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Determining the Value of Reservoir Data by Using Nonlinear Production Optimization Techniques

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Abstract

This paper describes a new method of analyzing the cost of uncertainty in reservoir data. The method is based on the use of nonlinear optimization techniques. Nonlinear optimization techniques are mathematical or heuristic methods of determining the set of decision variable values that maximizes an objective function value. Given the appropriate model, optimization techniques can be used to determine the best set of production engineering parameters for an oil or gas field. The optimization technique considered is the Genetic Algorithm (GA). However, the optimized engineering parameters depend largely upon the input reservoir rock and fluid properties. If the reservoir property values differ from the expected values, the engineering parameters selected as optimal by numerical optimization will probably be suboptimal.

This leads to a new technique for assessing the cost of uncertainty in reservoir data. The cost of uncertainty in a reservoir parameter depends upon the discrepancy between the optimal net present value (NPV) for the actual parameter value and the NPV realized when optimization is performed for the expected value of the parameter. For a parameter, such as porosity or permeability, a probability distribution is determined. From this distribution, five representative values are chosen to discretize the distribution. The engineering parameters are optimized for the expected property value (the third representative value). The NPVs based on these engineering parameter values and the other four reservoir parameter values are determined. Then the optimal NPVs are determined for the four remaining reservoir parameter values. Combining the probability of each representative parameter value and the discrepancy between optimal and suboptimal NPVs for that parameter value yields the cost of uncertainty for that reservoir parameter.

When the cost of uncertainty has been established for each reservoir parameter, the engineer will be able to decide which parameter should be further tested, and to what extent. This allows careful weighing of the cost of testing procedures, including seismic, logging, and transient testing, against the cost of uncertainty in the reservoir parameter values.

Field Model

This study was performed with an integrated field and well model composed of several smaller components. The components consisted of: a tank reservoir model, a multiphase flow wellbore model including gas lift, a multiphase flow choke model, and a separator model. Each component in the model was compositional, and used the Redlich Kwong equation of state to determine phase properties [1]. The structure of this model is illustrated in Fig. 1. Note that the model includes a feed-back loop as gas from the separator is injected as gas lift. This model was used for an earlier study of optimization techniques, and is described in greater detail in reference 2.

This model includes reservoir parameters which are beyond the control of the engineer, such as porosity and permeability. In this study, these parameters are also subject to some uncertainty. Furthermore, there are engineering parameters which must be optimized. The objective function is the NPV of the sales streams predicted for a given combination of reservoir parameters and engineering parameters. The object of the genetic algorithm routine is to select that combination of engineering parameters which offers the greatest possible NPV.

Genetic Algorithm Routine

Genetic algorithms are a method of optimization that draw an analogy to the process of natural selection [3]. Variables are discretized, and converted into binary strings referred to as members.

Each member of a generation has a chance to breed with another member. The odds that a member is able to breed depends on its fitness, or objective function value. The next generation of members is composed of the “offspring” of the prior generation. Because the odds of a member being able to reproduce depend on that member’s fitness, each progressive generation should be better than the last. In this fashion, the genetic algorithm should converge towards the global optimum.

The method is particularly apt for many petroleum problems, because the variables are discrete. Many petroleum engineering parameters are actually discrete, such as tubing diameter. For continuous variables, sufficient binary bits can be used to provide a reasonable approximation of continuity.

The genetic algorithm parameters used for this study were tuned through a thorough sensitivity study. They are considered to be both fast and robust for problems of the type encountered in this work.

Cost Of Information

Genetic algorithms are useful for finding the best combination of engineering parameters for a model with a given set of reservoir parameters. However, it is unusual for a petroleum engineer to know the value of a reservoir parameter, such as porosity or permeability, to a high degree of certainty. It is more common for the engineer to know a distribution, or range of parameter values. In general, certainty in a parameter can only be purchased at the price of well testing, logging, or coring. Engineers face difficulty in determining on which tests to spend resources. This project established that optimization techniques provide an opportunity for quantifying the value of greater certainty regarding reservoir data.

If an engineer selects a set of engineering parameters to optimize based on a given set of reservoir parameters, it is logical to ask what will happen if a reservoir parameter does not have the expected value. Typically, changes in reservoir parameters will have intuitively predictable changes in the objective function value (NPV). For instance, if permeability is greater than expected, the NPV will be greater. What is not as intuitive is how optimized engineering parameters vary with the reservoir parameter. For example, how does the optimized first separator pressure change if the permeability is greater than expected. It is likely that the engineering parameters optimized for the expected value will be suboptimal for the realized reservoir parameter value.

If the reservoir parameter has a value other than the expected value, it is tempting to describe the loss (or gain) as the difference between the optimized NPV for the realized value and the optimized NPV for the expected parameter value. For the purpose of determining the cost of uncertainty, this is not correct. In fact, the loss should be the difference between the optimized NPV for the realized reservoir parameter value, and the NPV based on the realized parameter value, produced with the engineering parameters optimized for the expected reservoir parameter value.

Fig. 2 illustrates this principle through a hypothetical case. The expected reservoir parameter (permeability) value is 10 md. The engineer plans for this permeability, and predicts an optimized NPV of A. Instead, the reservoir parameter value is 1 md, and even with perfect knowledge, the field NPV could only be B. However, the field is produced with a suboptimal separator pressure, one which would have been optimal for a permeability of 10 md. This results in a NPV of C. In this case, the cost of uncertainty in the reservoir parameter is the difference between the optimal and suboptimal NPVs for 1 md, i.e. B-C. If the cost of a well test to properly evaluate the permeability is less than B-C, then the cost-effectiveness of conducting the test will be positive. On the other hand, if the well test would cost more than B-C then the expense would be greater than the possible return.

