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# Improving Gas Storage Development Planning Through Simulation-Optimization

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# Improving Gas Storage Development Planning Through Simulation-Optimization

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## Abstract

This is the first of two papers describing the application of simulator-optimization methods to a natural gas storage field development planning problem. The results presented here illustrate the large gains in cost-effectiveness that can be made by employing the reservoir simulator as the foundation for a wide-ranging search for solutions to management problems. The current paper illustrates the application of these techniques given a deterministic view of the reservoir. A companion paper will illustrate adaptations needed to accommodate uncertainties regarding reservoir properties.

## Introduction

Although reservoir simulation is a well-established component of reservoir management throughout much of the petroleum industry, little use has been made of reservoir simulation coupled with systematic optimization techniques, i.e. simulation-optimization.

The main advantage of applying optimization tools, *per se*, to decision-making problems is that they are less restricted by human imagination than conventional case-by-case comparisons. As the number of competing engineering, economic, and environmental planning objectives and constraints increases, it becomes difficult for human planners to track complex interactions and select a manageable set of promising development strategies for examination. Using optimization techniques, the search can range over all possible combinations of variables, locating strategies whose effectiveness is not always obvious to planners.

The advantage of coupling the reservoir simulator to these optimization tools is that the search for strategies can be based on the simultaneous evaluation of reservoir performance measures and other economic/environmental/policy considerations. It is no longer necessary to treat technical decisions driven by simulator forecasts of reservoir response and these other components of the decision-making process as separate steps.

The single biggest obstacle to the application of optimization techniques using a reservoir simulator as the forecasting tool is the computational time required to complete a single simulation. Even the examination of 10 variations on a well-field design becomes cumbersome when a single run requires hours to complete. Extending the use of these simulators into optimization regimes involving hundreds or thousands of runs poses a computational problem bigger than most organizations are willing or able to tackle.

The ANN-GA solution to this problem is to train artificial neural networks (ANNs) to predict selected information that the simulator would normally predict. A heuristic technique such as the Genetic Algorithm (GA) then searches for increasingly better strategies (for example, the most productive in-fill drilling pattern), using the trained networks to evaluate the effectiveness of each strategy in place of the original simulator. After analysis of the results of the search, the best-performing strategies are submitted to the original simulator to confirm their performance. The components of the methodology are illustrated in **Fig. 1**.

The ANN-GA methodology was first developed to address computational bottlenecks in applying simulation-optimization techniques to groundwater remediation applications. Studies employing 2-D flow-and-transport models of a contaminated groundwater Superfund site have documented the benefits of simulation-optimization both with[1,2] and without[3] the assistance of ANNs. These studies are part of the long-standing interest in the field of water resources in the use of simulators in formal decision-making contexts[4].

The emphasis in the petroleum engineering literature, in contrast, has been on the evaluation of small sets of carefully selected scenarios, as exemplified by the work of Kumar and Ziegler[5], Coskuner and Lutes[6], and Kikani and Smith[7]. However, there are a few studies which have applied techniques which bear some resemblance to simulation-optimization methods.

Aanonsen and others[8] applied concepts from experimental design and response surfaces to optimize a reservoir response variable (e.g. oil production rate) according to reservoir management parameters (e.g. well location and flow rates). The goal was to build a response surface of discounted oil production from sample inputs consisting of the $x$ and $y$ coordinates of a single producer and the $x$ coordinate of a single injector. To account for uncertainties in the flow field, these three inputs were crossed, as in an experimental design, with eight different realizations of the deposition of channel sands. The response surface was examined for distinct maxima, which became the optimal solutions to the problem. This work is similar to the ANN-GA methodology in that the results of a sample of simulations are used to build surfaces which are then searched for solutions. In the ANN-GA approach, however, the sampling is performed to create a re-usable knowledge base, providing the examples from which many different networks figuring in many different searches are drawn.

Wackowski and associates[9] employed decision analysis techniques to examine over 2500 expansion, investment, operational, and $CO_2$ purchase/recompression scenarios to maximize net present value of a project at the Rangely Weber Sand Unit. This ambitious, long-range project pulled together information from many sources (including expert opinion, economic spreadsheet models and reservoir models) into decision trees, from which the highest probability paths were selected. The reservoir model combined the vertical response of a single detailed cross-section with the areal response of a full-field streamtube model to obtain full-field forecasts of injected and produced fluids. Since several techniques were used to reduce the number of paths in the decision tree which required full examination, it is unclear how many scenarios the simulator actually evaluated. This approach to optimization is similar to the ANN-GA methodology in that they both examine very large numbers of alternatives. The techniques, however, are quite dissimilar in their identification of optimal solutions. Unless it is exhaustive of all possibilities, which is unlikely in a real-world problem, a decision tree can only select solutions from paths that have been anticipated by its designers. Optimization techniques, in contrast, can uncover combinations of inputs which produce results which were not anticipated.

A classic application of optimization techniques to facility design is given by Fujii and Horne[10]. They compared three different search techniques (a derivative-based method, the polytope method, and the GA) applied to the optimization of a networked production system by varying parameters such as separator pressure, diameters of tubing, and pipeline vs surface. Calculations were restricted to relatively simple production rate equations because the use of a reservoir simulator was judged to be too time-consuming. Later, Bittencourt and Horne[11] used a GA combined with economics and simulation to determine the optimal relocation of wells in a proposed 33-well layout and the best platform location. Their experiences reinforce the motivation behind the ANN-GA approach: that the advantages of optimization techniques will not be fully exploited until some method is found to reduce the computational burden imposed by the reservoir simulator.

The first application of the ANN-GA in petroleum engineering concerned the proposed water flood of the Pompano field in the Gulf of Mexico[12]. The management problem was to locate the combination of 1-4 injection locations which would maximize the field's simple net profit over the next seven years. Using a 3-D black oil simulator, a knowledge base of 550 simulations sampling different combinations of 25 potential injection locations was created. ANNs were trained to predict peak injection volumes and volumes of produced oil and gas at three and seven years after the commencement of injection. The rapid estimates of these quantities provided by the ANNs were fed into net profit calculations, which in turn were used by a GA to evaluate the effectiveness of different well-field scenarios. The expanded space of solutions explored by the GA contained new scenarios which exceeded the net profits of the best scenarios found by simply querying the knowledge base.

Despite the success of the Pompano application, there are still questions regarding the range of simulators and planning problems to which the ANN-GA methodology can be applied. This paper describes the application to a natural gas storage field development planning problem. It varies from the Pompano case in that 1) the field development planning options are considerably more complex, 2) the reservoir simulator is coupled to a surface network facilities simulator, producing a potentially more complex set of relationships for the ANNs to map, and 3) the objective functions governing the search for best solutions deal not only with tangibles such as production constraints and costs but with intangibles such as the planners' aversion to risk. The current paper illustrates how the methods are applied given a deterministic view of the reservoir. The adaptations to the methodology which are required when the uncertainties associated with reservoir properties must be considered are covered in a separate paper.

