determine the best zonation of hydraulic conductivity. Lin and Yeh [2005] employed SA to predict the concentrations of trihalomethane (THM) species in a water distribution system. Chang et al. [2007] used SA to give an approximate result for a two-dimensional problem if decomposing the model area into a number of transects along the transverse direction, estimating the parameter values along the longitudinal direction for each transect, and then smoothing the estimated results.

2.3 Sensitivity Analysis

Cukier et al. [1973, 1975, and 1978] as well as Schibly and Shuler [1973] developed a statistical approach for sensitivity analysis to nonlinear algebraic equations. Kabala and Milly [1990] used sensitivity analysis for analyzing the effect of parameter uncertainty and soil heterogeneity on the transport of moisture in unsaturated porous media. Jiao and Rushton [1995] provided a sensitivity analysis of drawdown to parameters and its influence on parameter estimation for pumping tests in large-diameter wells. They concluded that the well storage reduces the sensitivities of drawdown to transmissivity and storativity, and increases the correlation between them. This leads to uncertainties in estimating the aquifer parameters, especially storativity. Kabala [2001] reviewed the basic concepts of sensitivity analysis and pointed out their limitations. He used logarithmic sensitivity to a model of a pumping test conducted on a fully penetrating well that accounting for the wellbore storage and an infinitesimal skin in a confined aquifer. The results demonstrated that transient flowmeter test measurements of drawdown and wellface flow rate should not be made during the early times of the wellbore storage phase. Shih et al. [2002] provided an analytical solution and sensitivity analysis to study the contaminant transport in fractured media considering pulse, Dirac delta and sinusoid input source. Kabala et al. [2002] also studied the logarithmic sensitivity, plausible relative errors, and deterministic parameter correlations in a simple semi-analytic no-crossflow model of the transient flowmeter test (TFMT) that accounts for a thick skin around the wall. Vachaud and Chen [2002] analyzed a large-scale hydrologic model problem by sensitivity theory. The results indicated that different levels of simplification of the input data can be selected depending on the objectives of the modeling and the level of acceptable losses of information on outputs. Ochs et al. [2003] used sensitivity analysis to study the radionuclide migration in compacted bentonite. The results indicated that the changes in radionuclide solution speciation leaded to different diffusing species under different conditions and the effects on diffusion through changes in the electric double layer properties of the clay pores was a function of ionic strength. Gooseff et al. [2005] performed sensitivity analysis of a conservative transient storage model and two different reactive solute transport models. The results showed that the reactive solute simulations appear to be most sensitive to data collected during the rising and falling limb of the concentration breakthrough curve.

CHAPTER 3 METHODOLOGY

3.1 Analytical Models of Leaky and Unconfined Aquifers

Leaky aquifer:

The analytical model without considering the storage effect in aquitard

Hantush and Jacob's model (three-parameter model in this study) describing the drawdown within a leaky aquifer in response to the pumping as a function of radial distance and time. The drawdown s is shown as [Batu, 1998; Hantush and Jacob, 1955]

$$s = \frac{Q}{4\pi T} \cdot W\left(u, \frac{r}{B}\right) \tag{3.1.1}$$

where T is transmissivity, B is the leakage factor and is defined as $\sqrt{(K'/b')/T}$, K' is the vertical conductivity of a leaky confining bed, b' is thickness of aquitard, $r/B = L$ is named as leakage coefficient, r is the distance between pumping well and observation well, u is the dimensionless variable and is defined as $r^2 S/4Tt$, S is storage coefficient, $W(u, r/B)$ is the leaky well function, and Q is the pumping rate. Note that the typical values of T, S, and L range from zero to 3000 (m^2/day), 10^{-3} to 10^{-5}, and zero to 5, respectively. The leaky well function $W(u, r/B)$ may be expressed as

$$W\left(u, \frac{r}{B}\right) = \int_u^\infty \frac{1}{y} \cdot \exp\left[-y - \frac{(r/B)^2}{4y}\right] \cdot dy \tag{3.1.2}$$

where y is a dummy variable. Since the right hand side of Eq. (3.1.2) is an integral form, a numerical approach is required to evaluate the integration. Both the Laguerre quadrature formula and Gaussian quadrature formula [Carnahan et al., 1969] are employed to evaluate the values of leaky well function with the accuracy to the fourth decimal. The Laguerre integration used to approximate an integral function is usually expressed as

$$\int_0^{\infty} f(x)\cdot e^{-x}dx = \sum_{i=1}^{n} w_i \cdot f(\bar{x}_i) \tag{3.1.3}$$

where the w_i is weighting factor and $\bar{x}_i$ is corresponding to zero of the *n*th order Laguerre polynomials. For a small value of *u*, the Laguerre quadrature formula can not give the desired accuracy. Therefore the Gaussian quadrature formula is employed to evaluate the integration of Eq. (3.1.2) when *u* is small.

The analytical model with storage effect in aquitard:

Neuman and Witherspoon developed a closed-form solution (four-parameter model in this study) for the problem of flow to a well in a confined infinite radial system composed of two confined aquifers that are separated by an aquitard [Neuman and Witherspoon, 1969]. Differing from Hantush and Jacob's work [1955], Neuman and Witherspoon's model includes the effect of the aquitard storage on the drawdown of the pumping aquifer. Their model may be written as

$$s = \frac{Q}{2\pi T}\int_0^{\infty} \frac{1}{y}\left[1 - \exp\left(-y^2 \bar{t}_D\right)\right]\cdot J_0\left[w(y)\right]\cdot dy \tag{3.1.4}$$

where $\bar{t}_D = t_D L^2/16\psi^2$, $t_D = Tt/r^2 S$, $L = r/B$, $\psi = \bar{\beta}/L$, $B = \sqrt{Tb'/K'}$,

$\overline{\beta} = r\sqrt{S'}/4B\sqrt{S}$, S' is the storage coefficient of the aquitard, and $w^2(y) = L^2 y^2/16\psi^2 - L^2 \cdot y \cdot \cot y$. Note that Eq. (3.1.4) is valid for all values of time intervals and the Bessel function of the first kind $J_0[w(y)]$ must be set to zero when $w^2(y) < 0$.

Unconfined aquifer:

The analytical model without considering well-bore storage effect

The solution for the equation describing the groundwater flow system in an unconfined aquifer developed by Neuman [1974] is

$$s(r,z,t) = \frac{Q}{4\pi T}\int_0^\infty 4yJ_0(y\beta^{1/2})\left[u_0(y) + \sum_{n=1}^{\infty} u_n(y)\right]dy \tag{3.1.5}$$

where z denotes the elevation of observation point, $J_0(x)$ is the zero order Bessel function of the first kind, $\beta = K_z r^2 / K_r b^2$ is a dimensionless parameter, K_r is radial hydraulic conductivity, K_z is vertical hydraulic conductivity, y is a dummy variable, and

$$u_0(y) = \frac{\{1-\exp[-t_s\beta(y^2 - r_0^2)]\}\cosh(r_0 z_D)}{[y^2 + (1+\sigma)r_0^2 - (y^2 - r_0^2)^2/\sigma]\cosh(r_0)} \cdot \frac{\sinh[r_0(1-d_D)] - \sinh[r_0(1-l_D)]}{(l_D - d_D)\sinh(r_0)} \tag{3.1.6}$$

$$u_n(y) = \frac{\{1-\exp[-t_s\beta(y^2 + r_n^2)]\}\cos(r_n z_D)}{[y^2 - (1+\sigma)r_n^2 - (y^2 + r_n^2)^2/\sigma]\cos(r_n)} \cdot \frac{\sin[r_n(1-d_D)] - \sin[r_n(1-l_D)]}{(l_D - d_D)\sin(r_n)} \tag{3.1.7}$$

where $t_s = Tt/Sr^2$ represents the dimensionless time since pumping started, S_s is the specific storage, S equals $S_s \times b$, $z_D = z/b$ is the dimensionless elevation of observation point, b is the thickness of the aquifer, $\sigma = S/S_y$ is a dimensionless parameter, S_y is specific yield, $d_D = d/b$ denotes the dimensionless vertical distance between the top of perforation in the pumping well and the initial position of water table, and $l_D = l/b$ is the dimensionless vertical distance between the bottom of perforation in the pumping well and the initial position of water table. The term of r_0 and r_n are respectively the roots of the following two equations

$$\sigma r_0 \sinh(r_0) - (y^2 - r_0^2)\cosh(r_0) = 0, \quad r_0^2 < y^2 \tag{3.1.8}$$

and

$$\sigma r_n \sin(r_n) + (y^2 + r_n^2)\cos(r_n) = 0, \quad (2n-1)(\pi/2) < r_n < n\pi \tag{3.1.9}$$

The analytical model with well-bore storage effect

Moench [1997] derived a Laplace domain solution for unsteady flow to a partially penetrating large-diameter well in an unconfined aquifer. The dimensionless drawdown in Laplace domain is

$$\bar{h}_D(r_D, z_D, p) = \frac{2E}{p(l_D - d_D)[1 + pW_D(A + S_w)]} \tag{3.1.10}$$

where

$$A = \frac{2}{(l_D - d_D)} \sum_{n=0}^{\infty} \frac{K_0(q_n)\{\sin[\varepsilon_n(1-d_D)] - \sin[\varepsilon_n(1-l_D)]\}^2}{\varepsilon_n q_n K_1(q_n)[\varepsilon_n + 0.5\sin(2\varepsilon_n)]} \tag{3.1.11}$$

$$E = 2\sum_{n=0}^{\infty} \frac{K_0(q_n r_D)\cos(\varepsilon_n z_D)[\sin(\varepsilon_n(1-d_D)) - \sin(\varepsilon_n(1-l_D))]}{q_n K_1(q_n)[\varepsilon_n + 0.5\sin(2\varepsilon_n)]} \tag{3.1.12}$$

$W_D = \pi r_c^{\,2} / 2\pi r_w^{\,2} S_s (l-d)$, $\bar{q}_n = \sqrt{(\varepsilon_n^2 \beta_w + p)}$, $\bar{q}_n r_D = \sqrt{(\varepsilon_n^2 \beta + p r_D^2)}$, $\beta_w = r_w^2 K_z / b^2 K_r$, $\beta = K_z r^2 / K_r b^2$, $S_w = K_r d_s / K_s r_w$, and $r_D = r / r_w$. The r_w and r_c represent the outside radius of the pumped well screen and casing, respectively. The symbol ε_n is the root of

$$\varepsilon_n \tan(\varepsilon_n) = \frac{p}{(\sigma\beta_w + p/\gamma)} \tag{3.1.13}$$

where $\sigma = S/S_y$, $\gamma = \alpha_1 b S_y / K_z$, and α_1 is a fitting parameter for drainage from the unsaturated zone and has units of inverse time (1/T). A large value of α_1 effectively eliminates the effect of this parameter from the solution. The Stefest method is used for the numerical Laplace inversion.

3.2 Simulated Annealing Algorithm

The basic algorithm of simulated annealing is motivated by an analogy to the thermodynamics of annealing in solids, such as growing silicon in the form of highly ordered, defect-free crystals. In order to accomplish this, the material is annealed. It is first heated to a temperature that allows many molecules to move freely with respect to each other. After that, it is cooled slowly until the material freezes into a crystal, which is completely ordered, and thus the system is at the state of minimum energy. In other words, the molecules have high activity when the temperature is high and the crystalline configurations have various forms. If the temperature is cooled properly, the crystalline configuration is in the most stable state; thus, the minimum energy level may be naturally reached. Based on the annealing concept, SA was constructed for solving the optimization problems. During the optimization procedure, the solution, which may not be the best one, is accepted to avoid the solution being trapped in a local optimum.

The probability distribution of system energy at a given temperature is defined by the Boltzmann probability [Pham and Karaboga, 2000]

$$P(E) \propto \exp(-E/(k \times Te)) \tag{3.2.1}$$

where E is the system energy, k is Boltzmann's constant, Te is the temperature, and $P(E)$ is the occurrence probability. From Eq. (3.2.1), it is possible that the system might have high energy even at low temperature. Hence, the statistical distribution of energies permits the energy level of the system to escape from a local optimum. That is why the solution may not be trapped in the local optimal solution. Boltzmann probability is applied in Metropolis's criterion [Karkpatrick et al., 1983] which takes place $\triangle E$, the difference between the objective function values of the current optimal solution and the trial solution.

As an iterative improvement method, the system starts from an initial state and is perturbed at random to a new state in the neighborhood, for which a change of ΔE in the objective function $f(x)$ takes place. Let x' be the neighbor of x and its objective function value is then $f(x')$. The x' is given as

$$x' = x + (2 * D_1 - 1) \times VM \tag{3.2.2}$$

where D_1 is a random number between zero and one from a uniform distribution and VM is the step length vector. The *VM* can be automatically adjusted so that approximately half of all evaluations are accepted. In the minimization problem, if *f(x')* is smaller than *f(x)*, then the current solution is replaced by the trial solution. If *f(x')* is larger than *f(x)*, the Metropolis's criterion is then tested and a new random number *D* is generated between zero and one. To solve the minimization problem, the Metropolis's criterion is given as [Metropolis et al., 1953]:

$$P_{SA}\{accept\ \mathrm{j}\} = \begin{cases} 1, & ,if\ \mathrm{f(j)} \le \mathrm{f(i)} \\ \exp(\dfrac{f(i) - f(j)}{\kappa Te}) & ,\mathrm{if\ f(j) > f(i)} \end{cases} \tag{3.2.3}$$

where P_{SA} is the acceptance probability of the trial solution, *f(i)* and *f(j)* are the function values when $x = x_i$ and $x = x_j$, and x_i and x_j are the current best solution and neighborhood trial solution of *x*. Generally, the control parameter *Te* is the current temperature and κ herein is a constant, usually taken as one, that relates temperature to the objective function. If the random number *D* is smaller than P_{SA}, the current solution would be replaced by the trial solution. Otherwise, SA would keep on generating the trial solution within the neighborhood of the current solution.

