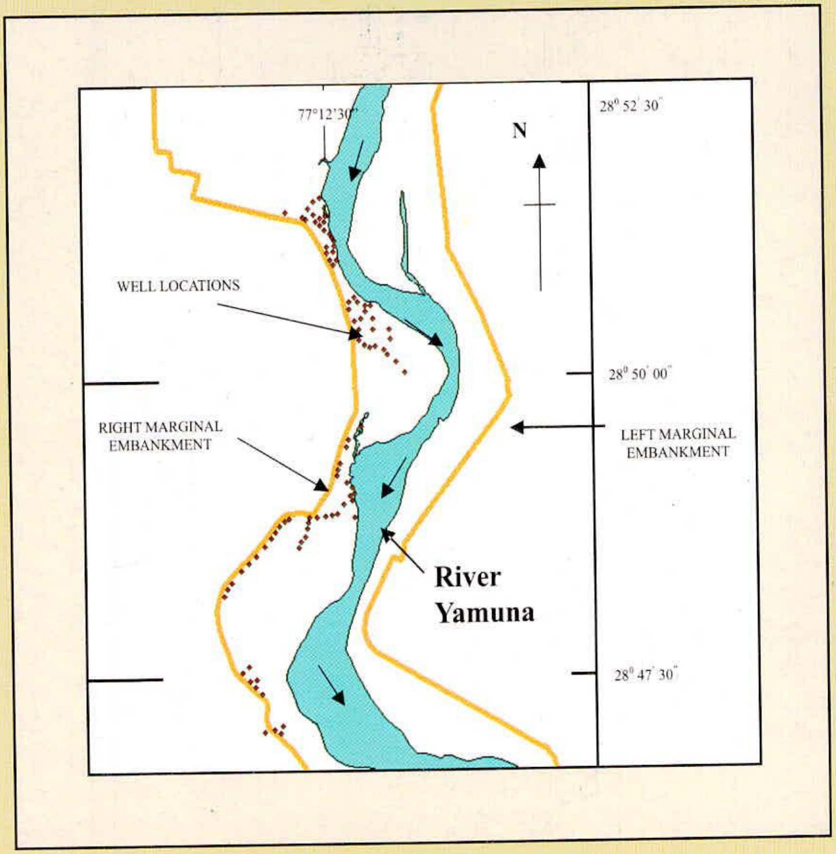
Project Report

AN OPERATIONAL MODEL FOR GROUNDWATER PUMPING AT PALLA WELL FIELDS, NCT DELHI



A Joint Study

By

NATIONAL INSTITUTE OF HYDROLOGY
ROORKEE

AND

CENTRAL GROUNDWATER BOARD
NEW DELHI

2005-06

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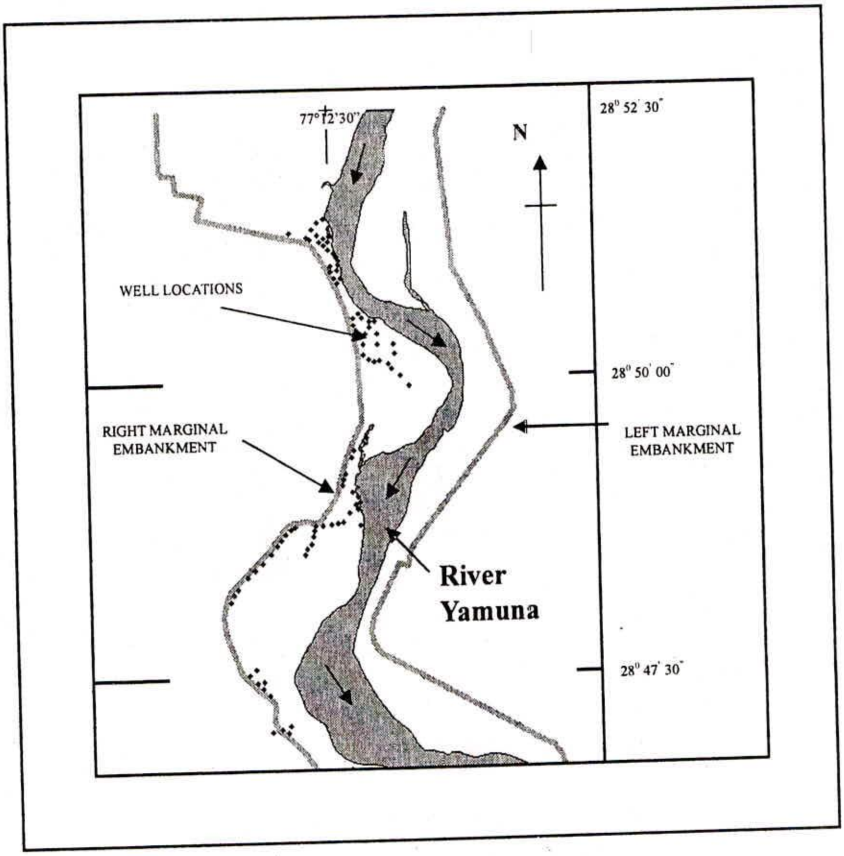

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PREFACE

In this study Operational Management Models are developed for implementation at Palla Well fields in the floodplain of River Yamuna, north west of NCT Delhi. The floodplain is largely recharged by the floodwaters during the monsoon season. The freshwater in the stream-aquifer system is underlain with deposits of geologically occurring saline water. Initially a simplified representation of the system is solved to obtain an insight into the problem. The real system is subsequently solved for the series of existing wells to augment drinking water needs of the city of Delhi. The study seeks to determine an optimum pumping schedule while controlling salinity due to upconing phenomena to desired levels.

The nonlinear, non-convex problem involving discrete (pumping locations) and continuous (pumpages) decision variables is solved within a simulation-optimization (S/O) framework. S/O approach provides an accurate representation of the aquifer responses but involve high computational burden. Therefore in the present study artificial neural network (ANN) is used as a virtual simulator of the variable density driven numerical flow model for aquifer simulation.

Scientists of NIH Roorkee and CGWB New Delhi jointly carried out the study. Dr S V N Rao, Scientist F and Dr Sudhir Kumar, Scientist E1 of NIH and Sh S K Sinha, Scientist C and Sh Shashank Shekhar, Scientist B of CGWB carried out the study.

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ACKNOWLEDGEMENT

The authors acknowledge the dynamic leadership of Dr K D Sharma, Director, National Institute of Hydrology Roorkee and Dr Saleem Romani, Chairman, Central Groundwater Board, New Delhi for conceiving the problem, providing financial, manpower, logistic and data support for undertaking this study. The cooperation of Dr Bhishm Kumar, Scientist F and Head of Hydrological Investigation Division and Dr Sanjay Jain, Water Resources Division, National Institute of Hydrology, is gratefully acknowledged.

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EXECUTIVE SUMMARY

Groundwater pumping along riverbank floodplains is commonly practiced in many countries. The problem of pumping groundwater from a stream-aquifer system becomes complex, when it is underlain with geologically occurring saline water. The amount of pumping in this case is mostly guided from water quality considerations rather than water quantity. This is because any excess pumping, results in upconing of saline water leading to deterioration of water quality especially for drinking water needs. Therefore optimal pumping must ensure both quality and quantity. This is accomplished through regulated pumping from production wells that control quantity and quality, namely skimming wells.

The nonlinear, non-convex problem involving discrete (pumping locations) and continuous decision variables (pumpages) is solved within a simulation-optimization (S/O) framework. S/O approach provides an accurate representation of the aquifer responses but involve high computational burden. Therefore in the present study artificial neural network (ANN) is used as a virtual simulator of a variable density driven numerical flow model for aquifer simulation. Simulated annealing (SA), a non-gradient based algorithm is used as an optimiser in this study.

In this study operational management models are developed and implemented for synthetic and real life aquifer systems. Synthetic examples representative of study area are initially analyzed to obtain insight into the problem. The real system involves pumping from a series of about 90 existing wells to meet drinking water needs, along the floodplain of river Yamuna, at Palla village northwest of Delhi. The river reach is significantly recharged by floodwaters, during the monsoon season. The freshwater in the aquifer system is underlain with deposits of geologically occurring saline water. The study seeks to determine optimal pumping schedules while controlling salinity due to upconing to desired levels.

In general the model results suggest that the existing group of wells must be operated such that they are staggered in space and time. This is to avoid interference in upconing process between neighboring wells. This interference enhances the advective velocities of solute (salt water) towards the grid cells, containing the well screens, leading to increased concentration or salinity. Therefore care must be taken while deciding the location of future wells in the study area or similar study areas.

The existing well spacing in the northern part of the study area is very close. Further since the locations and installed pumping capacities are already fixed for the study area, the model formulation is designed to optimize the duration of pumping (on a daily basis) and/ or their switching (on/ off) while constraining the salinity of water to desired levels. Two operational models are presented in this study. The first model seeks to determine maximum pumping from a group of 80 wells while restraining salinity levels that meet drinking water standards. The model predicts that about 25 – 30 MGD of water can be drawn safely during a normal water year during monsoon and non-monsoon seasons. A tradeoff curve prioritizes the amount of groundwater pumping from the group of wells. The second model seeks to minimize total salinity at grid cell locations for partial development of groundwater from a subset of wells. The second model is intended to supplement other supply sources when full potential need not be tapped.

The mass balance with and without optimal pumpages from Palla well field helps in understanding the aquifer flow dynamics. Palla well fields help in utilizing the induced flood recharge, which would otherwise join river boundary.

1.0 INTRODUCTION

Large-scale pumping to meet increasing demand for water from flood plains and bank storage near the river is commonly practiced all over the world. Under typical climate conditions in India the high runoff in Himalayan Rivers is mostly confined to a few months (3 months) during the monsoon season. The floods during this period recharge the adjacent riverbanks and flood plains in the vicinity of the river. Even though the floods are of short duration, they result in significant recharge in alluvial sandy floodplains. The relatively low flows during the non-monsoon season are mostly from snowmelt and base flow from bank storage along the river reach. Pumping from production wells along the banks from this naturally replenishing groundwater reservoir helps in meeting the demand especially during the non-monsoon season on a sustainable basis.

The problem of pumping groundwater from this stream-aquifer system becomes complex, when it is underlain with geologically occurring saline water. The amount of pumping in this case is mostly guided from water quality considerations rather than water quantity. This is because any excess pumping, results in up coning of saline water leading to deterioration of water quality especially for drinking water needs. Therefore optimal pumping must ensure both quality and quantity. This is accomplished through regulated pumping from production wells that control quantity and quality, namely skimming wells. Skimming wells also find wide application in coastal and deltaic regions prone to seawater intrusion.

In this study operational management models are developed and implemented on synthetic and real life aquifer systems. Synthetic examples representative of study area are initially analyzed to obtain insight in to the problem. The real system involves pumping from a series of about 90 existing wells to meet drinking water needs, along the floodplain of river Yamuna northwest of Delhi (India). The river reach is recharged by floodwaters besides rainfall-recharge from adjacent areas during the monsoon season. The freshwater in the aquifer system is underlain with deposits of geologically occurring saline water. The present study seeks to determine an optimum pumping schedule while controlling salinity due to upconing to desired levels.

The phenomenon of upconing is demonstrated using a simplified aquifer system (see figure 1.1) representative of the study area with a production well, a

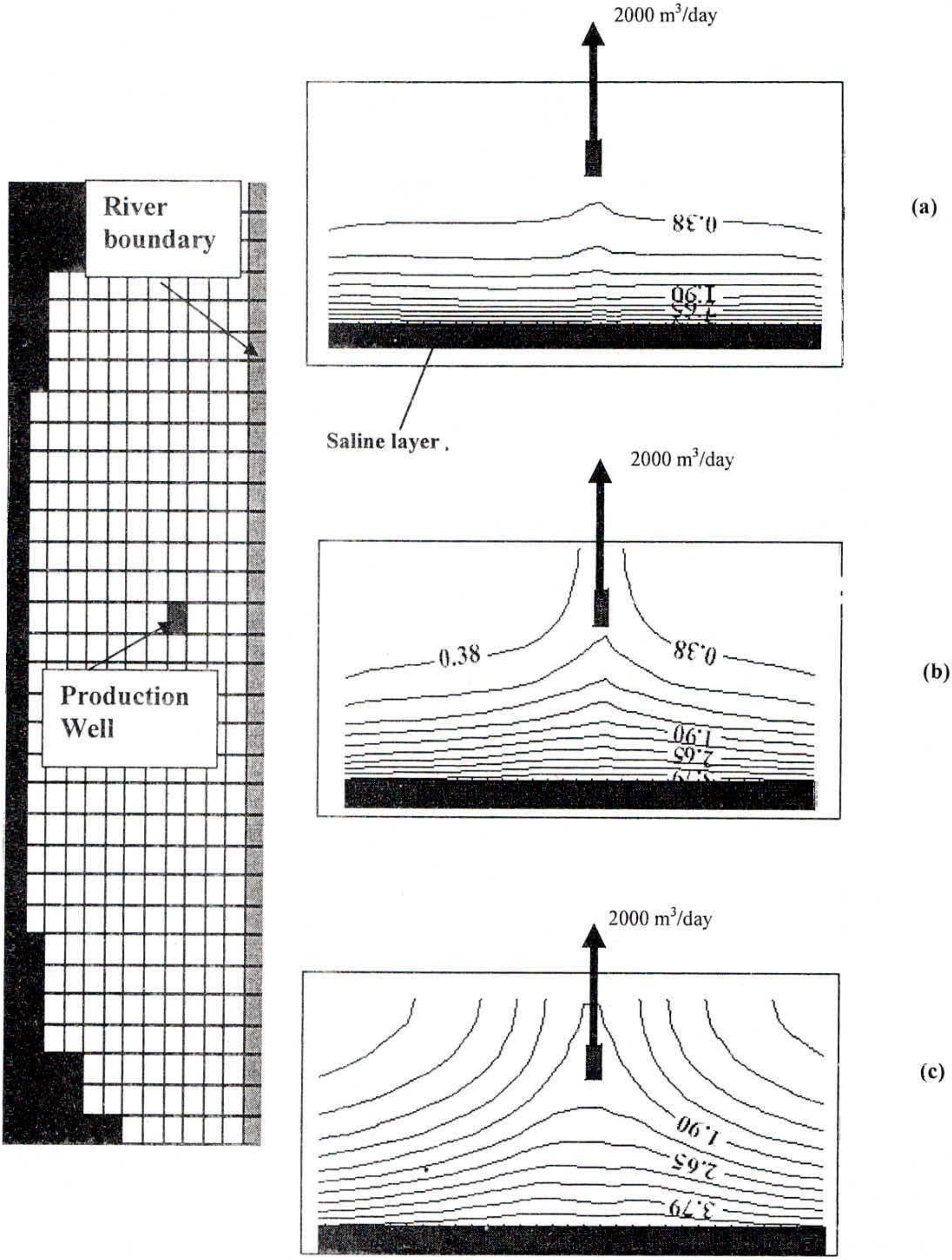

Fig. 1.1 Phenomena of upconing (isochlors) due to pumping from a hypothetical aquifer system at the end of (a) 50-days (b) 250-days and (c) 2000-days

river boundary and a saline bottom layer with a constant concentration of 5 kg/m^3. The aquifer system is simulated using a variable density flow model SEAWAT-2000 (Langevin et al 2004) beginning from steady state conditions. Upconing due to continuous pumping of 2000 m3/day at the end of 50, 250 and 2000 days under average recharge conditions (10% of rainfall) is shown in fig 1.1. The figure clearly indicates that the pumping rate is unsustainable in terms of quality of water over the planning horizon. Using optimisation techniques it is very easy to find out the optimal rate of pumping that meets the desired levels of salinity. Location or adjacent spacing among wells also influences the upconing process. This is demonstrated by comparing upconing responses with same rate of pumping (2000 m^3/day) for the two production wells that are: (i) closely spaced and (b) widely separated wells. The two cases are shown in fig.1.2. The velocity vectors and the isochlors for the closely spaced wells are relatively much higher due to the interference in process of upconing, which enhances the advective velocities of solute (salt transport). Therefore both location and pumping rates happen to be decision variables for skimming wells. However the real-life problems are much more complex in terms of aquifer properties, geometry, boundary conditions, confining conditions, input/ output stresses etc.

In the present study the nonlinear, non-convex problem involving discrete (pumping locations) and continuous decision variables (pumpages) is solved within a simulation-optimization (S/O) framework. S/O approach provides an accurate representation of the aquifer responses but involve high computational burden (Das and Datta, 1999, Zheng and Wang 2002a, Rao et al 2004a). Therefore in the present study artificial neural network (ANN) is used as a virtual simulator of a variable density driven numerical flow model SEAWAT 2000 for aquifer simulation.