## Description of the Reservoir

The gas storage field serving as the testbed for the project was discovered in 1889 and developed through 1930. Conversion of the field to storage began in 1947. The first storage pool was comprised of six wells completed in the Fifth sandstone. While studies and tests were being performed in this area, the possibilities of using a nearby Fifth sandstone pool for storage were explored. From 1950 through 1952, an intensive program was carried out in reconditioning, drilling, and inserting new casing and tubing in wells. By January 1953, the storage field was comprised of these two pools and had a total of 33 wells. Obvious communication existed between the two pools, but the mechanism for communication was poorly understood.

As part of a 1992 study, the field was divided into three areas of distinct reservoir performance (designated as West, Main, and East) based on the high- and low-end inventory pressures recorded from 1987 through 1992. In general, the West and East areas operated in a narrower pressure range than the Main area, which implies that these portions of the field were not operating at their fullest potential. Both volumetric and material balance calculations were used in quantifying the volumetric increase that would result from operating the West area under the same pressure conditions as the Main area. The results indicated that 400 to 700 MMcf of storage potential was not being utilized in the West area due to an insufficient number of wells. Thus, four new wells were drilled in 1992 to efficiently cycle this area and to increase field deliverability. These wells increased field deliverability by approximately 16 MMcfd and field capacity by 250 MMcf at 600 psig. Over the last three years, the company has cycled about 2.1 Bcf per year with a maximum field deliverability of over 40 MMcfd.

**Geologic Setting**. The storage field is located in the Fifth sandstone within the historic shallow gas belt of the Appalachian basin. This region is characterized by numerous overlapping stratigraphic traps within highly lenticular sandstones of the Upper Devonian Catskill Delta complex. Regional correlations by numerous authors have shown that the primary gas reservoirs of the shallow gas belt generally occur within a sandstone-rich facies that grades westward into marine shales and siltstones and eastward into non-marine red shales and fluvial sandstones. Harper and Laughrey[13] confirmed the marginal-marine origin of lower Venango sandstones through analysis of nearby outcrops. A sandstone isolith of the lower Venango Formation[14], including both the Fifth sandstone as well as the subjacent Bayard sandstone, shows a well-developed belt of sandstone with a north-south strike trend that is interpreted to mark the approximate paleoshoreline position. Dip-trending units are common to the east of the strike trend, and are interpreted as fluvial/

distributary feeder channels. The western edge of the strike trend is regular and abrupt, suggesting efficient redistribution of sediment along the shoreline by wave action. An understanding of these general characteristics of Venango sandstones was an important guide to the interpretation of sandstone geometry within the subject gas storage field.

## Prior Reservoir Modeling

**Geologic Analysis.** Geophysical well logs from over 100 gas wells completed in or around the field between 1902 and 1992 were used to perform the analysis. Since the majority of the logs were run in the 1950's, the suite generally consisted of only gamma ray, caliper, and temperature logs. Neutron-density and induction logs were available for only seven to eight of the newer wells. Initially, 50 percent clean sandstone was used to indicate potential pay zones for each of the three sandstone units. However, it was apparent that the zones where a neutron-density crossover occurred (indicative of the presence of gas) correlated only with the good permeability and porosity measurements from sidewall cores, and that these zones correlated well with 75 percent clean sandstone. Zones with gamma ray readings between 50 to 75 percent clean sandstone showed little to no crossover on the neutron-density logs and very low permeability and porosity from sidewall core measurements. Therefore, a 75 percent clean sandstone cutoff was used to represent the pay interval in all wells. The amount of 75 percent clean sandstone in each of the three sandstone units of the Fifth was then determined and mapped across the field to evaluate reservoir pay/permeability trends.

**History Match.** Data available for the history match began with the injection cycle in 1987 and ended with the withdrawal cycle in 1996. Only total field volumes and biannual inventory pressure (shut-in wellhead pressure) data were available between 1987 and 1993. Starting with the injection cycle in 1993, flowing rates and wellhead pressures, averaged over 1 to 3 week periods, were available for 20 of the 28 injection/withdrawal wells. In 1995, pressure transient tests were conducted on 15 of the injection/withdrawal wells. These well tests showed a very wide range of transmissibility and a high degree of damage for most wells. Permeability calculated from well test data and permeability based on flow rate data from the metered wells were used as a starting point in the history match.

The difference between actual inventory pressure and simulator predicted pressure for the 28 injection/withdrawal wells and 3 observation wells over the 10 year period averaged about 10.5 percent. This match was reasonable since individual well rates were dependent on permeability and skin factor (and no well treatment history was available to provide skin factor over the ten year period), and porosity and water saturation data were available for only 7 wells. The results of the history match indicated that 1) gas-in-place was lower than expected or was not effectively being cycled due to low permeability areas and the shorter withdrawal season with respect to the injection season, and 2) although connected, there were several very high permeability areas that appeared to be acting as localized pools (there are several areas of the field where active wells are separated by 4,000 to 6,500 feet).

The final permeability distribution used for all subsequent modeling is shown in **Fig. 2**. The white squares in the figure identify the locations of the 28 wells comprising the critical injection/production capacity of the field. A low permeability region in the mid-section of the field is clearly visible. There is some question of communication through this area, which forms the most prominent source of uncertainty regarding reservoir properties in this application. Analyses addressing this uncertainty are reserved for the second paper.

**Field Development Forecasts.** One of the field production scenarios that planners wanted to explore was offering a 10-day or 30-day peaking service in addition to the baseload service already provided. A base case run was set up using the results from the history match, i.e., existing wells and damage (skin factor), to cycle 2.0 Bcf annually. An additional 200 MMcf were injected during the first cycle to account for the difference between actual and history matched gas-in-place. Even with the additional gas, the prediction runs were considered very conservative.

The forecast runs consisted of either a 10-day peaking service of 10 MMcfd offered March 1st through March 10th, or a 30-day peaking service of 10 MMcfd offered February 15th through March 16th. This represented a worst case scenario where the peaking service was offered near the end of the withdrawal season when reservoir pressure was at its lowest. Several runs were made to investigate the effect of well remediation alone vs. well remediation coupled with either new vertical or horizontal wells.

The well remediation only forecast assumed that skin damage on 7 wells could be reduced from +20 (or higher) to +2. For this prediction run, wellhead pressures fell below minimum level during the peaking service. Thus, 4 new vertical wells were placed in areas of low well density. The results of this run were good, with the wellhead pressures remaining slightly above minimum level. The 4 new vertical wells were then replaced by one 1,500-foot horizontal well, which performed as well as the 4 new vertical wells. An additional run was made to determine the effect of when the peaking service was offered. For this run, the 30-day peaking service was offered January 1st through January 30th. Wellhead pressures remained almost 70 psia higher during the peaking service compared to earlier runs, indicating that higher rates could be met if the peaking service was offered earlier in the withdrawal season.