Case Study

Using the problem described in Table 1 as a base case, this principle is used to study the sensitivity of optimized parameters to reservoir uncertainty. Four reservoir parameters were analyzed. The cost of uncertainty is established by combining the probability distribution with the discrepancy between optimized NPV and the realized suboptimal NPVs. For the sensitivity study of each parameter, all other reservoir parameters were held constant. Thus, each sensitivity study is performed in a univariate context. Only two production control parameters were optimized, the tubing diameter and the first separator pressure.

Composition

The composition was varied by altering the mole percent of methane (C_1). As the methane quantity varied, the mole percent of C_{11+} was changed to balance. There is a twenty percent chance that the methane mole percentage falls between 0.0 and 3.0. There is a twenty percent chance that the value is between 3.0 and 7.0. The third quintile falls between 7.0 and 11.0 mole percent. The fourth quintile contains the range of 11.0 to 15.0 mole percent. There is also a twenty percent chance that the methane value is greater than 15.0 mole percent. Table 2 illustrates this distribution.

For each quintile, a representative mole percentage of methane was chosen, and the model was optimized for each representative mole percentage. These representative values are enumerated in Table 3. The engineering parameters were then optimized for each of the representative values using the genetic algorithm routine.

Table 4 contains the results of these optimization runs. Notice that the optimized engineering parameters changed as the mole percent methane changed. Fig. 3 illustrates the path taken by the optimal parameters as the mole fraction changed.

There is a clear trend in both the NPV and the optimized parameters. However, the interesting information is the NPV for each reservoir composition if produced at the optimized engineering parameters for the expected mole fraction of methane. Table 5 lists the NPV produced using the suboptimal engineering parameters.

The real cost of uncertainty in the composition is the difference in the NPVs listed in Table 4 and Table 5. These differences are illustrated in Fig. 4. Not surprisingly, the further the composition varies from the expected value, the greater the discrepancy between the NPVs. These differences must be weighted by the probabilities listed in Table 3. These calculations are demonstrated in Table 6. In this case, the cost of uncertainty in composition is $157,993. Any choice to spend money on testing composition should be measured against this cost.

Permeability

The permeability is distributed as described in Table 8. Five percent of permeabilities are less than 1.256 md. One quarter of the permeabilities fall between 1.256 md and 3.155 md. Forty percent of the permeabilities lay between 3.155 md and 7.924 md. Another 25 percent of the permeabilities are greater than 7.924 and less than 19.905 md. The final five percent of the permeabilities are greater than 19.905 md.

For each of these ranges, a representative value was selected, and the engineering parameters were optimized for those representative values. The representative permeabilities are presented in Table 9. Table 10 presents the results of the optimization runs. Figure 5 illustrates the path the optimum engineering parameters take as the permeability is changed. In this case, the path is more scattered than it was for changes in composition.

Again, the interesting information is how these optimized NPVs compare to the NPVs based on the engineering parameters optimized for the expected permeability. These NPVs are listed in Table 10. Fig. 6 demonstrates the discrepancy between the optimal and suboptimal NPVs. The cost of uncertainty was calculated to be $388,203, as is illustrated by Table 11. Costs of narrowing the uncertainty in permeability can be measured against this value. Furthermore, the relative merits of permeability vs. composition testing can be found by comparing this number to the value calculated for composition.

Porosity

Porosity is distributed as listed in Table 12. Five percent of porosities fall within 22.5 and 25.5 percent. A quarter of the porosities fall within 25.5 and 28.5 percent. The next 40 percent of porosities fall between 28.5 percent and 31.5 percent. Twenty-five percent of porosities fall within 31.5 and 34.5 percent. The final five percent of the porosities fall between 34.5 and 37.5 percent.

For each of these brackets, a representative value was selected, as listed in Table 13. For each of the representative values, the engineering parameters were optimized. The results of these optimization runs is presented in Table 14. The various optima are illustrated in Fig. 7.

The NPVs based on optimizing parameters for the expected porosity are listed in Table 15. The discrepancies between the suboptimal NPVs in Table 15 and the perfect knowledge, optimal NPVs in Table 14 are illustrated in Fig. 8. The cost of uncertainty in porosity is $194,328. The calculations leading to this figure are in Table 16.

Areal Extent

Table 17 illustrates the probability distribution for the areal extent of this reservoir. The first quintile ranges from 40 acres to 85 acres. The second quintile contains areal extents ranging from 85 to 130 acres. The third quintile ranges from 130 to 190 acres. The next 20 percent falls within the range of 190 to 255 acres. The last quintile contains areal extents from 255 to 350 acres.

Table 18 lists the representative values chosen for these quintiles. The engineering parameters were optimized for each of these representative values. The results of this optimization are presented in Table 19. The locus of these optimized engineering parameters is illustrated in Fig. 9.

The NPVs based on optimizing parameters for the expected porosity are listed in Table 20. The differences between these NPVs and the perfect knowledge NPVs from Table 19 are shown in Fig. 10. The cost of uncertainty in areal extent is $165,001. The calculations leading to this figure are in Table 21. The cost of shooting a seismic line, or drilling an exploratory well, or any other means of exploring the areal extent of this reservoir must be measured against this cost.

Comparison Of Uncertainty Costs

We have calculated the costs of uncertainty for composition, permeability, porosity, and areal extent, based on the given probability distributions. The costs are summarized in Table 22. These costs serve as a means of deciding how much can be spent on transient testing, fluid testing, coring, logging, and or any other data gathering technique. With the given probability distributions, permeability clearly has the highest cost of uncertainty. This indicates that additional transient testing may be worthwhile.