This report is a study intended for optimal operation of pumping wells prone to saline water upconing (often referred as skimming wells) for field implementation. The chapter 1 provides introductory background for operating a series of pumping wells in a floodplain underlain with saline water. The chapter 2 discusses model formulation. Chapter 3 deals with solution methodology. In chapter 4, model application is illustrated using a simplified aquifer system to obtain insight and understanding of the problem. Chapter 5 deals with model application to the real system involving a series of existing pumping tube wells at Palla village. The two models developed in chapter 2 are applied to obtain optimum pumping schedules for field implementation. Two pumping schedules are presented towards the end of

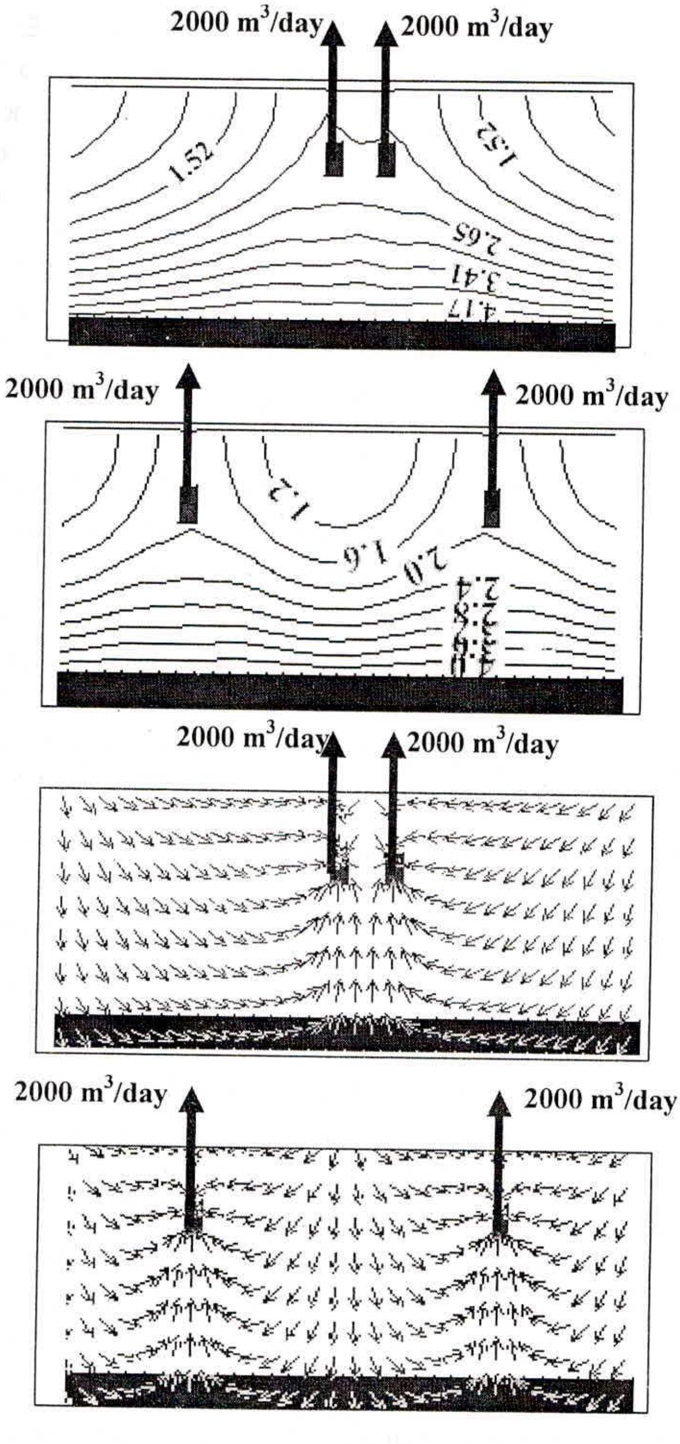

Fig. 1.2 Effect of adjacent spacing of production wells in terms of upconing (isochlors) and velocity vectors

the chapter. The first deals with operation of 80 wells during both monsoon and non-monsoon seasons. The second is intended to supplement demand during peak summer season by operating only part of the wells. The report concludes with suitable recommendations for optimal operation of wells.

2.0 MODEL FORMULATION

The study primarily aims to develop an operational model for field implementation using a combined simulation–optimisation (S/O) approach which seeks to maximize pumpages from a series of existing production wells, while controlling the process of upconing from underlying saline water to desired levels. The model is formulated considering this objective function with respect to the study area as discussed in chapter 5. Since the production wells already exist, their location cannot become decision variable. However, when only part (subset) of the wells operate, location could become discrete decision variable in terms of on or off (i.e. zero or one) from a set of candidate wells. Further since all the wells have pumps installed of fixed capacity the rate of pumping cannot be a decision variable. However since the duration of pumping in a day can be varied (say 12 to 18 hours per day), the rate of pumping could be considered as a continuous decision variable within a range. The optimal rate of pumping so determined by the model could be converted into equivalent fixed capacity via the duration of pumping per day. This however involves an implied assumption that the aquifer simulation in terms of heads and concentrations for the two cases is the same. This assumption is considered to be a reasonable approximation of the reality.

Two types of model formulations are considered in the present study. The first seeks to determine maximum pumping in space and time over a range of pumping subject to a set of constraints assuming all or part of the wells are operated. Here pumping rates are continuous decision variables and hence the formulation is mixed-integer model. The second formulation assumes that only part of the wells are operated and seeks to minimise the total salinity in space and time with fixed pumping rates and discrete pumping locations in terms of *on* or *off* (i.e. zero or one). The second formulation is a pure combinatorial model. The first model seeks to determine the maximum potential that can be developed for drinking water purposes over a planning horizon of one year. The second model is intended to manage target pumping to meet a given demand and therefore must be less than the maximum potential as obtained from the first model.

Mathematically the two models may be formulated in general within S/O framework as follows.

2.1 Model 1 Formulation

Max. $J1 = \sum_{n=1}^{N}\sum_{k=1}^{K}\sum_{j=1}^{J}\sum_{i=1}^{I} Q_{s(i,j,k)}^{n}$

Where, Q_s^n is the pumpage (decision variable) from production wells located at the node i, j, k (also a decision variable) at the end of the n^{th} time period.

2.2 Model 2 Formulation

Min. $J1 = \sum_{n=1}^{N}\sum_{k=1}^{K}\sum_{j=1}^{J}\sum_{i=1}^{I} C_{i,j,k}^{n}$

Where, $C_{i,j,k}^{n}$ is the salinity concentration (state variable) in the production well screen location at the node i, j, k at the end of the n^{th} time period, where the pump is *on*.

Subject to the following constraints:

a) Concentration (c) in production wells should be less than specified value c_s.

$c_{i,j,k}^{n} < c_s$ $\forall$ All production wells at the end of the n^{th} time period

b) Head (h) at nodes should not fall below a specified value h_s

$h_{i,j,k}^{n} < h_s$ $\forall$ All production wells at the end of the n^{th} time period

c) Nonlinear flow and transport equations should be satisfied.

$f(h,c,q)_{i,j,k}^{n} = 0$ $\forall$ All i, j, k and n; h and q represent heads and source/ sink terms

d) Lower and upper bounds for pumpages.

$Q_{min} < Q_{s(i,j,k)}^{n} < Q_{max}$

In the above equations, I, J, K, and N represent the number of rows, columns, layers and time periods relevant to the aquifer system. The decision variables are restricted to discrete values in respect of location and continuous values in respect of pumpages. The pumpages are however fixed in case of model 2. The first constraint relates to groundwater quality, which ensures that salinity is within desired limits. The second constraint relates to quantity of water that is available on a sustainable basis by restraining draw down. The third constraint relates to the physics of flow and is simply mass conservation and is accounted through the simulator. Q_{min} and Q_{max} correspond to lower and upper bounds for the pumpages. The last constraint does not apply to model-2 as they are fixed.

3.0 SOLUTION METHODOLOGY

3.1 Simulation – Optimisation (S/O) Framework

The conceptual management model, developed in this study uses a S/O framework (Rao et al 2004a, 2004b). The S/O framework in the present study has four important features. First, it interfaces the aquifer simulator (numerical model) to account for the complex behavior of groundwater flow in space and time. Second, the optimisation problem is nonlinear, non-convex and involves both continuous and discrete decision variables. Gradient-based optimisation methods do not work well in such situations. Therefore, simulated annealing (SA), a non-gradient based search algorithms is used. In this framework handling nonlinearities in objective function and constraints is not a difficulty as they are external to the optimiser. The third, relates to high computational burden that is inherent to all S/O based approaches. This is largely over come by replacing the simulator with trained artificial neural network (ANN). The fourth relates to algorithmic guidance to further reduce the computational burden

The general structure of S/O framework is shown in figure 3.1. It consists of a driver optimiser and an external simulator. The algorithm calls the simulator to verify the constraints and evaluates the objective function during each iteration. This procedure is repeated until either a near optimal solution or a preset termination criterion is met. The simulator and the optimiser are discussed in the following sections.

3.2 Simulator - SEAWAT 2000 model

It is a variable density-driven flow and transport model. The SEAWAT 2000 model was developed by Guo and Langevin (2002, 2004) by combining the popular MODFLOW 2000 (Harbaugh et al 2000) and MT3D (Zheng and Wang 1998) models. The governing equations for 3-Dimensional density-dependent miscible flow and transport model are written as follows:

Flow Equation

$$-\nabla.(\rho q)+\bar{\rho} q_s = \frac{\partial(\rho\theta)}{\partial t} \qquad \ldots(3.1)$$

In which,

∇ is the gradient operator $\frac{\partial}{\partial x}+\frac{\partial}{\partial y}+\frac{\partial}{\partial z}$

q is the specific discharge vector [LT^{-1}], with its components given by

$$q_x = \frac{k_x}{\mu}\frac{\partial P}{\partial x}; \quad q_y = \frac{k_y}{\mu}\frac{\partial P}{\partial y}; \qquad q_z = \frac{k_z}{\mu}[\frac{\partial P}{\partial z}+\rho g]$$

P is the fluid pore pressure [$ML^{-1}T^{-2}$];

$q_{x,}\ q_{y,}\ q_z$ are the individual components of specific discharge and $k_{x,,}\ k_{y,}\ k_z$ represent intrinsic permeability's [L^2] in the three coordinate directions;

g is the gravitational constant [LT^2];

μ is the dynamic viscosity [$ML^{-1}T^{-1}$];

ρ is the variable fluid density [ML^{-3}];

$\bar{\rho}$ is the density of water entering from a source or leaving through a sink [ML^{-3}];

q_s is the volumetric flow per unit volume of aquifer representing sources/ sinks [T^{-1}];

θ is porosity [dimensionless];

t is the time [T];

Transport Equation

$$\nabla . D(\nabla c) - \nabla (vc) + q_s = \frac{\partial c}{\partial t} \qquad \ldots(3.2)$$

In which,

c is the solute concentration [ML^{-3}]

D is the dispersion coefficient [L^2T^{-1}] and

v represents the seepage velocity [LT^{-1}]

The empirical equation for density, as a function of concentration (Baxter and Wallace 1916) may be written as,

$$\rho = \rho_f + Ec$$

In which, E is a dimensionless constant having an approximate value of 0.7143 for salt concentrations ranging from zero for freshwater to 35 kg/ m^3 for saline water and ρ_f is the fluid density of freshwater.

Both MODFLOW and MT3D use the implicit finite difference approach to solve the flow and transport equations, respectively. The SEAWAT does not solve the flow equation (3.1) directly. Appropriate modifications are incorporated to account for density variations between saline water and freshwater in MODFLOW. The pressure head is converted to equivalent freshwater head for the variable density water in space and time. This approach enables MODFLOW (constant density) to be used with minor changes. During any computational time step, the flow field is first solved by the MODFLOW and this is followed by the solution for concentration variations using MT3D. The updated density field is then determined from the new concentrations and is incorporated back into MODFLOW as relative density difference terms. The flow and transport equations are solved repeatedly through implicit coupling for the same time step until the difference in fluid density between consecutive iterations is less than a user specified tolerance (Figure 3.2)

3.3 Artificial Neural Network as the Simulator

The simulator involves the numerical solution of a system of nonlinear partial differential equations to determine the state variables. The iterative solution process

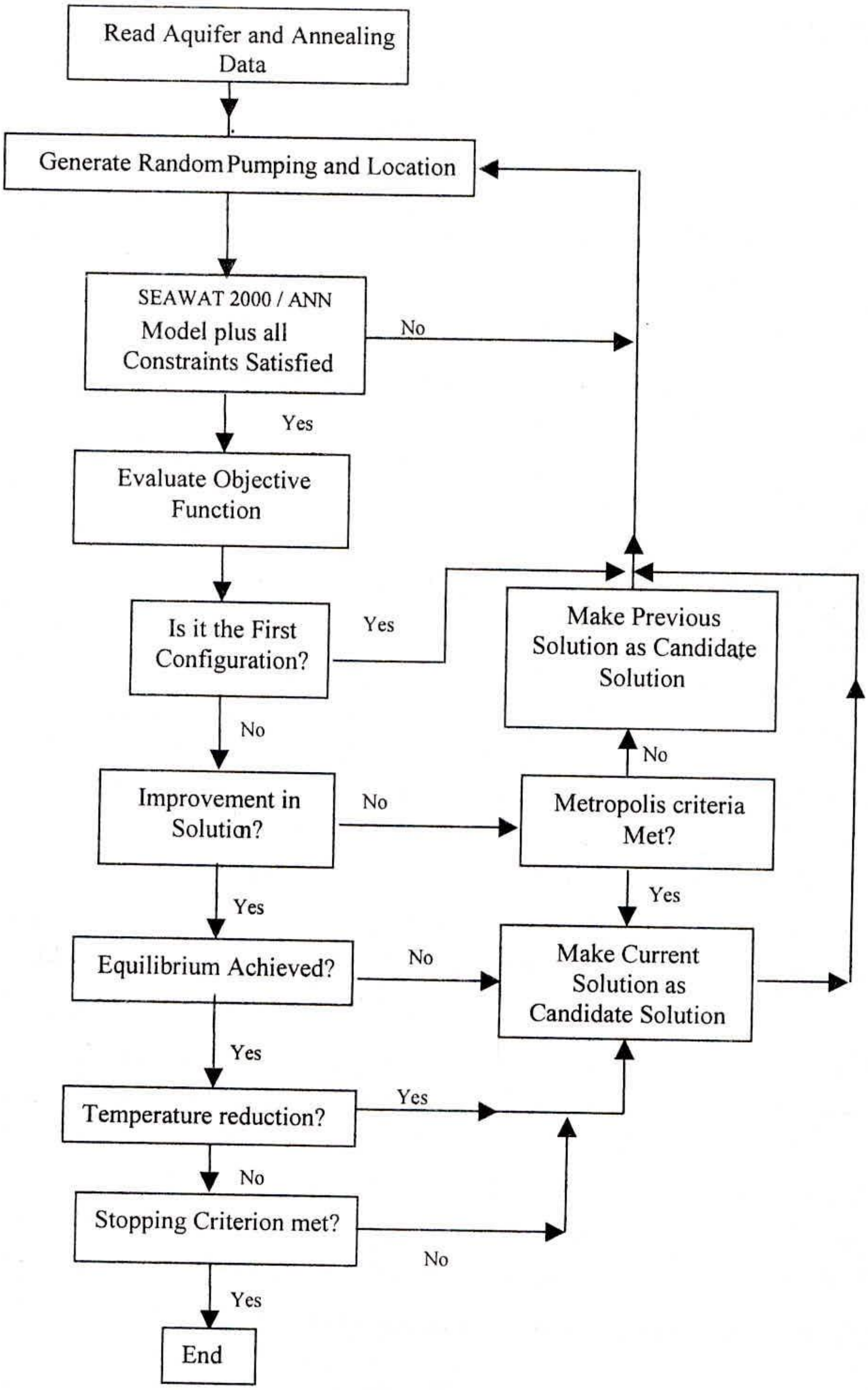

Fig 3.1 Scheme of Solution procedure using SA Algorithm

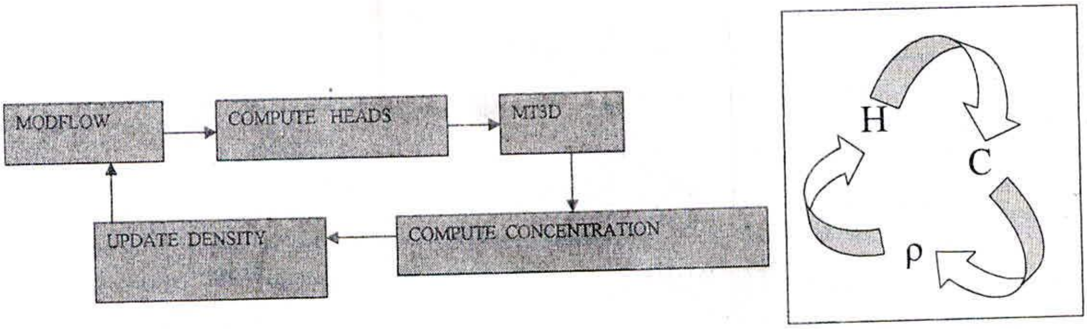

Fig. 3.2 Solution procedure of SEAWAT 2000 model

as discussed earlier involves high computational burden. Further the optimisation process involves calling the simulator several thousands of times to verify the constraints. This involves a significant amount of computational time, especially when heuristic optimizers such as SA are adopted (as discussed in a later section). Therefore, there is a need to reduce this computational time. This is largely achieved in this study by replacing the simulator with trained neural networks. The network is used to determine the aquifer response only at points of interest in space and not at all points in the region. This is similar to using nonlinear regression equations for replacing the simulator (Alley 1986).

3.4 Structure of ANN

There are no fixed rules for developing ANN, even though a general framework can be followed based on experience. Briefly, neural networks are composed of simple elements or neurons operating in parallel. A neural network is trained to perform a particular function by adjusting the weights and biases between the connecting elements. A neural network is characterized by its architecture representing the pattern of connection between nodes, and its method of determining connection weights and the transfer function. A typical ANN consists of a number of nodes that are organised according to a particular arrangement. In a feed-forward network the nodes are generally arranged in several layers, starting from the first input layer and ending at the final output layer. There may be one or more hidden layers in between (see figure 3.3). The number of nodes and the number of layers are generally determined by a trial and error procedure i.e., through supervised training. A detailed description of multi-layer neural networks is discussed in papers

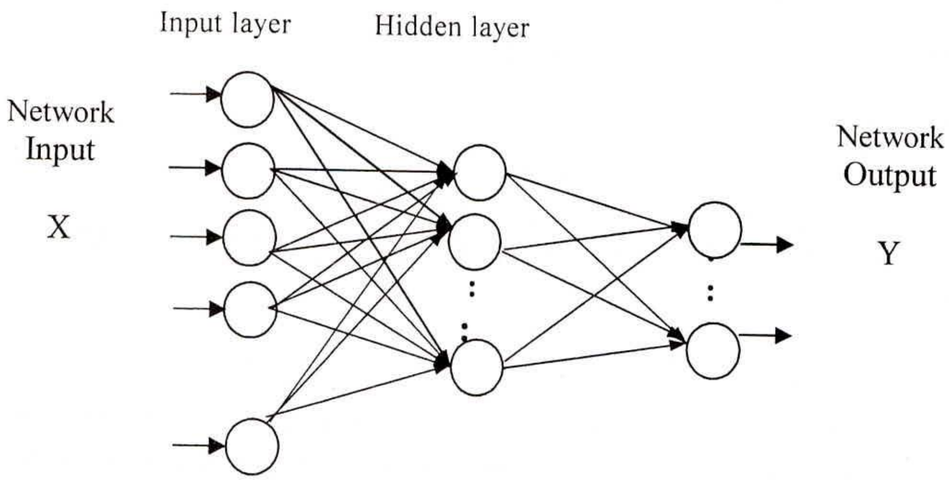

Fig. 3.3 General Configuration of a Feed forward Three-Layer ANN (ASCE, 2000)

by the Hsieh, C (1993), Rogers and Dowla (1994), ASCE (Task Committee of ASCE 2000), and in ANN toolbox (MATLAB 2000).

