Field Applicability of Design Methodologies for Groundwater Quality Monitoring Network

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Abstract: Protection of groundwater resources from contamination has been of increasing concern throughout the past decades. In practice, however, groundwater monitoring is performed based on the experience and intuition of experts or on the convenience. In dealing with groundwater contamination, we need to know what contaminants have the potential to threat the water quality and the distribution and concentration of the plumes. Monitoring of the subsurface environment through remote geophysical techniques or direct sampling from wells can provide such information. Once known, the plume can be properly managed. Evaluation of existing methodologies for groundwater monitoring network design revealed that one should select an appropriate design method based on the purpose of the network and the availability of field information. Integer programming approach, one of the general purpose network design tools, and a cost-to-go function evaluation approach for special purpose network design were tested for field applicability. For the same contaminated aquifer, two approaches resulted in different well locations. The amount of information, however, was about the same.

1. Introduction

Recently the dependency on groundwater and the groundwater contamination occurrence are steadily increasing. This leads to the necessity of systematic monitoring network for groundwater quality surveillance. In Korea, there are legal procedures for groundwater quality monitoring in practice. Their scientific basis, however, are weak and most monitoring wells are placed based on the experience and intuition of the geohydrologist and convenience. According to the law, the monitoring must be conducted for the potential groundwater contaminating facilities such as underground storage tanks for petroleum or toxic chemicals. As for the monitoring well locations, the law vaguely states that one at the upstream of the facility and "about" three at the downstream must be installed to detect the movement of the contaminant "immediately".

Therefore, the development of systematic and scientific methodology for the determination of well location, number, item and frequency, along with measurement and analysis techniques, is

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called for. This paper compares existing methodologies for groundwater quality monitoring and the field applicability of two representative methods is studied.

2. Considerations in Monitoring Network Design

When one designs a monitoring network, the questions he/she frequently faces are as follows:

1) What is the purpose of the network?
2) What are the legal, economical, or technical constraints?
3) How many monitoring wells are needed and where?
4) What should be measured?
5) How often should the measurement be taken?

Above questions are directly connected to the efficiency of the network, not to mention the installation and operating costs. Naturally some type of optimization must be introduced. In other words, a quantified objective function is maximized (or, minimized) under certain constraints so that monitoring well location, number and so forth must be determined.

There are two types of groundwater quality monitoring network. The first one is for general monitoring purpose, i.e., collection of information without specifying how the information will be used. The second one is for special purpose. One example is the network at the site of contaminated groundwater remediation. It collects the information to be used for developing cleanup strategies or for confirming the cleanup plans in action.

In a general purpose network, since it is not possible to quantify the monetary or other discernible benefits from their operation, statistical measures, such as the mean square error of estimation of concentration or some other quantity of general interest, are used as surrogates. The general idea is that the smaller the mean square error, the higher the value of the information obtained from the monitoring network. In a special purpose network, various objectives can be considered: Typically, the responsible party must pay for the decontamination and the monitoring needed to characterize the site, design the cleanup, and demonstrate that water quality criteria are met. So, the challenge is how to design a monitoring network that minimizes the total cost of meeting these objectives.

3. Review of Existing Methodologies

Table 1 lists the summary of representative methodologies for groundwater quality monitoring network design from the literature.

Massmann and Freeze (1987a, b) detailed a comprehensive framework for design of a landfill operation. Their objective was to maximize the net present value of a stream of benefits minus costs. Monitoring contributes to the objective function by reducing the probability of failure, or equivalently, increasing the probability of detection. They conducted Monte Carlo simulations to determine the probability of detection, given a certain monitoring network. This study presented a framework for decision analysis without dealing with technical issues of optimization and estimation.

Loaiciga (1988) selected the best sampling sites among a predetermined set of possible well

Table 1. Representative Methodologies for Groundwater Quality Monitoring Network

Author	Method	Objective function	Domain	Transport Eq.
Massmann and Freeze (1987a, b)	Enumeration	Max. net present value (= benefit-cost-risk)	2D	O
Loaiciga (1988)	BNP	Min. fixed cost plus estimation error	2D	X
Hsueh and Rajagopal (1988)	IP	Max. information coeff. based on detection probability	2D	X
Meyer and Brill (1988)	IP	Max. number of plumes detected	2D	O
Loaiciga (1989)	MIP	Min. variance of estimation error	2D	O
Knopman and Voss (1989)	Multi-objective programming	Max. prediction difference, Min. estimation variance, Min. cost	1D	O
Graham and McLaughlin (1989a, b)	Variance reduction	Min. concentration variance	2D	O
Tucciarelli and Pinder (1991)	QL	Min. pumping and measurement cost	2D	O
Lee and Kitanidis (1996)	Dual Control	Min. pumping and measurement cost	2D	O

BNP = Binary Nonlinear Programming, IP = Integer Programming, MIP = Mixed IP, QL = Linearity Algorithm

locations. He chose as objective function the sum of the well installation cost plus an expected loss associated with the estimation error of the concentration average over the domain. He assumed known shape of the contaminant plume so that there was no need to solve the solute transport equation.