Conclusions

1. Optimization techniques combined with a given probability distribution can provide estimates for the cost of uncertainty in reservoir data.
2. These estimates allow comparisons between different data gathering options.
3. The case study demonstrated should be modified to involve multivariate probability distributions. This would yield better estimates of uncertainty costs.
4. In the case that reservoir parameter certainty is not going to change, it is possible to optimize engineering parameters based on a multivariate probability distribution rather than on an expected value. That is, find an optimized set of engineering parameters that does not necessarily correspond to the expected reservoir parameters.

Acknowledgments

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References

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2.Palke, M.R., and Horne, R.N.: "Nonlinear Optimization of Well Production Considering Gas Lift and Phase Behavior," SPE 37428, SPE Production Operations Symposium, (1997).

3.Goldberg, D.E.: *Genetic Algorithms*, Addison-Wesley, Reading, MA, (1989).

Table 1 - Expected Reservoir Description

Areal Extent of Reservoir (acres)	160.
Thickness (feet)	50.
Porosity	0.30
Initial Res. Pressure	3,500.00
Reservoir Temperature (°Rankine)	650.
Permeability (md)	5.0
S_{wc}, S_{or}, S_{gr}	0.0, 0.3, 0.0
n_o, n_g (rel. perm factors)	1.5,1.0
Reservoir Depth	8,000

Reservoir Fluid, Mole Fraction

C_1	C_2	C_3	C_5	C_8	C_{10}	C_{11+}
0.09	0.13	0.12	0.13	0.19	0.19	0.15

Production Parameters (non-variable)

injection rate (Mscf/day),	300.0
choke diameter (1/64 inches),	30.0
surface line diameter (inches),	1.0
P_{sep2}/P_{sep1}	0.95
P_{sep3}/P_{sep2}	0.90

Table 2 - Distribution of Mole Percent Methane

Cumulative Distribution Function, Minimum	Cumulative Distribution Function, Maximum	Minimum Mole Percent Methane	Maximum Mole Percent Methane
0.0	0.2	0.0	3.0
0.2	0.4	3.0	7.0
0.4	0.6	7.0	11.
0.6	0.8	11.	15.
0.8	1.0	15.	100.

Table 3 - Representative Mole Percent Methane Values for Optimization

Cumulative Distribution Function, Minimum	Cumulative Distribution Function, Maximum	Representative Mole Percent Methane	Probability
0.0	0.2	1.0	20%
0.2	0.4	5.0	20%
0.4	0.6	9.0	20%
0.6	0.8	13.	20%
0.8	1.0	17.	20%

Table 4 - Optimization Results - Composition Distributed

Representative	Optimum Values		Optimal NPV
Mole Percent Methane	Tubing Diameter, inches	Separator Pressure, psia	
1.0	3.19	125.4	5,269,483
5.0	3.1	155.6	6,233,859
9.0	3.0	200.8	7,122,886
13.0	2.9	215.9	7,991,055
17.0	2.71	215.9	8,694,420

Table 5 - NPV if Engineering Parameters Optimized for Expected Composition

Representative Mole Percent Methane	NPV tubing - 3.0”; sep pressure - 200.8 psia
1.0	4,910,630
5.0	6,184,787
9.0	7,122,886
13.0	7,956,254
17.0	8,347,179

Table 6 - Value of Certainty in Composition

Representative Mole Percent Methane	Optimal NPV	NPV tubing - 3.0”; sep pressure - 200.8 psia	Discrepancy	Probability	Cost of Uncertainty
1.0	5,269,483	4,910,630	358,853	20%	71,771
5.0	6,233,859	6,184,787	49,072	20%	9,814
9.0	7,122,886	7,122,886	0	20%	0
13.0	7,991,055	7,956,254	34,801	20%	6,960
17.0	8,694,420	8,347,179	347,241	20%	69,448
				Sum	157,993

Table 7 - Distribution of Permeabilities

Cumulative Distribution Function, Minimum	Cumulative Distribution Function, Maximum	Minimum Permeability md	Maximum Permeability md
0.0	0.05	0.0	1.256
0.05	0.3	1.256	3.155
0.3	0.7	3.155	7.924
0.7	0.95	7.924	19.905
0.95	1.0	19.905	100.

Table 8 - Representative Permeabilities for Optimization

Cumulative Distribution Function, Minimum	Cumulative Distribution Function, Maximum	Representative Permeability, md	Probability
0.0	0.05	0.792	5%
0.05	0.3	1.99	25%
0.3	0.7	5.0	40%
0.7	0.95	12.56	25%
0.95	1.0	31.55	5%

Table 9 - Optimization Results - Permeability Distributed

Representative Permeability md	Optimum Values		Optimal NPV
	Tubing Diameter, inches	Separator Pressure, psia	
0.792	2.9	336.51	2,957,346
1.99	3.1	246.03	5,177,912
5.0	3.0	200.79	7,122,886
12.56	3.57	155.56	9,657,152
31.55	3.29	125.4	12,394,272

Table 10 - NPV if Engineering Parameters Optimized for Expected Permeability

Representative permeability	NPV tubing - 3.0”; sep pressure - 200.8 psia
0.792	1,874,792
1.99	4,694,564
5.0	7,122,886
12.56	9,052,743
31.55	11,151,548

Table 11 - Value of Certainty in Permeability

Representative Permeability, md	Optimal NPV	NPV tubing - 3.0”; sep pressure - 200.8 psia	Discrepancy	Probability	Cost of Uncertainty
0.792	2,957,346	1,874,792	1,082,552	5%	54,128
1.99	5,177,912	4,694,564	483,348	25%	120,837
5	7,122,886	7,122,886	0	40%	0
12.56	9,657,152	9,052,743	604,409	25%	151,102
31.55	12,394,272	11,151,548	1,242724	5%	62,136
				Sum	388,203