## Simulators Used in the ANN-GA Application

The modeling work described above employed the three dimensional black oil reservoir simulator, IMEX[15], to predict the performance of the reservoir. To more realistically model the surface facilities, the gas deliverability forecasting program, FORGAS[16], was added to model the multiphase flow in the wellbores, surface pipelines and facilities. In this coupling, the reservoir simulator provides the grid block pressure, water to gas ratio and the sandface inflow performance coefficients, using the LIT (Laminar-Inertial-Turbulent) equation, for each well to the surface model at the start of the timestep. The surface model uses these items with the specified plant delivery pressure, and contract, well and surface network constraints to calculate the flow rate of each well. The flow rate for each well is passed back to the reservoir simulator. The reservoir simulator then does the material balance calculations to determine the conditions (grid block pressure, water/gas ratio and inflow performance coefficients) for the start of the next time step. The new sandface conditions are then passed to the surface model which then redetermines the flow rate of each well. These flow rates are passed back to the reservoir simulator, so it can calculate the conditions for the next time step. This process continues until the end of the forecast period.

The reservoir simulator passes the maximum allowed time step length, based on the user-specified maximum allowed pressure change in each grid block per time step. The surface model may then shorten that time step to allow calculations on dates where changes happen in the surface and wellbore system (e.g. the addition of a new compressor or change from injection to withdrawal). When the reservoir model passes a non-zero volume of water, the surface model uses the appropriate multiphase correlations in the wellbore to predict the wellbore pressure loss and minimum flow rate to lift the liquids. The water volumes from each well are tracked through the gathering system, to determine the resulting multiphase pressure losses.

## ANN-GA Methods

The steps required to apply the ANN-GA methodology are described below:

**Determining the Scope of the Problem.** This step involves a review of the available geological and production data for the field, consideration of the overall goals for the field's initial or further development, and examination of the reservoir simulator that is being used to model the physical processes. The key outcomes of this step are 1) specification of the overall field development planning problem to be solved, 2) the definition of the problem's planning variables (i.e. the elements of the problem which will be allowed to vary, such as the type of well or the allowable spatial locations) and 3) the constraints (economic, environmental, engineering, etc.) under which the decision-makers must operate.

***Production Scenarios.*** Although prior modeling with IMEX alone had suggested that additional development was required to support 10- and 30-day peaking service on top of the base injection/withdrawal capacity of 2.0 Bcf/year, the introduction of a newly drilled horizontal production well and the addition of the FORGAS surface network management facilities increased the apparent capacity of the the field. To make the planning problem more challenging, 6 new production scenarios were considered: normal withdrawal and 10- and 30-day peaking service at baseloads of 2.5 and 3.0 Bcf. These new scenarios were modeled by proportionally increasing the flow rates that had served as the foundation for the 2.0 Bcf baseload scenarios.

Preliminary modeling indicated that simple field development plans involving remediation of one or two existing wells were sufficient to support all scenarios except the two involving 30-day peaking service. These two scenarios were selected for further study; and a knowledge base of just under 500 simulations was created for each scenario. Every simulation run consisted of three years of injection/withdrawal cycles, with an additional 200 Mmcf of gas injected in the first year for the same reasons as described in the history match. A single three-year simulation evaluating one development plan with respect to one production scenario required approximately three minutes on a dedicated personal computer running Windows NT 4.0.

***Planning Variables.*** The following field development planning options were systematically varied:

1. Remediating anywhere from 0 to all 7 of a set of existing wells with skin factors at or above 20.0. Remediation was implemented by simply changing their skin factors in the IMEX input data set to 2.0. More sophisticated methods to accommodate the uncertainty associated with the outcomes of remediation are presented in the second paper describing this project. These wells are identified throughout this paper as R1 – R7.

2. Augmenting a newly drilled and producing horizontal well's capabilities to include injection. The label IHOR is used to refer to the implementation of this option.

3. Drilling from 0 to 4 new vertical wells from a candidate pool of 15 new locations, identified as NV05, NV06, etc. NV01-NV04 refer to wells located in the disputed mid-section of the field, which is not considered in this first paper. **Fig. 3** displays the IMEX grid locations of the existing injector/producers and the new vertical well locations. The locations of the NV's were selected by randomly distributing locations over the higher-permeability IMEX blocks (see **Fig. 2**), making sure that a minimum drainage radius of 1,000 ft was observed. Skin factors for all newly drilled wells were set to 2.0.

*Constraints*. In addition to imposing limits on the number of new wells that could be drilled (4) and the total number of actions that could be taken (12) in any one plan, other engineering constraints were implicit in the problem setup: 1) no changes were to be made to surface facilities beyond the laying of new pipelines to any newly drilled wells, and 2) maximum wellhead pressures remained at 650 psia. Minimum wellhead pressures, on the other hand, were permitted to drop as low as 25 psia. A wellhead pressure below 70 psia was treated as an undesirable but manageable condition with economic consequences (see the "Cost of Low Pressure Conditions" component of the objective function definition below) rather than as an absolute constraint.

Spatial constraints were imposed by the fixed positions of the 15 prospective new well locations. Earlier efforts to express well locations in x-y coordinates to permit an ANN to make spatial interpolations produced greatly degraded predictive accuracy. So, the convention prevalent in water resources management of employing a set of preselected locations that constitutes the domain about which questions can be asked was followed here.

**Creating a Knowledge Base of Simulations**. Given the definition of the problem just described, a knowledge base was created by running FORGAS/IMEX on a set of nearly 500 development plans obtained by structured, random sampling over the ranges of the planning variables. Rationales for the selection of target sizes are discussed in the section on ANN training and testing. The set consisted of:

1. The no-action case which assessed the performance of an existing set of 28 injectors/producers under the challenges of the 30-day peaking service on top of 2.5 and 3.0 Bcf baseloads.
2. 23 single-action plans, assessing the effects of doing any one of the planning options outlined above.
3. 476 combined-action plans generated according to the following rules:
   a. Rehabilitation options: 1) Randomly select the number of wells (0-7) to rehabilitate (*nr*) and 2) randomly select wells from the list of candidates until *nr* wells have been picked.
   b. New vertical well options: 1) Randomly select the number of wells (0-4) to drill (*nd*) and 2) randomly select locations from the list of candidates until *nd* locations have been picked.
   c. Horizontal well injection option: randomly determine if the injection option is to be turned on.

For the combined-action set, a minimum of two and a maximum of 12 actions were permitted. Of the 476 combined-action plans, 7 encountered numerical convergence problems and were discarded.

***Archived FORGAS/IMEX Output***. The following items were recorded for each simulation:

1. The type (injection vs. withdrawal) and extent of contract shortfalls (i.e., when they occurred, how long they lasted, and the total volume of gas involved),
2. Any well-head pressures dropping below 70 psia (i.e., which wells, to what extent, and for how long), and
3. Cumulative injection and withdrawal volumes for each existing well or new location.

**Posing Specific Management Questions.** This is the point at which the actual optimization exercise begins. Based on the groundwork laid in the creation of the knowledge base of simulations, the following cycle is repeated as many times are there are different management questions to be addressed -

***Defining the Objective Functions***. There are many ways to construct the objective functions (i.e. the means by which plans are compared with each other and against the no-action case). For the purpose of these analyses, simple minimization functions were constructed.

*Plan Performance Measures.* The archived simulator output provided data from which the following performance measures could be translated into economic terms:

1. Cost of Contract Shortfall – Contract shortfall is the total volume of gas (in Bcf), cumulative over the three years of simulation, which could not be withdrawn under the given plan. For example, if the contract required withdrawal of 2.5 Bcf/year and the plan could only produce 2.45 Bcf/year, then the cumulative shortfall was 0.15 Bcf. When a shortfall occurs, the company must purchase natural gas on the open market to make up the difference. So contract shortfall is translated into a cost value by multiplying the shortfall by some appropriate price. For the preliminary analyses, $2.00/mcf was selected.