Hsueh and Rajagopal (1988) used a 0-1 integer programming model for deciding what and where to sample. They were concerned with groundwater quality over a large state-wide aquifer, not specifically with a plume in a single site. Thus, no site-specific information such as hydraulic conductivity was used, nor any estimation or simulation models. An "information coefficient", based on detection probabilities, significance of health and ecological effects, and the size of nearby populations, was minimized to select monitoring wells among two hundred possible well locations.

Meyer and Brill (1988) developed a method for the optimal placement of wells in a monitoring network using simulation models jointly with optimization methods. Contaminant transport simulation provides information about the location of plumes while an optimization model locates a given number of wells to maximize the probability of detection.

Loaiciga (1989) formulated the optimal sampling plan for groundwater quality monitoring as a mixed integer programming problem. A sampling plan consisted of the number and locations of sampling sites as well as the sampling frequency. He minimized the variance of estimation error subject to resource availability and unbiasedness constraints, accounting for changes in concentration through the advection-dispersion equation.

Knopman and Voss (1989) formulated the same problem as a multiobjective problem. They

considered the following objectives: model discrimination to identify the most descriptive mathematical model of transport, parameter estimation accuracy, and cost. A one-dimensional solute-transport problem was considered.

The variance reduction approach (Rouhani, 1985; Rouhani and Hall, 1988) adds to the network the groundwater sampling site that reduces the most the variance of estimation error associated with a set of established sampling locations. An "information response function" was used to select the location of each additional measurement, then a type of economic gain function was used to determine the number of new sites. Graham and McLaughlin (1989a, b) located new monitoring wells in areas where the concentration variance is highest. They found that a sequential groundwater quality monitoring program which evolves over time could provide better predictions, for a fixed budget, than a less flexible program which specifies well locations before samples are collected.

The methodology by Tucciarelli and Pinder (1991) can consider the effect of measurements on groundwater remediation. They determined pumping rates by minimizing the summation of pumping and measurement costs subject to chance constraints on concentration. The log-transmissivity covariance matrix, updated through new measurements, was related to the concentration covariance matrix using the transport equations and first-order analysis. Increased confidence in estimating concentrations contributed to reduction of the pumping rates, through the decrease in the magnitude of the stochastic part of the chance constraints. Problems like when and where to put monitoring wells were not addressed.

Lee and Kitanidis (1996) presented a method to determine the installation time and location of an additional monitoring well while the aquifer is being cleaned up. While rates of pumping and treatment are determined by the dual control method (a method for optimization with incomplete information) candidate well locations are ranked according to a "cost-to-go" index that measures the costs expected until the goals of remediation are met. This index accounts for the cost associated with uncertainty about the system and thus is useful in appraising the value of information from new measurements in the context of the specific cleanup effort. The usefulness of the method was illustrated through application to a hypothetical two-dimensional aquifer with uncertain initial estimates of the system parameters and variables.

More details can be found in Loaiciga et al. (1992).

4. Applicability Study

Two representative design methods were selected and their field applicability was studied by applying them to a hypothetical aquifer contaminated. The first method targets the plume detection and the second best fits to the situation when a contaminated aquifer is cleaned up via pump-and-treat in which additional monitoring well installation is questioned and the location and timing must be decided. Each method is based on the work of Meyer and Brill (1988), and Lee and Kitanidis (1996) respectively. The former determines the well location through a one-shot optimization (integer programming) procedure, and the latter through an adaptive one.