Figure 2 displays the flowchart of the SA algorithm. In the first step, SA initializes the solution and sets it as the current optimal one. The second step is to update the current optimal solution by comparing it with the generated trial solutions within a specified boundary. If a trial solution is better than the current optimal solution or if the trial solution satisfies the Metropolis's criterion, the current solution is replaced by the new one, otherwise, SA continues generating trial solutions. The temperature will be decreased by multiplying a temperature reduction factor R_t when there is no improvement to the optimum after a specified number (n_1) of iterations are performed. Based on Eq. (3.2.3), the acceptance probability becomes small with low temperature *Te*. The temperature should be cooled properly to guarantee that the obtained solution is the global optimum [Zheng and Wang, 1996]. The algorithm will be terminated when SA obtains the optimal solution or the obtained solution satisfies the stopping criteria. In general, the stopping criteria are defined initially to check if the temperature is cool at the appropriate level and then to check if the difference between the optimal objective function values and those obtained in the current iteration has reached the specified value.

3.3 Integration of the SA with Analytical Models

This study applies the SA to estimate the aquifer parameters based on the Hantush and Jacob's model [1955] and Neuman and Witherspoon [1969] in leaky aquifer, and Neuman's model [1974] in unconfined aquifers, respectively. The aquifer parameters can be estimated when minimizing the sum of squared errors between the observed and estimated drawdowns. Therefore, the objective function used to replace the energy defined in Eq. (3.2.1) and to be minimized is defined as

$$f(x) = \sum_{i=1}^{n} (O_{h_i} - P_{h_i})^2 \tag{3.3.1}$$

where O_{h_i} and P_{h_i} are respectively the observed and estimated drawdowns at different time step and n is the total number of time steps.

The SA searches for the optimal parameters depending on the objective function value. The initial guesses for SA are provided by the user; however, SA algorithm allows the initial guesses to be randomly given. After the initial guesses are made, the estimated drawdown can be calculated from Eqs. (3.1.1), (3.1.4), or (3.1.5). Then all the possible solutions (trial solutions) will be kept and improved based on the objective function value. If the objective function value meets the specified stopping criterion, the SA process will be terminated and the optimal parameters are found. The procedures of PEM using the conventional approach and SA are illustrated in Figures 3(a) and 3(b), respectively.

3.4 Sensitivity Analysis

The sensitivity is defined as a rate of change in one factor with respect to a change in another factor. The parametric sensitivity may be expressed as [McCuen, 1985]

$$S_{pi} = \frac{\partial O}{\partial P_i} = \frac{O(P_i + \Delta P_i; P_{j|j\neq i}) - O(P_1, P_2, \ldots, P_n)}{\Delta P_i} \tag{3.4.1}$$

where O is the output function of the system (i.e., the aquifer drawdown) and P_i is the ith input parameter of the system. However, the values of the parametric sensitivity for various parameters are useless for making comparison if the unit and/or the order of magnitude of the parameters are different. Thus, the normalized sensitivity is used and defined as [Kabala, 2001]

$$S_{i,t} = \frac{\partial O}{\partial P_i / P_i} = P_i \frac{\partial O}{\partial P_i} \tag{3.4.2}$$

where $S_{i,t}$ is the normalized sensitivity of ith input parameter at time t. Note that O is a function of P_i and t. The partial derivative of this equation may be approximated by a forward differencing formula as

$$\frac{\partial O}{\partial P_i} = \frac{O(P_i + \Delta P_i) - O(P_i)}{\Delta P_i} \tag{3.4.3}$$

The increment in the denominator may be approximated by the parameter value times a factor of 10^{-3}, i.e., $\Delta P_i = 10^{-3} P_i$. Eq. (3.4.2) measures the influence that the fractional change in the parameter, or its relative error, exerts on the output.

3.5 Assessment for Estimated Errors

The mean error (*ME*) is defined as

$$ME = \frac{1}{n} \cdot \sum_{i=1}^{n} e_i \tag{3.5.1}$$

The principle of least squares assumes that the errors are normally distributed with zero mean and constant variance [McCuen, 1985]. When the *ME* value is equal to or very close to zero, the assumption that errors having zero mean will be satisfied.

The standard error of estimate (*SEE*) is defined as

$$SEE = \sqrt{\frac{1}{\nu}\sum_{i=1}^{n} e_i^2} \tag{3.5.2}$$

where v is the degree of freedom, which is equal to the number of observed data points minus the number of estimate parameters.

CHAPTER 4 RESULTS AND DISCUSSION

4.1 Parameter Estimation Using the PEM Based on the SA

4.1.1 Estimation of leaky aquifer parameters

Table 1 lists the observed drawdown data obtained from a test with three monitoring wells reported in Cooper [1963] and cited by Lohman [1972] for parameter identification using the three-parameter model. The *r* for observation wells 1, 2, and 3 are, respectively, 30.48 m, 152.4 m, and 304.8 m. The *Q* and total pumping time are 5450.98 m^3/day and 1000 minutes. In the four-parameter model, the time-drawdown data is taken from Sridharan *et al.* [1987] and listed in Table 2. The *r* is 29.0 m and the *Q* is 136.26 m^3/day.

Three-parameter model

The upper and lower bounds for parameters estimated by SA when analyzing field data using the three-parameter model are 3000 and 0 m^2/day for parameter *T*, 10^{-3} and 10^{-5} for the parameter *S*, and 5 and 0 for the parameter *L*, respectively. The control parameters of SA, initial temperature, reduction factor R_t, and number of algorithm iteration, are 10, 0.75, and 100, respectively. The choice of the initial temperature is generally case by case. Nevertheless, Kirkpatrick et al. [1983] gave a guideline for setting the initial temperature that the acceptance probability happened at the lower part of Eq. (3.2.3), i.e., when the trial solution is worse than the current solution, should be larger than 80% initially. This criterion has the merit of avoiding the situation that the current solution is trapped in a local optimum at early search. The process of SA will be terminated if the absolute differences between the two successive values of the optimal objective function are all within less than 10^{-6} through four iterations. The results determined from SA are compared with those obtained from the EKF and NLN method [Yeh and Huang, 2005] and listed in Table 3. The estimated T for drawdown data obtained from those three wells by the proposed methods, EKF, and NLN range from 1200 to 1300 m^2/day. The estimated S ranges from 9.7×10^{-5} to 1.0×10^{-4} and the estimated leakage factor L ranges from 0.05 to 0.51. These results indicate that the aquifer of the study site is relatively homogenous. Figure 4 shows the observed drawdowns measured from those three wells and the estimated drawdowns generated by Hantush and Jacob's model with those parameters obtained from the SA. Apparently, the estimated drawdowns quite suitably fit the pumping test data, as indicated in the figure.

Four-parameter model

In the data analysis of the four-parameter model, the upper and lower bounds for parameters T, S, L, and Ψ are 3000 to 0 m^2/day, 10^{-3} to 10^{-5}, 5 to 0, and 10^{-3} to 10^{-5} respectively. The initial temperature, reduction factor, and number of algorithm iteration are the same as previous section. The results of the estimation for parameters T, S, L, and ψ are listed in Table 4. The estimated parameters obtained from SA almost agree with those obtained from NLN [Yeh and Huang, 2005], as indicated in Table 4. Figure 5 shows the observed drawdowns and the estimated drawdowns determined by Neuman and Witherspoon's model and those parameters obtained from SA.

4.1.2 Estimation of unconfined aquifer parameters

The upper and lower bounds of K_r are respectively 10^{-2} and 10^{-4} (m/sec), of K_z are respectively 10^{-3} and 10^{-5} (m/sec), of S are respectively 5×10^{-3} and 10^{-5}, and of S_y are respectively 3×10^{-1} and 10^{-2} for an unconfined aquifer when applying SA. The initial temperature, reduction factor R_t, and number of algorithm iteration of SA are 10, 0.75, and 100, respectively. The other control parameters of SA are similar to those of the leaky aquifer case given in the previous section.

Table 5 lists the analyzed results and the estimated errors from the graphical methods such as the Neuman type-curve method and Neuman's semilogarithmic method [Batu, 1998]. In addition, the estimated parameters and related errors resulting from the computer methods such as NLN, EKF [Leng and Yeh, 2003], and the present methods are also listed in Table 5. The estimated parameters obtained by the SA are: 2.23×10^{-3} m/s for K_r; 1.67×10^{-5} m/s for K_z; 1.31×10^{-3} for S; and 3.83×10^{-2} for S_y, respectively. The estimated errors by SA are generally much smaller than those by two graphical methods, indicating that the estimated parameters of SA give a better fit to the observed drawdown data. Figure 6 displays the estimated drawdown and the pumping test data in the unconfined aquifer. This figure also indicates that the proposed methods can optimally search the parameters of the unconfined aquifer. Clearly, these estimated results and related errors demonstrate that the proposed methods are much superior to the graphical methods and give the results with the same degree of accuracy when compared with those of NLN and EKF.

4.1.3 The sensitivity analysis of SA's control parameters

The use of control parameters in SA, such as the initial guess value and the temperature reduction factor R_t, may affect the results of the parameter estimation. For demonstrating robustness and reliability of SA in parameter identification, this study presents two sensitivity analyses of the control parameters in SA for the parameter estimation when analyzing pumping-test data from Sridharan [1987].

Table 6 lists the aquifer parameters with a different reduction factor R_t. The estimated parameter T ranges from 23.34 to 23.36 (m^2/day), the parameter S ranges from 1.64×10^{-4} to 1.65×10^{-4}, the parameter L is 0.13 and keeps the same in different R_t cases. The results of estimated aquitard storage coefficient Ψ range from 8.60×10^{-4} to 9.59×10^{-4} with slight variation. The means of T, S, L, and Ψ are 23.4 (m^2/day), 1.64×10^{-4}, 0.13, and 9.29×10^{-4}, respectively, which is very close to those estimated by various methods as shown in Table 4. The standard deviations of T, S, L, and Ψ are 6.90×10^{-3}, 3.78×10^{-7}, 0, and 3.93×10^{-5}

respectively, which are very small when compared with their mean values, indicating that the identified results are independent of R_t values. In other words, the influence of choosing various values of R_t on the results of the parameter estimation is negligible.

If the initial guess values are far away from the target parameters, gradient-type methods for solving the nonlinear least-square equations might give divergent results. This is the major disadvantage of employing the NLN method in solving nonlinear least equations. Therefore, different initial guess values for SA are chosen to examine the performance of SA in parameter estimation. Table 7 displays the estimated parameters with fourteen different combinations of initial guesses. The estimated parameters are almost identical, even if the initial guesses are different from several orders of magnitude. These results indicate that SA can not only successfully estimate the aquifer parameters but also give a consistent estimation when using different temperature reduction factor and initial guesses.

4.2 Sensitivity Analysis of Aquifer Parameters

The synthetic time-drawdown data for a leaky aquifer listed in Table 8 are generated from Hantush and Jacob's model [1955]. The Q is 3000 m^3/day, r is 30 m, T is 1000 m^2/day, S is 10^{-4}, and L is 0.03. The observed pumping period ranges from 0.017 to 1000 minutes. The time-drawdown data and the normalized sensitivities are plotted in Figure 7. This figure indicates that the distribution curve of each normalized sensitivity of the aquifer parameters reflects the temporal change of the drawdown in response to the relative change of each parameter. In other words, the non-zero periods in the normalized sensitivity curves imply that the aquifer parameters have influences on the drawdown at that time. In addition, this figure also indicates that all aquifer parameters have their own influence period to the drawdown. The influence period of parameter S increases from the start of pumping and decreases after 3 minutes. The drawdown is very sensitive to T except at the early period of the pumping and the normalized sensitivity is continuously increased through the end of the pumping. The parameter of leakage coefficient L appears to have influence on the drawdown from 1.5 minutes through the end of pumping. Such a phenomenon can be related to the physical behavior of the leaky aquifer. The normalized sensitivity of L keeps zero before 1.5 minutes, and it may ascribe to the fact that there is a time lag between the start of pumping and the response of the drawdown to the leakage effect. In contrast, the normalized sensitivities indicate that the parameters T and S have influence on the drawdown right at the beginning of pumping. In addition, the influence of S is larger than that of T at early pumping period. This result to some extend reflects the physical behavior of parameters T and S during the pumping.

The time-drawdown data set 1 of an unconfined aquifer, generated by Neuman's model [1974], for pumping starting from 1 to 176360 seconds (49 hours) in an unconfined aquifer are listed in Table 9. The b is 10 m, Q is 3000 m^3/day, and r is 10 m. The parameters K_r,

K_z, S, and S_y are set to 1×10^{-3} m/sec, 1×10^{-4} m/sec, 1×10^{-4}, and 1×10^{-1}, respectively. The time-drawdown data and related normalized sensitivities are plotted in Figure 8. Similar to Figure 7, the distribution curve of each normalized sensitivity reflects the temporal change of the drawdown in response to the relative change of each parameter, and all aquifer parameters affect the drawdown at different periods. The normalized sensitivity of parameter S starts from 1 to 10 seconds, K_z ranges from 1 to 1000 seconds, and S_y appears from 80 seconds to the end of pumping. The drawdown is most sensitive to the parameter K_r except at the early period of the pumping and the influence of K_r on the drawdown increases at the beginning and through the end of the pumping. The normalized sensitivity of S starts with highest value and drops quickly after the beginning of pumping. The normalized sensitivity of K_z reaches its highest value in a range between 10 and 1000 seconds, implying that the slow decline of the water table is attributed to the contribution of the K_z at the moderate pumping time. The drawdown stops increasing when the normalized sensitivity of K_z approaches its maximum. The temporal distribution of K_r's normalized sensitivity, displaying three segments during the pumping period, is similar to the drawdown curve. The second segment appears at 10 seconds and vanishes at 1000 seconds (16.67 min). Figure 8 shows that the drawdown increases in the third segment along with the decrease of K_z's normalized sensitivity, clearly indicating rapid decrease of vertical drainage. The sensitivity curve demonstrates that the aquifer parameter S_y does not have any contribution in response to the pumping at the beginning of the test and starts to react at about 80 seconds (1.33 min).