The goal of ANN in general is to establish a relation of the form:

$$(Y^m) = f(X^n) \qquad \ldots(3.3)$$

in which, Y^m is an m dimensional output or target vector consisting of resulting variables of interest $y_1, y_2, ..y_n$ and X^n is an n dimensional input vector consisting of $x_1, x_2, \ldots x_n$. Each input is associated with a quantity called weight or connection strength. The sum of the inputs and weights form an intermediate scalar, s, given by

$$s = \sum_{n=1}^{N} (w_n x_n) = w^T x \qquad \ldots(3.4)$$

in which, w = $(w_1, w_2, ..., w_N)$ denotes the weight vector of the neuron. The quantity s is passed through a nonlinear transfer function f to yield the output y = f(s) and f is the commonly used sigmoidal transfer function given by,

$$f(s) = 1/(1+\exp(-s)) \qquad \ldots(3.5)$$

This function can map most non-linear processes. Generally, the network is trained using a back propagation algorithm that will adjust the weights and biases so as to minimise the error function E given by,

$$E=\sum_{P}\sum_{p}(y_i-t_i)^2 \qquad \ldots(3.6)$$

in which, y_i is the ANN output, t_i is the desired output, p is the number of output nodes, and P is the number of training patterns or data sets.

3.5 Methodology

The basic idea of the approach used in this study is to design neural network that behaves as a virtual simulator to obtain aquifer responses for given inputs. In the present study, ANN seeks to mimic the numerical model (or predictor of the predictor). This is achieved in three stages as under:

1. Obtaining the data sets for ANN training in the region of interest.
2. ANN training (or supervised learning) using a back propagation algorithm.
3. Network response using optimal weights and biases.

The first step involves generating data sets (or patterns) for ANN training using actual simulators. For this purpose, the numerical simulator is executed repeatedly for random input stresses (within a range) and the aquifer responses (output) in the region of interest are obtained. These input-output data sets are used for ANN training. Two aspects are important, while generating data sets. The first relates to the number of patterns that must be used for training and the second concerns the range of input data variation. In general ANN's are data driven models and therefore, more the number of patterns or realizations, the better is the training or learning process. In the present study, this is not a restriction as any number of training patterns could be generated using the numerical simulator. The range of input variation is also important in ANN learning process. This is because ANN's are known to be good interpolators rather than extrapolators. Therefore, input data should preferably cover the full range of expected inputs.

The second step involves ANN training or in other words input-output mapping. The data sets are first normalized (scaled between zero and one) before being subjected to training. The training is accomplished using a back propagation (BP) algorithm (MATLAB 2000). The BP algorithm in general consists of a forward pass and a backward pass. In the forward pass initially random weights are generated to compute network response for a given input in the data sets. This response is compared with the target value as determined by the actual simulator from the data sets. The difference is the error. The goal of the BP algorithm is to minimise this error. This is achieved by adjusting the weights and biases during the backward pass. The procedure is repeated iteratively until the goal of minimizing the error is achieved to desired level.

On successful completion of training optimal weights and biases are obtained. For any given input (preferably within the range of training), the output response can now be computed by the network using these weights and biases. This process involves only matrix operations. The goodness of fit or the efficiency of the network can be evaluated using statistical measures from calibration and validation data sets.

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3.6 Optimiser - Simulated Annealing Algorithm

In this study simulated annealing (SA) algorithm (Kirkpatrick et al. 1983, Aarts and Korst 1989, Dougherty and Marriott 1991) is used as an optimiser. The SA algorithm uses an *imperfect* analogy between the way solids cool and anneal and the optimisation of a function with many degrees of freedom. The annealing process involves slow cooling of solids from a very high temperature (when its molecules are highly mobile) to a low or minimum energy state (optimal) of crystalline lattice. If the cooling is rapid the system does not reach highly ordered state but ends up in a higher energy state (sub-optimal).

The basic idea of the method (see figure 3.1) is to generate a random configuration (decision vector) iteratively through perturbation, and evaluate the objective function and the constraints after determining the state variables by using the simulator. If the trial point results in infeasibility i.e., if the constraints are violated, it is rejected and a new point is generated. If the trial point is feasible and the objective functions value is smaller than the current best value (for a minimization problem), then the point is accepted and the record for the best value is updated. If the trial point results in feasibility, but the objective function is higher than the current best value, then the trial point is either accepted or rejected using the Metropolis criterion (Metropolis et al.. 1953). This is implemented by generating a random deviate, uniformly distributed on the interval (0,1). If the random deviate thus generated is smaller than the acceptance probability, then the uphill move is accepted. In computing the probability for the acceptance of an uphill move, a parameter called 'temperature' is used. It is important to note that this temperature (has no units) and is simply a control or iteration parameter. For the optimisation problem, this temperature can be a target value for the cost function corresponding to a global minimum. Initially, a larger temperature or target value is selected. As the trials progress, this value is progressively reduced using a cooling factor. The acceptance probability of uphill moves steadily decreases to zero as the temperature is reduced. Thus in the initial stages, the method is likely to accept worse configurations, while in the final stages, the worse designs are almost always rejected. The entire process is terminated after performing a fairly large number of trials or chains (iterations). The strategy avoids getting trapped in a local minimum. The initial temperature, cooling factor, chain length and termination criteria are referred to as annealing parameters. The annealing parameters are difficult to determine (Wang and Zheng, 1998a). However, certain guidelines have been defined by Dougherty and Marryott (1991), Press et al. 1989), Cunha (1999) and others for choosing the values of these parameters.

3.7 Computational Time Burden

In general, the computational burden is substantial in all S/O problems. This is much more when heuristic algorithms, such as SA, are used for optimisation. The CPU (central processing unit) time depends on a number of factors. These include the time consumed by the simulator, the number of decision variables, the tightness of constraints, the speed of the processor, the efficiency of perturbation procedure (genetic rearrangement) and the annealing parameters (initial temperature, cooling factor, number of configurations or iterations at each temperature i.e., chain length and termination criterion) used. The SA procedure in the present methodology introduces a computational time burden that has two distinct components.

The first component is due to the time consumed by the function calls to the simulator and is associated with every trial configuration. This is virtually reduced to near zero with ANN as the simulator. An increase in the areal extent of study domain or number of nodes in the aquifer system does not affect the computational time as long as ANN replaces the simulator. Nevertheless, obtaining data patterns for training can be time consuming. Also, larger study area implies increase in the number of decision variables and constraints and hence the computational burden.

The second component is the average time consumed for generating a feasible configuration. This time is significant when the number of decision variables is large. The second component is kept to a minimum through efficient perturbation procedure discussed earlier. The total CPU time is determined by sum of the two components multiplied by the total number of iterations or chains prescribed in SA procedure and are problem specific.

It is important to note that while ANN reduces the computational burden in terms of time, and facilitates longer chain lengths (for SA) and tighter constraints for optimisation, it reduces the probability of finding a global optimal solution. This is because ANN mimics the simulator imperfectly, which in turn mimics the real physical system. Although the simulations by ANN are very good in general, the reproduction cannot be exactly the same, resulting in a slightly altered feasible domain, which may or may not contain the optimal solution obtained with the simulator. Johnson and Rogers (2000) have, however, concluded that ANN virtually replaces the full model. This is indeed true only within the range of input values for which ANN is trained, but not otherwise (ASCE Task Committee 2000). In general, there will be a successive dilution in the optimal solution with respect to the true global optimum. This is due to both, the SA procedure itself, which provides only near optimal solutions, and the ANN.

4.0 ILLUSTRATIVE APPLICATION OF MODEL USING SYNTHETIC DATA

4.1 Application of Model-1

To illustrate the conceptual model discussed in the previous chapter and to obtain an initial understanding of the problem a simplified aquifer system representative of the real problem in terms of geometry, boundary conditions and aquifer properties is analyzed. The analyses of the results are intended to provide an insight and confidence in tackling the complex real problem discussed in the next chapter.

The operational management model proposed in this study seeks to control up coning of underlying saline water while providing an optimal pumping schedule. To illustrate this concept and methodology a simplified aquifer system with wells representative of the study area and the aquifer parameters is considered here. A 7 layer, 25 rows, 13 column finite difference grid was constructed using a pre-processor (see figure 4.1). Typically a river boundary with constant head on one side and a groundwater divide contour (no-flow boundary) on the other side and a few wells pumping from different layers is considered. The lower-most layer is assumed to have constant salinity concentration of $5kg/m^3$. The input variables and aquifer parameters are listed in table 4.1.

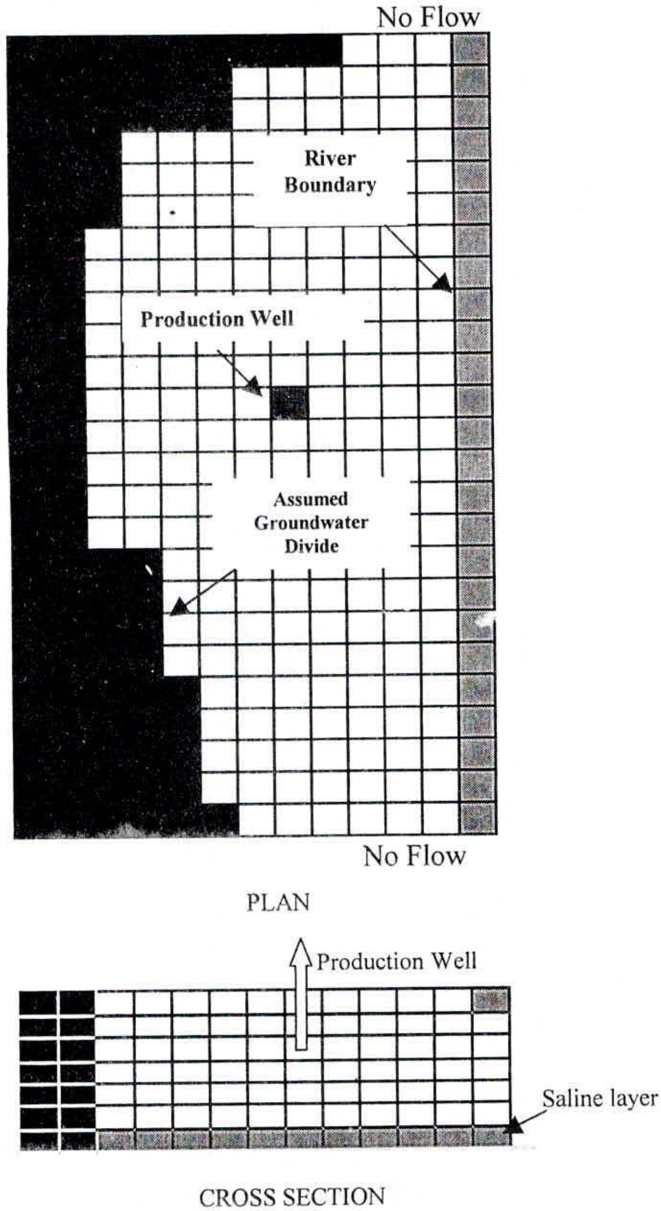


Fig. 4.1 Conceptual representation of the aquifer system

Table 4.1
Aquifer and other parameters used for SEAWAT 2000 model

S. No	Particulars	Values
1	Hydraulic conductivity in X, Y and Z directions	45, 45 and 4.5 m/day 2
	Porosity, specific yield	0.35, 0.15
3	Specific Storage (/ m.)	0.001
4	Longitudinal and vertical dispersivity (μ_l, μ_t)	66 and 11 m
5	Uniform rainfall recharge	0.12 m/monsoon season
6	Grid in X and Y directions (Dx, Dy)	100 m
7	Grid in Z direction (Dz)	10 m
8	Time step (Dt)	3 months
9	Concentration of freshwater	0
10	Max. Conc. of saline water (bottom-most layer)	5 kg/ m^3
11	Maximum density of saline water	1003.5 kg/ m^3
12	Density of freshwater	1000 kg/ m^3

The SEAWAT-2000 model was implemented using a false transient approach under average recharge conditions for a long time period (5000 days) until steady state conditions in terms of heads and concentrations were achieved. This approach simulates initial conditions for the S/O model as discussed in the next section. To ensure computational burdens were manageable the coupling parameter, DNSCRIT in the advection package of MT3D was set at 0.1 kg/ m^3 for early convergence. For real aquifer systems this needs to be further reduced for improving the accuracy of simulated concentrations. The courant's numbers was set at unity in the advection package of MT3D.

4.1.1 Skimming well and Proof of Concept Test

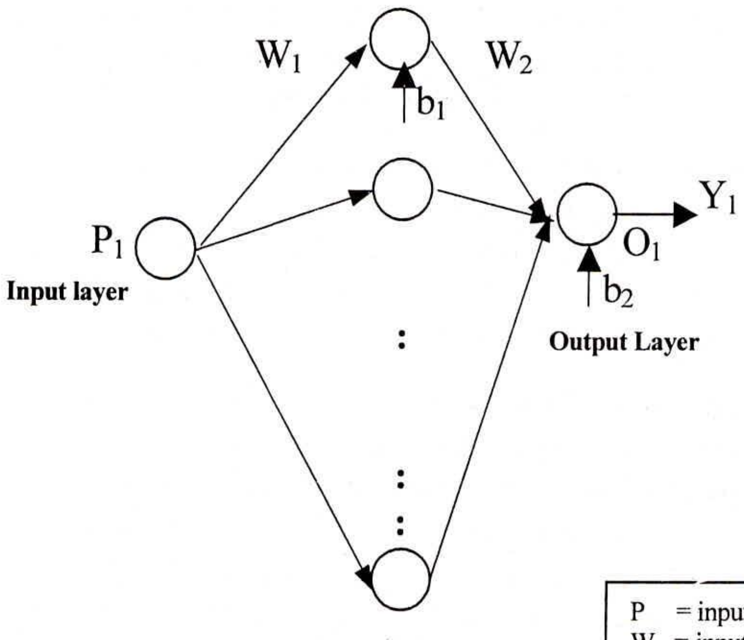
Initially a single skimming well pumping at steady rates from different layers to control up coning is considered (see figure 4.1). Intuitively a skimming well pumping from a layer farthest from the layer that is saline (in Z-direction) is likely to contain least amount of salinity consistent with a density dependent flow phenomena. The solution in terms of optimal location and rates arrived by the management model (S/O) must be consistent with this intuition. In reality the problem involves determination of maximum pumpages in space and time, which satisfy the constraints in terms of heads and concentrations. The head constraint in the uppermost layer ensures that the quantity of water that is pumped does not exceed the quantity of water that is replenished on an annual basis. The concentration constraint ensures that salinity does not exceed desired levels. This constraint is applied only to the grid cell from which pumping takes place during a given stress period or season.

The time of one year is typically divided into four seasons of three months (90 days) each with reference to climatic conditions prevalent in India. Thus the problem involves discrete (location in the Z-direction) and continuous (rate of pumping) decision variables. The S/O model simulation begins from steady state conditions discussed earlier. During the first time step beginning monsoon season 15 – 20 percent of average rainfall is assumed as uniform recharge over the study area. Additional recharge of 1.8 m is assumed arbitrarily along the left bank (for one grid width of 100m) from floodwaters during the monsoon season. No recharge (being negligible) is assumed during the remaining 3 seasons.

For any given set of pumpages the SEAWAT-2000 model takes on an average of 45 seconds to execute four stress periods (360 days) involving iterative solution of flow and transport on a desktop PC (Pentium 4 with 2.4 G. Hertz processor). Since the optimization process by SA involves several thousands of function calls to the simulator a virtual ANN simulator was developed to reduce the computational burden.

To generate training sets (patterns) for the ANN the SEAWAT-2000 model was repeatedly executed to generate random pumpages (input) assuming a uniform distribution for the single well pumping in the range of 500 – 5000 m^3/day at any one random location (i.e. 3rd, 4th or 5th layer) while setting the remaining two locations to zero pumping during each of the four stress periods. No constraints are imposed for generating data sets. The corresponding aquifer responses (output) in terms of heads (upper layer) and concentration in well pumping screen locations (i.e. 3rd, 4th and 5th layer) are recorded. Repeated execution of SEAWAT-2000 involved some 25 hrs of computer run to obtain nearly 2000 data sets of input-output. The data sets covered a full range over which each input variable (i.e. pumping) is varied. This is because ANN's are known to be good interpolators rather than extrapolators.

Before training the input-output data sets are standardized (Rao et al 2004). A 3-layer feed-forward network with an input, sigmoid and linear output layers were trained using ANN toolbox of MATLAB (2000) to obtain optimal weights and biases for each network. The supervised training was accomplished with the help of a back-propagation algorithm as implemented in MATLAB. Typically, to train a 3-6-1 ANN architecture (see figure 4.2) for concentration of solute at one of the locations (i.e. 3 input values pertaining to pumping in 3rd, 4th and 5th layer) for 1st stress period would mean 3 input neurons, 6 hidden neurons and one output neuron. Similarly there will be 12 neurons as input and 6 hidden neuron and one output neuron for training of concentration at any one location at the end of 4th stress period. This training procedure is repeated for each output variable i.e. head and concentration at each location of well screen (layer) at the end of each stress period. Training process for a single output in general takes only a few seconds. However it takes much more time if more than one output is trained simultaneously.



$$Y_1 = f\ (P^T W_1 + b_1).W_2 + b_2$$

Where f is given by equation 3.5

P = input layer vector;
W_1 = input weights matrix;
W_2 = hidden layer matrix;
b_1 = bias vector for hidden layer;
b_2 = bias vector for output layer; and
Y = output layer vector

Fig. 4.2 A typical neural network

The network with optimal weights and biases in the form of a small program involving simple matrix multiplication and addition works as a virtual simulator of SEAWAT-2000. The behavior of ANN virtual model in general showed high goodness-of-fit (R^2 = 0.97 to 0.99) which in fact nearly replaces the full numerical model for calibration and validation sets (Johnson and Rogers 2000, Rao et al 2004). The ANN virtual simulator is subsequently interfaced with SA for optimisation. The SA model was implemented while confining heads in the 3rd layer and concentrations in the grid cell from where pumping is resorted to 63 meters and 2.5 kg/m^3 respectively.