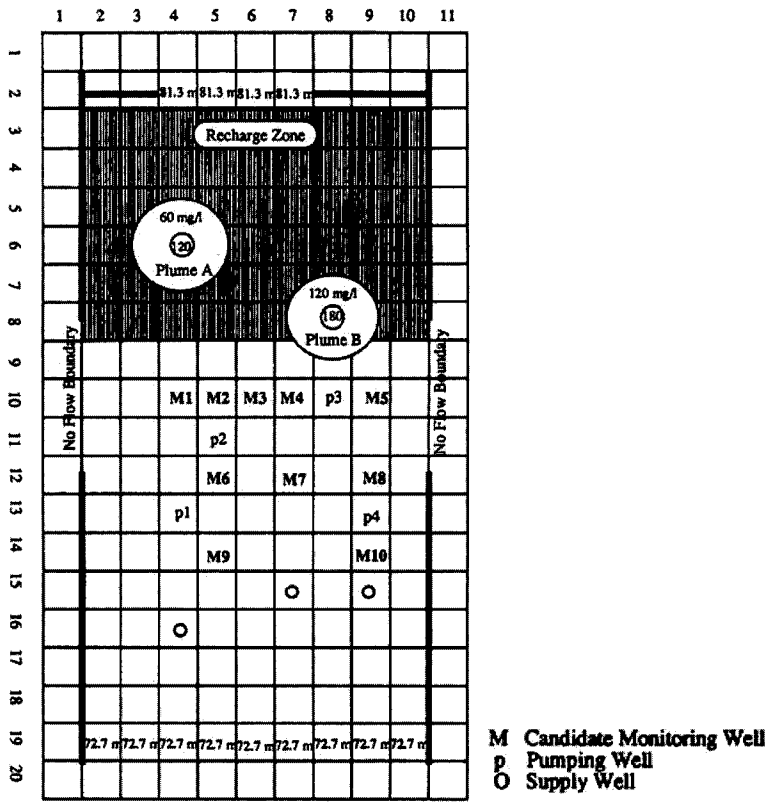

Fig. 1. Contaminated Aquifer with Pumping, Supply and Candidate Monitoring Wells

Studied area is shown in Fig. 1. The location of two plumes and wells (ten candidate well locations M1-M10, four pumping wells p1-p4, and three supply wells) are also shown in the figure. Parameters for aquifer simulation are listed in Table 2. Three zones of transmissivity are assumed. Note that, in practice, the best estimates of the parameters may be smaller or

Table 2. Parameters for Aquifer Simulation

aquifer width	220m
aquifer length	400m
aquifer thickness	4.2m
storativity	2.2×10^{-4}
effective porosity	0.3
retardation factor	2.5
longitudinal dispersivity	17m
transversal dispersivity	1.7m
recharge	2.2×10^{-3} m/d
Δx	20m
Δy	20m
Δt	11 days

Table 3. Estimates for Transmissivity

(Unit: m^2/day)

	Zone 1	Zone 2	Zone 3
Mean	18.4	4.9	130.4
Variance	30	5	110
True value	23	7	142

Table 4. Initial Estimates of Head and Concentration

head(m)	mean of upstream boundary mean of downstream boundary head gradient variance	81.3 72.7 0.024 9
plume A(mg/l)	range of mean variance	60 ~ 120 100
plume B(mg/l)	range of mean variance	120 ~ 180 300

larger than the true values. The initial estimates of transmissivities in the three zones differ from the true values. The best estimates (mean values) and estimation variances are given in Table 3. Correlation between different zone estimates is neglected. For each zone, the true transmissivity value is given in the same table. Initial estimates of hydraulic heads and solute concentrations are tabulated in Table 4. They are taken as independent random variables with means and variances. The mean values of the estimates are assumed to be the true values.

First, we consider the first method. The application procedure of this method is shown in Fig. 2.

Step 1 Collect field information needed for simulation.

Step 2 Formulate the optimization problem. Here, the following formulation was made.

$$\text{Maximize } Z = \sum_{i \in I} a_i y_i \tag{1}$$

subject to

$$\sum_{j \in N_i} x_j \geq y_i \qquad \forall i \in I,\ N_i \neq 0 \tag{2}$$

$$\sum_{j \in J} x_j = P \tag{3}$$

where a_i is the weighting factor assigned to plume i, d_{ij} is the concentration of plume i measured at well j, I is the set of plumes, J is the set of well locations, $N_i = \{j \in J \mid d_{ij} \geq S\}$; 0 if $d_{ij} \leq S\ \forall j \in J$; P is the number of wells to be installed, S is the water quality standard, $x_j = 1$ (when well is installed at location j); 0 (otherwise), and $y_i = 1$ (when plume i is detected); 0 (otherwise).