The time-drawdown data set 2 listed in Table 10 is generated by Moench's model [1997]. The pumping starts from 0.6 to 600000 seconds (1000 minutes). The b is 10 m, Q is 1000 m^3/day, and the r is 10 m. The parameters K_r, K_z, S, S_y, and r_w, are set to 1×10^{-3} m/sec, 1×10^{-4} m/sec, 1×10^{-4}, 1×10^{-1}, and 1 m respectively. The time-drawdown data and related normalized sensitivities are plotted in Figure 9. The upper part of Figure 9 is the same plot but the normalized sensitivity of K_r is removed because the magnitude of K_r's normalized sensitivity is relatively large at the end of pumping, and removing it is much helpful to recognize the small change of other parameter's normalized sensitivities at the early period of pumping. The normalized sensitivity of r_w ranges from 2 to 2000 seconds, S starts from 0.6 to 1000 seconds, K_z ranges from 100 to 10000 seconds, and S_y appears from 100 seconds to the end of pumping. The drawdown is most sensitive to the parameter K_r after pumping for 300 seconds and the influence of K_r on the drawdown increases at the beginning and through the end of the pumping.

The normalized sensitivity of r_w starts at the beginning of the pumping, reflecting the physical phenomenon that the effect of well bore storage contributes to the drawdown immediately after pumping. The normalized sensitivity of S is relatively small compared with those of other parameters. The normalized sensitivity of K_z reaches its highest value in a range between 600 and 2000 seconds. Similar to Figure 8, the drawdown slowly increasing when the normalized sensitivity of K_z approaches its maximum, indicating that the slow decline of the water table is attributed to the contribution of the K_z at the moderate pumping time. Figure 9 also shows that the effect of well bore storage is larger than that of K_r at early pumping period. This phenomenon indicates that the water is removed from the well first after pumping and the groundwater flow into the well since the head difference between the well and the aquifer. Certainly, the parameter S_y still does not have any contribution in response to the pumping at the beginning of the test and starts to react at about 100 seconds (1.67 min). Figures 8 and 9 indicate that the normalized sensitivities of parameters K_r, K_z, S, and S_y have similar temporal distributions but different magnitudes. In Moench's model, the effect of S is relatively small, the influence periods of S and K_z are longer than that of Neuman's model, and the effect of r_w is smaller than that of K_r at the beginning of pumping.

4.3 Parameter Estimation using On-line PEM

Table 11 lists the number of observations (drawdown data) used in the data analysis and the estimated parameters for a hypothetical leaky aquifer case. The estimation process starts with three observations (shown at the first column) since the number of unknown parameter is three. The target values of the parameters T, S and L are 1000 m^2/day, 10^{-4}, and 3×10^{-2}, respectively. The parameter estimation indicates that T and S are correctly identified even at the beginning of the pumping. The results of estimated L using three, four, five, and six observation data points have the same order of magnitude as the target value, and the relative errors of estimated L are 63%, 16%, 8.7%, and 2%, respectively. The parameters are stably identified using more than seven observation data, i.e., after 1.5 minutes. These results indicate that the aquifer parameters are determined when the corresponding normalized sensitivities start to respond to the pumping. Moreover, the temporal curve of estimated L exhibited in Figure 10 shows fluctuation at first few steps and approaches a constant value after about 1.5 minutes. These results imply that the on-line PEM can successfully identify the parameters of leaky aquifer when the estimated L starts to be stabilized. The last row of Table 11 shows the estimated results by analyzing 20 observations during 0.1 minute (i.e., the time interval is setting as 0.005 minute). The estimated T, S, and L are 1000.83 m^2/day, 1.00×10^{-4}, and 1.25×10^{-2}, respectively. This result demonstrates that the inaccurate estimate of parameter L is mainly due to the insensitivity of drawdown to the aquifer parameter at early period but not caused by the insufficiency of the observations.

Table 12 displays the field time-drawdown data and the estimated parameters for a leaky aquifer using different number of observations. The time-drawdown data measured from observation wells, as reported in Cooper [1963] and cited by Lohman [1972, p.31, Table 11], are selected for the data analysis. The r is 30.48 m, Q is 5450.98 m^2/day, b is 30.48 m, and total pumping time is 1000 minutes (16.67 hours). It is clear that the estimated values of parameters T and S do not fluctuate drastically when the number of observation using by on-line PEM is larger than 7, i.e., after 20 minutes. The estimated parameters T and S are 1203.80 m^2/day and 1.04×10^{-4}, respectively. Comparing with the estimated parameters calculated based on the total number of observations (1239.28 m^2/day for T and 9.80×10^{-5} for S), the relative errors of parameters T and S are both smaller than 5% when the number of observation is larger than 7. Similarly, the estimated values of parameter L remain almost the same when the number of the observation utilized by the on-line PEM is larger than 9. In this case, the on-line estimation can be terminated after 100 minutes. The on-line PEM saves tremendous 90% time and 3407 m^3 groundwater resources if compared with total pumping time and pumped water volume required by conventional graphical approaches. Note that small fluctuation in the estimated parameters at the late period of pumping and a longer parameter estimation time than that of the hypothetical case may be attributed to aquifer heterogeneity and/or measurement errors in the observed drawdowns

The estimation results with different number of observation using on-line PEM for the synthetic unconfined aquifer data set 1 are listed in Table 13. The identification process starts with four observation data points because the number of unknown parameter is four. The target values of the parameters K_r, K_z, S, and S_y are 1×10^{-3} m/sec, 1×10^{-4} m/sec, 1×10^{-4}, and 1×10^{-1}, respectively. This table only lists the results when the number of observations is less than 20 because the estimated parameters are almost the same as the target values when the number of observation is larger than 20. Figure 8 shows that the normalized sensitivities of parameters K_r, K_z, and S have immediate response to the pumping but the normalized sensitivity of parameter S_y has a time lag in response to the pumping. The identification results also reflect this phenomenon. The estimated S_y ranges from 4.44×10^{-2} to 2.01×10^{-1} and the largest relative errors are 101% when using 12 observation data. The identification results of S_y did not approach the target value until the number of observation is over 20, i.e., about 80 seconds. Therefore, the on-line PEM may not obtain accurate results of S_y if the time-drawdown data is too short to cover the response period of S_y. Similar to Figure 10, the curve of estimated S_y versus time displayed in Figure 11 shows dramatic fluctuation in the early period and converges to a constant value after about 80 seconds. Figures 8 and 10 demonstrate that the on-line PEM can successfully identify the aquifer parameters when S_y just starts to affect the drawdown. Therefore, the on-line estimation based on Neuman's model can be terminated once the identified parameters become stable.

Similar to Table 13, the identification results for the synthetic data set 2 are listed in Table 14. The target values of the parameters K_r, K_z, S, S_y, and r_w are 1×10^{-3} m/sec, 1×10^{-4} m/sec, 1×10^{-4}, 1×10^{-1}, and 1 m, respectively. The estimated parameters are all the same as the target values when the number of observation is larger than 30. The parameters K_r, K_z, S, and r_w are accurately determined at first few seconds. The estimated S_y ranges from 1.00×10^{-2} to 2.91×10^{-1} and did not approach the target value until the pumping time is over

125 seconds. The curve of estimated S_y versus time displayed in Figure 12 also shows dramatic fluctuation in the early period and converges to a constant value after about 125 seconds. Hence, the on-line estimation can be terminated even based on Moench's model.

Table 15 shows the estimated parameters for the first field pumping test in an unconfined aquifer using different number of observations. The site of Cape Cod, Massachusetts is selected for the study [Moench et al., 2000]. Its aquifer was composed of unconsolidated glacial outwash sediments that were deposited during the recession, 14,000 to 15,000 years before present, of the late Wisconsinan continental ice sheet. The depth of the pumping well was 24.4 *m* below the land surface. The top and bottom of the screen were located 4.0 and 18.3 *m*, respectively, below the initial water table, which was approximately 5.8 *m* below land surface. The aquifer saturated thickness was about 48.8 m. Well F507-080 was pumped at an average rate 1.21 m^3/min for 72 hours. The data set of the observation well F505-032 is selected in this case. The distance between pumping well and observation well is 7.28 m. From Table 15, the estimated K_r ranges from 2.20×10^{-4} m/sec to 1.97×10^{-3} m/sec, the estimated K_z ranges from 1.0×10^{-6} m/sec to 2.25×10^{-4} m/sec, the estimated S ranges from 3.45×10^{-3} to 7.29×10^{-3}, and the estimated S_y ranges from 0.016 to 0.3. It can be found that the ranges of estimated K_r and S are small as compared with those of the K_z and S_y. This phenomenon may attribute to the fact that the parameters K_r and S have influence on the drawdown as the pumping starts and thus can be estimated using only few observations.

Oppositely, the influence periods of parameters K_z and S_y have time lags after the start of pumping and the estimated results fluctuate significantly at the early period of the pumping. Note that the estimated parameter S_y keeps the largest value (0.3) at early pumping period then dramatically decreases to small value (0.016) after 20 minutes (18 observations). This result implies that S_y does not affect the estimation for other parameters before that time, i.e., the variation of parameter S_y does not significantly change the estimation result. Figure 13 displays the estimated S_y versus pumping time (different number of observations). In addition, the value of S_y versus logarithmic time is also shown in the upper part of the figure. The estimated S_y keep almost constant before 20 minutes and decreases to a small value. Then the estimated S_y gradually increases and becomes flatly after 1000 minutes implying that the on-line estimation can be terminated at that time. In this case, the on-line PEM can save 77% pumping time if the test is terminated and 4041.4 m^3 groundwater resources if compared with total pumping time and pumped water volume required by conventional graphical approaches. Note that the gradual increasing of the estimated parameters at the late period and a longer parameter estimation time than that of the hypothetical case also occur in this real unconfined case.

4.4 The Tests of Other Impacts to the Influence Period of the S_y

The normalized sensitivity of parameter S_y has the longest time lag in response to the pumping than other parameters as indicated in Figures 8 and 9. The on-line PEM can correctly identify the aquifer parameters only when the parameters start to influence the drawdown. In the unconfined aquifer case, the S_y was assigned to 0.1 where the reasonable value is 0.01 to 0.3 [Batu, 1998]. It is interesting to examine the temporal distribution of normalized sensitivity for different value of S_y. Moreover, r is another problem deserved attention because the drawdown in response to the pumping becomes smaller when the distance from the pumping well goes farther. For investigating the effect of various value of S_y or r on the on-line parameter estimation, two tests are performed. The first test assigns three different values of S_y including two extreme values, i.e., 0.01 and 0.3, while the other parameters are kept the same as those given in previous unconfined aquifer case. The second test examines the effect of distance on the normalized sensitivity when the observation well is located at 10, 30, or 50 m from the pumping well.

The normalized sensitivity of S_y versus time for the first test is demonstrated in Figure 14. The influence period starts slightly later when the S_y value gets larger. The S_y starts to influence the drawdown at 5 and 100 seconds when the value of S_y is 0.01 and 0.3, respectively, indicating that the time lag of the S_y may not be larger than 2 minutes in these two extreme cases. Figure 14 indicates that the largest normalized sensitivities are about the same in those cases because of the normalization of S_y. The results of the second test shown in Figure 15 indicate that a longer distance from the well has a slower response time. The shortest response time is about 10 seconds and the latest one is about 100 seconds. Comparing with the total pumping time of 176360 seconds (2.04 days), the differences of the estimated parameters in these three cases may be negligible. In addition, the sensitivity analysis may be performed along with the on-line parameter estimation and provide a double check in terminating the pumping.

CHAPTER 5 CONCLUSIONS

A novel approach is developed based on simulated annealing (SA) integrated with aquifer drawdown models to identify aquifer parameters of leaky and unconfined aquifer systems. In the leaky aquifer system, Hantush and Jacob's analytical model [1955] is chosen to combine with SA to optimally determine the aquifer transmissivity T, storage coefficient S, and leakage coefficient L. Except these three parameters, Neuman and Witherspoon's model [1969] is used to estimate the additional parameter ψ which describes the effect of the aquitard storage. Three sets of drawdown data given by Cooper [1963] and the drawdown data given by Sridharan [1987] were chosen for data analyses. The aquifer parameters obtained from SA suitably agree with those obtained from NLN or EKF coupled with Hantush and Jacob's model or Neuman and Witherspoon's model when analyzing those available drawdown data.

Likewise, the Neuman solution [1975] can also be employed with SA to estimate the horizontal and vertical hydraulic conductivities K_r and K_z, storage coefficient S, and specific yield S_y for an unconfined aquifer if the assumptions of Neuman model are satisfied. Two sets of pumping test data in the confined aquifers and one set in the unconfined aquifer are utilized to demonstrate the application of the proposed method in parameter identification. The results show that the present method can determine the aquifer parameters with very good accuracy. The identified results and related estimated errors indicate that the proposed method is superior to the graphical methods and gives results with the same degree of accuracy when compared with those of NLN and EKF.

The analyzed results based on SA with various control parameters are compared and discussed. The results indicate that the temperature reduction factor does not seem to affect the results of the parameter estimation. In addition, the estimated results are almost identical for various initial guesses which is different from several orders of magnitude. This fact shows that SA has a wide range of initial guess values and is a significant advantage over the NLN and EKF approaches. These analyses demonstrate that the proposed method is robust and reliable even if the user is not experienced in using SA.

The sensitivity analysis is used to investigate the influence period of aquifer parameters in both leaky and unconfined aquifers. The influences of parameters L and S_y on the drawdown are shown to have time lag in response to pumping in the leaky and unconfined aquifers, respectively. An on-line parameter estimation model is applied to estimate the parameters based on the data obtained from hypothetical and field pumping tests for both leaky and unconfined aquifers. The results indicate that the on-line estimation can be terminated when the estimated parameters are stabilized and their corresponding normalized sensitivities start to response to the pumping. In the hypothetical cases, the termination time of the on-line estimation is consistent with the influence period of the parameter which has longest time lag from the beginning of the pumping. This fact indicates that the on-line estimation can be terminated if all identified parameters tend to be stabilized, i.e., the drawdown already reacts to the affect of aquifer parameters. In the field cases, the results indicate that the on-line parameter estimation model can save 90% pumping time in the leaky aquifer and 77% pumping time in the unconfined aquifer. Note that the small fluctuation in the estimated parameters at the late period of pumping and a longer on-line estimation time than that of the hypothetical case occur. These results may be mainly caused by aquifer heterogeneity and/or measurement errors in the observed drawdown data. Finally, different values of the specific yield and distance between pumping well and observation well do not significantly affect the influence period of specific yield during the pumping. These results may provide a useful reference for on-line aquifer parameter estimation.