Table 12 - Distribution of Porosities

Cumulative Distribution Function, Minimum	Cumulative Distribution Function, Maximum	Minimum Porosity, %	Maximum Porosity, %
0.0	0.05	22.5	25.5
0.05	0.3	25.5	28.5
0.3	0.7	28.5	31.5
0.7	0.95	31.5	34.5
0.95	1.0	34.5	37.5

Table 13 - Representative Porosities for Optimization

Cumulative Distribution Function, Minimum	Cumulative Distribution Function, Maximum	Representative Porosity %	Probability
0.0	0.05	24.0	5%
0.05	0.3	27.0	25%
0.3	0.7	30.0	40%
0.7	0.95	33.0	25%
0.95	1.0	36.0	5%

Table 14 - Optimization Results - Porosity Distributed

Representative Porosity %	Optimum Values		Optimal NPV
	Tubing Diameter, inches	Separator Pressure, psia	
24	4.14	125.4	6,177,130
27	3.19	155.6	6,544,556
30	3	200.8	7,122,886
33	2.9	200.8	7,657,688
36	2.81	200.8	8,162,199

Table 15 - NPV if Engineering Parameters Optimized for Expected Porosity

Representative Porosity	NPV tubing - 3.0”; sep pressure - 200.8 psia
24%	5,766,110
27%	6,088,088
30%	7,122,886
33%	7,509,493
36%	7,709,976

Table 16 - Value of Certainty in Porosity

Representative Porosity, %	Optimal NPV	NPV tubing - 3.0”; sep pressure - 200.8 psia	Discrepancy	Probability	Cost of Uncertainty
24	6,177,130	5,766,110	411,020	5%	20,551
27	6,544,556	6,088,088	456,468	25%	114,117
30	7,122,886	7,122,886	0	40%	0
33	7,657,688	7,509,493	148,195	25%	37,049
36	8,162,199	7,709,976	452,223	5%	22,611
				Sum	194,328

Table 17 - Distribution of Areal Extents

Cumulative Distribution Function, Minimum	Cumulative Distribution Function, Maximum	Minimum Areal Extent, acre	Maximum Areal Extent, acre
0.0	0.2	40	85
0.2	0.4	85	130
0.4	0.6	130	190
0.6	0.8	190	255
0.8	1.0	255	350

Table 18 - Representative Areal Extents for Optimization

Cumulative Distribution Function, Minimum	Cumulative Distribution Function, Maximum	Representative Areal Extent acres	Probability
0.0	0.2	62.5	20%
0.2	0.4	107.5	20%
0.4	0.6	160	20%
0.6	0.8	222.5	20%
0.8	1.0	302.5	20%

Table 19 - Optimization Results - Areal Extent Distributed

Representative Areal Extent acre	Optimum Values		Optimal NPV
	Tubing Diameter, inches	Separator Pressure, psia	
62.5	1.67	170.63	3,481,980
107.5	3	155.56	5,281,408
160	3	200.79	7,122,886
222.5	2.62	215.87	8,751,967
302.5	2.81	246.03	10,693,290

Table 20 - NPV if Engineering Parameters Optimized for Expected Areal Extent

Representative Areal Extent	NPV tubing - 3.0”; sep pressure - 200.8 psia
62.5	3,005,747
107.5	5,121,758
160	7,122,886
222.5	8,696,940
302.5	10,559,195

Table 21 - Value of Certainty in Areal Extent

Representative Areal Extent, acre	Optimal NPV	NPV tubing - 3.0”; sep pressure - 200.8 psia	Discrepancy	Probability	Cost of Uncertainty
62.5	3,481,980	3,,005,747	476,233	20%	95,247
107.5	5,281,408	5,121,758	159,650	20%	31,930
160	7,122,886	7,122,886	0	20%	0
222.5	8,751,967	8,696,940	55,027	20%	11,005
302.5	10,693,290	10,559,195	134,095	20%	26,819
				Sum	165,001

Table 22 - Summary of Uncertainty Costs

Property	Uncertainty Cost
Composition	$157,993
Permeability	$388,203
Porosity	$194,328
Areal Extent	$165,001