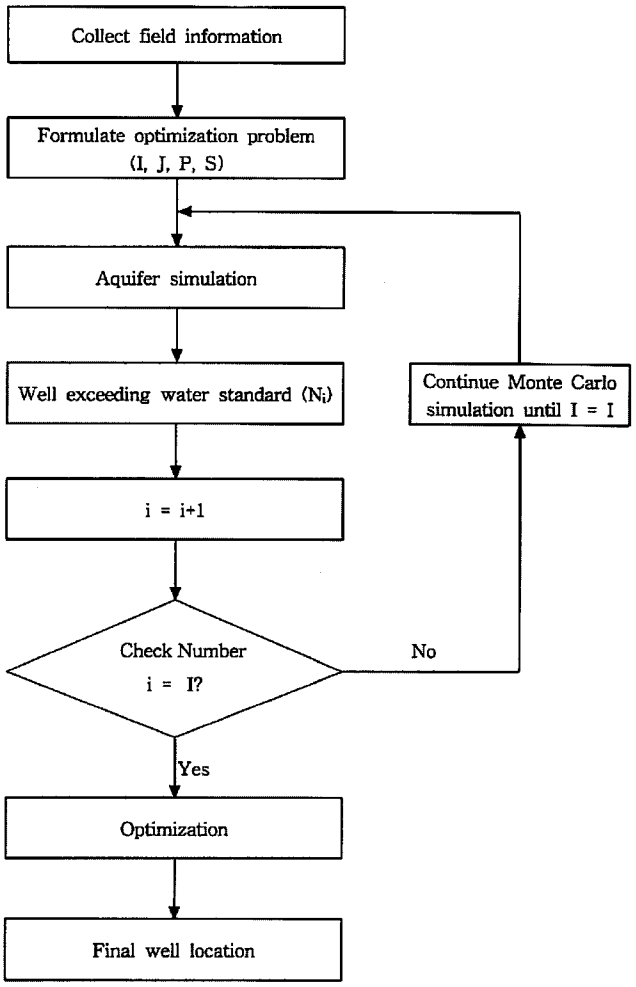

Fig. 2. Design Procedure Using Integer Programming

Step 3 Calculate the concentration for each realization using aquifer information in Tables 2-4. Concentration is calculated until the plume reaches a prescribed border (for instance, a line connecting M1 and M10 upstream of supply wells) For each realization, the set, N_i, of candidate well locations exceeding the water standards is identified.

Step 4 Integer programming is solved under constraints.

The objective function (Eq. 1) can be interpreted as maximizing the detection possibility of contaminants. Since 300 statistically identical plumes are generated for Monte Carlo simulation, I equals to 300. J becomes 14 because ten monitoring wells plus four pumping wells can be candidate locations. The problem of how many wells are needed is designer's choice. Therefore, P can be determined by law or budget. In this work P was set to 3 according to the law. S was 10 mg/l and a_i was set to 1 since all the plumes were generated from identical

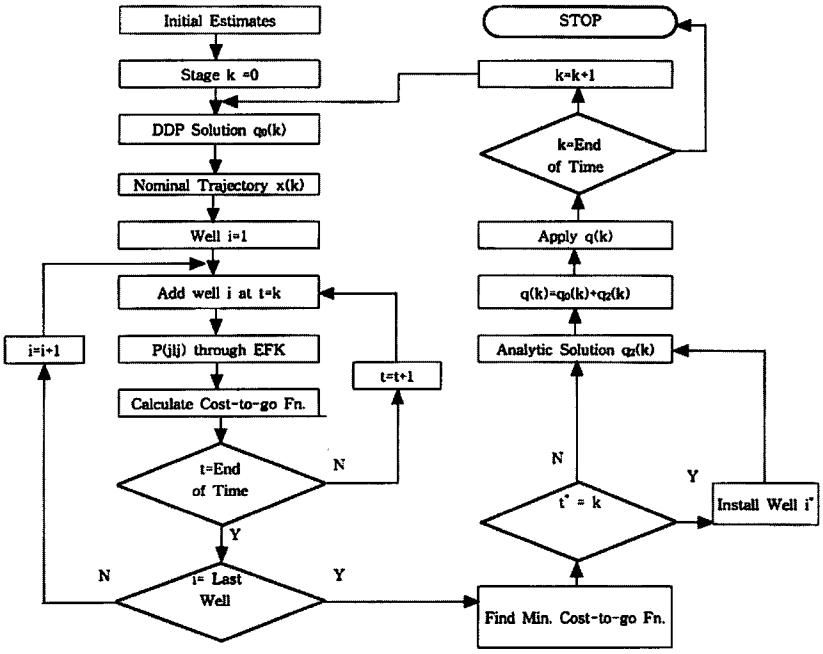

Fig. 3. Design Procedure Based on Cost-to-go Function Evaluation

conditions.