2. Cost of Low Pressure Conditions – Ideally, FORGAS's compressor modeling facilities would be used to evaluate the impact of low wellhead pressures. Since the information needed to apply this feature was unavailable, a cruder method was implemented. Any time a wellhead pressure dropped below 70 psia, the extent and duration of the pressure deficit were recorded. The deficits were accumulated across all three years of simulation and totaled across all wells to yield a single pressure deficit (in psia) that would have to be compensated for by the plant's compressors. The deficit was translated into a cost figure by multiplying it by $0.10/lb. This figure is intended to cover both the energy cost of running the compressors and additional wear on equipment.

*Plan Implementation Costs*. Each plan carries with it certain incremental installation and maintenance costs. For this analysis, the following costs were applied:

Rehabilitation Costs –
$ 6,000 for R3
$ 10,000 for R1 and R4
$ 15,000 for R2, R5, R6, and R7

Drilling New Vertical Wells –
$300,000 in drilling costs for each new well
$ 2,000 in yearly maintenance expenses

Equipping the Horizontal Well for Injection – $2,000

*Calculation of Total Dollar Cost ($Cost)*. This was simply the sum of Contract Shortfall Costs, Low Pressure Conditions Costs, and Plan Costs.

*Definition of Risk.* Contract shortfalls involve more than purchasing gas on the open market to make up the difference. They also introduce considerable uncertainty into the planning situation because there is no way to know what the cost of gas is going to be when the shortfalls occur. Decision-makers' tolerance for risk is highly individual. However, an effort has been made to incorporate this dimension into the cost function so that the definition of an optimal plan will be one which not only minimizes dollar costs but also minimizes that risk. This involved the following steps.

The shortfalls (SF) for each plan *p* were converted to percentages of improvement (PctImp) over the corresponding shortfalls in the no-action case:

$$\mathrm{PctImp} = \mathrm{SF}_p/\mathrm{SF}_{\text{no-action}} \tag{1}$$

The greater the percentage of improvement, the less risk is associated with the plan. For example, if PctImp is 100%, the plan completely eliminates the shortfall and, consequently, the risk. So, Risk% is simply defined as 100 – PctImp.

*Final Objective Functions.* For any given production scenario, plan *p* was evaluated by the weighted combination of risk and the dollar cost:

$$\text{Total} = w_1\$\text{Cost} + w_2\text{Risk\%} \qquad (2)$$

Since this is a minimization problem, the lower the value of Total, the better. Both Risk% and $Cost were scaled between 0.0 and 1.0 prior to applying the weights, which themselves sum to 1.0.

For the current analyses, two versions of the objective function were analyzed. In the first, denoted as "$Cost Emphasis", $w_1$ was set to 0.67 and $w_2$ to 0.33. In the second, "Risk% Emphasis", the weightings are reversed. The purpose of employing two versions of the objective function was to demonstrate how using ANNs in place of the full simulator facilitates experimentation on the part of planners.

***Training/testing the ANNs.*** The performance measures described above, Contract Shortfall and Low Pressure Conditions, are the two attributes for which ANN predictors were required. The 493 examples in the knowledge base were divided into two sets: 343 for the training set and 150 for the generalization test set. Because of the manner in which the training/testing cycle was organized (see below), no validation set was required. The two sets were random selections from the overall 493 cases with the exception that the no-action and single-action cases were present only in the training set. The desired size of the training set is whatever size is necessary to achieve the required level of accuracy on the generalization test set, which itself must be an adequate representative sample from the space which will be covered by the search technique. Prior experience with similar planning problems suggested that a total of roughly 500 examples might be adequate. If initial generalization test results indicate otherwise, the knowledge base would have to be augmented with additional simulations.

The ANN architecture used for this prediction task was a feedforward network, trained by the familiar backpropagation learning algorithm[17]. In this paradigm, a network is initialized with small random weights. Training consists of presenting example inputs to the network and calculating the corresponding outputs, given the current values of the connection weights. The calculated output values are compared to the target values from the examples; and the connection weights are updated according to any of several learning algorithms to minimize the difference between calculated and target values on the next iteration. Over time, the connection weights associated with important relationships grow large and those associated with trivial relationships decay to zero. For the current analyses, a conjugate gradient optimization method[18], employing the Polak-Ribiere weight update rule, was used to speed convergence and reduce the likelihood of becoming trapped in local minima. A sigmoid was used as the transfer function. To avoid over-fitting of the network weights to idiosyncratic features of the training examples, batch updating of weights and a relatively short number of training epochs (300) were employed. This last parameter was determined by trial and error experimentation.

The goal of training is to construct a predictor with maximal capacity to generalize its predictions to unseen patterns. Factors that are known to contribute to generalization in ANNs include the complexity of the network as reflected in the number of connection weights, the size of the training set, and the degree of noise in the training set[19]. In applications where the "data" is generated by a deterministic model, noise in the usual sense of the term is not a problem. On the other hand, training/testing set size is definitely pertinent, as has already been discussed.

A third factor, network complexity, is addressed by the manner in which variations on a given network are constructed and tested. The size of the input layer was fixed by the problem formulation at 23, one node for each of the 7 remediation candidates, the IHOR option, and the 15 prospective new vertical wells. The output layer was similarly kept simple by constructing networks which only predicted one performance measure (i.e. Contract Shortfall or Low Pressure Conditions) at a time. The only variable element was the number of nodes in the hidden layer. This decision was made by training and testing variant networks having anywhere from one to 10 hidden nodes and selecting the variant with the best test set accuracy.

There is one final source of complexity that was addressed by the training/testing procedure. Backpropagation training is, itself, a nonlinear optimization problem and suffers from vulnerability to entrapment in local minima in the error-surface, depending on the randomly-assigned initial values of the connection weights. The variance caused by those initial values is partly a function of the complexity of the input-output relationships being mapped and can be reduced by increasing the size of the training set. However, with the relatively small training/testing set sizes in the gas storage problem, some other procedure had to be developed to confront the initial-weights issue.

Each hidden-layer node size was evaluated based on the mean and maximum of the predictive accuracy of 10 ANNs, all having the same number of hidden nodes but with a different random weight initialization. The complete training of variant networks for each attribute (e.g. contract shortfall) required a total of 100 training/testing cycles. The task was performed by a batch process that required about 20 minutes to complete, per attribute. The purpose of this exercise was to select a size for the hidden layer having the *best and most stable* generalization. Having selected the size of the hidden layer, the particular network chosen to participate in the searches was simply the variant with the maximum predictive accuracy.

***Conducting the Optimization.*** Readers requiring an introduction to genetic algorithms should consult the excellent introductions in Goldberg[20] and Michalewicz[21]. Goldberg is the source for all information concerning the GA presented below, unless otherwise noted.

The 23 planning options which form the decision variables are represented in the GA as a string of 23 bits, each of which can either be on or off. The spatial location of each well is fixed and implicit in the representation. The order of the well locations in the string is indicated by their identification numbers in **Fig. 3**. The numbering is arbitrary, as is their location in the bit-string.