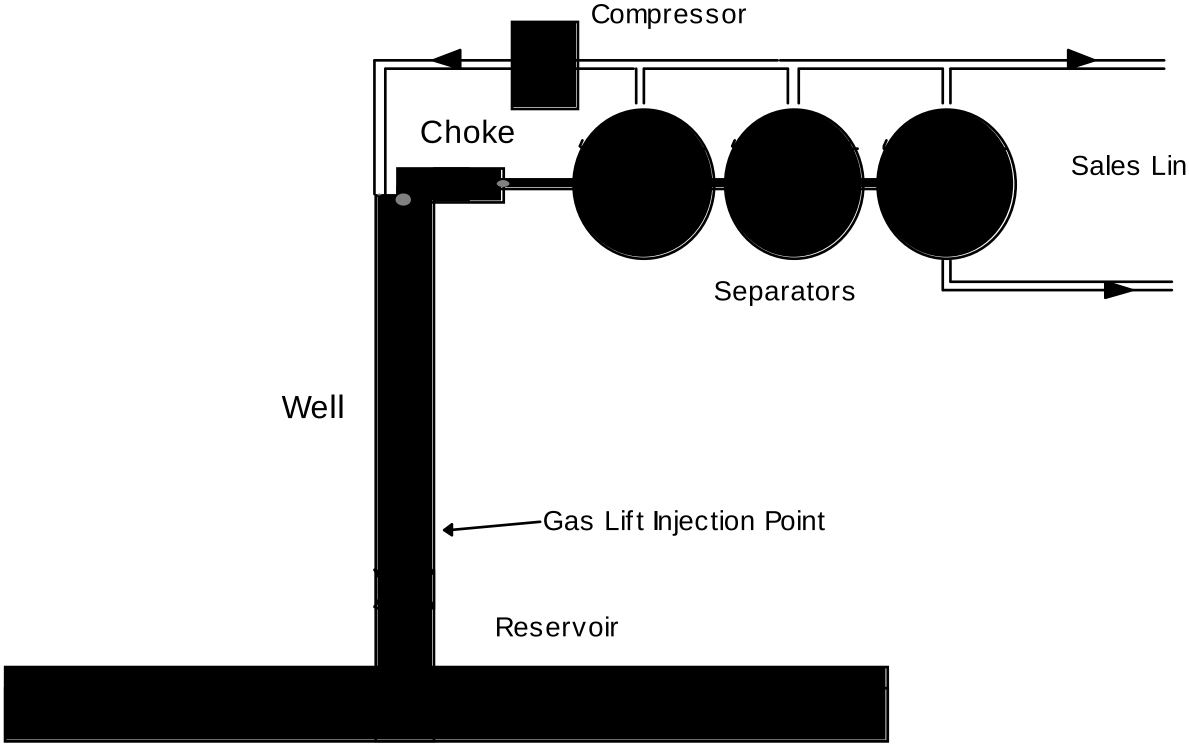

Fig. 1 - Diagram illustrates the model used for this project. Gas from the separator is sold or reinjected for gas lift.