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Table 1 Time-drawdown data of three observations wells [Cooper, 1963, p. 31]

	Drawdown at observation well (m)		
time(min)	1	2	3
0.2	0.536	0.003	0.000
0.5	0.838	0.043	0.000
1	1.094	0.137	0.006
2	1.298	0.284	0.043
5	1.609	0.536	0.168
10	1.798	0.713	0.302
20	1.972	0.869	0.445
50	2.109	1.009	0.594
100	2.167	1.067	0.640
200	2.195	1.070	0.643
500	2.198	1.073	0.643
1000	2.198	1.073	0.643

Table 2 Time-drawdown data [Sridharan, 1987, p. 170]

time(min)	Drawdown(m)
5	0.30
28	0.95
41	1.10
60	1.25
75	1.34
250	1.75
500	1.90
700	1.95
970	1.98
1000	1.99
1200	1.99

Note: $Q = 136.26 \ m^3 / day$, $r = 29.00 \ m$

Table 3 Comparison of results from three-parameter model when using SA, EKF, and NLN to analyze Cooper's data [Cooper, 1963]

Observation well	Estimated parameters			Errors	
	T (m^2/day)	S ($\times 10^{-4}$)	L	ME ($\times 10^{-4}$)	SEE ($\times 10^{-3}$)
			SA		
1	1239.4	0.98	0.05	3.50	13.30
2	1243.4	0.97	0.25	-0.39	5.73
3	1221.2	1.01	0.51	-1.54	3.43
			EKF		
1	1257.9	0.91	0.05	-6.53	19.90
2	1311.4	0.93	0.23	37.20	8.62
3	1228.0	1.00	0.51	-2.44	4.09
			NLN		
1	1239.1	0.98	0.05	-1.10	13.30
2	1242.1	0.98	0.25	4.98	5.69
3	1215.2	0.97	0.51	-1.90	3.72

Table 4 The estimated parameters and estimated errors when using SA, EKF, and NLN to analyze Sridharan's data [Sridharan et al., 1987]

Method	Estimated parameters				Errors	
	T (m²/day)	$S\ (\times 10^{-4})$	L	$\Psi\ (\times 10^{-4})$	ME $(\times 10^{-3})$	SEE $(\times 10^{-2})$
SA	23.4	1.64	0.13	9.04	-1.81	1.02
EKF	22.6	1.73	0.14	3.16	1.49	1.36
NLN	23.3	1.65	0.13	7.04	-1.78	1.00

Table 5 Comparison of results when applying graphical methods, NLN, EKF, and SA methods to analyze the pumping test data obtained from an unconfined aquifer

Method	Estimated parameters				Errors	
	$K_r \times 10^{-3}$ (m/s)	$K_z \times 10^{-5}$ (m/s)	$S \times 10^{-3}$	$S_y \times 10^{-2}$	$ME \times 10^{-3}$ (m)	$SEE \times 10^{-3}$ (m)
Graphical methods						
Neuman type curve	2.40	1.62	1.46	5.73	32.90	34.59
Neuman semilograithmic	2.40	1.62	1.87	2.13	14.23	14.96
Computer methods						
NLN	2.22	1.68	1.31	3.85	0.28	8.06
EKF	2.25	1.56	0.97	4.10	1.68	8.36
SA	2.23	1.67	1.31	3.83	0.31	8.06

Table 6 Estimated parameters using different temperature reduction factor

Temperature reduction factor R_t	Estimated parameters			
	T (m^2/day)	S ($\times 10^{-4}$)	L	Ψ ($\times 10^{-4}$)
0.90	23.36	1.64	0.13	9.06
0.80	23.35	1.64	0.13	9.58
0.75	23.36	1.64	0.13	9.04
0.70	23.35	1.64	0.13	8.60
0.60	23.35	1.64	0.13	9.57
0.50	23.34	1.65	0.13	9.59
0.30	23.35	1.64	0.13	9.58
Mean	23.35	1.64×10^{-4}	0.13	9.29
Standard deviation	6.90×10^{-3}	3.78×10^{-7}	0.00	3.93×10^{-5}

Table 7 Comparison of the results in leaky aquifer considering storage effect when using different initial guesses

Initial guess				Estimated parameters				Convergence or not?
T (m^2/day)	*S* ($\times 10^{-4}$)	*L*	*Ψ* ($\times 10^{-4}$)	*T* (m^2/day)	*S* ($\times 10^{-4}$)	*L*	*Ψ* ($\times 10^{-4}$)	
0.0	0.1	2.5	1.0	23.3	1.64	0.13	9.58	Yes
	1.0			23.3	1.64	0.13	9.58	Yes
	10.0			23.3	1.64	0.13	9.57	Yes
	0.1	0.0	0.1	23.3	1.64	0.13	9.57	Yes
		0.1	10.0	23.3	1.64	0.13	9.57	Yes
1000.0	0.1	2.5	1.0	23.3	1.64	0.13	9.59	Yes
	1.0			23.3	1.64	0.13	9.59	Yes
	10.0			23.4	1.64	0.13	9.57	Yes
	1.0	0.1	10.0	23.4	1.64	0.13	9.04	Yes
3000.0	0.1	2.5	1.0	23.3	1.64	0.13	9.59	Yes
	1.0			23.4	1.64	0.13	9.57	Yes
	10.0			23.4	1.64	0.13	9.57	Yes
	10.0	5.0	10.0	23.3	1.64	0.13	9.58	Yes
		0.0	0.1	23.4	1.64	0.13	9.04	Yes

Table 8 The synthetic drawdown data for the leaky aquifer

No	Time (min)	Drawdown (m)
1	0.017	0.013
2	0.050	0.099
3	0.100	0.203
4	0.250	0.380
5	0.750	0.621
6	1.000	0.687
7	1.500	0.781
8	2.000	0.847
9	2.500	0.899
10	3.500	0.977
11	4.500	1.035
12	5.000	1.059
13	10.000	1.215
14	20.000	1.365
15	50.000	1.539
16	100.000	1.640
17	200.000	1.702
18	500.000	1.728
19	700.000	1.730
20	1000.000	1.730

Q = 3000 m^3/day, r = 30 m

Table 9 The synthetic drawdown data set 1 for the unconfined aquifer

No	Time (s)	Drawdown (m)	No	Time (s)	Drawdown (m)	No	Time (s)	Drawdown (m)
1	1	0.22	20	87	0.44	39	6000	0.76
2	2	0.31	21	120	0.44	40	8000	0.83
3	3	0.36	22	149	0.44	41	9354	0.86
4	4	0.38	23	176	0.44	42	11429	0.91
5	5	0.4	24	212	0.45	43	14925	0.98
6	6	0.41	25	272	0.45	44	18235	1.03
7	7	0.41	26	332	0.46	45	22274	1.09
8	8	0.42	27	393	0.46	46	25882	1.13
9	9	0.42	28	472	0.47	47	32696	1.19
10	10	0.42	29	600	0.48	48	41295	1.25
11	11	0.43	30	792	0.49	49	47195	1.29
12	12	0.43	31	967	0.5	50	59224	1.35
13	13	0.43	32	1143	0.52	51	69279	1.4
14	14	0.43	33	1350	0.53	52	81302	1.44
15	15	0.43	34	1723	0.55	53	95126	1.48
16	30	0.43	35	2154	0.58	54	118168	1.54
17	44	0.43	36	2632	0.61	55	151775	1.61
18	58	0.43	37	3215	0.64	56	176360	1.65
19	74	0.43	38	4385	0.7			

Table 10 The synthetic drawdown data set 2 for the unconfined aquifer

No	Time (s)	Drawdown (m)	No	Time (s)	Drawdown (m)	No	Time (s)	Drawdown (m)
1	0.6	0.0001	17	24	0.0155	33	1138	0.2130
2	1	0.0003	18	27	0.0178	34	1722	0.2251
3	2	0.0008	19	31	0.0204	35	1977	0.2290
4	3	0.0014	20	36	0.0234	36	2992	0.2424
5	4	0.0020	21	41	0.0268	37	5970	0.2741
6	5	0.0028	22	47	0.0306	38	11912	0.3189
7	6	0.0034	23	54	0.0348	39	18029	0.3507
8	7	0.0040	24	63	0.0396	40	35973	0.4088
9	8	0.0047	25	72	0.0449	41	62514	0.4577
10	9	0.0055	26	82	0.0507	42	94619	0.4950
11	10	0.0064	27	95	0.0572	43	124732	0.5200
12	12	0.0075	28	125	0.0722	44	188789	0.5578
13	14	0.0087	29	189	0.0993	45	328078	0.6084
14	16	0.0101	30	249	0.1199	46	600000	0.6638
15	18	0.0116	31	497	0.1720			
16	21	0.0134	32	655	0.1892			

Table 11 Number of observations used in the synthetic data analysis and the estimated parameters for a leaky aquifer

Number of observations	Time (min)	Estimated parameters		
		T (m^2/day)	$S\times10^{-4}$	$L\times10^{-2}$
3	0.10	1000.53	1.00	1.12
4	0.25	1000.32	1.00	2.52
5	0.75	1000.52	1.00	2.74
6	1.00	999.93	1.00	3.06
7	1.50	1000.02	1.00	3.00
8	2.00	999.96	1.00	3.03
9	2.50	999.98	1.00	3.01
10	3.50	999.99	1.00	3.00
11	4.50	999.99	1.00	3.01
12	5.00	999.95	1.00	3.01
13	10.00	1000.06	1.00	3.00
14	20.00	1000.02	1.00	3.00
15	50.00	1000.01	1.00	3.00
16	100.00	1000.02	1.00	3.00
17	200.00	1000.02	1.00	3.00
18	500.00	1000.04	1.00	3.00
19	700.00	1000.06	1.00	3.00
20	1000.00	1000.05	1.00	3.00
20	0.10	1000.83	1.00	1.25

Target values: T = 1000 (m^2/day), S = 10^{-4}, and $L = 3\times10^{-2}$

Table 12 The field time-drawdown data and the estimated parameters for a leaky aquifer using different number of observations

Number of Observations	Time (min)	Drawdown (m)
1	0.2	0.536
2	0.5	0.838
3	1	1.094
4	2	1.298
5	5	1.609
6	10	1.798
7	20	1.972
8	50	2.109
9	100	2.167
10	200	2.195
11	500	2.198
12	1000	2.198

Estimated results using on-line PEM

Number of Observations	Estimated values		
	T (m^2/day)	$S \times 10^{-4}$	$L \times 10^{-2}$
4	1060.40	1.12	15.70
5	1182.30	1.05	1.61
6	1182.70	1.04	6.76
7	1203.80	1.03	5.85
8	1211.33	1.02	5.61
9	1222.18	1.00	5.32
10	1232.32	0.99	5.09
11	1236.93	0.98	4.99
12	1239.28	0.98	4.93

Table 13 Number of observations used in the data analysis and the estimated parameters based on the synthetic data set 1

Number of observations	Time (s)	Estimated parameters			
		K_r (m/s)$\times10^{-3}$	K_z (m/s)$\times10^{-4}$	$S\times10^{-4}$	$S_y\times10^{-1}$
4	4	0.997	1.006	1.000	0.612
5	5	1.000	0.999	1.000	0.616
6	6	1.000	0.999	1.000	1.190
7	7	0.997	1.010	1.000	0.444
8	8	1.000	0.998	1.000	1.570
9	9	0.999	1.000	1.000	0.933
10	10	1.000	1.000	1.000	0.972
11	11	0.998	1.000	1.000	0.712
12	12	1.000	0.995	1.000	2.010
13	13	1.000	0.997	1.000	1.140
14	14	1.000	0.998	1.000	1.220
15	15	0.998	0.998	1.000	0.816
16	30	1.000	1.000	1.000	1.040
17	44	0.998	0.997	1.000	0.987
18	58	1.000	1.000	1.000	1.010
19	74	1.000	1.000	1.000	0.993
20	87	1.000	1.000	1.000	1.000

Target Values: $K_r = 1\times10^{-3}$ (m/s), $K_z = 1\times10^{-4}$ (m/s), $S = 1\times10^{-4}$, and $S_y = 1\times10^{-1}$

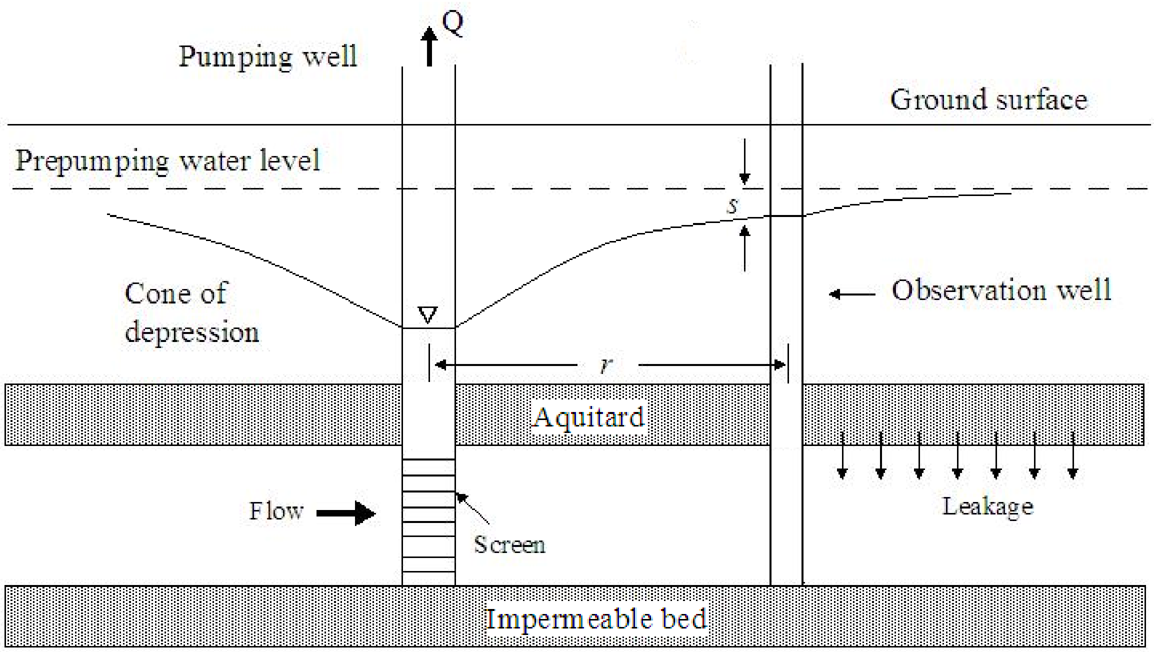
Table 14 Number of observations used in the data analysis and the estimated parameters based on the synthetic data set 2