In this study, all 300 Monte Carlo simulations resulted in concentrations exceeding 10 mg/l at the predetermined border. This means that N_i and J are identical. Integer programming was solved using LINDO. The resulting three monitoring well locations turned out to be p2, p3, and M4 (see Fig. 1).

The core of the second method is comparing the cost-to-go function evaluated at the time of decision with those of future times. The procedure of the method is given in Fig. 3.

Step 1 Assume initial estimates of the aquifer parameters and pumping schedule.

Step 2 Set k = 0. (Note that the procedure can be initiated at any stage k.)

Step 3 Obtain the deterministic pumping policy, $\mathbf{q}_0(k)$, using constrained DDP.

Step 4 Calculate the nominal trajectory, $\mathbf{x}(k)$, using $\mathbf{q}_0(k)$ and the state-transition equation.

Step 5 Choose one candidate monitoring well. Add to the measurements the head and concentration at the new monitoring well.

Step 6 Propagate and update state estimation covariance, $\mathbf{P}(j/j)$, using the extended Kalman filtering based on $\mathbf{x}(k)$, $\mathbf{q}_0(k)$, and the fact that measurements will be collected at all monitoring points including the new well.

Step 7 Calculate the cost-to-go function.

Step 8 Repeat steps 5-7 assuming the well is installed at different stages. If a case is found that the cost-to-go function is lower than that of the current stage, go to step 9.

Step 9 Choose another well and repeat steps 5-8.

Step 10 Find the time stage which gives the lowest cost-to-go value for all monitoring well locations.

Step 11 If the resulting time stage is the current one, install the corresponding monitoring well now.

Step 12 If not, calculate the stochastic pumping rate, $q_2(k)$. Pump and treat with pumping rate $q(k)$, $q_0(k)$ plus $q_2(k)$, and go to the next time stage.

Step 13 Repeat steps 3-12 until the decision is made.

The objective function considered is

$$\begin{aligned} \text{Minimize} \quad Z = \; & 10,000 + 500(47-k) \\ & + E\,[\sum_{k=0}^{46}\{\, \boldsymbol{e}^T \boldsymbol{q}(k)\}^{0.6}(57.17 + 7.6[\{90\,\boldsymbol{e} - \boldsymbol{h}_p(k)\}^T \boldsymbol{q}(k)]^{0.5})] \end{aligned} \tag{4}$$

expressed in million dollars. This function is interpreted as the stagewise operation and maintenance costs summed up over the whole time horizon plus the cost of monitoring. E is the expectation operator, $\boldsymbol{e}$ is a column vector of ones and, $\boldsymbol{h}_p(k)$ is the hydraulic head at the pumping well at time k. Hydraulic lifts (90 $\boldsymbol{e}$ - $\boldsymbol{h}_p(k)$) times pumping rate determines the electric power cost that is a major portion of operating cost. The total time horizon (1.4 years) was divided into 47 stages. The cost of well installation ($10,000/well) and for operation such as well maintenance and sampling ($500/period) accounts for the cost for monitoring.

Since hydraulic head and concentration cannot be predicted with certainty, constraints on these variables must be described probabilistically, through the distribution of possible values. Here, the following reliability constraints are imposed. The probability that concentration over the aquifer should meet the water quality standard ($c^* =$ 10 mg/l) at the end of the time horizon, after decreasing with time (in this case, linear decrease), should not exceed some reliability level. Similarly, the probability of the hydraulic head dropping lower than the aquifer thickness ($h^* =$ 50 m) at any time should be less than some reliability level. In this work, the reliability level is chosen as 95%.

$$q_j(k) > 0 \quad \text{for all } j \tag{5}$$

$$\Pr\{c_i(k+1) \geq \frac{k(c^* - c_i(0))}{N-1} + c_i(0) \mid c_i(k)\} \leq 0.05 \quad \text{for all } i, k \tag{6}$$

Table 5 summarizes the results of Monte Carlo analysis. Different timings and locations were

Table 5. Savings due to Additional Monitoring Well

(Unit for cost: million $)