The search is initialized with a set of 100 randomly generated plans. In fact, this initial population is simply a random subset of the 150 cases in the ANN testing set. The population size of 100 chosen for the current study is a fairly small value. A larger population helps maintain greater diversity but does so at considerable computational cost when the full model is being used to generate performance predictions. Since time-consuming full-model comparisons formed an important component of the current analyses, a small population size was considered most practical.

The basic cycle of the GA is as follows. The initial population of 100 well plans is evaluated according to an objective function. A new generation of 100 plans is created from the old population by means of three mechanisms: selection, reproduction, and mutation. The new population is then evaluated according to the objective function; and the entire process is repeated until some termination criterion is reached. The manner in which the three mechanisms have been implemented is as follows:

*Selection.* This mechanism determines which members of the current generation will be selected for carry-over, in one form or another, to the new generation. To make sure that the highest-ranking plans are not lost to the population through accidents of selection and crossover, the top three plans are copied over to the new generation intact. The remaining 97 slots in the new population are filled by a form of sexual reproduction, a process for which parents must be selected.

The most popular method of selection is the roulette wheel, in which each member's likelihood of being selected for reproduction is the ratio of its own performance score to the total performance score of the population. The larger a given member's score is in relation to the other members', the larger portion of the roulette wheel it occupies, increasing the odds that the member will be selected one or more times for reproduction. When large discrepancies exist in the scores of individual members, the members with the higher scores come to dominate the population too quickly. Conversely, when differences between members become very small, the selection process becomes random. To avoid these cases, the current GA employs selection based on the plans' rank order[22] rather than their proportional scores. Plans are selected by sampling from a uniform distribution over the ranks, with a bias factor of 1.5 serving to favor high-ranking plans over lower-ranked plans.

Selections for reproduction are made, two at a time, to obtain parent plans from which a child plan will be formed. This process is repeated until 97 children have been generated. The same plan may constitute both members of the pair, in which case the child is simply a clone of the parent.

*Reproduction (Crossover).* The most common form of reproduction is single-point crossover. Child plans are constructed by breaking the parent plans apart at some randomly selected crossover position in the bit-string and joining segments from each parent. For example, given two parents in a 5-bit problem (0 1 0 0 0 and *1 1 0 1 1*) and a crossover point of 2, two different children could be constructed (0 1 *0 1 1* and *1 1* 0 0 0).

Creating new plans from "chunks" of old ones makes the most sense when proximity in the bit-string is important. That is, the proximity of wells in the bit-string should reflect one or more dimensions of relatedness in the physical problem it represents. This is not necessarily the case in this problem. In fact, the earlier groundwater studies employing the GA had discovered a "sticky" well problem. That is, particular wells kept appearing in the optimal solutions sets whose individual contributions to the efficiency of remediation were minimal but which were adjacent in the bit-string to wells making major contributions. To break up these spurious associations, a different reproductive mechanism, uniform crossover, is used[23]. In this method, the value of each bit in the child string is set independently of every other bit. A coin-toss at each bit-position determines from which parent the child will inherit the value for that particular bit. The exchange probability can be biased to favor the fitter parent, if any; but in this study the exchange probability is kept at an impartial 0.5.

*Mutation.* Mutation is a way to maintain diversity in a population by arbitrarily changing the values of bits in the child plans according to some rate, often the inverse of the population size. A high mutation rate can undermine the effects of crossover; a low one limits the introduction of "novelty" into the population. For this study, the inverse rule yields a mutation rate of 0.01.

*Termination Criteria.* Termination criteria in optimization are usually based on some notion of convergence to a single best solution. In keeping with the philosophy of heuristic search, however, the current study is more interested in generating *sets* of near-optimal solutions rather than a single best solution. This goal is achieved by tying termination criteria to the performance score of the population rather than the performance of the highest-ranking individual plan. Search terminates when either a) the population's $90^{th}$ percentile score fails to improve over five consecutive generations, or b) some maximum number of generations have elapsed, whichever comes first. This maximum was set to 10 so that the full-model searches which serve as the benchmark for evaluating the ANN-assisted searches would be more practical to complete. At the end of every generation, plans with scores below a predetermined cutoff were saved to a file. The 100 top-ranked unique plans in this file became the set of near-optimal solutions.

The outcome of a GA search can be influenced by the particular random choices that are made along the way. To improve the stability of the outcome, the results of each search in the current analysis actually consist of combined results from 5 searches, each with a different seed initializing the pseudo-random number generator.

***Confirming Top-performing Plans***. Since the scores of the near-optimal plans generated by the GA are based on ANN estimates which are subject to some degree of error, it is important to check their performance with the original simulator. In an actual engineering application of the ANN-GA methodology, planners would choose to only submit a handful field development plans to the simulator. For this analysis, however, the top 100 plans from the near-optimal sets generated by each search were submitted for verification. The resulting FORGAS/IMEX predictions of Contract Shortfall and Low Pressure Conditions were used to recalculate the $Cost and Risk% components of the objective functions. It is these *updated* scores which become the measure for subsequent analysis and decision-making.

## Results

**Initial ANN Predictive Accuracies.** Accuracy is defined here as the square of the Pearson product-moment correlation, $r^2$, between the ANN's and the simulator's predictions for a given attribute on some set of examples. Training set accuracy is the $r^2$ between the ANN and simulator predictions on the 343 examples in the training set. High levels of training set accuracy are a necessary but not sufficient condition for testing or generalization accuracy, which is the same measure on the 150 examples in the test set.

Table 1 presents summary statistics on the test set accuracies of four clusters of ANNs: predictors of Contract Shortfall and Low Pressure Conditions for 30-day peak service at both the 2.5 and 3.0 Bcf baseload production scenarios. The columns labelled "Hidden Nodes" identify the size of the hidden layer, from 0 to 10, being evaluated. In general, predictive accuracy improves, peaks, and then declines as the number of hidden nodes increases. This is because adding hidden nodes initially allows the network to capture more of the key features of the data. At some point, however, the addition of more nodes merely allows the net to capture idiosyncratic aspects of the training set, a phenomenon referred to as over-fitting, which actually interferes with subsequent generalization.

A node-size of 0 represents the special case of a linear predictor. Because linear predictors have unique solutions, the entries in the "Mean $r^2$" columns are simply the $R^2$ obtained by regressing the 23 decision variables on the attribute in question. In all other rows, the entries for "Mean $r^2$" are averages of the 10 $r^2$ values obtained from ANNs all having the specified number of hidden nodes but trained from different random initializations of the network weights. The "Maximum $r^2$" columns contain the highest accuracies achieved for the specified number of hidden nodes.

Boldface entries identify the ANN chosen to supply predictions for the optimizations. There are no fixed rules for the selection process. But there are rules of thumb, as follows:

1. The highest mean coupled with the highest maximum is ideal. This condition was met for both the Contract Shortfall and Low Pressure Conditions attributes at the 2.5 Bcf baseload scenario.

