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Analysis of Real-Time Reservoir Monitoring: Reservoirs, Strategies, & Modeling

Scott P. Cooper, Gregory J. Elbring, Larry W. Lake, Mary F. Wheeler, Rafael Banchs, Bob Gilbert, Blake E. Jakaboski, Jim Jennings, Chris Jablonowski, Hector Klie, John C. Lorenz, Seethambal S. Mani, Randy A. Normann, Emilio J. Nunez, Michael Rightley, Adolfo Rodriguez, Sunil G. Thomas, Bart G. Van Bloemen Waanders, Chester J. Weiss

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Abstract

The project objective was to detail better ways to assess and exploit intelligent oil and gas field information through improved modeling, sensor technology, and process control to increase ultimate recovery of domestic hydrocarbons. To meet this objective we investigated the use of permanent downhole sensors systems (Smart Wells) whose data is fed real-time into computational reservoir models that are integrated with optimized production control systems.

The project utilized a three-pronged approach 1) a value of information analysis to address the economic advantages, 2) reservoir simulation modeling and control optimization to prove the capability, and 3) evaluation of new generation sensor packaging to survive the borehole environment for long periods of time.

The Value of Information (VOI) decision tree method was developed and used to assess the economic advantage of using the proposed technology; the VOI demonstrated the increased subsurface resolution through additional sensor data. Our findings show that the VOI studies are

a practical means of ascertaining the value associated with a technology, in this case application of sensors to production. The procedure acknowledges the uncertainty in predictions but nevertheless assigns monetary value to the predictions. The best aspect of the procedure is that it builds consensus within interdisciplinary teams

The reservoir simulation and modeling aspect of the project was developed to show the capability of exploiting sensor information both for reservoir characterization and to optimize control of the production system. Our findings indicate history matching is improved as more information is added to the objective function, clearly indicating that sensor information can help in reducing the uncertainty associated with reservoir characterization. Additional findings and approaches used are described in detail within the report.

The next generation sensors aspect of the project evaluated sensors and packaging survivability issues. Our findings indicate that packaging represents the most significant technical challenge associated with application of sensors in the downhole environment for long periods (5+ years) of time. These issues are described in detail within the report.

The impact of successful reservoir monitoring programs and coincident improved reservoir management is measured by the production of additional oil and gas volumes from existing reservoirs, revitalization of nearly depleted reservoirs, possible re-establishment of already abandoned reservoirs, and improved economics for all cases. Smart Well monitoring provides the means to understand how a reservoir process is developing and to provide active reservoir management. At the same time it also provides data for developing high-fidelity simulation models. This work has been a joint effort with Sandia National Laboratories and UT-Austin's Bureau of Economic Geology, Department of Petroleum and Geosystems Engineering, and the Institute of Computational and Engineering Mathematics.

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NOMENCLATURE

ANN	Artificial Neural Networks
BEG	Texas Bureau of Economic Geology
CPARM	Center for Petroleum Asset Risk Management
CAPEX	Capital Expenses
CSRL	Compound Semiconductor Research Laboratory
DOE	Department of Energy
DT	Decision Tree
EOR	Enhanced Oil Recovery
FEM	Finite Element Modeling
FY	Fiscal Year
HT/HP	High Temperature/High Pressure
ICES	Institute for Computational Engineering and Sciences
IPARS	University of Texas Simulator
IPS	Interconnect Protection Structure
LDRD	Lab Directed Research and Development
MAC	Monitor Analyze and Control
MDL	Microelectronics Development Laboratories
MEMS	Micro Electro Mechanical Sensors
OPEX	Operating Expenses
PGE	Department of Petroleum Systems Engineering
SAGD	Steam Assisted Gravity Drainage
SNL	Sandia National Laboratories
SPE	Society of Petroleum Engineers
SPSA	Simultaneous Perturbation Stochastic Approach
SwIFT	Surface micromachined with Integrated Fluidics Technology
SVD	Singular Value Decomposition
UTA	University of Texas Austin
UTIG	Institute for Geophysics
VOI	Value of Information

1.0 INTRODUCTION

Sandia National Laboratories and the University of Texas system have many diverse components that are involved in energy related research and, in recent years, both have made significant advances in the science and engineering of modeling, and have developed new procedures for verification and validation of predictions. A primary objective of this effort was to bring together critical components of this existing work to prove the value and feasibility of linked reservoir monitoring and modeling, and to encourage the use of future instrumented wells that use downhole sensing and flow control to increase production. Such instrumented wells, known as “Smart Wells”, are currently being successfully used in the North Sea and the Middle East in high rate wells to identify and isolate sections of wells in advance of water entry (Yeten et al., 2004).