Number of observations	Time (s)	Estimated parameters				
		K_r (m/s)$\times 10^{-3}$	K_z (m/s)$\times 10^{-4}$	S $\times 10^{-4}$	S_y $\times 10^{-1}$	r_w (m)
8	7	1.66	1.63	1.67	0.10	1.01
9	8	1.00	1.00	1.00	0.53	1.00
10	9	1.00	1.00	1.00	2.91	1.00
11	10	1.00	1.00	1.00	0.20	1.00
12	12	1.00	1.00	1.00	0.67	1.00
13	14	1.00	1.00	1.00	1.17	1.00
14	16	1.00	1.00	1.00	0.48	1.00
15	18	1.00	1.00	1.00	0.56	1.00
16	21	1.00	1.00	1.00	0.69	1.00
17	24	1.00	1.00	1.00	0.65	1.00
18	27	1.00	1.00	1.00	0.77	1.00
19	31	1.00	1.00	1.00	0.85	1.00
20	36	1.00	1.00	1.00	1.23	1.00
21	41	1.01	1.01	1.01	0.59	1.00
22	47	1.00	1.00	1.00	0.96	1.00
23	54	1.00	1.00	1.00	1.03	1.00
24	63	1.00	1.00	1.00	0.90	1.00
25	72	1.00	1.00	1.00	1.00	1.00
26	82	1.00	1.00	1.00	0.99	1.00
27	95	1.00	1.00	1.00	1.03	1.00
28	125	1.00	1.00	1.00	1.00	1.00
29	189	1.00	1.00	1.00	1.00	1.00
30	249	1.00	1.00	1.00	1.00	1.00

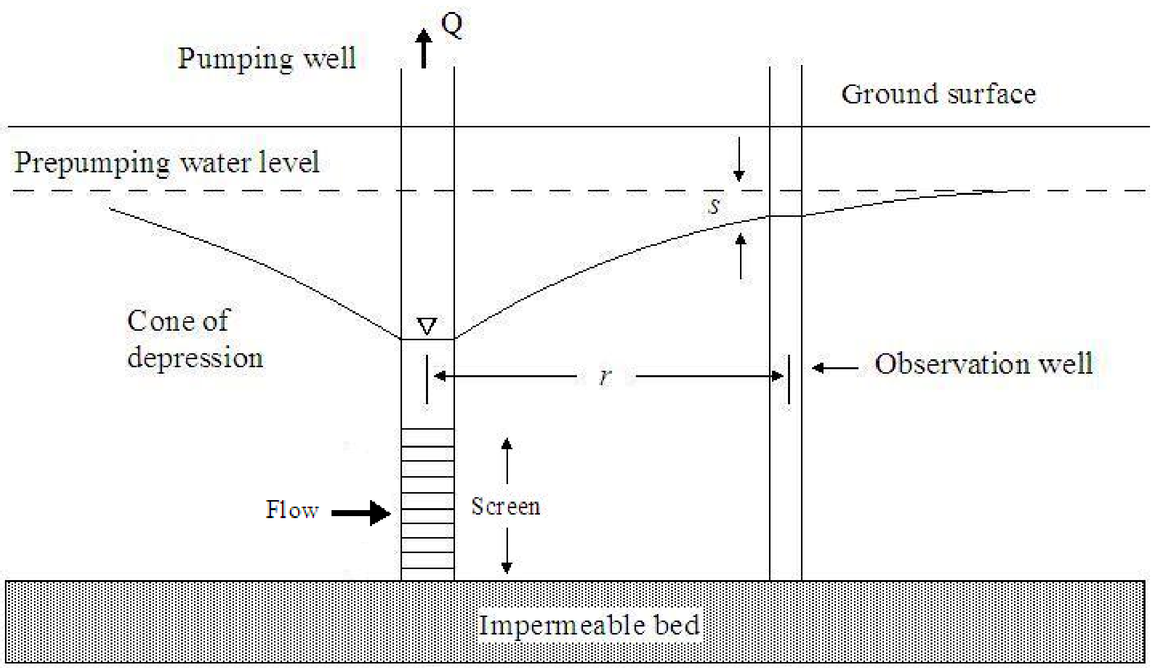
Target Values: $K_r = 1\times10^{-3}$ (m/s), $K_z = 1\times10^{-4}$ (m/s), $S = 1\times10^{-4}$, $S_y = 1\times10^{-1}$, and $r_w = 1$ m

Table 15 The estimated parameters for an unconfined aquifer (Cape Cod site) using different number of observations

Number of observations	Time (min)	Estimated parameters			
		$K_r \times 10^{-3}$ (m/s)	$K_z \times 10^{-5}$ (m/s)	$S \times 10^{-3}$	$S_y \times 10^{-1}$
5	0.15	0.65	0.10	7.18	3.00
6	0.22	0.73	1.05	7.29	3.00
7	0.32	0.91	0.98	7.45	3.00
8	0.47	0.88	1.18	7.17	3.00
9	0.68	0.96	1.19	7.16	3.00
10	1.00	0.51	1.89	5.61	3.00
11	1.47	0.32	2.15	4.28	3.00
12	2.15	0.22	2.23	3.32	3.00
13	3.17	0.24	2.41	3.52	2.91
14	4.75	0.30	2.78	4.31	3.00
15	6.75	0.26	2.60	3.83	3.00
16	10.10	0.25	2.20	3.64	2.95
17	14.90	0.44	2.34	5.64	3.00
18	21.90	1.01	1.51	8.14	1.49
19	31.90	1.39	0.74	7.00	0.56
20	46.90	1.74	0.48	6.21	0.27
21	67.90	1.92	0.39	5.65	0.18
22	99.90	1.96	0.37	5.52	0.16
23	151.00	1.97	0.36	5.49	0.16
24	221.00	1.92	0.38	5.63	0.18
25	325.00	1.82	0.42	5.98	0.24
26	492.00	1.70	0.46	6.39	0.33
27	675.00	1.60	0.49	6.71	0.43
28	1050.00	1.54	0.51	6.94	0.52
29	1470.00	1.50	0.52	7.10	0.59
30	2190.00	1.47	0.53	7.19	0.64
31	3100.00	1.46	0.54	7.26	0.68
32	4330.00	1.45	0.54	7.29	0.69



(a)



(b)

Figure 1 The sketch of the pumping tests of (a) leaky aquifer and (b) unconfined aquifer

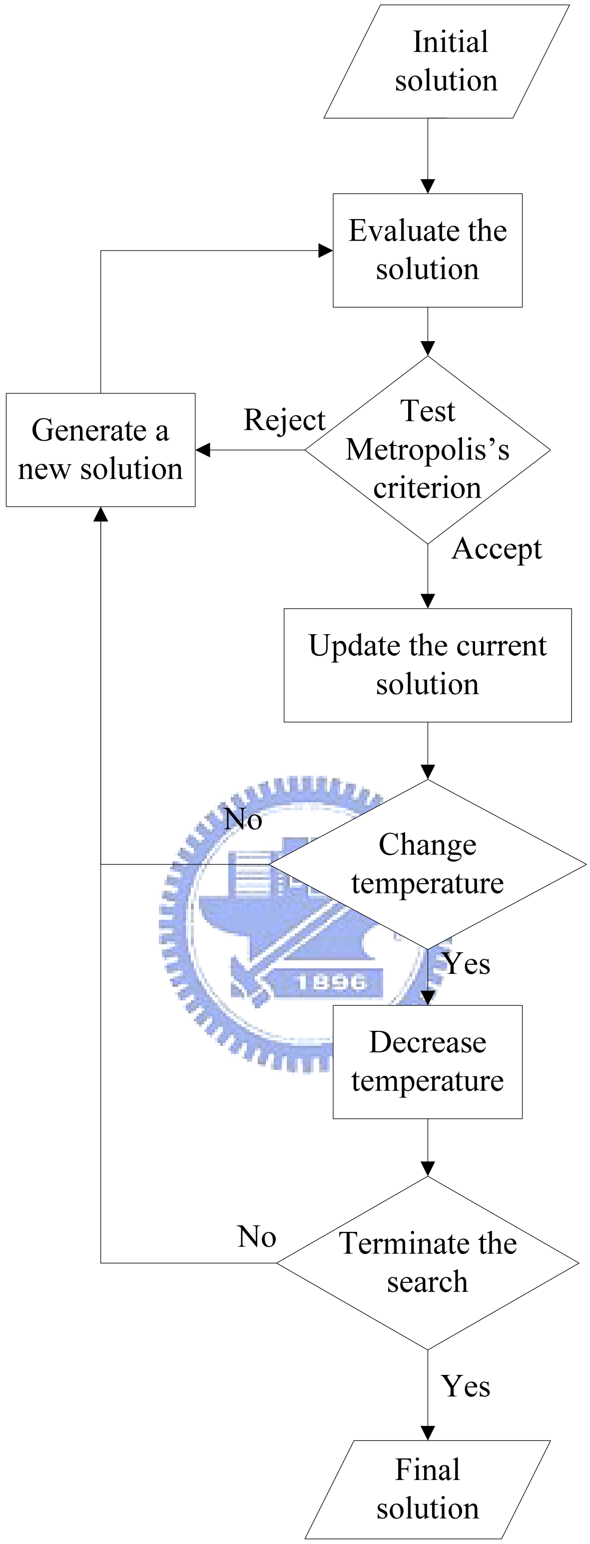


Figure 2 Flowchart of the SA

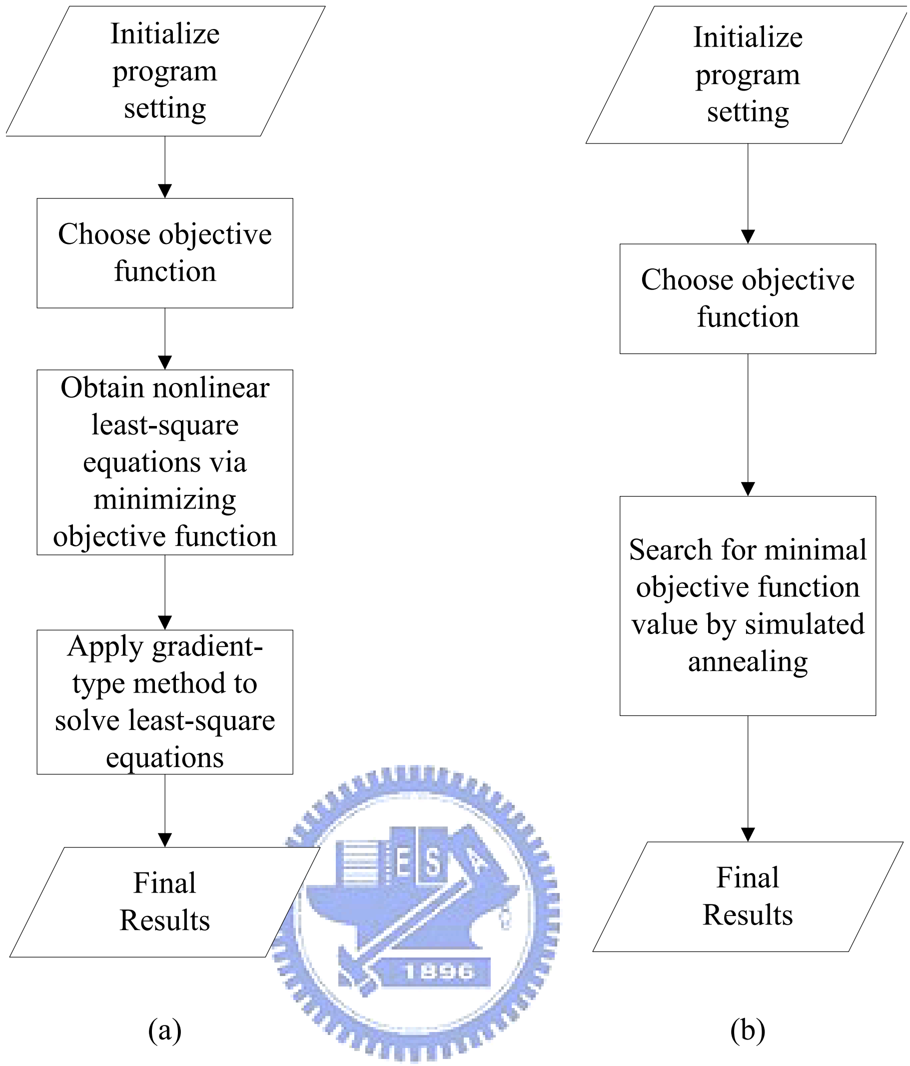


Figure 3 The flowchart of the identification procedure (a) conventional method, (b) present method