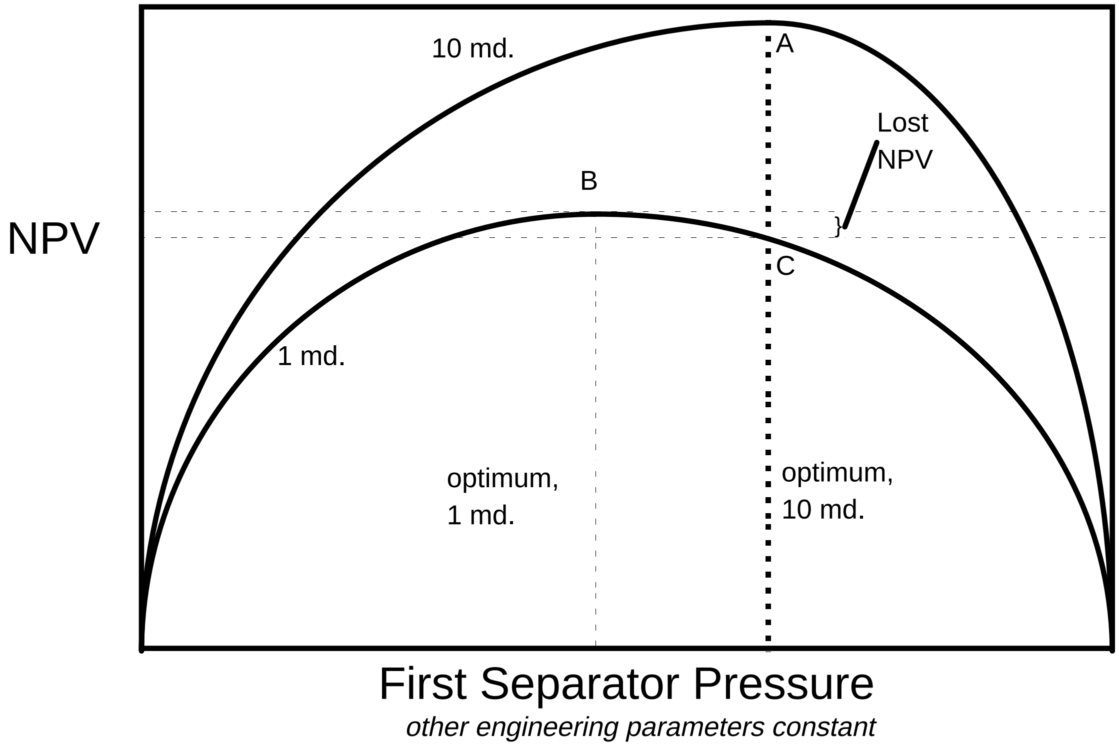

Fig. 2 - Lost NPV Due to Uncertainty

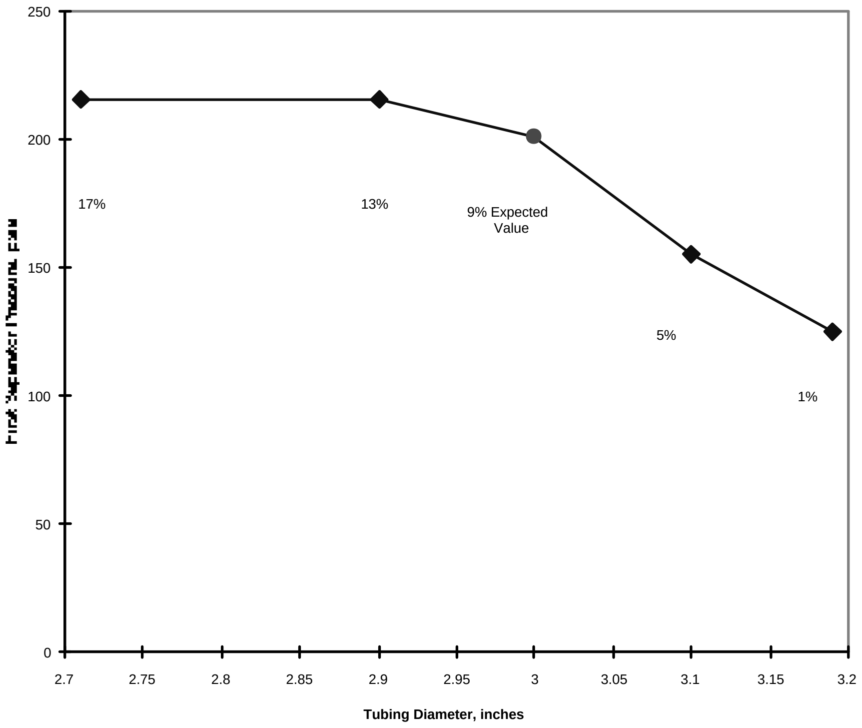

Fig. 3 - Optimal Parameter Path - Composition

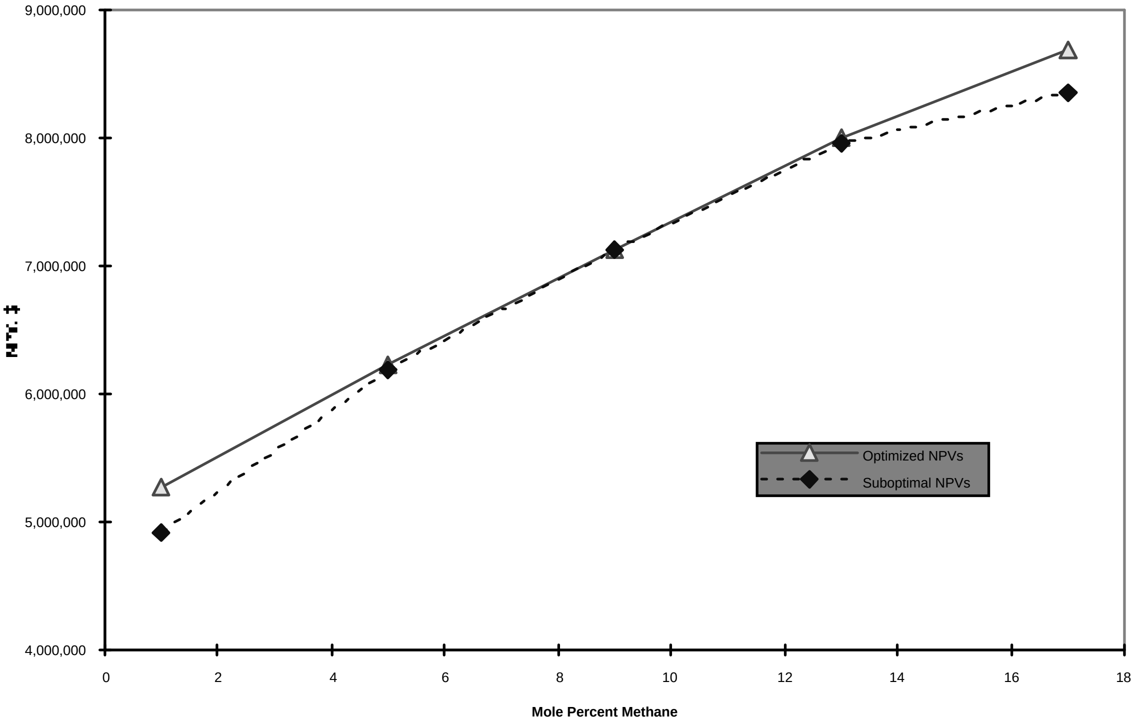

Fig. 4 - Discrepancy in NPV vs. Composition