2. A significantly higher maximum may "trump" a high mean. For the Contract Shortfall attribute at the 3.0 Bcf baseload scenario, the 5-node ANN set was selected over the 4-node set because of the latter's higher maximum of 0.6720.

3. In contrast, on the Low Pressure Conditions attribute at the 3.0 Bcf baseload scenario, the 8-node ANN was selected over the 10-node ANN not only because of its higher mean but because simpler networks tend to generalize better than more complex networks. The 10-node ANN's maximum was not sufficiently high to justify over-riding this rule.

Since the selected node-size represents a set of 10 ANNs, the single net chosen to participate in the searches was the one responsible for producing that set's maximum $r^2$.

Another notable feature of Table 1 are the dramatic differences in the overall levels of accuracy on the four attributes. For the 2.5 Bcf production scenario, the levels are highly satisfactory for Contract Shortfall but only marginally acceptable for Low Pressure conditions. As will be seen, however, the predictive errors introduced by the ANN for the latter attribute have no effect on the results because Low Pressure Conditions make only a small contribution to the objective functions.

The accuracies observed for both attributes at the 3.0 Bcf baseload scenario would normally be unacceptably low and would prompt either more sampling to increase the size of the knowledge base and/or a re-examination of the model itself. For example, it is possible to question the reasonableness of increasing the baseload from 2.0 to 3.0 Bcf/year with no alterations in model parameters. However, a complete optimization was conducted for the 3.0 Bcf baseload production scenario, using the best available ANNs from Table 1, *so that an assessment could be made of the consequences of employing such weak predictors.*

**Optimized Plans for the 30-Day Peak/2.5 Bcf Baseload Production Scenario.** Table 2 displays the three best-scoring plans generated by various methods as solutions to the management questions reflected in the two versions of the objective function: $Cost Emphasis, where the $Cost component of the objective function is assigned a weight of 0.67, and Risk% Emphasis, where the Risk% component is given the greater weight. The significance of the different weighting is two-fold: 1) it is reasonable to expect that the sets of near-optimal plans will be somewhat different, depending on whether it is most important to minimize dollars or uncertainties, and 2) the results from the search emphasizing risk minimization may be more vulnerable to predictive errors generated by the ANNs because the Contract Shortfall attribute, which accounts for only a portion of the $Cost component, accounts for all of the Risk% component.

The entries under "Search Method" indicate the method by which the near-optimal plans were obtained. An entry is included for Baseline so that comparisons can be made with the case where an attempt is made to meet the production scenario with existing, unremediated wells. Next, the best plans already contained in the knowledge base are presented. This is also an important frame of reference because the knowledge base may already contain the best possible answers to the question, without introducing any errors of estimation. The next method is the focus of the current analysis: the best plans generated by means of the GA, using ANNs to generate the necessary predictions of Contract Shortfall and Low Pressure Conditions. Finally, to assess the effects of prediction errors introduced by the ANNs, plans generated by another GA search which *did* call FORGAS/IMEX to supply predictions of Contract Shortfall and Low Pressure Conditions are presented. The computational resources required to complete these full-model-assisted searches are described in the Discussion section.

The total score entry for each plan represents the weighted linear combination of the scaled $Cost and Risk% components. This variable ranges from 0.0 to 1.0, with lower values being desirable. The reason why the baseline cases, while possessing fairly high scores, do not have scores of 1.0 is that there are more expensive plans in the knowledge base involving many development options that perform no better or even worse than the no-action case. To make the reasons why a particular plan is better than another more apparent, each plan's unscaled Risk% and $Cost components are also reported. To make the presentation of results more manageable, only the top three of the 100 plans in the near-optimal sets are presented. It is also important to recall that the values reported in the table are the *updated* values from the simulator verification runs (see **Fig. 1** to review the sequence of events in the methodology).

There are a number of conclusions to be gleaned from the contents of Table 2. First, a very large improvement over the performance of the no-action case is gained by examining the contents of the knowledge base, especially on the risk-oriented objective function. Second, it is still worth the effort of conducting the optimization. The optimized plans are considerably less costly than the best plans in the knowledge base. Third, the top plans identified by the GA relying on the ANNs for its predictions and the GA calling FORGAS/IMEX each time it required predictions were identical. In other words, any predictive errors introduced by the ANNs were trivial. Finally, the top plans generated using different versions of the objective function still yield identical results. This is a fortunate outcome for management since they would not be required to choose between saving on capital costs and reducing uncertainty regarding the future price of gas.

**Optimized Plans for the 30-Day Peak/3.0 Bcf Baseload Production Scenario.** The results shown in Table 3 tell a somewhat different story. The knowledge base still contains plans which make a large improvement over the no-action case in the ability of the field to meet this very challenging production scenario. However, neither of the two optimization methods produce results that represented the degrees of improvement over the knowledge base plans noted in Table 2. On the cost-oriented objective function, both GA searches did edge out the knowledge base and also agreed with each other on the best-scoring plan. However, on the risk-oriented objective function, the ANN-assisted search was unable to beat the best plan in the knowledge base and the FORGAS/IMEX-based search produced a better plan by only a small margin. The FORGAS/IMEX-based search also bested the ANN-assisted search by a small amount. Considering that the predictive accuracies of the ANNs used in these two searches were quite low (see Table 1), it is somewhat surprising that the full-model search results were not more superior to the ANN-assisted search results.

## Discussion

The results in Tables 2 and 3 raise two main issues regarding the application of the ANN-GA methodology to this field development planning problem.

**Impact of ANN Resolution on Verification Procedures**. Although the tables only show the top three plans, the near-optimal sets submitted for verification consisted of the top-scoring 100 plans. The reason for this large number of plans involves the declining accuracy of even highly accurate ANNs as the resolution required of them becomes increasingly fine. For example, in the cost-oriented search for the 2.5 baseload production scenario, which employed the most accurate ANNs (see Table 1), the $r^2$ between the original and updated total scores on the 100 plans in the near-optimal set was only 0.2046. The corresponding correlation on the cost-oriented search for the 3.0 baseload production scenario, with its substantially weaker ANNs, was effectively zero.

How, then, is it possible for the ANN-assisted GA to perform so well relative to the full-model-assisted GA? The answer lies with the GA itself and the manner in which it is implemented here. Even the weak ANNs have sufficient accuracy to direct the search to the general region(s) where near-optimal solutions can be found. They do not, however, have the resolution necessary to make subtle distinctions between good plans and even better plans. So, the GA effectively performs what amounts to a thorough, random sample of plans in those regions. The goal is not to reach convergence on a single globally-optimal plan but to conduct as wide-ranging a search as possible over the promising regions.

While additional sampling during knowledge base creation might increase the accuracy of the ANNs at finer degrees of resolution, it is probably not worth the effort. The purpose of the knowledge base is to support a wide variety of searches having different objective functions, each with its own promising regions. Since it is difficult to anticipate where those regions will be, it is more cost-beneficial to put the additional modeling effort into verification runs.

An exception to this rule occurs when an ANN's initial generalization test results are as poor as they were on the 3.0 baseload production scenario. Even though they generated results that were competitive with the full-model-assisted searches, the initial performance results are a red flag that either the knowledge base sample size is inadequate or there is some more fundamental modeling problem obscuring the relationship between decision variables and outcomes.