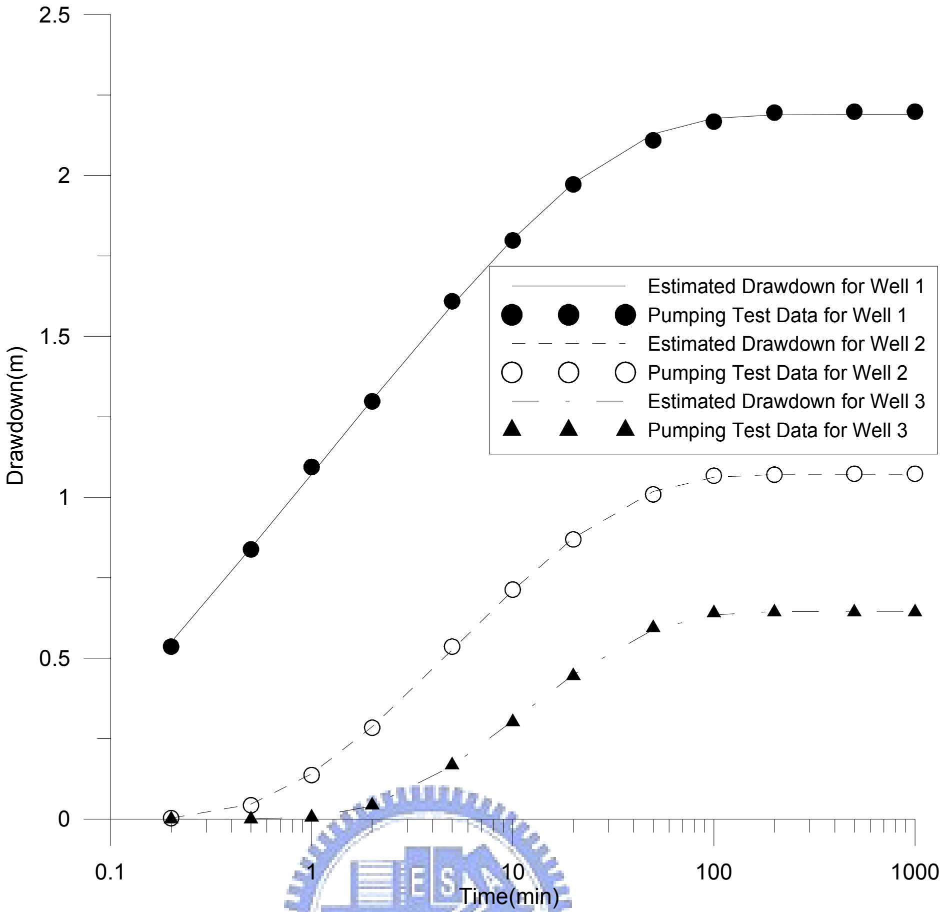


Figure 4 The estimated drawdowns and the pumping test data for the observation wells in the leaky aquifer without considering storage effect

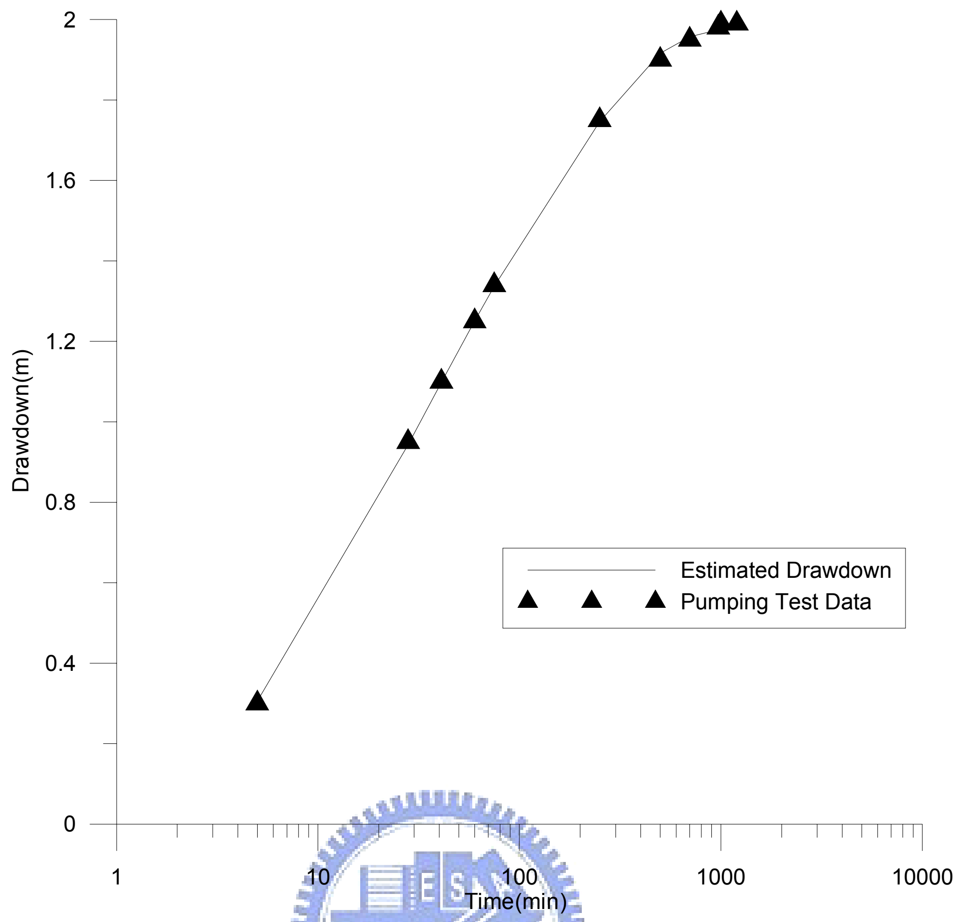


Figure 5 The estimated drawdowns and the pumping test data for the observation wells in the leaky aquifer with considering storage effect

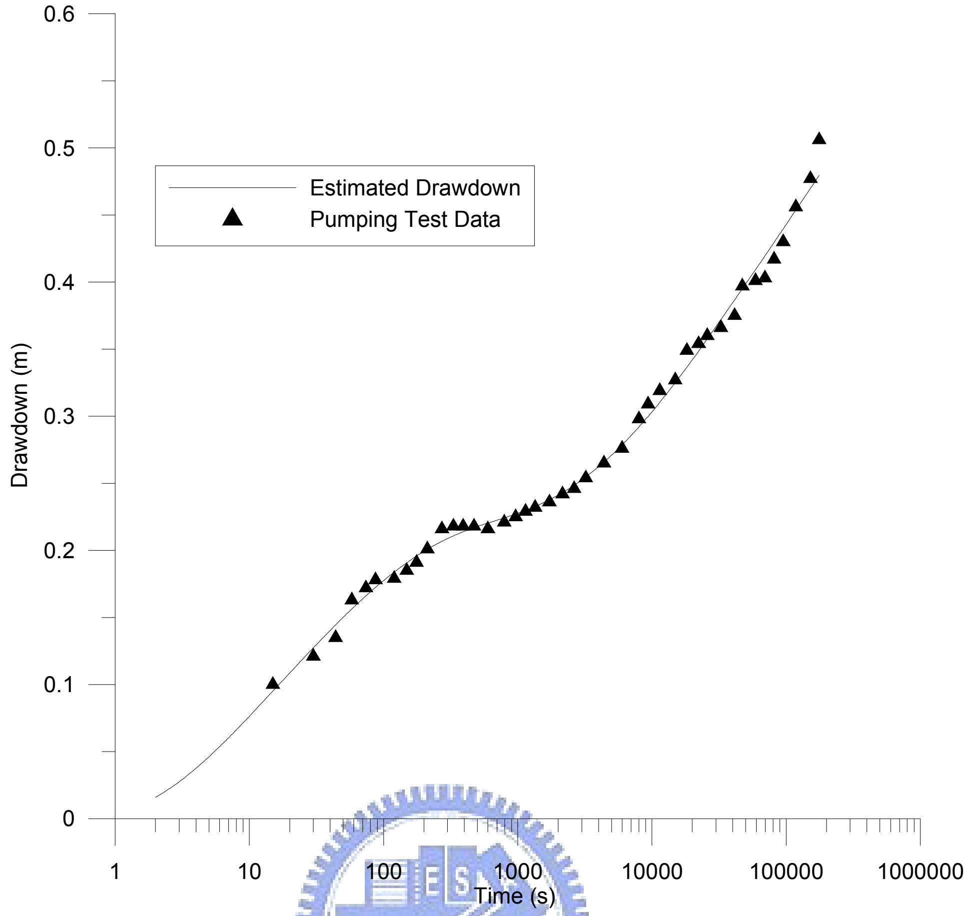


Figure 6 The estimated drawdown and the pumping test data obtained from an unconfined aquifer using SA

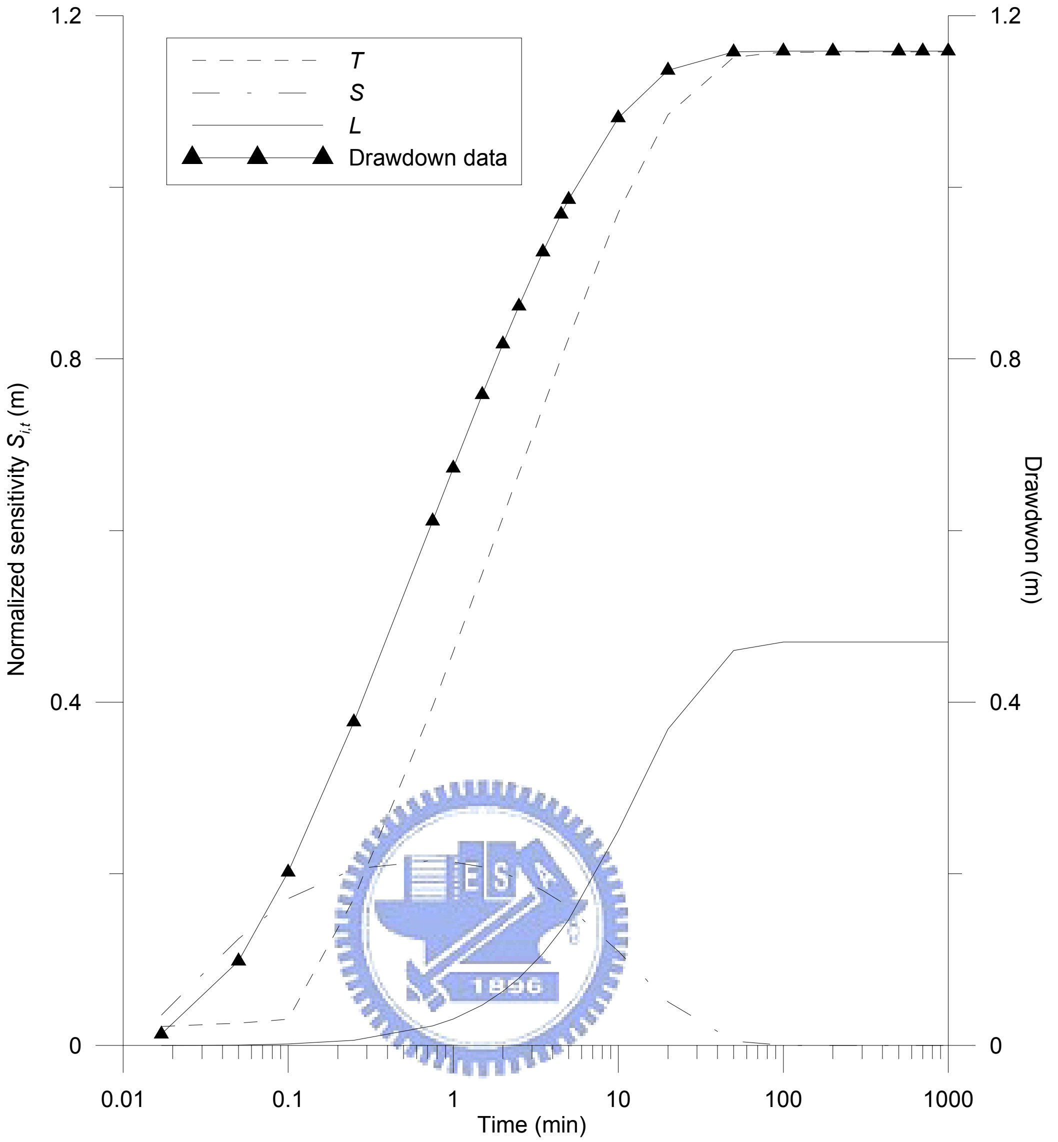


Figure 7 The time-drawdown data and the normalized sensitivities of the leaky aquifer parameters

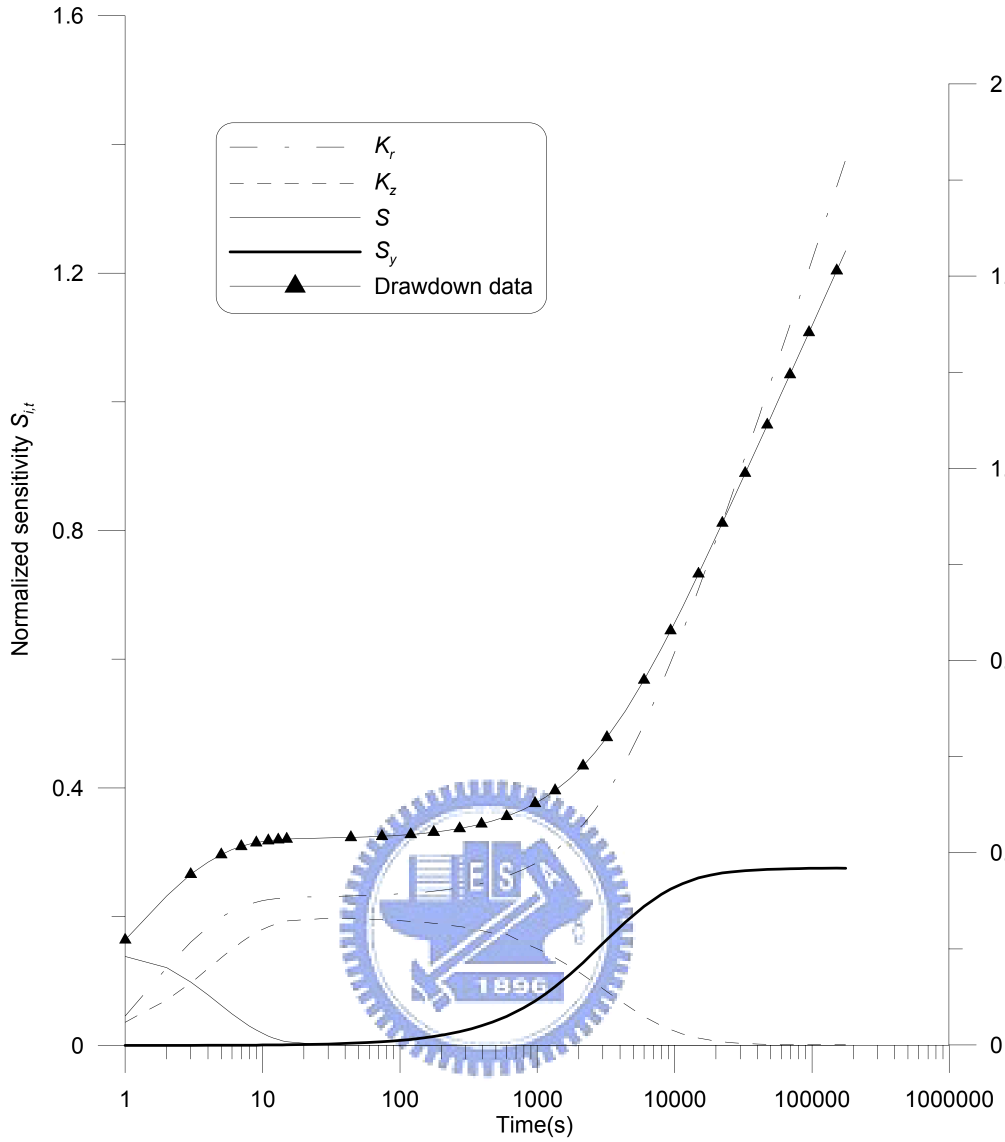


Figure 8 The time-drawdown data and the normalized sensitivities of the unconfined aquifer parameters (Neuman's model)