The annealing parameters for SA were arrived through trial and error (Dougherty et al 1991, Cunha 1999, Rao et al 2004). The initial temperature is set such that more than 75% of the feasible configurations are accepted in the beginning. The chain length (equilibrium criterion) was set in the range of 50 – 60 times the number of decision variables) and the cooling factor (rate of reducing the temperature) was varied in the range of 0.4 to 0.6. The SA procedure was terminated when four successive temperature reductions did not yield improvement in solution. The optimal solution is presented in table 4.2.

The solution was consistent with the intuition that pumping must confine to the topmost layer for all stress periods and verifies the management model for optimality in terms of location. The values pertaining to rate of pumping at these locations depend on the tightness of the constraint in terms of concentration and cannot be verified for global optimality. However, the solution (near-optimal) was verified with the actual simulator i.e. SEAWAT-2000 for heads and concentrations as listed in table 4.2. For most solutions (near-optimal) concentration rather than head was the limiting constraint. This is evident from table 4.2 wherein concentration in third layer reaches its limiting value at the end of the 4th stress period i.e. 2.5 kg/m^3. It is also worth noting that over 25,000 calls to simulator could be made with ANN as the simulator in less than 30 minutes of CPU time. The computational burden in the present study is discussed in a later section. The evolution of model solution using SA procedure is depicted in figure 4.3.

4.1.2 Optimal Pumping Cycle

To arrive at an optimum pumping schedule the illustration was designed, consistent with the real life problem discussed in the next chapter. A series of 5

Table 4.2

Optimal Solution for Pumpages for a Skimming Well and Corresponding Head and Concentrations

Stress Period (Season)	Particulars	3rd Layer	4th Layer	5th Layer
First (0 - 90 days)	Pumpage (m^3/day)	568.7	**0**	**0**
	Head (m)	64.80	64.86	64.89
	Concentration (Kg/m^3)	0.80	1.18	1.88
Second (90-180 days)	Pumpage (m^3/day)	3147.5	0	0
	Head (m)	63.91	64.19	64.36
	Concentration (Kg/m^3)	1.69	2.00	2.55
Third (180-270days)	Pumpage (m^3/day)	3957.7	0	0
	Head (m)	63.61	63.97	64.17
	Concentration (Kg/m^3)	2.18	2.46	2.93
Fourth (270-360days)	Pumpage (m^3/day)	3678.0	0	0
	Head (m)	63.68	64.02	**64.21**
	Concentration (Kg/m^3)	2.50	2.75	3.16

Note:

1. Heads are constrained in the 3rd layer only (not less than 63m.)
2. Concentration is constrained in the layer from which pumping takes place (not more than 2.5kg/m3)

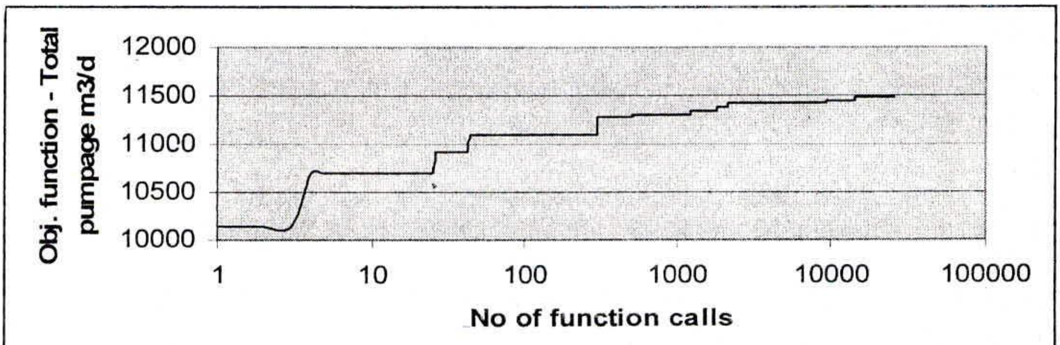
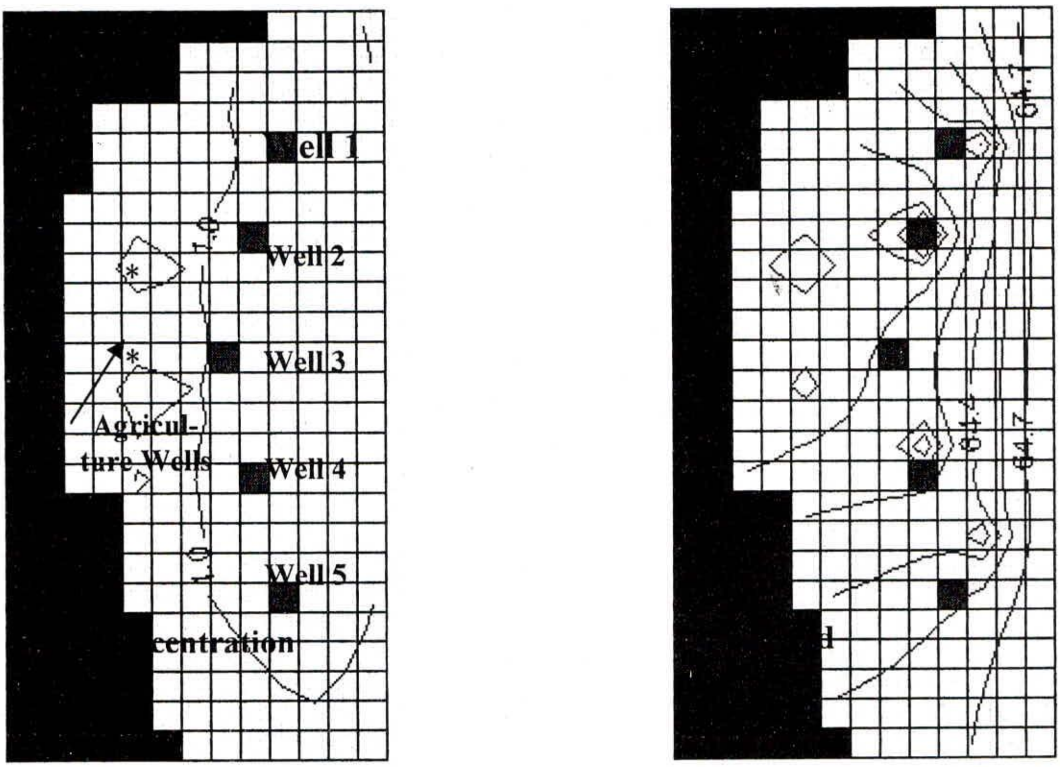


Fig. 4.3 Evolution of solution using SA Algorithm

wells pumping from 3rd layer is considered for four stress periods as shown in figure 4.4. The third layer was chosen consistent with the results of the previous section. The number of wells (in series) and time steps is kept small to ensure that the number of decision variables is minimum in space and time. An optimal pumping schedule for operating 2, 3 or 4 wells out of 5 wells is planned. The pumping was varied in the same range of 500 – 5000 m^3/day as discussed in the previous section. Two additional wells are assumed to be pumping at a fixed rate of 900 m^3/d to meet agricultural demand in the neighboring areas through out the year. The problem involves determination of optimal location and their steady rates of pumping during each stress period.

The initial conditions were kept the same as in previous section and data sets were generated using SEAWAT-2000. The range of variation of head and



Concentration Head

Fig. 4.4 Head (m) and concentration (kg/m^3) distribution at the end of 4th stress period for the optimal solution for a series of 5 wells in the 3rd layer.

concentration at the end of each stress period is listed in table 4.3. The ANN model was later trained and interfaced with SA code. For this study the average head (at five pumping locations) and concentration at each location are constrained at 63 m. and 2.5 kg/m^3 respectively. It is important to note at this stage, that the concentration limit of 2.5 kg/m^3 was chosen arbitrarily based on the range of values over which the concentration varied for the range of pumpages and not from drinking water requirements. For the real aquifer system this must meet drinking water standards. The SA code was implemented on similar lines as discussed in the previous section. The optimal solution is listed in table 4.4. The optimal solutions were also tested with the actual simulator to ensure that the constraints were satisfied in terms of heads and concentrations.

Table 4.3

Data range generated using SEAWAT – 2000 Model for ANN Training For a series of 5 wells

Stress period		Concentration in kg/m^3					Average Head (m) in 5 wells
		Well 1	Well 2	Well 3	Well 4	Well 5	
First	Max.	0.429	0.371	0.489	0.323	0.411	64.530
	Min.	1.815	1.923	1.967	1.93	1.806	63.403
Second	Max.	0.723	0.629	0.869	0.578	0.719	64.416
	Min.	2.311	2.537	2.554	2.489	2.268	63.512
Third	Max.	1.274	1.045	1.359	1.006	1.089	64.618
	Min.	2.634	2.962	2.931	2.913	2.601	63.321
Fourth	Max.	1.567	1.446	1.808	1.334	1.497	64.431
	Min.	2.813	3.274	3.193	3.249	2.791	63.371

Interestingly, the optimal solution (table 4.4) suggests, that operating only 3 wells rather than 4 wells out of 5 wells in series gives the maximum pumpage. This is due to the interference from neighboring wells (including two additional agricultural wells), which enhance the advective velocities leading to increase in concentration in the grid cells from where pumping is resorted. Here interference refers to interference in upconing process from adjacent wells. Once the concentration level exceeds the permissible level the trial solution is rejected leading to lower pumpages in the intermediate wells (Wells# 2, 3 and 4 in figure 4.3). The wells 1 and 5 have relatively less interference being on extreme edges of the series of wells. Therefore

Table 4.4
Optimal Pumping Cycle and corresponding Heads and Concentrations
For a Series of 5 Wells (m^3/day)

Season (Stress period)	Well Operation Plan	Well 1	Well 2	Well 3	Well 4	Well 5	Total
First	2-Wells	0	4815.7	0	0	4593.9	34924.2
Second		0	0	0	3260.2	4943.4	
Third		0	4841.3	0	0	4458.8	
Fourth		3784.2	4226.6	0	0	0	
First	3-Wells	4833.9	4926.1	0	0	3686.4	45864.8
Second		3421.0	4168.2	0	0	4460.0	
Third		4798.2	0	2769.6	0	3771.0	
Fourth		4948.1	0	2738.3	0	1344.1	
First	4-Wells	1456.3	0	1379.3	3766.3	750.7	44807.5
Second		4187.1	0	2021.3	779.0	4855.2	
Third		4953.7	1454.7	3712.7	0	4462.5	
Fourth		2464.2	4170.6	0	2316.9	2077.1	

higher pumpages are mostly located in wells 1 and 5 as evident from table 4.4. This leads to an important inference that operating more wells does not necessarily yield more water from skimming wells in general. This is unlike constant density flow phenomenon. In other words, for maximizing pumpages, the group of wells that must be operated should be staggered in space and time such that there is minimum interference from neighboring wells.

4.1.3 Computational Burden

The CPU time in general depends on a number of factors. This includes the time consumed by the simulator, the number of decision variables, the tightness of constraints, the speed of the processor and annealing parameters (initial temperature, cooling factor, chain length or equilibrium and termination criterion). The SA procedure in the present methodology introduces a computational time burden that has two distinct components.

The first component is due to the time consumed by the function calls to the simulator and is associated with every trial feasible configuration. This virtually reduces to near zero with ANN as the virtual simulator. The second component is the average time consumed in for feasible solutions until equilibrium and termination criteria are met. The second component can be kept to minimum through efficient coding and algorithmic guidance such that infeasible trials are terminated at the earliest stage and improved solutions are found that are problem specific. The total CPU time is determined by sum of the two components multiplied by the total number of iterations or chains. At initial temperature the number of iterations is large mainly due to infeasible solutions. At final temperature the uphill moves are too many in general. The total number of iterations is problem specific and therefore can be determined only after actual model execution. In the present study the computational times were 2, 5 and 90 minutes of CPU time corresponding to 2, 3 and 4 well pumping schedules respectively listed in table 4.4 on a desktop PC with moderately tight constraint concerning concentration (limiting constraint was set at 2.5 kg/m^3). However under tighter constraints this could take several hours.

4.2 Application of Model-2

The proposed model seeks to control up coning of saline water from a pre-selected set of candidate well in series. The goal is to determine a subset of optimally located wells that provide groundwater of minimal salinity in space and time. To illustrate this concept and methodology a simplified homogeneous, isotropic aquifer system representative of the study area and aquifer parameters is considered. An 8 layer, 32 rows, 13 column finite difference grid was constructed using a pre-processor (see figure 4.5). Typically a river boundary with constant head on one side and a groundwater divide contour (no-flow boundary) on the other side is considered. The lower-most layer is assumed to have constant salinity concentration of 5kg/m^3. The input variables and aquifer parameters are listed in table 4.5. To obtain initial conditions for the S/O model the SEAWAT-2000 model was implemented using a false transient approach under average recharge conditions for a long time period (5000 days) until steady state conditions in terms of heads and concentrations was achieved.

4.2.1 Optimal Location of Wells

The illustrative example was conceived and designed consistent with the real problem discussed in next chapter. The planning horizon of one year is assumed to be divided into two stress periods (seasons) of 180 days each. The two stress

Table 4.5.
Aquifer and other parameters used for SEAWAT 2000 model

S. No	Particulars	Values
1	Hydraulic conductivity in X, Y and Z directions	40, 40 and 4 m/day
2	Specific yield, Specific storage	0.15, 0.001 (/m)
3	Longitudinal and vertical dispersivity (μ_l, μ_t)	30 and 10 m
4	Uniform rainfall recharge	0.12 m/monsoon season
5	Grid in X and Y directions (Dx, Dy)	50 m
6	Grid in Z direction (Dz)	10 m
7	No of Rows, Columns and layers	32, 13 and 8
8	Stress period	6 months (180 days)
9	No of stress periods, times steps	2, 18
9	Concentration of freshwater	0
10	Max. Conc. of saline water (bottom-most layer)	5 kg/ m^3
11	Maximum density of saline water	1003.5 kg/ m^3
12	Density of freshwater	1000 kg/ m^3
13	Aquifer top and bottom elevation	80m, 0m
14	Constant head in river	75m
15	Courant number, Coupling parameter DNSCRIT	1, 0.01 kg/ m^3

periods correspond to monsoon and non-monsoon seasons, typical of Indian rainfall conditions. Recharge is assumed to occur only during the monsoon season.

A series of eight candidate wells is considered (see figure 4.5). It is assumed that only four wells operate at a fixed rate (say, 500 m^3/day) during any given stress period or season. It is required to determine their optimal location in space and time. All the wells were assumed to pump from the uppermost layer i.e. 3rd layer (barring 1st and 2nd layers for possible variation in draw down due to pumping). The idea of pumping from the 3rd layer is obvious as salinity concentration is expected to be least towards topmost layer in a density driven flow phenomenon. The illustrative problem was designed such that the optimal solution is known intuitively, as a proof of concept.

The eight candidate wells considered in this study, implies 16 decision variables for two time steps. If each decision variable takes 2 values i.e. zero or one, this results in 2^{16} possible configurations. For any given set of pumpages the

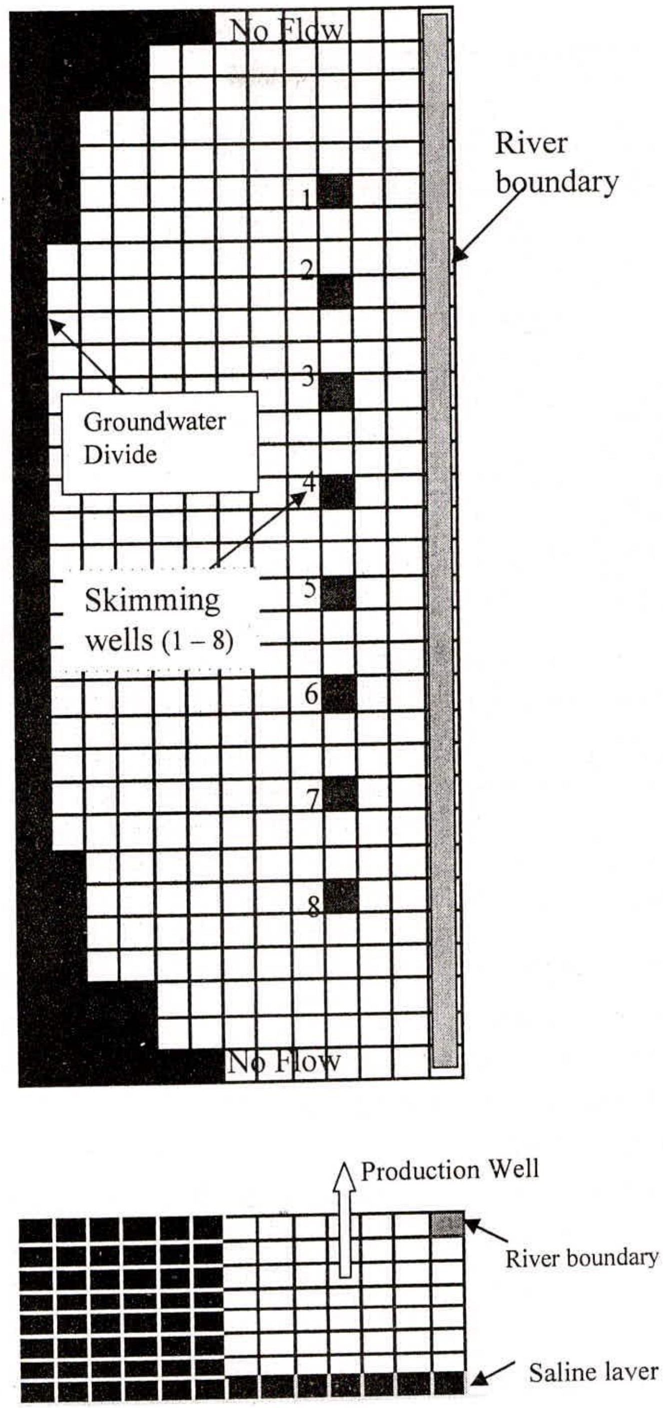


Fig. 4.5 Plan and cross section of simplified aquifer

SEAWAT-2000 model takes on an average, 60 seconds to execute two stress periods (360 days) involving iterative solution of flow and transport on a desktop PC. Since brute force technique is impractical and the optimisation (SA) process involves several thousands of function calls to the simulator a virtual ANN simulator was developed to reduce the computational burden.