**Computational and Human Effort Required.** 700 FORGAS/IMEX runs were required to support the ANN-GA methodology for one production scenario: 500 runs to create the knowledge base and 100 verification runs for each of the two objective functions. At approximately 3 minutes/run, this amounted to 35 CPU hours, which is a small investment of machine time. In applications such as the Pompano case study where the model required several hours/run, 700 runs could be viewed as burdensome. However, there are several factors that serve to put that investment into perspective.

First, these runs are not carried out in the typical human-intensive fashion. The original history match and testing of various production scenarios were the stages of the project in which the results of each run were carefully scrutinized. After that, all simulations were under the control of automated scripts that generated plans according to a sampling plan, tailored the necessary input files, launched the simulators, and filtered the results. In one groundwater application[24], even the location of a machine on which to run the simulator was handled by an automatic job scheduler. As was described earlier, the training/testing cycles for the ANNs and, of course, the GA searches were also automated tasks. Creating the software necessary to support these activities is well within the capacity of most IT departments.

The 700 runs required by the ANN-assisted GA is a small effort compared to the runs required for the full-model-assisted GA. These latter searches employed identical procedures except that FORGAS/IMEX was called to supply predictions for Contract Shortfall and Low Pressure Conditions instead of obtaining those predictions from the ANNs. For greater efficiency, a cache of results was maintained so that when the search returned to a plan it had previously encountered, a redundant call to the simulators was avoided. The cache was also shared between the two versions of the objective function. Even so, 6274 unique calls to the simulators, taking 313.7 hours to complete, were required to generate results that were, at least on the 2.5 baseload production scenario, identical to the ANN-assisted results. The difference in effort is almost an order of magnitude, even without taking in account that the data archived from the knowledge base runs can be reused to train other ANNs for a variety of other searches.

## Conclusions

Each organization must determine for itself whether the promise of simulation-optimization, assisted by ANNs or otherwise, is worth the effort in acquiring and mastering new technologies. However, some reflection on the results shown in Table 2 are in order. It is certainly possible that a team of planners might have settled on one or more of the 5-well remediation plans which proved to be the most cost-effective. On the other hand, the results of both the original modeling work and even the random sampling step could have biased planners in favor of drilling at least one new vertical well. It is not until the optimizations are carried out, with their clear specification of costs and risks and thorough coverage of the range of possibilities, that it becomes clear that the problem might be solved by simply remediating 5 wells. To discover this, and to also know that this discovery is the outcome of a far more thorough examination of the posibilities than is normally feasible under current common practices, would seem to be worth the investment in new technologies.

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## Nomenclature

R1 .. R7 = Ids of wells to be remediated
IHOR = Id of injection facilities for the horizontal well
NV = Prefix of ids of new vertical wells
*nr* = number of wells to remediate
*nd* = number of new wells to drill
PctImp = Percentage of improvement
SF = Contract shortfall
$Cost = first major component of the objective function
Risk% = second major component of the objective function
*w* = weights assigned to the components of the objective function
$r^2$ = squared Pearson product moment correlation coefficient
$R^2$ = percentage of variance in total score accounted for by the decision variables

**Subscripts**

*p* = plan
no-action = no-action case

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**TABLE 1—MEANS AND MAXIMA OF ANNS' PREDICTIVE ACCURACY ON TWO PERFORMANCE MEASURES FROM TWO PRODUCTION SCENARIOS**

30-Day Peaking Service at 2.5 Bcf Baseload

| Contract Shortfall | | | Low Pressure Conditions | | |
|---|---|---|---|---|---|
| Hidden Nodes | Mean $r^2$ | Maximum $r^2$ | Hidden Nodes | Mean $r^2$ | Maximum $r^2$ |
| 0[a] | 0.8665 | -- | 0 | 0.7984 | -- |
| 1 | 0.9435 | 0. 9440 | 1 | 0.7816 | 0.7820 |
| **2**[b] | **0.9479** | **0. 9550** | **2**[b] | **0.8129** | **0.8190** |
| 3 | 0.9312 | 0.9460 | 3 | 0.7615 | 0.8060 |
| 4 | 0.9056 | 0.9270 | 4 | 0.6758 | 0.7690 |
| 5 | 0.8898 | 0.9310 | 5 | 0.6934 | 0.7470 |
| 6 | 0.8744 | 0.9320 | 6 | 0.6209 | 0.7050 |
| 7 | 0.8531 | 0.9060 | 7 | 0.6396 | 0.6920 |
| 8 | 0.8575 | 0.8900 | 8 | 0.6098 | 0.6580 |
| 9 | 0.8370 | 0.8910 | 9 | 0.6181 | 0.7050 |
| 10 | 0.8417 | 0.8820 | 10 | 0.6296 | 0.7100 |

30-Day Peaking Service at 3.0 Bcf Baseload

| Hidden Nodes | Mean $r^2$ | Maximum $r^2$ | Hidden Nodes | Mean $r^2$ | Maximum $r^2$ |
|---|---|---|---|---|---|
| 0[a] | 0.2597 | -- | 0 | 0.1857 | -- |
| 1 | 0.4227 | 0.4320 | 1 | 0.3280 | 0.3919 |
| 2 | 0.4742 | 0.6240 | 2 | 0.4586 | 0.5010 |
| 3 | 0.5048 | 0.6460 | 3 | 0.3767 | 0.6060 |
| 4 | 0.5220 | 0.6320 | 4 | 0.4160 | 0.6480 |
| **5**[b] | **0.5089** | **0.6720** | 5 | 0.4113 | 0.6920 |
| 6 | 0.4556 | 0.5800 | 6 | 0.4190 | 0.4860 |
| 7 | 0.4371 | 0.5690 | 7 | 0.3614 | 0.5240 |
| 8 | 0.4415 | 0.5550 | **8**[b] | **0.5244** | **0.6980** |
| 9 | 0.4651 | 0.6410 | 9 | 0.4888 | 0.6580 |
| 10 | 0.4314 | 0.5450 | 10 | 0.5206 | 0.7020 |

a. Refers to a linear model having a unique solution. In all other cases, statistics are summarized over 10 ANNs having the same architecture (i.e. number of hidden nodes) but different random initializations of the connection weights.
b. Boldface indicates the ANN variant selected for use in the searches.