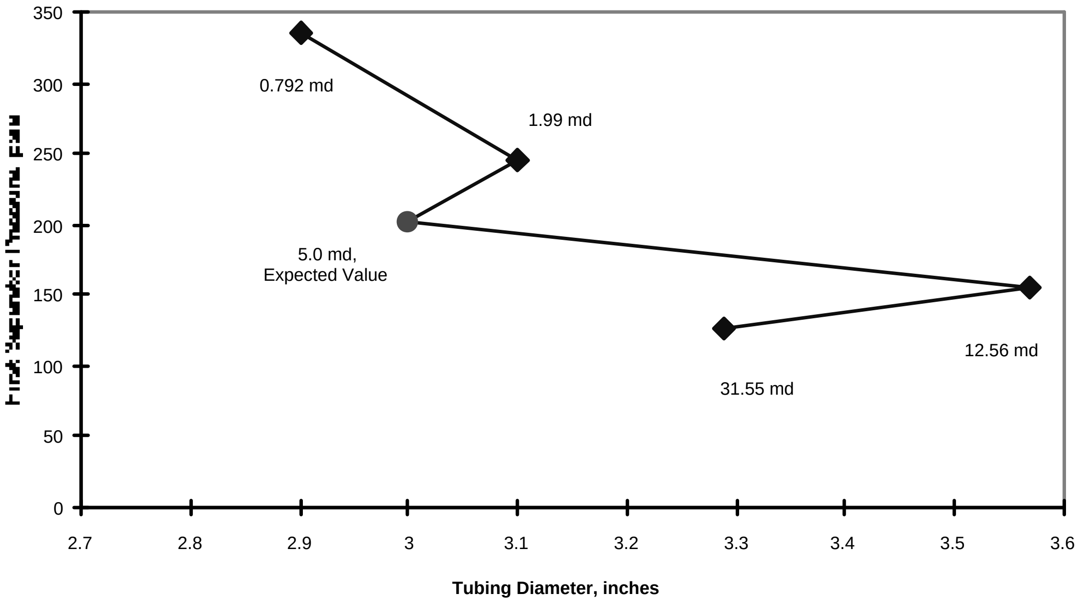

Fig. 5 - Optimal Parameter Path - Permeability

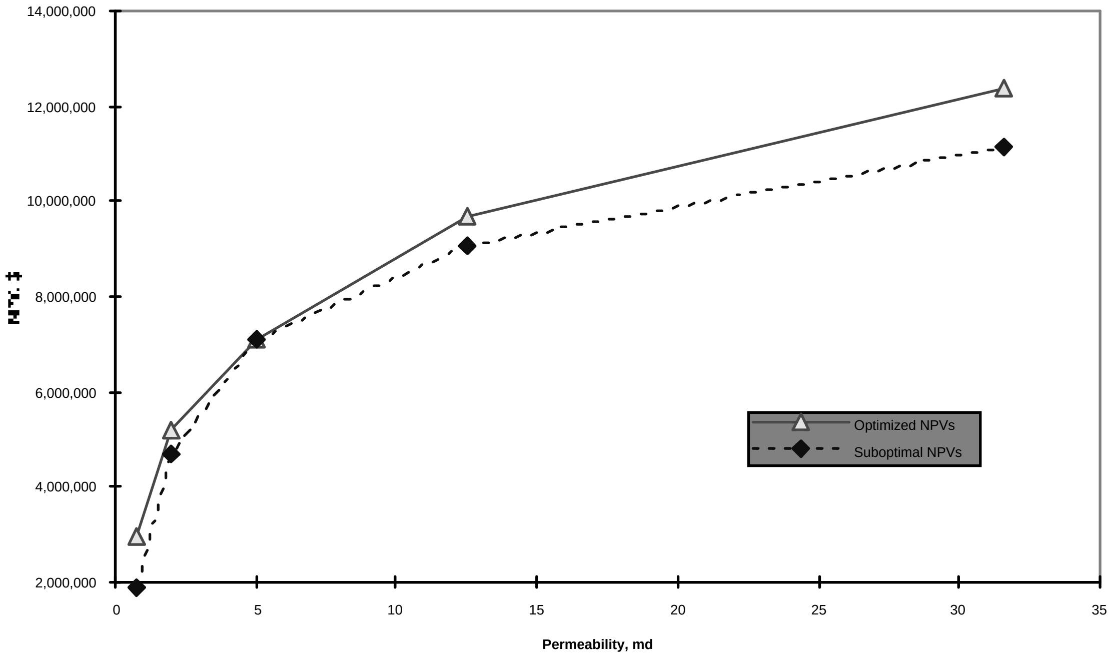

Fig. 6 - Discrepancy in NPV vs. Permeability

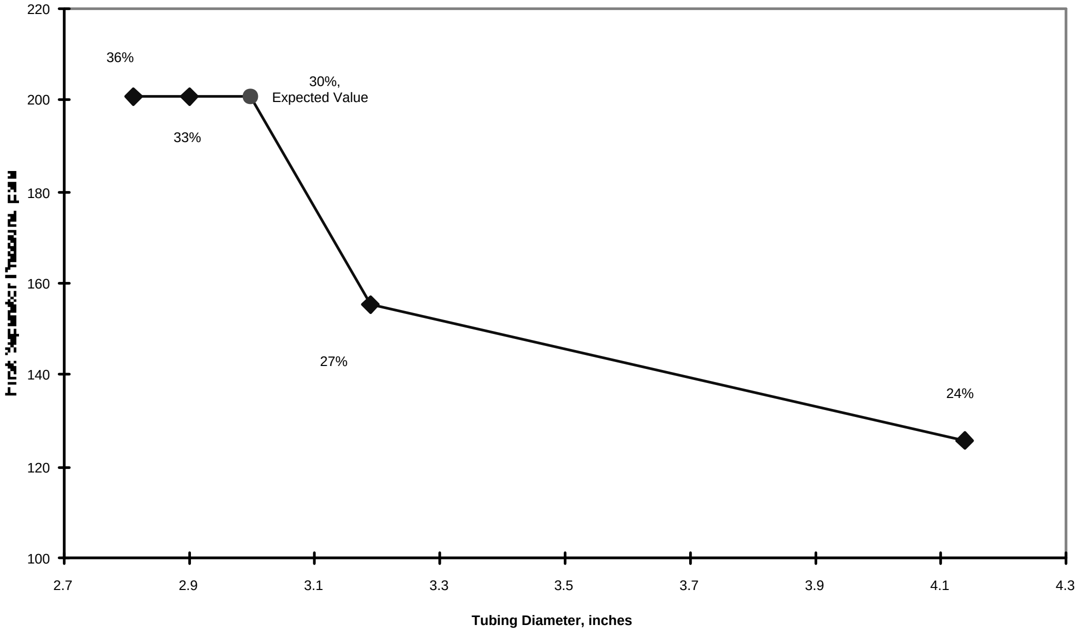

Fig. 7 - Optimal Parameter Path - Porosity