To generate training sets (patterns) for the ANN the SEAWAT-2000 model was repeatedly executed to pumping at random pumping (assuming uniform distribution) locations. During each run random locations were generated at any four locations out of eight possible candidate wells and were assigned a fixed pumping rate of 500m^3/day. The remaining 4 locations were assigned zero pumping. After the model execution, the corresponding aquifer responses (output) at each well in terms of concentration at the screen located grid cells were recorded. Repeated execution of SEAWAT-2000 involved some 30 hrs of computer run to obtain more than 1800 realizations (data sets) of input-output.

Initially the input variables (0.0 or 500.0 m^3/d) pertaining to pumping are converted into zero-one variables (a typical data set is shown in table 4.6). The input-output patterns are then standardized before ANN training. For this purpose, the input-output data series (patterns) are scaled between zero (0.0) and one (1.0). A 3-layer feed-forward network with an input, sigmoid and linear output layers were trained using ANN toolbox of MATLAB (2000) to obtain optimal weights and biases for each network. The supervised training was accomplished with the help of a back-propagation algorithm as implemented in MATLAB. Typically, to train an 8-6-1 ANN architecture for concentration of solute at one of the locations for 1st stress period would mean 8 input neurons, 6 hidden neurons and one output neuron. Similarly there will be 16 neurons as input and 6 hidden neuron and one output neuron for training of concentration at any one location at the end of 2nd stress period. This training procedure was repeated for each output variable i.e. head and concentration at each location of well screen (layer) at the end of each stress period

The network with optimal weights and biases in the form of a small program involves only simple matrix operations to behave as a virtual simulator of SEAWAT-2000. The behavior of ANN virtual model in general showed high goodness-of-fit (R^2=0.97 to 0.98). Similar details have been discussed in Rao et al (2004). The virtual model was subsequently interfaced within S/O model to replace the SEAWAT-2000 simulator.

The annealing parameters for SA were arrived through trial and error (Dougherty et al 1991, Cunha 1999, Rao et al 2004). The initial temperature (set at 0.2) was arrived such that more than 80% of the feasible configurations are accepted in the beginning. The chain length (equilibrium criterion) was set in the range of 80 – 90 times the number of decision variables) and the cooling factor (rate of reducing the temperature) was varied in the range of 0.7 to 0.9. The SA procedure was terminated when four successive temperature reductions did not yield improvement in solution. The optimal solution is presented in table 4.7. Evolution of model solution using SA procedure is depicted in figure 4.6.

The optimal solution was found to be along expected lines and consistent with the intuition. In the first stress period the model allocates the fixed pumpage (500 m^3/day) in the 1st, 3rd, 5th and 7th locations, while in the second stress period it chooses 2nd, 4th, 6th, and 8th locations. The only other alternative solution, which the model can find with same value of objective function, could be to interchange the locations between first and second stress periods. The net effect was to stagger the pumpages in space and time. The model staggers in order to minimize the effect of interference from neighboring wells which enhance the advective velocities leading to increase in concentration in grid cells from where pumping is resorted as evident from table 4.6.

4.2.2 Computational Burden and Algorithmic guidance

The computational burden was discussed with the model-1 and is the same with the model-2. For the unconstrained problem the optimal solution was attained after 4262 feasible calls to the simulator with CPU time of 60 seconds. The number of calls however, depends on the beginning search point, which actually depends on the random seed. Therefore this could be achieved with much less or even more number of calls depending on the random seed. In any event the computational burden is largely controlled with ANN as the simulator.

If the problem is constrained for salinity (say 0.4 kg/m3) at each pumping location (which is on) the computational burden increases to 1075 seconds. This is due to increase in the number of infeasible calls that get rejected by the constraint. Here the computational burden arises from the second component also as discussed earlier. This can only be controlled through efficient algorithmic guidance.

Table 4.6 Typical data set used for training concentration at 8 pumping locations during two time periods

Zero-one input variables at 8 locations for two time periods (16 decision variables)	Concentration during 1st time period	Concentration during 2nd time period
0 0 0 1 1 1 1 0 1 1 0 1 0 0 1	0.877 0.784 0.429 0.260 0.628 0.549 0.639 0.787	0.873 0.766 0.404 0.267 0.618 0.553 0.637 0.782
1 0 0 1 0 0 1 1 0 0 1 1 1 0 0	0.857 0.765 0.431 0.260 0.628 0.576 0.669 0.787	0.848 0.763 0.428 0.264 0.618 0.553 0.670 0.788
0 1 1 0 0 0 1 1 0 0 1 1 0 0 1	0.857 0.784 0.408 0.257 0.646 0.570 0.669 0.787	0.847 0.782 0.406 0.270 0.626 0.573 0.665 0.782
0 0 1 0 0 1 1 1 0 0 0 1 0 1 1	0.857 0.784 0.430 0.264 0.646 0.571 0.648 0.787	0.847 0.782 0.428 0.261 0.627 0.572 0.636 0.782
0 0 1 1 1 1 0 0 0 1 1 0 1 0 1	0.877 0.784 0.430 0.264 0.628 0.549 0.639 0.807	0.873 0.782 0.410 0.267 0.626 0.554 0.646 0.786
0 1 0 0 1 1 1 0 1 0 0 1 1 1 0	0.877 0.784 0.408 0.267 0.646 0.560 0.640 0.787	0.873 0.766 0.409 0.263 0.628 0.549 0.625 0.787
1 1 0 0 1 0 1 1 1 0 0 0 1 0 1	0.877 0.767 0.403 0.267 0.646 0.560 0.673 0.787	0.855 0.757 0.405 0.263 0.644 0.558 0.671 0.782
1 1 0 0 1 0 1 0 1 0 1 0 1 1 0	0.877 0.767 0.403 0.267 0.646 0.560 0.673 0.787	0.874 0.759 0.403 0.271 0.644 0.559 0.641 0.788
0 0 0 1 1 0 1 0 1 1 0 0 1 0 1	0.857 0.784 0.429 0.260 0.628 0.549 0.674 0.787	0.855 0.767 0.403 0.267 0.627 0.554 0.671 0.782
0 0 1 1 0 1 0 0 0 1 0 1 0 1 1	0.857 0.784 0.430 0.264 0.627 0.575 0.646 0.807	0.855 0.782 0.409 0.270 0.617 0.573 0.634 0.785
1 1 0 0 0 0 1 1 1 1 1 0 0 0 0	0.857 0.765 0.403 0.267 0.646 0.570 0.669 0.787	0.849 0.756 0.403 0.265 0.644 0.567 0.665 0.788
1 0 0 0 0 1 1 1 0 0 1 1 0 0 1	0.857 0.765 0.431 0.260 0.646 0.571 0.648 0.787	0.848 0.763 0.428 0.264 0.627 0.574 0.645 0.782

Table 4.7
Optimal Pumping (500 m^3/day) location and Salinity (kg/m^3) in Screen Located grid cells in the third layer at the end of each stress period

Stress period (Days)	Pumping Locations								Objective function
	1	2	3	4	5	6	7	8	
First (1 – 180)	500.00 0.30205	-	500.00 0.27857	-	500.00 0.27522	- -	500.00 0.28448		2.56608
Second (180 – 360)		500.00 0.36425		500.00 0.34725	-	500.00 0.34413		500.00 0.37013	

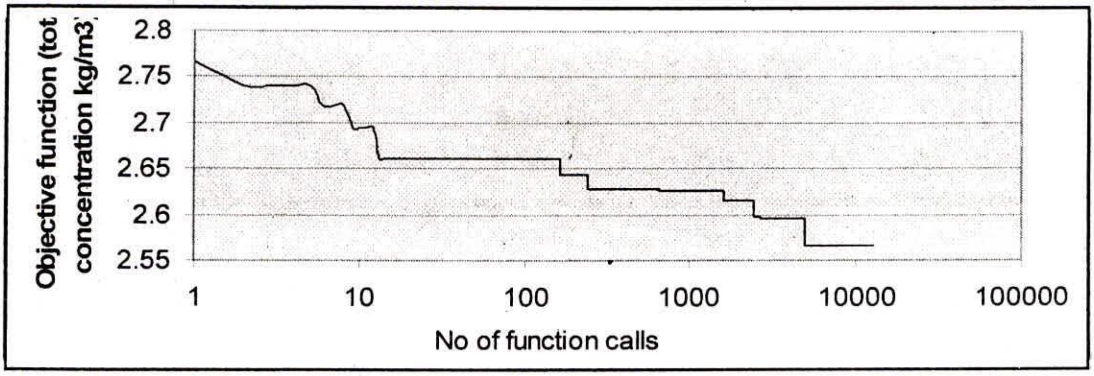


Fig. 4.6 Evolution of model solution using SA Algorithm

A simple algorithmic guidance, which is problem specific, was designed from intuitive understanding of the density driven flow phenomenon that is reflected in the optimal solution in table 4.7. A small subroutine was coded to ensure that the trial random allocations of fixed pumpages were staggered in space and time. Computationally this is achieved in space and time as follows. For the simplified problem under consideration, staggered allocations in *space* were made while ensuring that center of gravity (C.G) of allocated pumpages lies some where in the middle band along the arm of the series of pumpages 1st through 8th, beginning 1st location (see figure 4.4). Along *time* this is achieved by avoiding allocation at the same location in the next time period. With this approach the computational burden could be reduced to 120 seconds. In fact with this algorithmic guidance the annealing algorithm could be directly linked to numerical simulator (without virtual simulator ANN) for the illustrative example presented in this study.

However it is important to note that this approach has been applied to a simplified aquifer system. Real systems involve many other aspects, such as external stresses, variation aquifer properties, geometry and boundary and confining conditions. Nevertheless this concept can be extended in general to the real systems to determine optimal locations of skimming wells and to reduce computational burden via algorithmic guidance.

4.3 Discussion of results of model-1 and model-2

The analysis of results of model-1 and model-2 clearly indicate the implications of a density driven flow phenomena involving upconing. Unlike a constant density flow phenomena well interference from closely spaced wells adversely affects the advective flow and transport of salts in the aquifer zone below the well screens. The advective velocities get enhanced in the vertical direction from neighboring wells, there by increasing the salt concentrations. Therefore both location and pumping rates are decisive factors to determine the amount of pumping in space and time.

To control pumping or in other words the salinity of extracted groundwater staggering in space and time are absolutely essential. The extent of staggering in spatial and temporal would however depend on the aquifer system under consideration in terms of geometry, boundary conditions, aquifer properties and input/ output stresses. These conditions are unique for any aquifer system. Therefore each one has to be analyzed separately to determine maximum groundwater that can be tapped on a sustainable basis.

5.0 MODEL APPLICATION TO PALLA WELL FIELDS USING REAL DATA

5.1 Description of Study area and Data Availability

The study area near Palla Village lies northwest of Delhi in survey of India toposheet 53H/1/SE. The study area (figure 5.1) is approachable from NH-1 via Bakhtarpur village. The river Yamuna receives much of its flows during the monsoon season (July to September). The study area is often flooded during this season. The palla flood plains within the embankments get significant recharge during this period. A battery of 90 tube wells (plate 1) was constructed in various stages since year 2001 along the periphery of left embankment to augment drinking water supply from this induced recharge. The wells (see details in appendix A) also draw groundwater from rainfall recharge from adjacent areas along the reach besides the river boundary (Figure 5.2). At present the wells are pumping 30 – 35 MGD of groundwater by operating these wells for 12 – 16 hours a day. The land use in and around the study area is mainly agriculture, involving cultivation of seasonal crops

The cross sections typical of model area (figure 5.3) indicate predominantly sandy soils with intermittent clay lenses. Recent alluvial deposits are predominant, consisting of sand, silt, clay, Kankar or occasional gravel. Fine mica flakes are noticed often in sandy formations. The generalisation of the subsurface geology

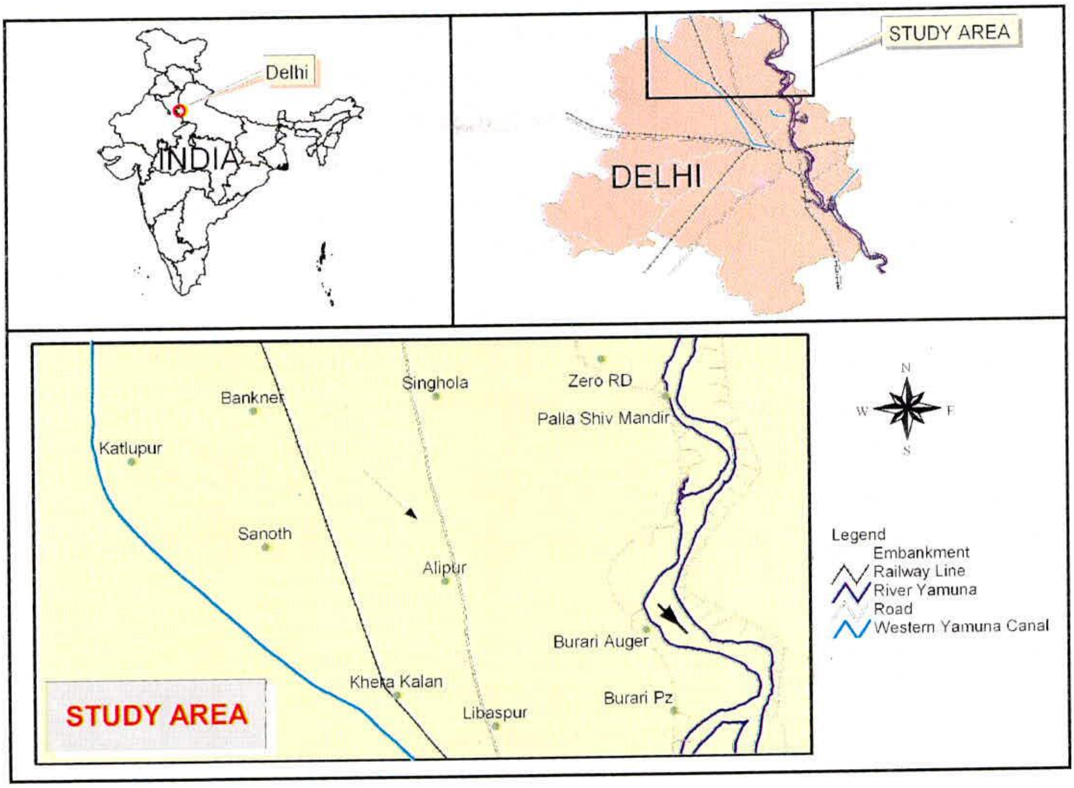


Fig. 5.1: Index map of the study area.

reveals that there are broadly four formations. The first and the topmost formation is characterized by medium to fine grained colored Yamuna sand with few gravels. This is followed by a zone characterized by medium to coarse-grained gray colored Yamuna sands with gravels and kankars. In the southern part of the well field and near to margin of first and second zone a gravel predominant zone with coarse sand and kankars have been observed. The bulk of this gravel predominant zone lies in second zone characterized by medium to coarse sand. As one moves from the southern part of the well field towards extreme north the occurrence of the gravel predominant zone reduces drastically. Below the above-mentioned layers are layers characterized by fine-grained brownish sand with consolidated silt, clay, *kankar* and gravels.

In general the study area is underlain with geologically occurring saline water everywhere at varying depths. The saline-freshwater interface is observed at a depth of 60 – 70 in the northern part of the study area. In the southern part it is

Plate 1. Production wells in series at Palla sector in river Yamuna floodplain

rather shallow and is noticeable at 30 – 40 meters. The salinity is expected to increase with depth. While modeling, to be on safer side, the maximum salinity below the interface has been assumed to be 2000 mg/l for the bottom layer. The depth of water varies from 3 – 4 m below ground level. The water level fluctuation between pre and post monsoon varies from 1.0 to 1.5 m. The groundwater quality from the production wells is good and is suitable for drinking purposes. The average

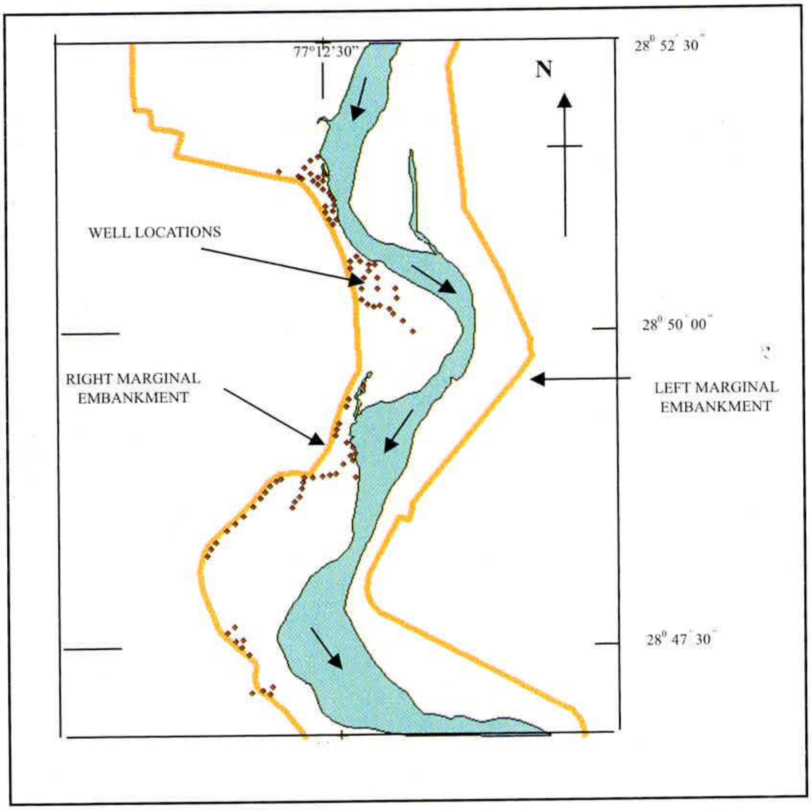
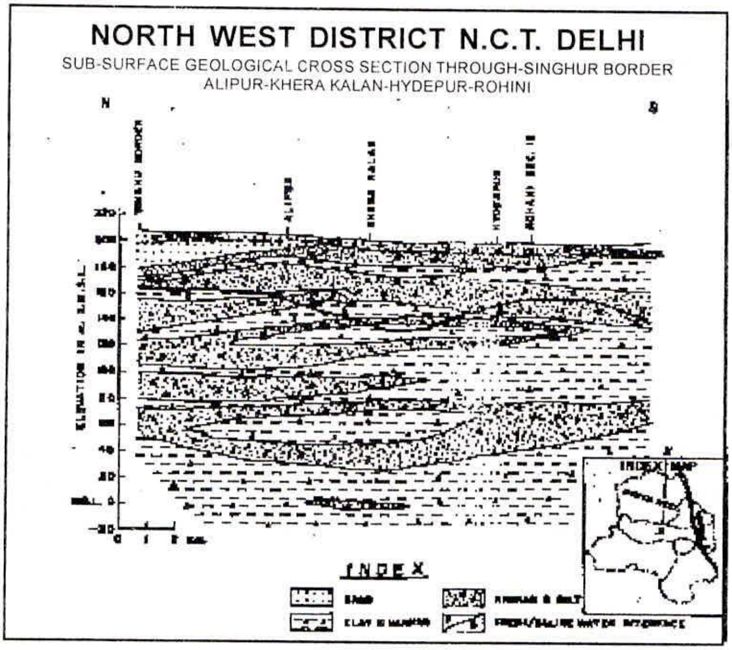


Fig. 5.2 River Yamuna near Delhi showing well locations in the flood plain

EC (electrical conductivity) and pH values of the groundwater from production wells tapping multiple aquifers upto a depth of 40-45 m has been measured as 400mS/cm and 7.5 respectively

Data pertaining to rainfall, lithologs, groundwater levels in space and time and a few pumping tests are available. Data pertaining to groundwater quality in the saline zone (especially in AOI), river stage, cross-sections, and river flow along space and time are not available and hence these have been assumed suitably with limited field checks.