This technology is used much less frequently in US reservoirs, in part because of the expense, but also because the advantages of their use to overall increased production are less clear in mature fields. This project provides explicit estimates of the economic value of such technology, expanding the modeling and control of a reservoir that incorporates the sensor data into both refined reservoir models and improved real-time production control. We also examine the feasibility of long-term (> 5 year) survival of such sensors in the hostile borehole environment.

This LDRD project addressed these issues with a three-pronged approach: a value of information (VOI) analysis to address the economic advantages, reservoir simulation modeling, control and optimization to prove the capability, and evaluation of new generation sensor packaging to survive the borehole environment for long periods of time. The first two parts are jointly performed between UT and SNL; the last is entirely conducted at SNL.

The working partnership included Sandia National Laboratories (SNL) and components of The University of Texas at Austin (UT), specifically, the Bureau of Economic Geology (BEG), the Department of Petroleum and Geosystems Engineering (PGE), the Institute for Computational Engineering and Sciences (ICES), and the Institute for Geophysics (UTIG). A group of industry participants was also used for the Value of Information (VOI) analysis. The work was supported through Laboratory Directed Research and Development (LDRD) funds from SNL.

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2.0 VALUE OF INFORMATION

2.1 Technical Approach

Our hypothesis was that with improved monitoring, rapid interpretation, and appropriate intervention, ultimate hydrocarbon recovery from a variety of reservoirs could be increased. Quick response to such things as changes in flow rate, pressure, and fluid chemistry will also improve the effectiveness of primary and secondary oil recovery. For oil production, accurately locating remaining unswept oil would also aid the design of effective enhanced oil recovery (EOR) technologies and successful infill drilling. Changing the instrumented Smart Well measurements into action will require understanding, and/or simulation.

VOI was developed as a tool to direct efforts toward technologies with the maximum potential benefit. As used here, VOI uses a decision tree (DT) that breaks the hydrocarbon recovery objective into basic units or components and then assigns the probability of attaining each component along with its expected value. For example as part of first year tasks a joint SNL/UT group developed a DT to reflect the components affecting production decisions in a typical mature oil reservoir in the Permian Basin of West Texas. The main objective of this exercise was to analyze and compare how different technologies could increase the ability to identify missed zones and drill a horizontal well targeted to them. These values were then compared with the actual base case technology to determine the potential economic impact of adding sensors. This VOI analysis is shown in Figure 1 and described below:

It was considered that the Permian Basin field under analysis was subject to waterflood. Due to vertical and spatial heterogeneity some layers or zones are not swept. If these zones could be identified and drilled ultimate oil recovery could be increased.

The first uncertainty considered was the existence of continuous or discontinuous layers in the well. The next uncertainty is the total production rate; it could be high or low depending on the pressure and permeability found in the layer. High rates were considered to be 1000 barrels of oil per day (bopd), and low rates 200 bopd. The costs considered in all the cases are: 1) Drilling cost : \$1,000,000 (horizontal well leg 1000-2000 ft) / (drilling depth 6000 ft), 2) Oil price: \$50 per barrel (\$/bbl; net value, includes operating expenditures deductions) and 3) Water Processing cost: 0.50 \$/bbl.

In this analysis it was assumed that Smart Wells will improve monitoring allowing the measurement of layer by layer flow, pressure, saturation, and chemical properties in real time. This would drastically change the amount of information available and allow the building of better simulation models. The simulation models would in turn allow the better detection of by-pass zones through increased data density.

In the Smart Well Case the chance of hitting a continuous layer is changed to 80% from 70% in the Base Case (Figure 1). The use of Smart Wells will change this probability since it will allow the detection of by passed zones by measuring flow and chemical components of the production fluids. For analogous reasons the probability of finding high rate layers is also increased.