No. of realization	Installation stage	Well	No. of samples	Sampling cost	Total cost	Savings	Relative savings(%)
217	16	M4	31	0.0155	3.76~3.86	0.62~0.52	14.2~11.9
42	15	M4	32	0.0160	3.78~3.86	0.60~0.52	13.7~11.9
41	14	M5	33	0.0165	3.90~3.95	0.48~0.43	10.9~9.8

resulted in for the installation of a monitoring well for 300 realizations. Distinct timing and location incurred different operating cost. Maximum savings of 0.62 million dollars were obtained by installing well 4 at the beginning of stage 16. The recommended time of well installation varied among realizations. The optimal stages were: 14, 15, and 16 with a frequency of 13.7%(41/300), 14%(42/300), and 72.3%(217/300) of being selected as the best time to locate an additional well. Actual situation could be considered as one the realizations, and Monte Carlo analysis makes it possible to predict the field situation statistically.

Fig. 4 shows how the new information from the additional monitoring well affects the pumping rate for the case of well 4 installation at the beginning of stage 16. Due to the additional information coming from the extra well, there is less incentive to learn the system by pumping or to provide a safety factor. Less pumping resulted in less hydraulic lift and they both contributed to lowering the cost. The difference between pumping rates and thus the benefit of having an additional source of information became increasingly large with time.

Fig. 5 compares the solute concentration at the end of the time horizon with the two different pumping schedules explained above (no additional well and well 4 added at stage 16). Both cases satisfy the water quality standard, while the additional monitoring well case can save a maximum of 14.2% of the total cost through more effective redistribution of pumping.

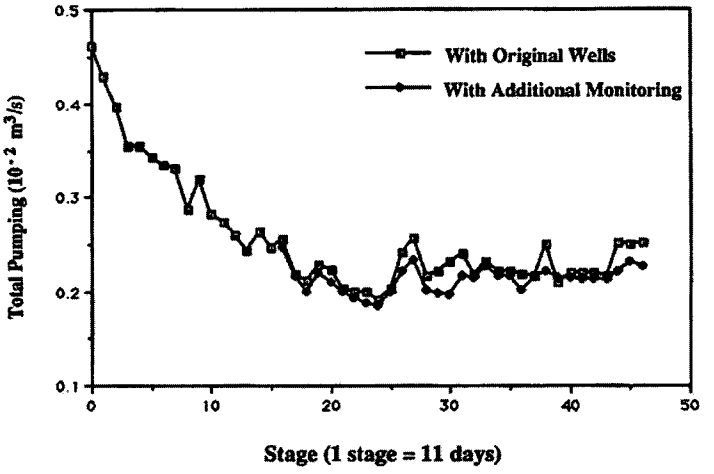

Fig. 4. Change of Total Pumping Rates with and without Monitoring Well

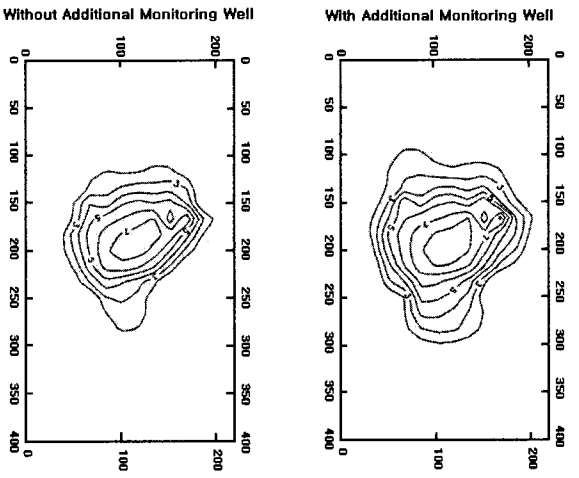

Fig. 5. Concentration at the end of Time Horizon with and without Monitoring Well

5. Conclusions

Groundwater quality monitoring is of importance for the protection of groundwater resources and human health. But the network design practice is frequently done based on non-scientific basis. This study reviewed the existing methodologies for groundwater quality monitoring network design and two representative methods were compared from the aspect of field applicability. The following conclusions were drawn.

(1) The purpose of the monitoring network to be developed must be clearly set and understood.

(2) The integer programming approach, a design method suited for general purpose monitoring network, and the cost-to-go function evaluation approach for aquifer cleanup resulted in different well locations. But the required amount of information was about the same.

(3) Two methods studied could be applied to a field relatively easily, if typical information necessary for groundwater solute transport simulation is available.

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