In summary there is very little variation in sub-surface configuration of aquifer material along the stretch of Palla flood plain. In general finer material (clay) increases with depth in varied proportion of *kankars*. Therefore the hydraulic conductivity in the study area is expected to vary between 10 – 25 m/ day, with higher values at the top. In the Z direction the values are expected to be one tenth of the above-mentioned



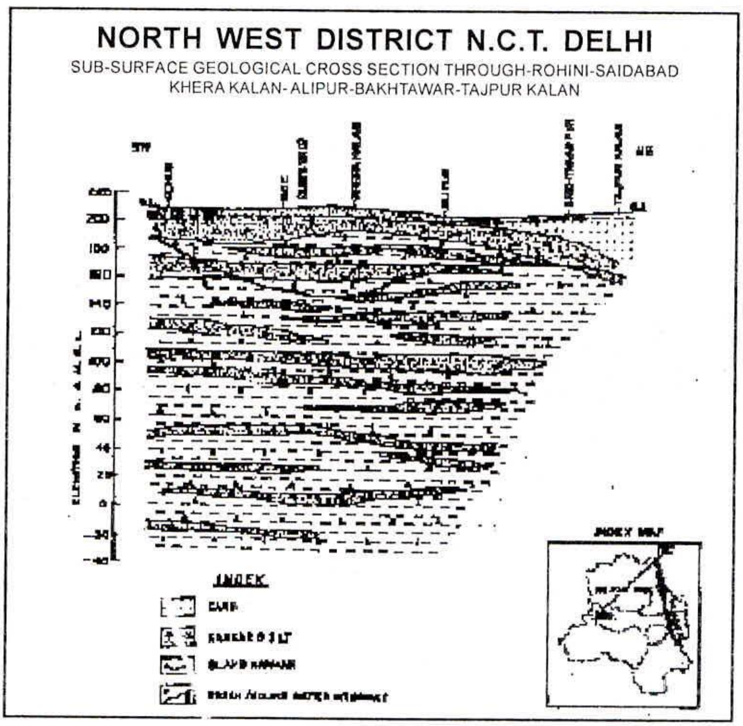


Fig. 5.3 Geological cross sections based on lithologs in the study area

values. The specific yield and specific storage values are expected around 0.2 and 0.0001 respectively. The above values in the present study including dispersivity, however, are arrived by trial and error or through a parameter estimation procedure.

5.2 Development and Calibration of Regional Aquifer Model (RAM)

The focus of present study is to develop an optimal pumping schedule in space and time for the group of 90 wells in the flood plain of river Yamuna near Palla Village bordering Haryana. The aquifer system pertaining to the area of interest (AOI) marked ABCD (figure 5.4) has been modeled. To model the AOI, suitable boundary conditions have been defined along the four sides and the bottom. In the absence of a hydrologic boundary, it is difficult to determine the western boundary condition along edge AB or to assess the amount of flux from this direction, therefore, the areal extent of study area in this direction has been extended until a well-defined hydrologic boundary condition is encountered. In the present case the western Yamuna canal along a ridge happens to be the boundary condition on the western side.

With the western Yamuna canal as boundary condition on one side and the river Yamuna on the other side, the study encompasses an area of about 240 km^2. Modeling this area has helped in defining the boundary condition along AB. This approach is sometimes referred as *regional to local* scale. Generally a coarser grid is defined for modeling at regional level and a finer grid at local level i.e. the AOI. It is important to note that AOI is kept as minimum as possible to ensure that computational burdens are kept to minimum with a density dependent flow simulator – SEAWAT 2000. Further SEAWAT 2000 involves a transport model, which in general requires a finer grid. Although in the present study the simulator is replaced with ANN model, ANN in turn requires a large number of data patterns, which can be obtained only by running the original simulator.

The regional model extending upto Yamuna canal has been first calibrated and then the AOI is cut using telescopic mesh refinement (TMR) approach, which is built in pre-processors of many groundwater models (Rumbaugh, 2004). The TMR model at local scale with appropriate boundary conditions along the edges is expected to behave like the original model (RAM). The calibration is intended to simulate initial conditions in RAM in terms of groundwater heads and concentrations beginning monsoon season when the system is assumed to be in quasi-steady state condition.

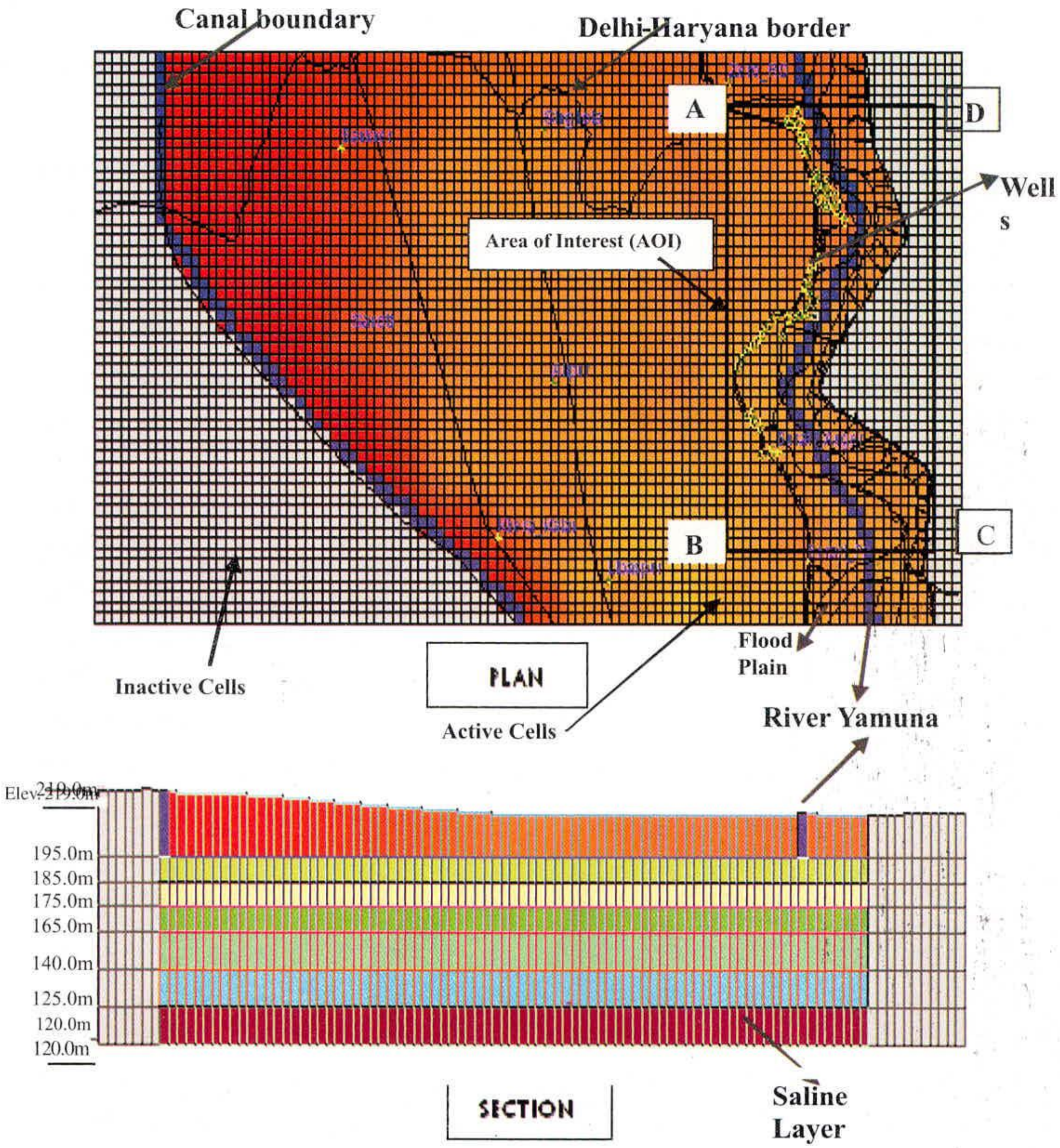


Fig. 5.4 Plan and Cross-section of 7-layer Palla Regional aquifer model (RAM) and area of Interest

The study area map was digitized for river boundary, floodplain embankments, well locations and wesmtern Yamuna canal alignment. A finite difference grid (250 x 250m) with 53 rows, 99 columns and 7 layers was constructed to represent the aquifer system. The ground elevations in the upper-most layer were made to conform to the topography in the region (figure5.4). The upper most layer shows variable thickness in space due to varying topography.

As hard rock or impervious bed is not encountered for several hundreds of meters in depth and since the production wells tap up to a depth of 45 meters, a no-flow boundary was set at a depth of 80 - 100 meters. The remaining layers were assigned constant thickness as indicated in figure 5.4. Keeping in view the groundwater flow direction on regional scale and based on the topography, which in general is falling from western Yamuna Canal (on the ridge line) towards the river Yamuna, the northern and southern edges are considered as no-flow boundaries. The groundwater table also follows this topography indicating general flow direction towards river Yamuna. The western Yamuna canal and the river Yamuna are considered as constant or specified head boundaries on the basis of available data. The bottom-most layer (7th layer) is assumed to be saline with a constant TDS of 2000 mg/l. In the 6th and 5th layers the southern most 10 and 5 rows were assigned the same constant TDS (2000 mg/l) respectively to represent rising saline-freshwater interface towards southern part of study area, as indicated by borehole logging data. All remaining cells were set at an initial concentration of zero. The grid cells in all the layers, left of western Yamuna canal and right of river Yamuna were made inactive. Thus the model contains some 26000 active cells.

The Aquifer parameters used in the present study are listed in table 5.1. These were arrived based on available data of lithologs and limited pumping test data analysis. Recharge was assumed to vary in the range of 10 – 15 percent of rainfall. Additional recharge (0.5m) was assumed in the flood plain within the embankments to account for recharge from intermittent flood pondage during the monsoon season. Draft (abstraction) for various water uses (mainly agricultural) per grid cell was arrived at after conducting sample field survey in the study area as presented in appendix B.

Initial parameter calibration in terms of observed and simulated heads was accomplished using a constant density model – MODFLOW (Harbaugh et al 2000) and PEST (Daugherty et al 1998) in arriving at reasonable value of equivalent hydraulic

Table 5.1

Regional Aquifer model parameters used by SEAWAT – 2000

S. No	Particulars	Values
1	Hydraulic conductivity in X, Y and Z directions (in the upper most layer taken as 20 m/day)	9.8, 9.8 and 1.0 m/day
2	Specific yield, Specific storage	0.2, 0.0001 (/m)
3	Longitudinal and vertical dispersivity. (μ_l, μ_t)	60 and 10 m
4	Uniform rainfall recharge	0.10 m/monsoon season
5	Grid in X and Y directions (Dx, Dy)	250 m
6	Grid in Z direction (Dz)	10 – 25 (variable)
7	No of Rows, Columns and layers	53, 99 and 7
8	Concentration of freshwater	0
9	Max. Conc. of saline water (bottom-most layer)	2 kg/ m^3
10	Maximum density of saline water	1001.43 kg/ m^3
11	Density of freshwater	1000 kg/ m^3
12	Courants number, Coupling parameter DNSCRIT	1, 0.01 kg/ m^3
13	Density – Concentration slope	0.71

conductivity (K) in the X-Y directions for steady state conditions. This value of K was subsequently improved in the variable density simulator –SEAWAT -2000.

In the present study approximate calibration of the RAM is intended to arrive at initial conditions in terms of heads and concentrations in general and AOI in particular at the beginning of the water year (i.e. July) before onset of monsoon season where in it is assumed that the aquifer system is in quasi-steady state conditions. To arrive at this initial condition the SEAWAT-2000 model was implemented with initial arbitrary heads/ concentrations and the model was run for a long period such as 5000 days under average draft/ recharge stresses. This approach is sometimes referred as false-transient approach. At this stage it was assumed that a quasi-steady state condition beginning monsoon season was accomplished since the simulated heads were in reasonable agreement with observed heads at the beginning of water year typically for the year 2004. The observed and simulated heads and concentrations are shown in figure 5.5. Since the observed data pertaining to concentrations are not available, these are not plotted.

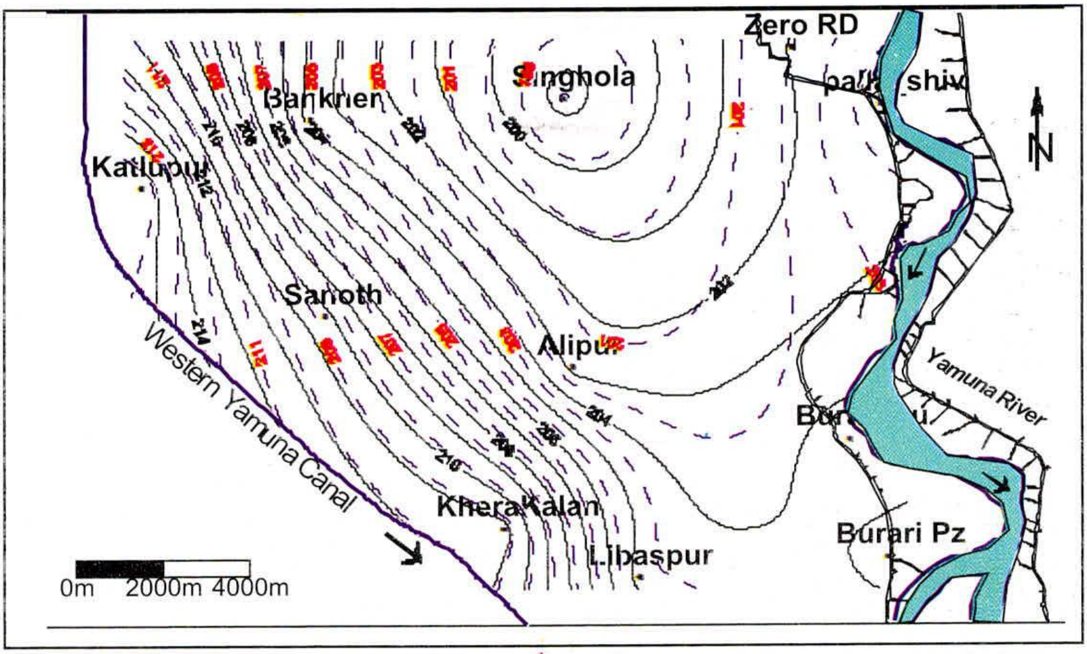


Fig. 5.5 Observed (continuous line) and Simulated (dashed line) contours of groundwater levels - first layer beginning monsoon season, year 2004.

5.3 Modeling Area of Interest – TMR model

The actual area of interest (AOI) as discussed earlier is the region close to the production wells defined by boundaries ABCD in figure5.4. The TMR feature built in the pre-processor (Rumbaugh 2004) was used to isolate the AOI from the RAM. A finer grid with 125 x 125 m is used for the TMR model. Almost all features (with some exceptions) of the original model are exported into the TMR model. The western boundary (i.e. edge AB of AOI in figure 5.4) within the TMR model is now represented as an equivalent constant head boundary varying in space and not in time (a CHD file of MODFLOW 2000 is created). The TMR model with more that 36000 active cells were separately run and were found to behave approximately similar to original model in terms of aquifer responses i.e. heads and concentrations.

The TMR aquifer model for the AOI is used for further analysis. However, since the TMR model still involves high computational burden (due to finer grid despite reduction in areal extent) it needs to be further replaced with ANN model as discussed in the next section.

5.4 Application of Model–1 to Real System at Palla using Virtual TMR model for full groundwater development

5.4.1 Data generation, ANN Training and Optimal Solution

Illustration of management models 1 & 2 using simplified aquifer models were discussed earlier in chapter 4. Model-1 seeks to maximize pumpages from production wells in space and time subject to a set of constraints. In the real system under consideration there are 89 production wells. Assuming 10 percent of the wells need maintenance and repair at any time, it is proposed to operate only 80 wells at any given time.

Since the solution methodology uses S/O technique, the number of decision variables need to be restricted, failing which the computational burden will become unmanageable even with ANN as the virtual simulator on a desktop PC. Therefore the 80 wells were grouped into 8 subgroups with each group containing 10 wells (see figure 5.6). This implies 8 decision variables during each time step or season. In all there are 16 decision variables corresponding to monsoon and non-monsoon seasons.