**TABLE 2—TOP DEVELOPMENT PLANS LOCATED BY THREE SEARCH METHODS FOR 30-DAY PEAKING SERVICE AT 2.5 BCF BASELOAD CAPACITY**

| Objective Function | Search Method | Total Score | Risk% | $Cost | Development Plan |
|---|---|---|---|---|---|
| $Cost Emphasis | Baseline | 0.5447 | 100.0 | 536,822 | None |
| | Random Sampling | 0.1776 | 6.4 | 391,371 | R2, R3, R4, R7, NV20 |
| | | 0.1846 | 4.3 | 426,124 | R1, R2, R3, R4, R5, R6, R7, NV12, IHOR |
| | | 0.1850 | 5.5 | 417,457 | R1, R2, R3, R4, R5, R6, NV06, IHOR |
| | Optimization/ ANNs | 0.0389 | 1.4 | 85,944 | R1, R2, R3, R5, R6, R7 |
| | | 0.0421 | 2.3 | 85,917 | R1, R3, R4, R5, R6, R7 |
| | | 0.0434 | 2.6 | 87,339 | R1, R2, R3, R4, R6, R7 |
| | Optimization/ Models | 0.0389 | 1.4 | 85,944 | R1, R2, R3, R5, R6, R7 |
| | | 0.0421 | 2.3 | 85,917 | R1, R3, R4, R5, R6, R7 |
| | | 0.0434 | 2.6 | 87,339 | R1, R2, R3, R4, R6, R7 |
| Risk% Emphasis | Baseline | 0.7758 | 100.0 | 536,822 | None |
| | Random Sampling | 0.1127 | 4.3 | 426,124 | R1, R2, R3, R4, R5, R6, R7, NV12, IHOR |
| | | 0.1169 | 4.8 | 429,118 | R1, R2, R3, R4, R5, R6, R7, NV08, IHOR |
| | | 0.1189 | 5.5 | 417,457 | R1, R2, R3, R4, R5, R6, NV06, IHOR |
| | Optimization/ ANNs | 0.0260 | 1.4 | 85,944 | R1, R2, R3, R5, R6, R7 |
| | | 0.0326 | 2.3 | 85,917 | R1, R3, R4, R5, R6, R7 |
| | | 0.0344 | 2.6 | 87,339 | R1, R2, R3, R4, R6, R7 |
| | Optimization/ Models | 0.0260 | 1.4 | 85,944 | R1, R2, R3, R5, R6, R7 |
| | | 0.0326 | 2.3 | 85,917 | R1, R3, R4, R5, R6, R7 |
| | | 0.0344 | 2.6 | 87,339 | R1, R2, R3, R4, R6, R7 |

**TABLE 3—TOP DEVELOPMENT PLANS LOCATED BY THREE SEARCH METHODS FOR 30-DAY PEAKING SERVICE AT 3.0 BCF BASELOAD CAPACITY**

| Objective Function | Search Method | Total Score | Risk% | $Cost | Development Plan |
|---|---|---|---|---|---|
| $Cost Emphasis | Baseline | 0.7860 | 100.0 | 2,295,903 | None |
| | Random Sampling | 0.1388 | 8.7 | 554,410 | R2, R3, R4, R7, NV20 |
| | | 0.2220 | 11.5 | 926,735 | R1, R2, R3, R6, NV12, NV13 |
| | | 0.2244 | 27.7 | 670,205 | R2, R6 |
| | Optimization/ ANNs | 0.0941 | 10.7 | 296,317 | R1, R2, R4, R7 |
| | | 0.1000 | 11.1 | 318,954 | R3, R4, R5, R6, R7, IHOR |
| | | 0.1120 | 12.8 | 351,707 | R4, R5, R6, R7, IHOR |
| | Optimization/ Models | 0.0941 | 10.7 | 296,317 | R1, R2, R4, R7 |
| | | 0.1196 | 14.0 | 369,056 | R2, R3, R3, R7 |
| | | 0.1277 | 15.1 | 392,720 | R1, R2, R3, R7 |
| Risk% Emphasis | Baseline | 0.8946 | 100.0 | 2,295,903 | None |
| | Random Sampling | 0.1125 | 8.7 | 554,410 | R2, R3, R4, R7, NV20 |
| | | 0.1579 | 7.0 | 1,137,031 | R1, R2, R3, R4, R7, NV06, NV11, NV19 |
| | | 0.1676 | 11.5 | 926,735 | R1, R2, R3, R6, NV12, NV13 |
| | Optimization/ ANNs | 0.1185 | 9.2 | 581,255 | R3, R4, R5, R6, R7, NV14, IHOR |
| | | 0.1200 | 12.8 | 351,707 | R4, R5, R6, R7, IHOR |
| | | 0.1221 | 9.7 | 585,896 | R4, R5, R6, R7, NV20, IHOR |
| | Optimization/ Models | 0.1006 | 10.7 | 296,317 | R1, R2, R4, R7 |
| | | 0.1122 | 8.7 | 554,410 | R2, R3, R4, R7, NV20 |
| | | 0.1129 | 8.6 | 565,293 | R1, R2, R3, R5, R6, NV06 |

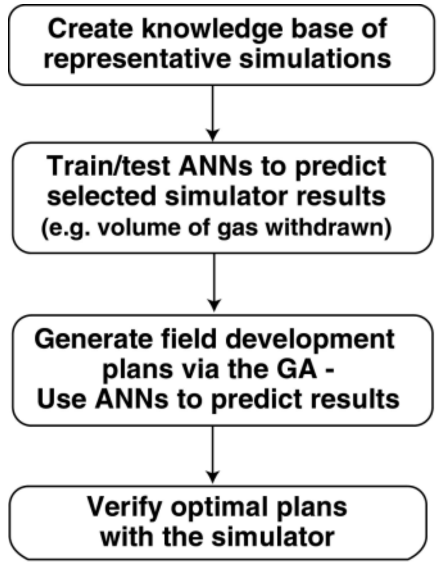


**Fig. 1--Components of the ANN-GA methodology.**

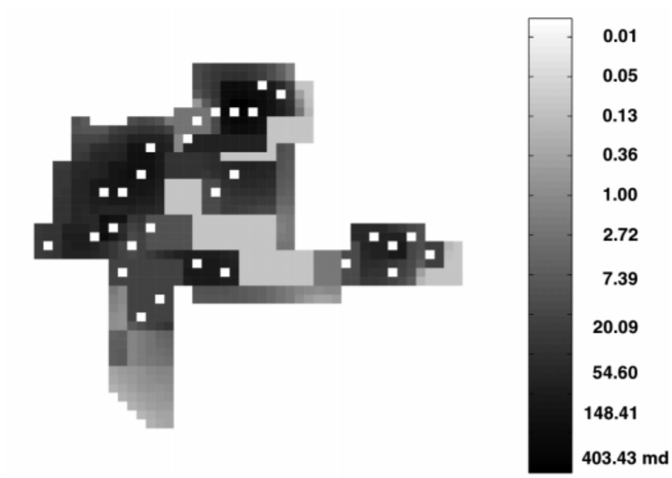


**Fig. 2—Natural log scaling of permeabilities (in md) in the gas storage field. White squares indicate the locations of existing wells.**

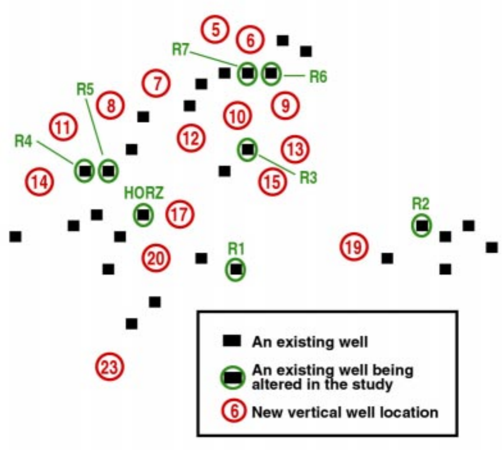


**Fig. 3—Relative locations of wells and well locations being manipulated in the optimization study.**