The resulting VOI comparison shows the Base Case expected oil recovery is 24MBls of oil per well over a six month period and the expected value of this investment is 189M\$ and the expected oil recovery in the Smart Well Case is increased to 28MBls of oil per well and the resulting expected Value is 354 M\$ (given the economic values listed previously; Figure 1).

Base Case

BASE CASE - EXISTING STATE OF PRACTICE

				Total Probability	Qo bpd	Qw bpd	Oil Recovery Mbo	Value M\$			
Unswep Beds	100%	Continuous along well bore	70%	High total production rate (1000 bpd)	20%	60% Oil	2.8%	600	400	108	4364
					20%	30% Oil	8.4%	300	700	54	1637
					20%	1% Oil	2.8%	10	990	1.8	(999)
			80%	Low total production rate (1000 bpd)	60%	60% Oil	33.6%	120	80	21.6	73
					20%	30% Oil	11.2%	60	140	10.8	(473)
					20%	1% Oil	11.2%	2	198	0.36	(1000)
	30%	High total production rate (1000 bpd)	50%	60% Oil	1.5%	600	400	108	4364		
			60%	30% Oil	9.0%	300	700	54	1637		
			30%	1% Oil	4.5%	10	990	1.8	(999)		
		50%	Low total production rate (1000 bpd)	20%	60% Oil	3.0%	120	80	21.6	73	
				60%	30% Oil	9.0%	60	140	10.8	(473)	
				20%	1% Oil	3.0%	2	198	0.36	(1000)	
				100.0%		Expected	24	189			

Smart Well Case

USING DATA FROM "SMART" (INSTRUMENTED) WELLS IN VICINITY

				Total Probability	Qo bpd	Qw bpd	Oil Recovery Mbo	Value M\$			
Unswep Beds	100%	Continuous along well bore	80%	High total production rate (1000 bpd)	20%	60% Oil	4.8%	600	400	108	4364
					60%	30% Oil	14.4%	300	700	54	1637
					20%	1% Oil	4.8%	10	990	1.8	(999)
			70%	Low total production rate (1000 bpd)	60%	60% Oil	33.6%	120	80	21.6	73
					20%	30% Oil	11.2%	60	140	10.8	(473)
					20%	1% Oil	11.2%	2	198	0.36	(1000)
	20%	High total production rate (1000 bpd)	60%	60% Oil	1.2%	600	400	108	4364		
			60%	30% Oil	7.2%	300	700	54	1637		
			30%	1% Oil	3.6%	10	990	1.8	(999)		
		40%	Low total production rate (1000 bpd)	20%	60% Oil	1.6%	120	80	21.6	73	
				60%	30% Oil	4.8%	60	140	10.8	(473)	
				20%	1% Oil	1.6%	2	198	0.36	(1000)	
				100.0%		Expected	28	354			

Figure 1: Example of preliminary VOI decision tree analysis for a Permian Basin mature oilfield.

This example shows that the VOI analysis can be a primary tool to evaluate the economic advantage of permanently emplaced sensors in wells used to control production. The analysis accomplishes several objectives:

1. Forces decisions to be considered as a combination of small decisions (components) that are more understandable (and more discussable) than large decisions.
2. Allows discussion of the components of a decision by a group of experts so as to build consensus.
3. Incorporates the experience of the analysis participants through assignment of probabilities.
4. Forces internal consistency on the value assignments across multiple scenarios.

5. Creates the opportunity for group involvement and buy-in.

In the decision process the conceptual use of sensors follows three steps:

Accumulation of data - Capturing and amassing of data at a time rate appropriate to the ability to change operations in a reservoir. This step includes high-density storage options as well as data mining considerations.

Interpretation of data - Using the accumulated data in a calculation to develop a model of the type of issues being experienced. At the current stage of understanding, this step involves using the data to calibrate or identify alternatives in the input to a numerical model, which is one of the reasons for the numerical modeling portion of this report.

Implementation - Using the calibrated model to develop alternatives in operating procedure. The changed operating procedure will result in more hydrocarbon production either through larger rates (than before the change), increased ultimate recovery, or both. Implementation must face the challenges of downhole conditions as is discussed in the sensor development portion of this report.