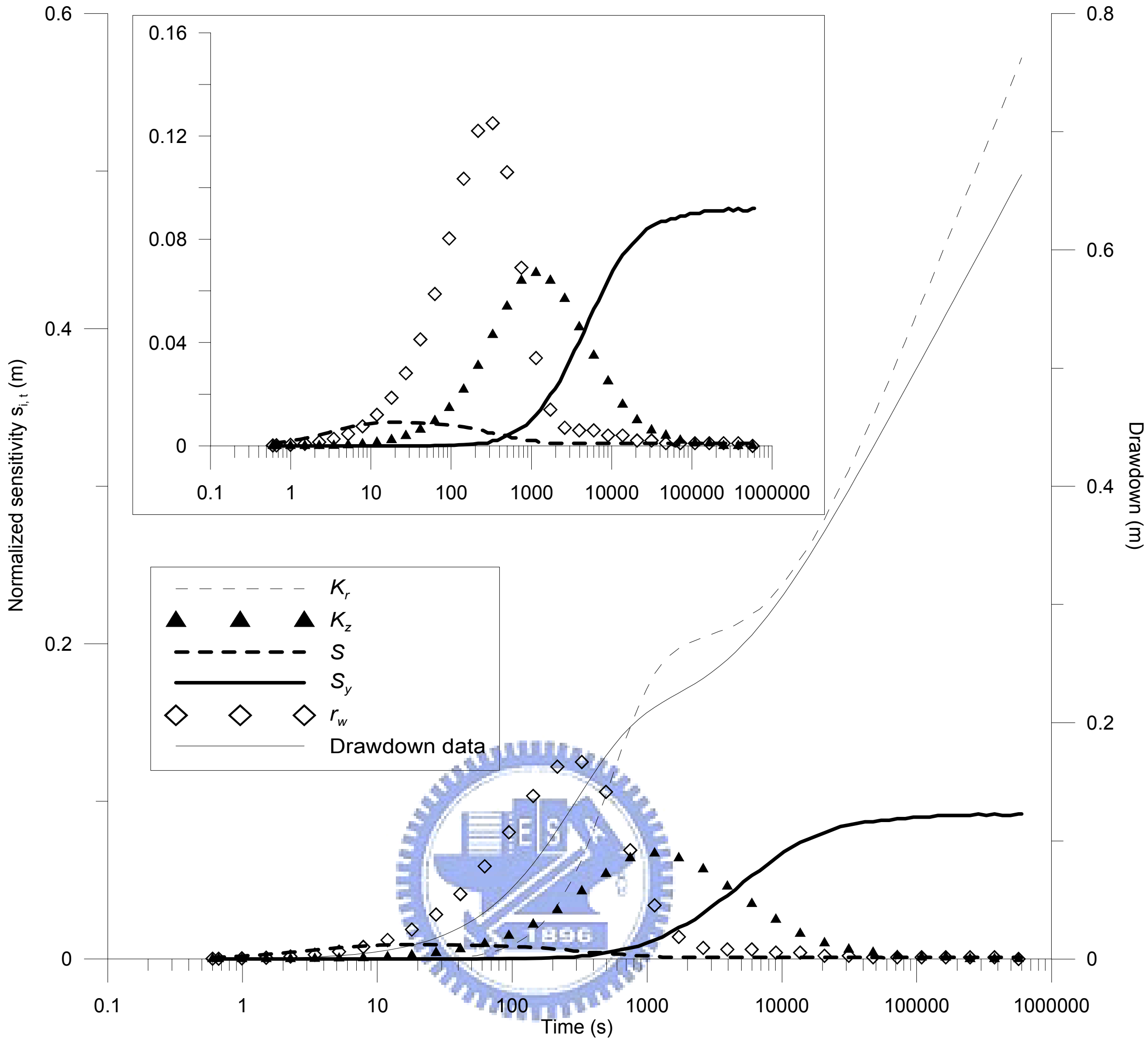


Figure 9 The normalized sensitivities of the unconfined aquifer parameters (Moench's model)