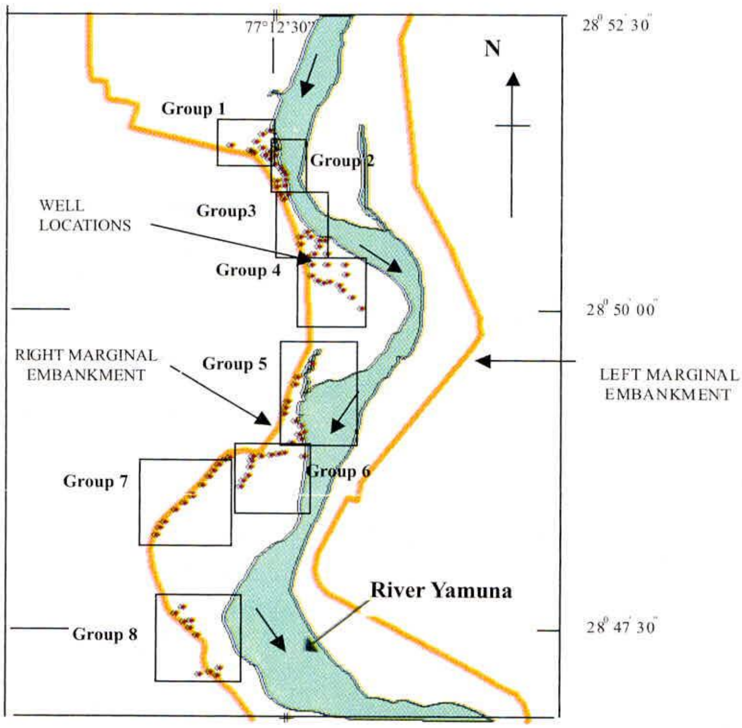


Fig. 5.6 River Yamuna near Delhi showing group well locations

The range of pumping for each group was restricted between 200 to 2000 m^3/d with respect to the installed pumping capacities of the real system. Within each group same rate of pumping was assumed. Thus random pumpages were generated within the above range and were assigned to the 8 groups during each of the two stress periods corresponding to monsoon and nonmonsoon season. Uniform rainfall recharge (10 percent of rainfall) and additional flood recharge within the embankment (0.5m) was assumed for monsoon season (see figure 5.7). No recharge was assumed during the non-monsoon season. The SEAWAT – 2000 was repeatedly executed with TMR aquifer model discussed earlier for generating data sets for ANN training. No constraints were imposed for generating data sets for ANN training. Each run was found to take nearly 20 minutes (Pentium IV PC, 2.4 GHz processor) involving 2 stress periods of 180 days each corresponding to the two seasons.

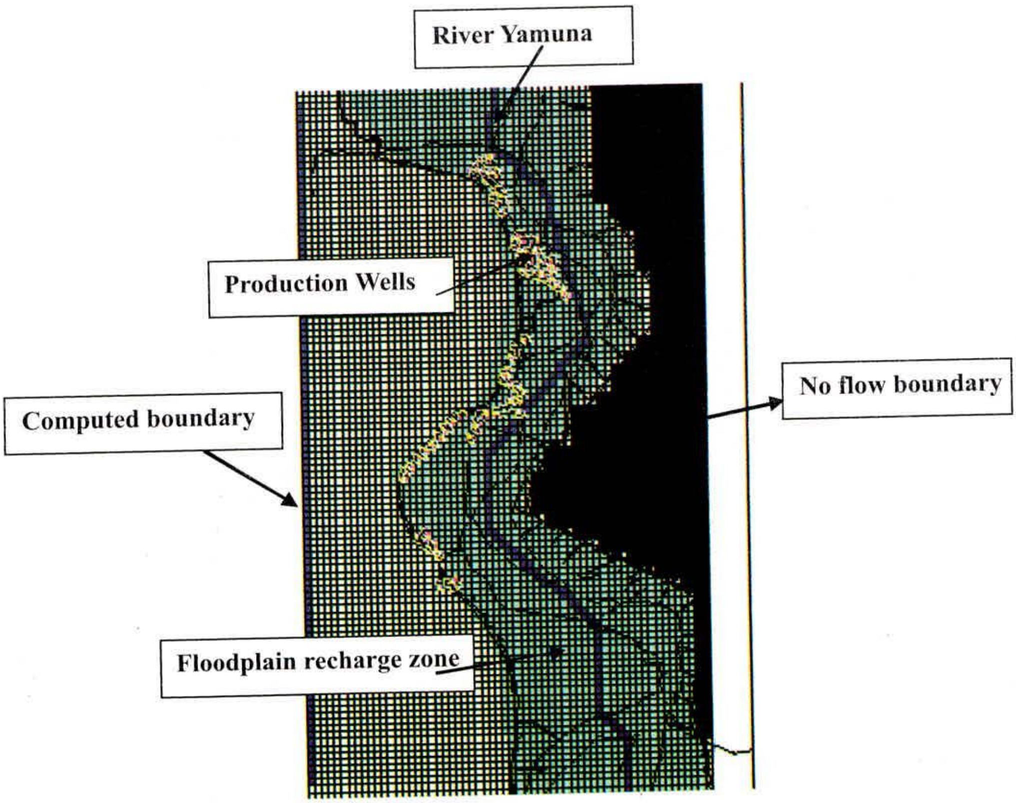


Fig. 5.7 Finite difference grid of TMR model showing extent of floodplain recharge

During each stress period the 8 pumpages and their corresponding concentrations were recorded at typical well locations representative of the subgroup of 10 wells. This meant during each run 16 pumpages and their corresponding concentrations. Heads were not recorded as it was presumed that water quality and not quantity was a limiting constraint. Some 250 data sets were generated and appended in stages involving nearly 83 hours of total computer execution time. The ANN training was carried out on similar lines as discussed before in section 4.

The S/O model was implemented with ANN as virtual simulator. The model-1 seeks to determine maximum pumpage subject to water quality constraint to meet drinking water requirements. The total dissolved solids of water should not exceed 1kg/m^3 (1000 mg/l) as per drinking water standards in India. The optimal solution where in the average salinity of the 8 groups (in grid cells at well screen locations in fourth layer) during each stress period was restricted to 720 mg/l corresponding to pumping of 24 MGD is presented in table 5.2. Clearly if the salinity level is relaxed a higher objective function can be realized. This leads to a tradeoff curve as shown in figure 5.8. The tradeoff curve prioritizes the amount of groundwater pumpage with respect to acceptable levels of salinity.

Table 5.2.
Optimal Pumping Schedule from a group of 80 wells with average salinity of all groups constrained at 720 mg/l to pump 24 MGD

	Group 1	Group 2	Group 3	Group 4	Group 5	Group 6	Group 7	Group 8
Installed	2993	1922	2267	2611	1196	2700	1250	2000
Capacities of	2938	3000	2500	2500	1310	1950	2779	2146
Production	2500	2410	2500	2500	2339	2104	1639	2267
wells	2500	3250	2500	2500	1950	2400	1739	2074
(m^3/day)	2543	2550	2500	2500	2600	1922	3243	850
Running at	2267	900	2500	2500	2260	1922	2939	1660
full capacity	2267	3150	2907	1971	2500	1922	1310	1979
for duration	2543	2679	3000	2104	2100	2188	1488	2074
indicated	2267	2543	2500	2500	2407	2675	1628	1979
below	2814	2407	2500	2819	2100	2747	2000	1475
Optimal pumpage per day (m^3/day)								
Monsoon	18738	19661	8212	18763	6439	8382	17226	14739
Nonmonsoon	17593	18637	6038	14151	9448	7831	12465	17484
Duration of pumping per day (hours)								
Monsoon	17.5	19.0	7.7	18.4	7.4	8.9	20.7	19.1
Nonmonsoon	16.5	18.0	5.6	13.9	10.9	8.3	14.9	22.7

5.4.2 Mass balance and effect of Induced flood recharge

The optimal solution (table 5.2) when implemented using the actual simulator SEAWAT – 2000 gives the picture of total flux mass balance (kgs) on an annual basis

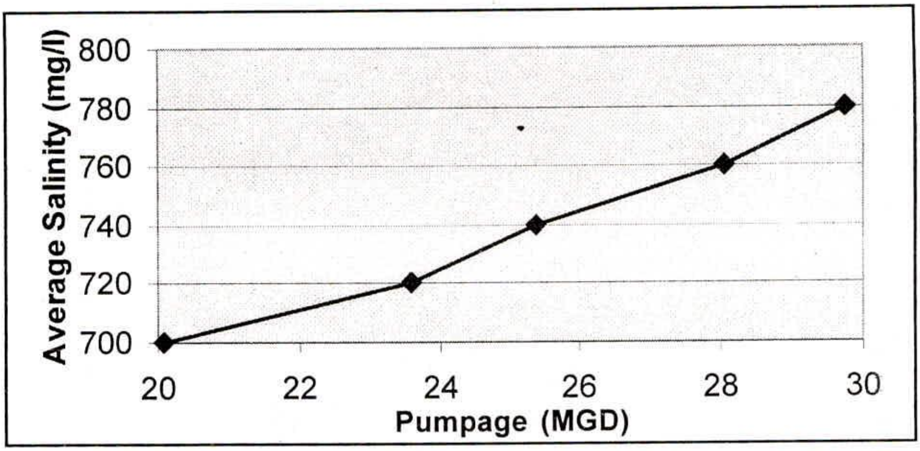


Fig. 5.8 Tradeoff curve between total pumpage and salinity

(360 days) as under. The mass balance with and without optimal pumpages from Palla well field helps in understanding the aquifer flow dynamics.

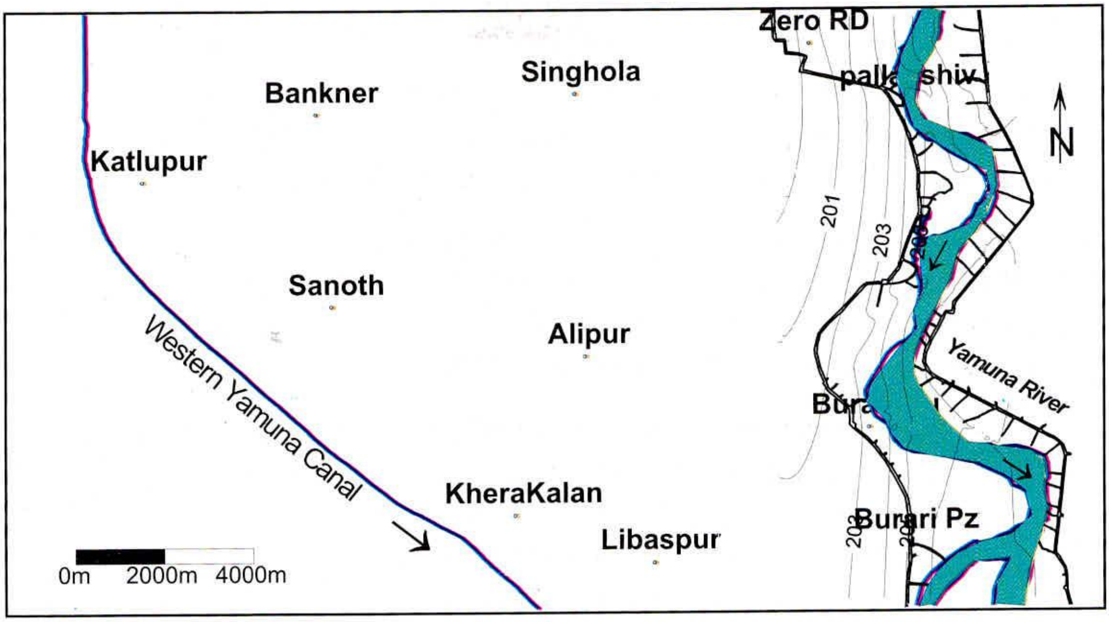
	With Palla Well pumping	*Without Palla Well pumping*
MASS INFLOW		
1. Storage	17210954422.7	7394235191.2
2. Constant head (flux from western side)	349135740.7	95267435.1
3. Wells	0.0	0.0
4. River leakage	25870685059.5	4341989678.0
5. Recharge	22185506250.0	22185506250.0
6. Correction for Vol.	6311470.4	3422899.4
7. Total inflow	65622592943.4	34020421453.9
MASS OUTFLOW		
1. Storage	4110891021.9	8245771662.6
2. Constant head (flux from western side)	1094317742.4	1957334680.1
3. Wells	57455247430.0	18582724402.5
4. River leakage	2898353462.0	5177833471.3
5. Recharge	0.0	0.0
6. Correction for Vol.	63790004.2	56763850.4
7. Total outflow	65622599660.8	34020428067.2
8. Inflow - Outflow	-6717.3	-6613.3
9. Percent error (not significant up to 4th decimal place)	0.0	0.0

While the amount of recharge on a seasonal basis is the same for the two cases above, the aquifer storage, river leakage, flux from western boundary and the draft (pumpage) are different. The flux from western boundary is not significant (relative to total inflow/ outflow). This indicates that a no-flow boundary could as well be used as an approximation in place of a constant head boundary condition arrived using TMR model along the western side of study area (AOI).

From the mass balance table above with Palla wells pumping about 57 billion kg of groundwater will meet demand from agricultural (18 billion kg) and drinking water at Palla (39 billion kg corresponding to 24 MGD). This pumping comes from rainfall and induced flood recharge (40%), river boundary (38%) and aquifer storage (22%).

The aquifer storage is depleted due to Palla well fields pumping. It is important to note the values of flow into and out of aquifer storage for the two cases. For the first case with Palla well pumping a net storage space of approximately 13 billion kgs is created due to a modest draft of 2 to 4 meters at the end of a year (see figure 5.9). On the other hand without Palla well pumping a negative or excess storage of about one billion kg joins the river (constant head) boundary. Therefore Palla well pumping helps in utilizing groundwater recharge, which would otherwise join the river boundary.

It is important to note that recharge in the present study was estimated on the assumption that 10% of the annual rainfall (700 mm) reaches the groundwater table. Further an additional flood recharge of 500 mm during the monsoon season is assumed to occur in the flood plain. These values were verified through approximate calibration of the regional model in terms of observed groundwater levels (figure 5.5). However this value needs to be experimentally determined for reliable estimation by installing a network of peizometers in the floodplain. This will help assess flood recharge for each flood event during the monsoon season to arrive at a dependable recharge on a seasonal basis. This assessment could be highly variable for a flood year when compared to a drought year. Reportedly, the flood level reaches 210.6 meters (high flood level) at least 2 or 3 times near the well fields at Palla on an average during the monsoon season. The alluvial sandy soils in the top layer with high hydraulic conductivity and storage properties can easily recharge the draft space of 2 to 3 meters discussed in the previous paragraph during a normal flood during the monsoon season.



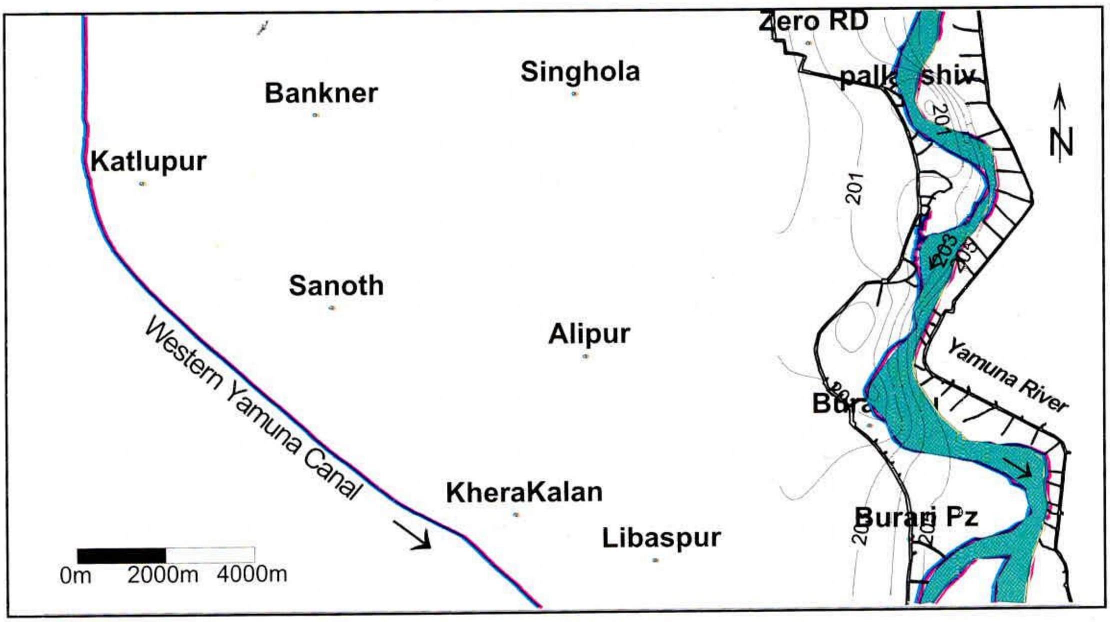


Fig. 5.9 Isoheads in the area of interest (AOI) at the beginning and end of the year for a constant to pumping of 24 MGD at Palla.

The river leakage (which could be either way) or conductance depends mainly on hydraulic conductivity (of bed material and its thickness) and the head difference between river stage and the groundwater level in the well field. The amount of river leakage in terms of mass balance needs to be looked with caution in the context of constant head boundary as an infinite source of supply. A significant amount of water comes directly in the well field due to proximity of the river boundary. River as a constant source of supply in the model is a reasonable assumption given the fact that the river Yamuna is perennial.

5.4.3 Discussion of results

The results of model 1 application are consistent with the philosophy of operating skimming wells discussed in illustrative application using hypothetical data in chapter 4. The evolution of model solution is indicative of the near optimal solution considering the large number of iterations involved in arriving at the solution. The model prefers to pump more quantity of groundwater from locations, which have minimum interference in upconing. In other words it chooses locations from which the average salinity is minimum.

In northern part the cluster of wells are very closely spaced, therefore except the first group of wells, which does not have interference from one side, the second and third groups show reduced pumpage. In the southern part although the saline interface is raised the model still prefers to pump from these wells due to the wide spacing among the wells.

The tradeoff curve helps the decision maker to prioritize groundwater pumpage with respect to acceptable salinity of water (figure 5.8). The tradeoff curve shows approximately a linear trend.