The principal tool of the VOI analysis is the decision tree (DT). Decision trees consist of a succession of nodes of different types to diagrammatically illustrate the component decisions and possible outcomes. DT's have been in use for several decades in many industries. The ones being used here consist of decision and chance nodes. Experts quantify their knowledge through the outputs of the node in three ways; they define the 1) type of outcomes, 2) quantitative value of the outcomes, and 3) probability of that outcome occurring.

2.2 VOI Analysis

VOI is an attempt to combine the three above steps (accumulation of data, interpretation of data, and implementation) in a semi-quantitative fashion. The procedure does not rely on modeling or data, but it does allow all aspects of the steps to be considered to avoid undue emphasis in any one area or to avoid technology development in isolation.

UT and SNL personnel conducted a preliminary VOI analysis in the summer of 2005. During the summer of 2006, this analysis was repeated with a broad industry group, using more technologies, and a more refined DT. UT and SNL along with a group of industrial contacts provided the analysis. Some of the companies that participated include ExxonMobil, Chevron, British Petroleum, Petrobras, Anadarko, Marathon, Baker Hughes and WesternGeco. Appendix A gives a summary of the industry Workshop.

The following is a description of the preparation for this workshop as developed through several UT/SNL meetings.

The VOI Scope. Considering all reservoirs, sensors and technologies is beyond the ability of any organized workshop. Hence some initial work was needed to limit the scope.

Sensors. The explosion in sensor technology and the presumed benefits of this technology motivate this work. High resolution bottom hole measurement of fluid content (saturation) has been possible for several decades as has surface measurement of rates. Current technology allows the near-continuous in time measurement (one measurement per second) of bottom hole temperature and pressure with good spatial (about one measurement per meter) and measurement resolution (less than 0.1 degree F for temperature or 0.1 psia for pressure). Bottom hole measurements of rate (usually deduced from temperature or pressure change) and chemical composition are on the horizon. Here *sensor* refers to all of these; we presume a prudent operator will chose a sensor that is best for a given application. See Section 4 of this report for more details.

Reservoir/Technologies. Early on we established a collection of reservoirs and appropriate technologies on which to perform the VOI analysis. The combination of reservoir and technology is a *scenario*. The scenarios are

- S1. Conventional mature onshore oil reservoirs in which a CO₂ enhanced oil recovery (EOR) project is being considered.
- S2. Unconventional gas reservoirs to be produced by multilateral or horizontal wells.
- S3. Heavy oil reservoirs for which a Steam Assisted Gravity Drainage (SAGD) thermal EOR project is considered.
- S4. Deepwater oil production being considered for waterflooding.

Decision Trees. The primary tool of the VOI workshop is the decision tree or a succession of nodes of different types to diagrammatically illustrate the component decisions and possible outcomes. DTs have been in use for several decades in many industries. The ones being used here consist of decision and chance nodes. See schematics in Fig. 2 for this discussion.