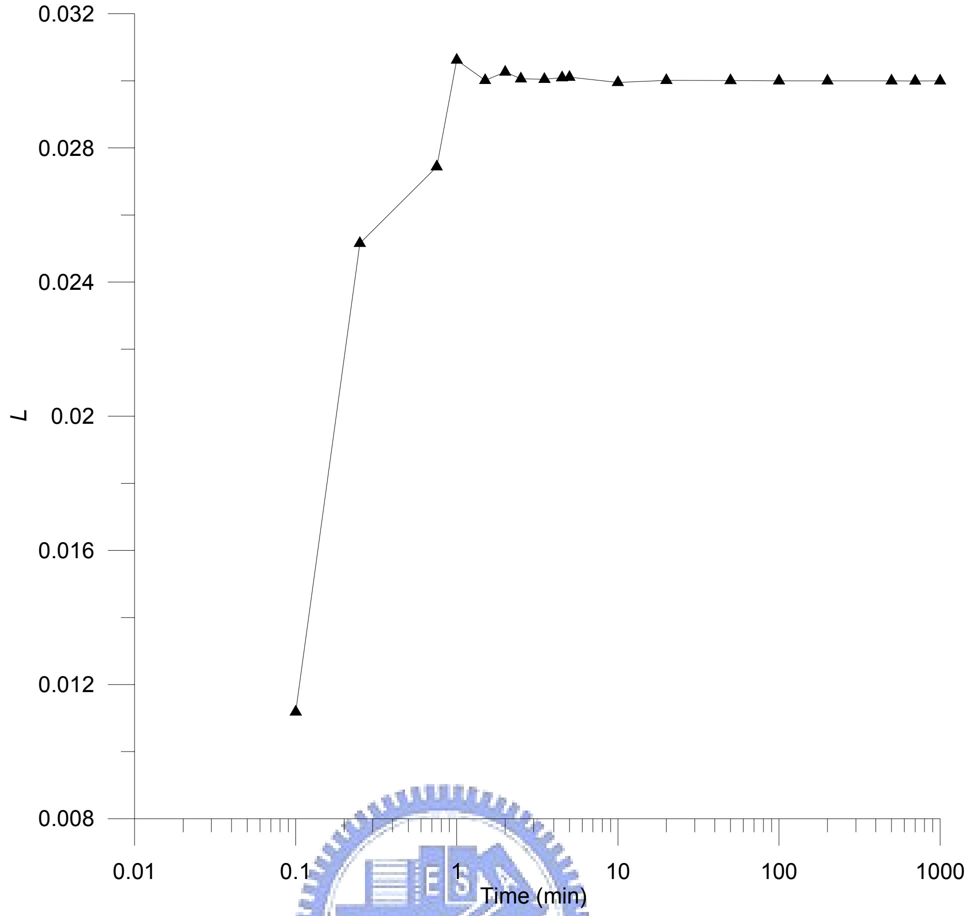


Figure 10 The estimated L versus time in the leaky aquifer case

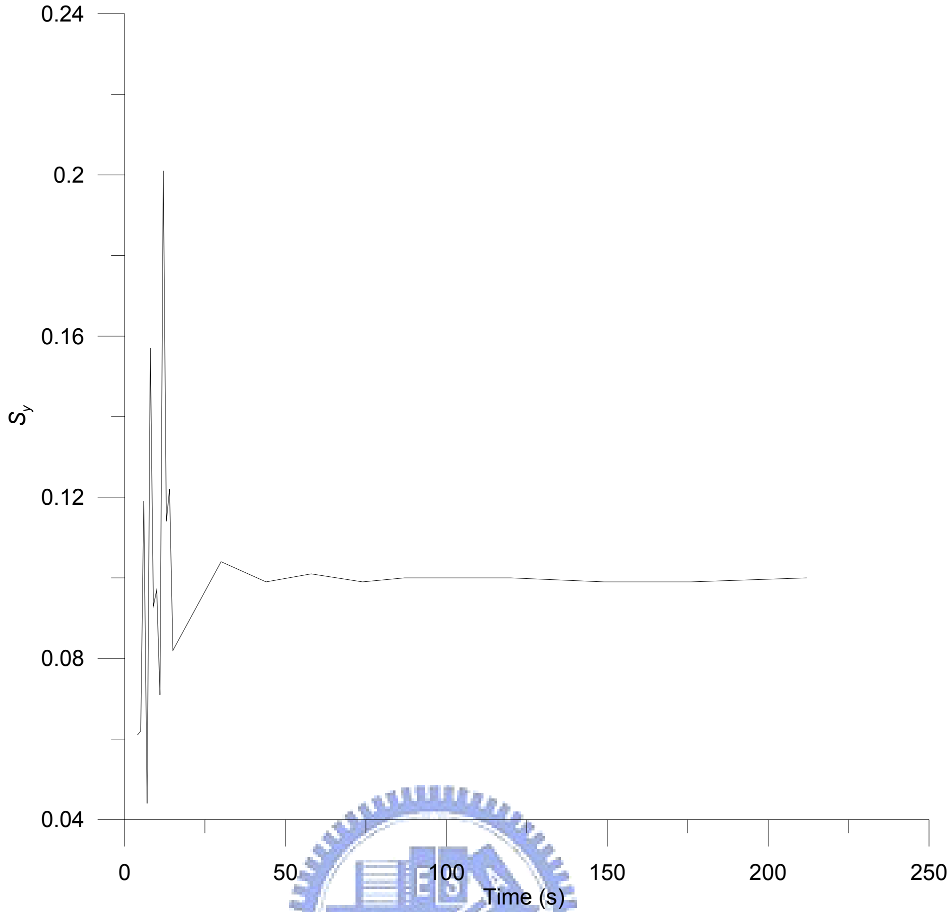


Figure 11 The estimated S_y versus time using the synthetic data set 1

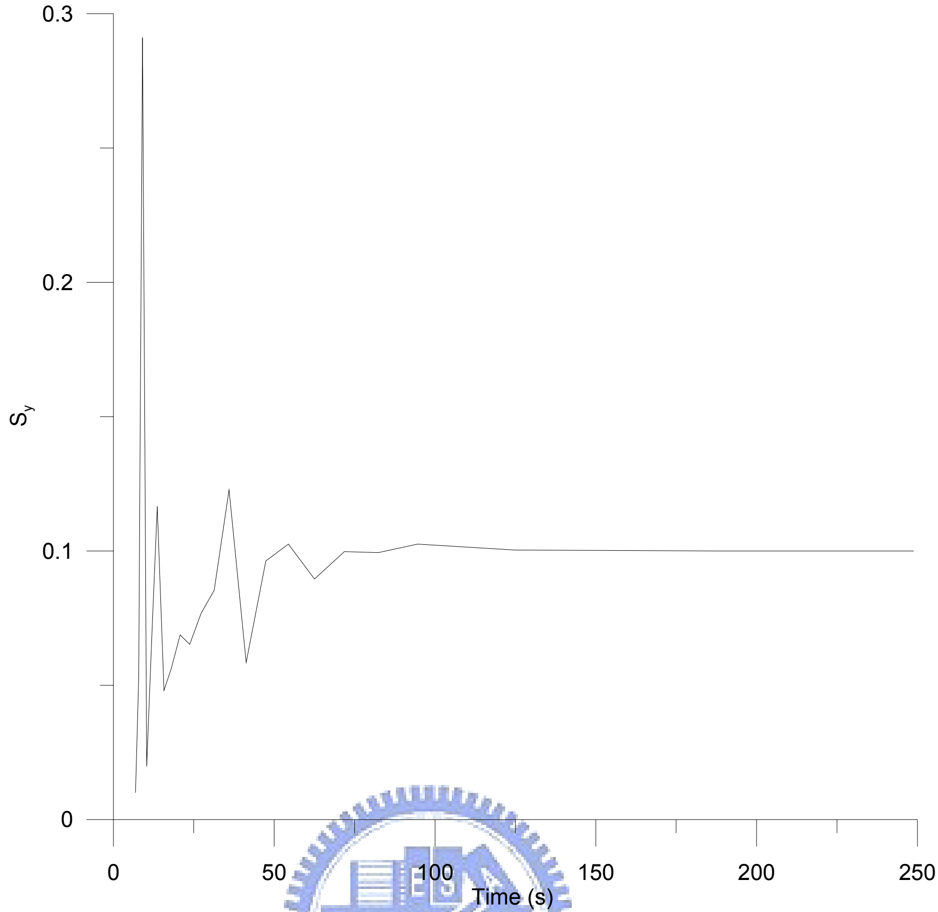


Figure 12 The estimated S_y versus time using the synthetic data set 2

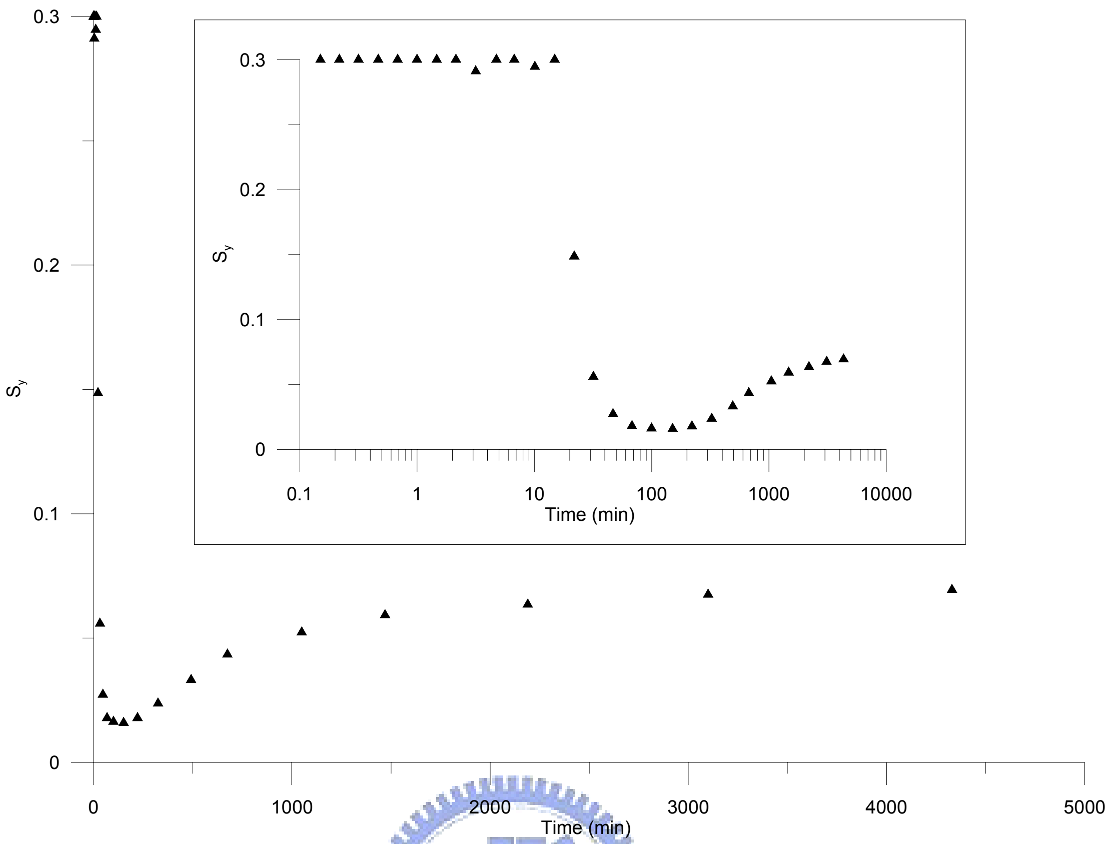


Figure 13 The estimated S_y versus time in the field unconfined aquifer

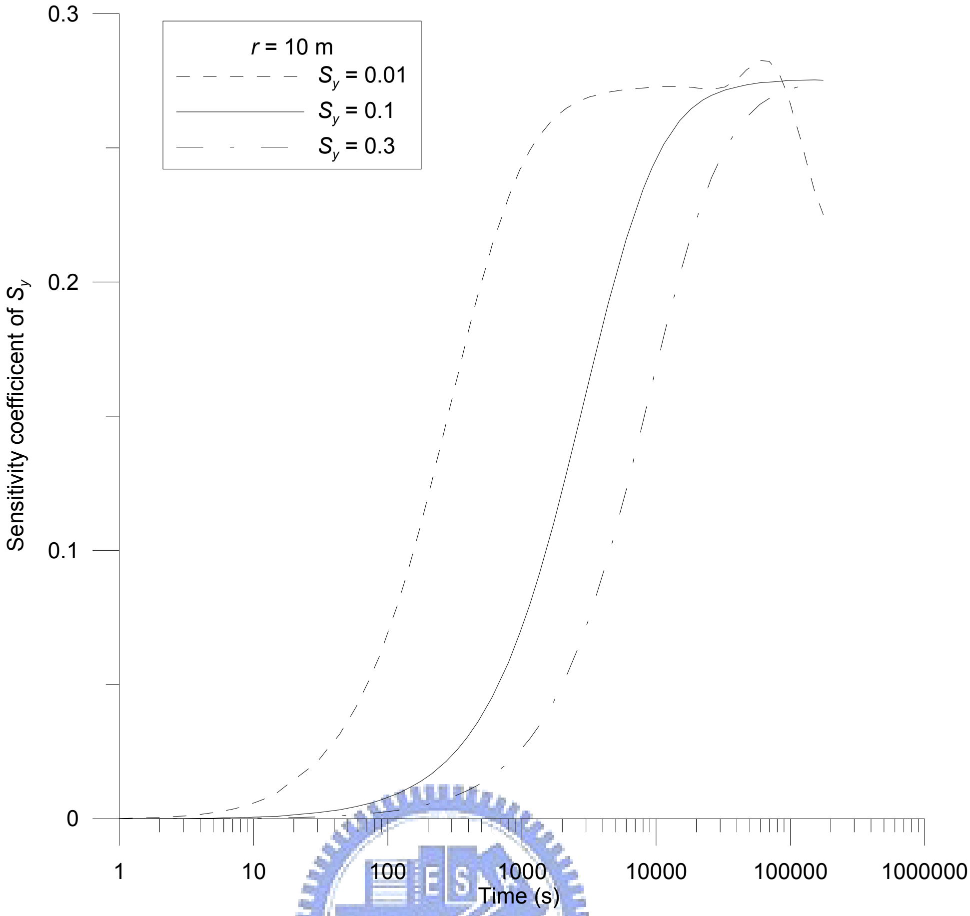


Figure 14 The normalized sensitivity of S_y for S_y = 0.01, 0.1, or 0.3 and r = 10 m

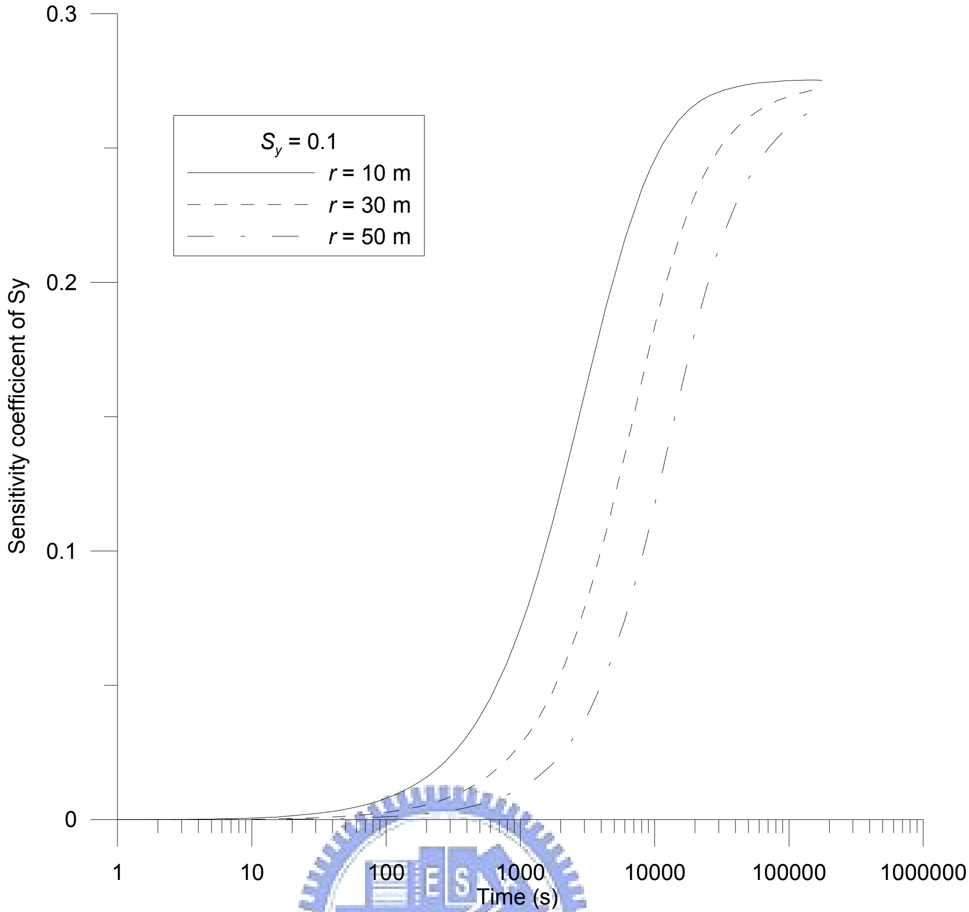


Figure 15 The normalized sensitivity of S_y for S_y = 0.1 and r = 10, 30, or 50 m

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PUBLICATION LIST

(A) Journal Papers

1. Yeh, HD, Huang, YC, 2005, Parameter estimation for leaky aquifers using the extended Kalman filter, and considering model and data measurement uncertainties, Journal of Hydrology, 302(1-4), 28-45.

2. Yeh, HD, Huang, YC, 2005, Comment on “Application of BEM with extended Kalman filter to parameter identification of an elastic plate under dynamic loading” by Tanaka, M., T. Matsumoto, and H. Yamamura. Engineering Analysis with Boundary Elements, 29(1) 93-94.

3. Yeh, HD, Lin, YC, Huang, YC, 2007, Parameter Identification for Leaky Aquifers Using Heuristic Approaches, Hydrological processes, 21, 862-872, doi:10.1002/hyp.6274.

4. Huang, YC, Yeh, HD, 2007, The Use of Sensitivity Analysis in On-line Aquifer Parameter Estimation, Journal of Hydrology, 335 (3-4), 406 – 418 doi:10.1016/j.jhydrol.2006.12.007.

5. Huang, YC, Yeh, HD, 2007, Review of the pipeline leak detection methods in the water distribution systems, Journal of Chinese Institute of Civil and Hydraulic Engineering, 34(2), 82-90. (In Chinese).

6. Huang, YC, Yeh, HD, Lin, YC, 2007, A Computer Method Based on Simulated Annealing to Identify Aquifer Parameters Using Pumping Test Data, International Journal for numerical and analytical methods in Geomechanics, 2007. (In press).

7. Chang, YC, Yeh, HD, Huang, YC, 2007, Parameter identification in multi-layer aquifer systems using Simulated Annealing, Hydrogeology Journal. (accepted).

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9. Huang, YC, Yeh, HD, Determination of the Specific Yield in unconfined aquifers: Composite Analysis or not? (In preparation).

10. Wang, CT, Huang, YC, Yeh, HD, The analysis of groundwater sampling data using multivariate analysis. (In preparation)

(B) Conference papers

1. 黃彥禎、葉弘德，91 年 9 月，擴展式卡門濾波應用於滲漏含水層參數之檢定，第一屆海峽兩岸土壤與地下水污染整治研討會，台灣土壤及地下水環境保護協會，台北，論文集 C91-C98。

2. 林郁仲、葉弘德、黃彥禎，92 年 6 月，應用模擬退火演算法於滲漏水層參數之檢定，九十二年電子計算機於土木水利工程應用論文研討會，國立台灣科技大學，台北市，，摘要集 72 頁、論文集(光碟版)數位水利 16。

3. 黃彥禎、葉弘德、林郁仲，92 年 6 月，應用模擬退火演算法於拘限及自由水層參數之檢定，九十二年電子計算機於土木水利工程應用論文研討會，國立台灣科技大學，台北市，，摘要集 74 頁、論文集(光碟版)數位水利 18。

4. 黃彥禎、葉弘德、徐年盛、林郁仲，92 年 11 月，禁忌演算法於拘限及自由水層參數之檢定，環工學會第十五屆年會及第一屆土壤與地下水技術研討會，國立中興大學，台中，論文集 2-10，論文集(光碟版)B-03。

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7. 張君豪、葉弘德、黃彥禎、林郁仲，93 年 7 月，以模擬退火演算法方法推求定流量試驗受壓含水層之雙層參數，第十四屆水利工程研討會，國立交通大學，新竹市，論文集(下冊)F30-F36 頁。

8. 黃彥禎、葉弘德、林郁仲，93 年 7 月，滲漏含水層參數即時檢定模式之比較，第十四屆水利工程研討會，國立交通大學，新竹市，論文集(下冊)F186-F192 頁。

9. 林郁仲、葉弘德、黃彥禎，滲漏含水層多口觀測井參數檢定，第十四屆水利工程研

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10. Huang, YC, Yeh, HD, 2004, Uncertainty and Sensitivity Analyses in Identifying Leaky Aquifer Parameters using Extended Kalman Filter, Western Pacific Geophysics Meeting, AGU, Hawaii, WP60.

11. 黃彥禎、葉弘德，93 年 10 月，含水層參數即時檢定的敏感度分析，九十三年度農業工程研討會，中國農業工程學會，桃園，論文摘要集 258 頁，論文集光碟版 1637-1644 頁。

12. Yeh, HD, Chang, YC, Huang, YC, 2005, Identifying horizontal multi-zone unconfined aquifer parameters using simulated annealing, AOGS 2nd annual meeting, Singapore, 58-HS-A0504.

13. 黃彥禎、葉弘德，94 年 10 月，探討以單口或多口觀測井洩降數據推求自由水層比出水量參數的差異，九十四年度農業工程研討會，中國農業工程學會，苗栗，論文摘要集 104 頁。

14. 黃彥禎、王智澤、葉弘德、洪慧念、莊士群、邱志昇，94 年 11 月，應用主成分分析探討地下水污染檢測數據，第三屆土壤與地下水研討會，環境工程學會，桃園，論文摘要集 453 頁。

(C) Others

1. Huang, YC, 2002, Application of extended Kalman filter for identifying leaky aquifer parameters, Master thesis, Institute of Environmental Engineering, National Chiao-tung University, Hsinchu, Taiwan.