5.5 Application of Model–2 to Real System at Palla using Virtual TMR model for partial groundwater development

5.5.1 Data generation, ANN Training and Optimal Solution

Application of model-2 is intended where in only part of the wells are operated to supplement a given demand or to meet a partial demand. Model-2 was applied to the same group of 80 wells in 8 subgroups. Here the model seeks to minimise total concentration at specific locations that are optimal out of 8 groups. Since at each location 10 wells operate the concentration is chosen at any one representative location.

To illustrate the model it is assumed that peak demand is required to be met for a period of one month during the summer season i.e. with no recharge. The model begins from quasi-steady state condition as discussed in the previous section. The pumps are assumed to be operated for 12 hours a day. It is required to determine the optimal locations of 3, 4 and 5 groups out of the possible 8 groups in terms of zero-one (on-off) decision variables. Since there are only 8 decision variables (zero-one) the combinatorial problem can be solved by enumeration or brute force method. However the simulator has to be replaced with ANN virtual model.

As discussed previously the data patterns (about 200) were generated by randomly choosing any 4 groups for pumping while assigning remaining groups with zero pumping with SEAWAT-2000 simulator. This was followed by ANN training. The goodness of fit for calibration and validation using typically 10 and 50 data patterns respectively is shown in figure 5.10 and figure 5.11. The virtual TMR model was subsequently embedded in S/O model for optimisation using the SA algorithm. The SA parameters are arrived by trial as discussed in the previous section. The optimal solution is presented in table 5.3 below.

Table 5.3.
Optimal Spatial Pumping locations (On/ Off) of a subset of ells which seeks to minimize salinity using model-2 (duration of pumping is one month)

	Group 1	Group 2	Group 3	Group 4	Group 5	Group 6	Group 7	Group 8
Installed Capacities of Production wells (m^3/day) Running for 12 hours a day	2993	1922	2267	2611	1196	2700	1250	2000
	2938	3000	2500	2500	1310	1950	2779	2146
	2500	2410	2500	2500	2339	2104	1639	2267
	2500	3250	2500	2500	1950	2400	1739	2074
	2543	2550	2500	2500	2600	1922	3243	850
	2267	900	2500	2500	2260	1922	2939	1660
	2267	3150	2907	1971	2500	1922	1310	1979
	2543	2679	3000	2104	2100	2188	1488	2074
	2267	2543	2500	2500	2407	2675	1628	1979
	2814	2407	2500	2819	2100	2747	2000	1475
Optimal Solution for operating part of the group of wells								
30-wells operation Demand met =8.0 MGD	**Off**	**Off**	**On**	**On**	**Off**	**On**	**Off**	**Off**
40-wells operation Demand met =10.3 MGD	**Off**	**Off**	**On**	**On**	**On**	**On**	**Off**	**Off**
50-wells operation Demand met =12.5 MGD	**Off**	**Off**	**On**	**On**	**On**	**On**	**On**	**Off**

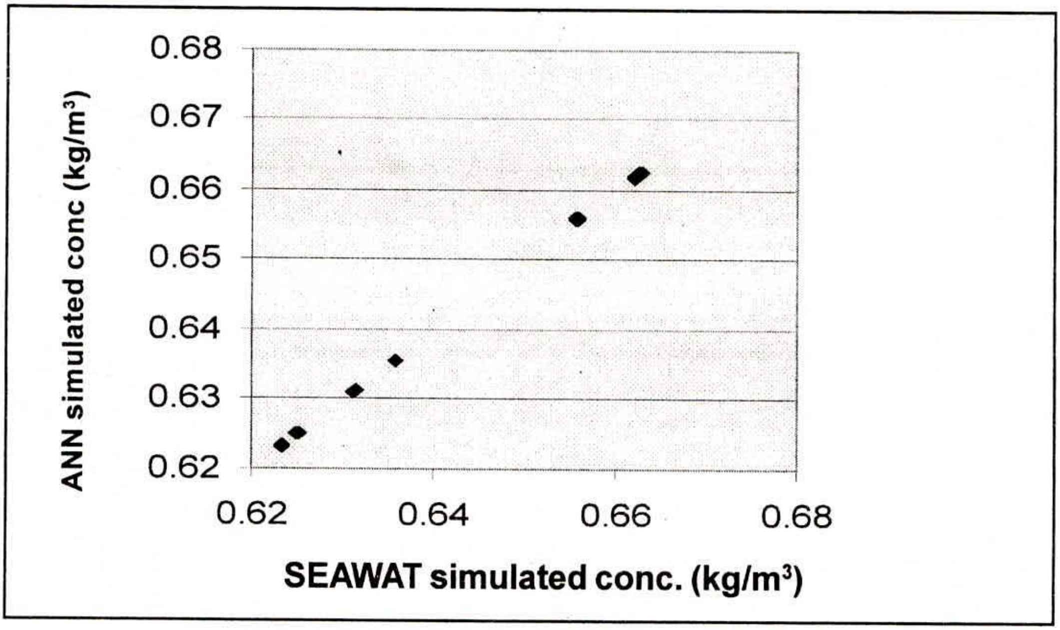


Figure 5.10 Typical SEAWAT/ ANN computed concentrations at one representa tive location for calibration

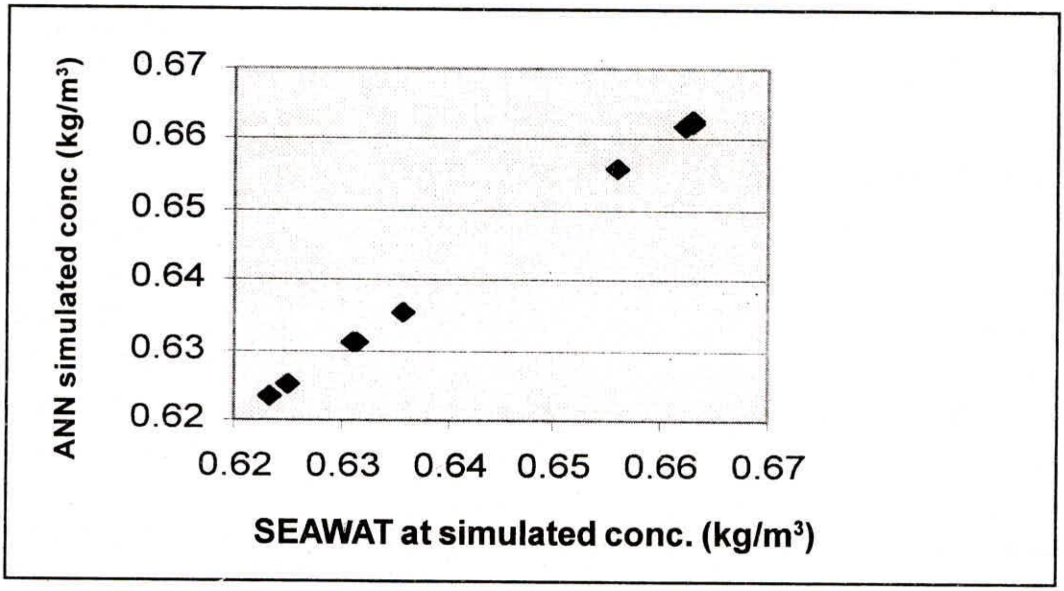


Figure 5.11 Typical SEAWAT/ ANN computed concentrations at one representative location for validation

Partial groundwater development for a given period say 30 days could be operated by alternating different group of wells during two time steps. In other words staggering along both space and time. The model was therefore implemented on similar lines after going through the steps of ANN training and optimisation using the S/O model in two time steps of 15 days each (i.e. 16 decision variables for the same 8 groups during two time steps. The optimal solution is presented in table 5.4

Table 5.4.

Optimal Spatial and temporal Pumping locations (On/ Off) of a subset of wells which seeks to minimize salinity using model-2 (duration of pumping is one month

	Group 1	Group 2	Group 3	Group 4	Group 5	Group 6	Group 7	Group 8
Installed Capacities of Production wells (m^3/day) Running for 12 hours a day	2993	1922	2267	2611	1196	2700	1250	2000
	2938	3000	2500	2500	1310	1950	2779	2146
	2500	2410	2500	2500	2339	2104	1639	2267
	2500	3250	2500	2500	1950	2400	1739	2074
	2543	2550	2500	2500	2600	1922	3243	850
	2267	900	2500	2500	2260	1922	2939	1660
	2267	3150	2907	1971	2500	1922	1310	1979
	2543	2679	3000	2104	2100	2188	1488	2074
	2267	2543	2500	2500	2407	2675	1628	1979
	2814	2407	2500	2819	2100	2747	2000	1475
Optimal Solution for operating part of the group of wells								
During first 15 days	**Off**	**Off**	**On**	**On**	**On**	**On**	**Off**	**Off**
During next 15 days	**Off**	**Off**	**On**	**On**	**On**	**On**	**On**	**Off**

5.5.2 Discussion of results

The Relative concentrations for different combinations of 3, 4 and 5 well groups among eight well groups invariably decide the optimal solution. The peak demand that can be met for the 3, 4 and 5 well groups are 8.0, 10.3 and 12.5 MGD respectively. The model prefers to choose such groups from which least salinity is encountered at the end of the pumping period i.e. one month. The 3-Well group prefers 3rd, 4th and 6th groups as evident from the figure 5.6. These wells encounter least salinity due to spatial staggering. While the groups 7th and 8th also have wide spacing along the river but have a raised saline interface and hence not included. Similar argument can be said in respect of 4 and 5 well groups.

In table 5.4 the model prefers groups 3, 4, 5 and 6 for both the time periods. Evidently the model prefers above locations because of the wide spacing among this group of wells. This also implies that in this particular case the spatial staggering clearly dominates the temporal staggering for minimising the total salinity from the 4 groups of wells.

5.6 Limitations of Modeling Study and Data Availability

Limitations of a modeling study mainly stem from assumptions that are built in numerical and conceptual models. Further a modeling study is demanding in terms of data requirement that are often not available. The present study is no exception to these limitations. The limitations include the following:

1. It is difficult to represent the boundary condition pertaining to geologically occurring saline water in deeper layers, which causes upconing phenomenon. The only information available is that a certain amount of salinity (TDS or EC) is known at some known depth. Details of hydraulic conditions (or peizometric head) are not known. Therefore a constant concentration (2 Kg/m^3) is assumed in the bottom-most layer in the present study. This may be the only a reasonable approximation of the reality.
2. River is represented as a time invariant specified head boundary condition based on riverbed details and site inspection. Data pertaining to river discharge, flood levels and cross-sections are not available.
3. There is no data pertaining to water quality (salinity) in space and time. Therefore even though a density dependent model is used only heads are calibrated to field conditions. However it can be assumed that concentration is indirectly reflected through heads in a density dependent flow phenomena.

6.0 CONCLUSIONS AND RECOMMENDATIONS

1. The guiding philosophy of skimming wells prone to upconing in general must be based on optimal spacing and operating the wells by staggering both in space and time.
2. The proposed optimum pumping schedules (tables 5.2, 5.3 and 5.4) can be used for field implementation based on existing locations and installed pump capacities at Palla well field.
3. The existing well locations, their adjacent spacing (of 90 wells) i.e. the group of wells (especially northern side) is closely spaced resulting in well

interference i.e. upconing below the pumping screen locations. This interference enhances the advective velocities of solute (salt water) towards the grid cells, containing the well screens, leading to increased concentration or salinity. Therefore care must be taken while deciding the location of future wells in the study area or similar study areas.

4. The flood recharge during the monsoon season in the upper alluvial sandy layer is expected to be abundant. The aquifer properties (specific yield and hydraulic conductivity) are conducive for causing significant recharge during floods even if they are of short duration. Nearly 25 – 30 MGD of water can be drawn safely during both monsoon and nonmonsoon seasons to meet drinking water standards (i.e. salinity less than 1000 mg/l). More groundwater extraction could be limited by quality and not quantity. However this will lead to withdrawal of water from the river boundary. The tradeoff curve (figure 5.8) prioritizes groundwater development in the study area.

5. Palla well fields help in utilizing the induced flood recharge, which would otherwise join river boundary.

6. When part of the wells must be operated to supplement demand from other sources or to meet peak demand during the pre-monsoon season model 2 provides (table 5.3) the best solution. This minimizes the salinity and prefers group of wells, which have minimum well interference (due to upconing). The model in general prefers wells other than those in the northern side clusters of wells. Preferably groups 3 through 6 may be operated in view of wide spacing of wells. In other words spatial staggering is more dominant to temporal staggering.

7. In the present study each group of well contained 10 wells. This was done to minimise the number of decision variables and constraints to minimum. The ultimate goal was to keep computational burdens that could be managed on a desktop PC. However more improved solutions could be obtained if smaller group of wells (say 5 wells per group) with more number of decision variables. This could be achieved through parallel processors.

8. Considering the limitations of model assumptions and data availability the results from this study are suggestive and subjective.

9. Further improvements in model could be considered when transient data pertaining river stage and groundwater salinity in space and time are made available.

6.1 Scope of future Work

The results of a combined simulation-optimisation model largely depend on the extent of calibration of an aquifer model to field conditions. There is further scope in transient model calibration to realistic field conditions through improved data collection and understanding of the aquifer system under study. The data collection must include:

1. A network of peizometers with in the flood plain to make a realistic assessment of flood recharge during the monsoon season.
2. Water quality data (salinity) in shallow and deeper layer aquifers in the study area.
3. A realistic assessment of depth and salinity of underlying aquifer in the river Yamuna flood plain.
4. Isotope data to assess groundwater contribution to river Yamuna at specific locations.
5. River stage and regulated discharge of river Yamuna near Palla village.

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DISCLAIMER

The opinions expressed in this report are solely those of the authors i.e. scientists. National Institute of Hydrology (NIH) and Central Ground Water Board (CGWB) are not responsible whatsoever.

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APPENDIX A

DEPOSIT WELLS CONSTRUCTED IN PALLA AREA, YAMUNA FLOOD PLAIN, NCT DELHI

Deposit Well No.	Depth of const-ruction	Water LeveL	Discharge
	M.bgl	*Mbgl*	*Lpm*
1.	44.00	3.42	2550
2.	45.00	4.07	3250
3.	46.00	4.08	3150
4.	45.00	2.72	3000
5.	40.50	4.07	2410
6.	46.00	4.00	900
7.	46.00	2.78	2815
8.	45.00	6.07	2680
9.	43.00	4.17	3000
10.	40.00	3.50	2500
11.	44.00	3.70	2500
12.	44.00	3.80	2500
13.	38.00	3.65	2500
14.	38.00	3.90	2500
15.	55.00	3.80	2907
16.	55.00	4.05	2820
17.	51.00	—	2500
18.	53.00	4.57	2612
19.	44.00	3.74	2994
20.	44.00	3.72	2938
21	44.00	—	2500
22	45.00	—	2500
23	50.00	—	2500
24	41.00	—	2500
25	44.00	—	2500
26	45.00	—	2500
27	44.00	—	2500
28	41.00	—	2500

(Contd.)

29	43.00	—	2500
30	61	4.67	2100
31	51	5.23	2400
32	64	5.05	2500
33	57	—	2260
34	49	4.34	2700
35	53.00	—	2600
36	41.00	5.10	2100
37	42.00	5.01	1950
38	45.00	—	1950
39	39.00	—	1980
40	31.00	—	1980
41	39.00	5.31	2340
42	40.00	5.13	1628
43	44.00	4.74	2267
44	43.00	6.75	1310
45	40.00	—	1640
46	46.00	—	1488
47	45.00	6.18	2267
48	44	5.80	1196
49	37	—	2780
50	34	—	2074
51	37.00	6.27	1250
52	47.00	5.60	2544
53	43.00	8.32	1250
54	43.00	—	1310
55	34.00	—	850
56	43.00	5.92	1740
57	47.00	8.10	1476
58	51.00	5.35	2267
59	39.00	5.10	2267
60	44.00	6.72	2940
61	47.00	5.90	2408
62	44.00	6.28	3244
63	43.00	4.80	2544

(Contd.)

64	36.00	6.69	2074
65	44.00	4.75	2676
66	48.00	7.34	2267
67	45.00	4.86	2748
68	33.00	3.42	1660
69	45.00	5.67	1923
70	35.00	5.23	2146
71	38.00	4.50	2188
72	42.00	3.81	2105
73	50.00	4.96	2105
74	44.00	—	—
75	51.00	4.99	1972
76	45.00	4.83	—
77	43.00	3.43	2408
78	43.00	4.70	1923
79	51.00	5.50	1923
80	48.00	5.20	1923
81	51.0	4.70	1128
82	42.0	4.43	2105
83	50.0	4.78	1734
84	40.0	4.35	1874
85	40.0	5.26	2105
86	41.0	4.90	2544
87	46.0	5.63	2408
88	40.0	5.63	2188
89	45.0	—	2680

APPENDIX B

GROUNDWATER DRAFT

				Weighted Average	
For Irrigation Purpose					
Monsoon (3 months) (Meter^3/day)	182667	Non Monsoon (9 months) (Meter^3/day) 119564	302231	135123.644	38.38739
For domestic, Industrial and farmhouses etc		Non Monsoon (9 months) (Meter^3/day) 13200	20422		
Monsoon (3 months) (Meter^3/day)	7222				
For Industries		Non Monsoon (9 months) (Meter^3/day) 21200	42422		
Monsoon (3 months) (Meter^3/day)	21222				
(Meter^3 /day in 220 Sq. Km		**Total**	365075		
		Per grid			
Weighted Average		38.38739 m³/day/grid cell			

यस्था समुद्र उत सिन्धुरापो यस्यामत्न कृष्टयः संवभूवुः।
यस्यामिंद जिन्वति प्राषदेजत सा नो भूमिः पूर्व पेयें दधातु।।
(अथर्व वेद)

Those who use rainwater wisely by means of rivers, wells, canals etc. for the purposes of navigation, recreation, agriculture etc. prosper all the time.
(Atharva Veda)

शंत आपो हेमवतीः शमु ते सन्तु वर्ष्याः।
शं ते सनिष्पक्ष आपः शमु ते सन्तु वर्ष्याः।।
(अथर्व वेद)

One should take managerial action to use and conserve the water from mountains, wells, rivers and also rainwater for use in drinking, agriculture, industries etc.
(Atharva Veda)

Conserve Water - Save Life

Series of Existing Tubewells at Palla Village, North-west of NCT Delhi