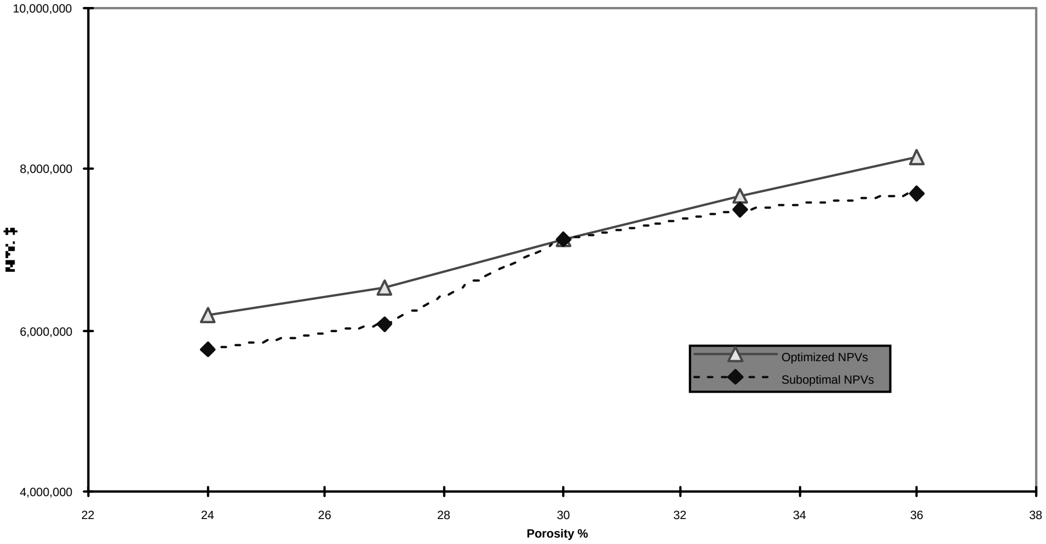

Fig. 8 - Discrepancy in NPV vs. Porosity

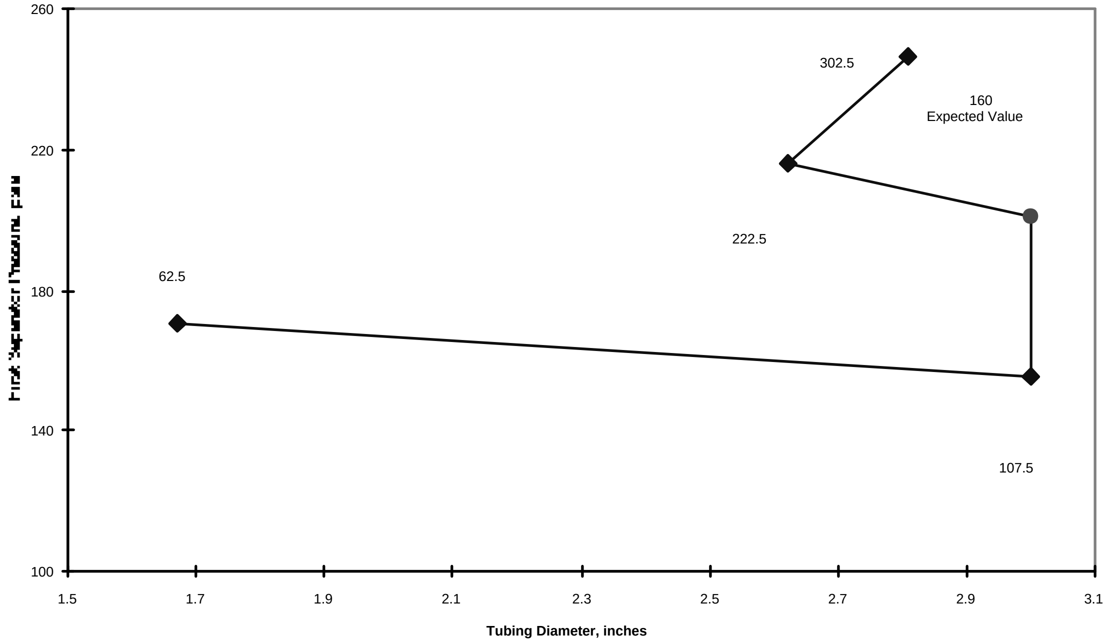

Fig. 9 - Optimal Parameter Path -Areal Extent

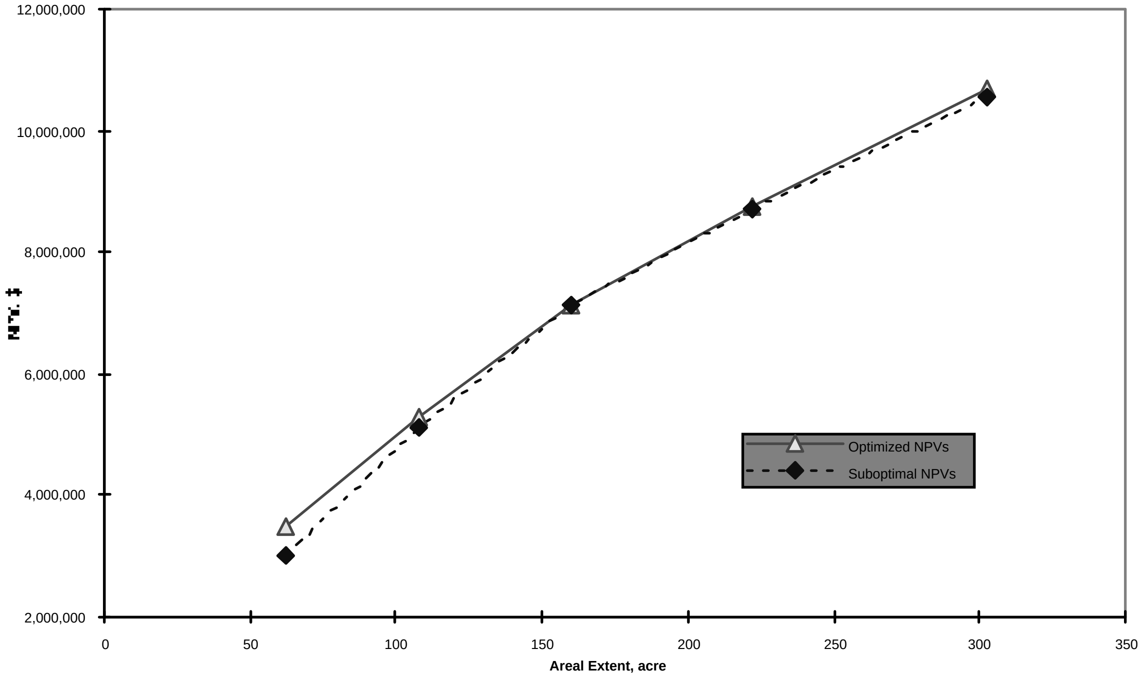

Fig. 14 - Discrepancy in NPV vs. Areal Extent