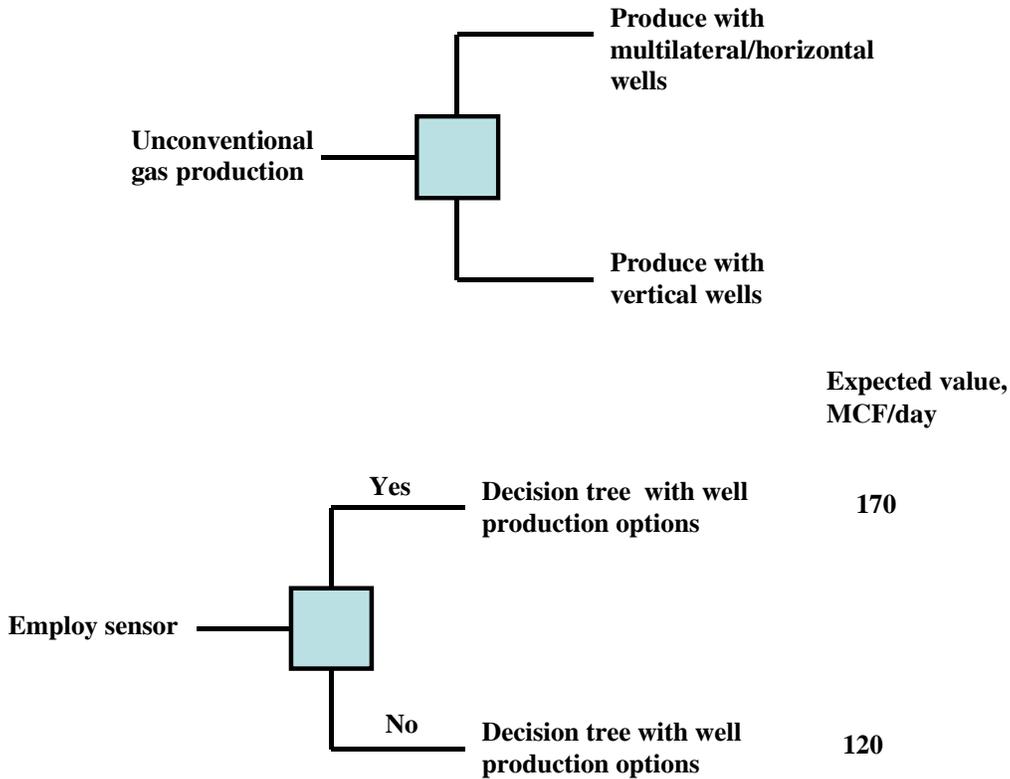


Figure 2: Schematics of decision nodes used in a decision tree.

Nodes. A decision node is designated by a box with at least two outputs. The outputs represent the possible choices and the input is the decision itself. For example, for S2 above a decision node would be “use horizontal wells” or “fracture vertical wells” (see Figure 2). We will use decision nodes with two outputs in the VOI analysis.

The second type of node is the *outcome* or *chance* node represented by a circle in Fig. 3. The inputs to the circle (line intersecting the circle from the left) come from a decision node. The outputs (lines to the right) of the chance node illustrate the possible outcomes and probability of that outcome occurring--100 MCF/day and 0.8 for the upper branch in Fig. 3.

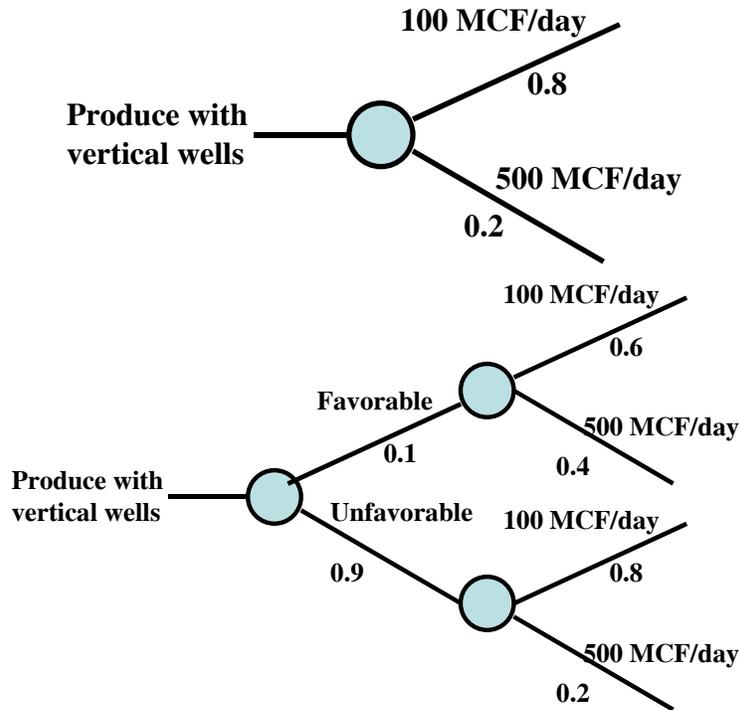


Figure 3: Schematics of outcome nodes used in a decision tree.

Workshop experts quantify their knowledge through the outputs of the outcome nodes in three ways;

1. Type of outcomes, for example the use of rates in the above figure
2. Quantitative value of the outcomes
3. Probability of that outcome occurring.

One of the first tasks of the workshop was to agree on the outcome definitions. These items express the inevitable uncertainty in the outcome. Chance nodes with multiple or even continuous outputs are possible but we will use only binary outputs.

We make the DTs used here manageable by restricting the number of outcome node levels to only two, one that depicts the state of the reservoir and another the effect of the decision in each state. The state of the reservoir (favorable or unfavorable above) is an attempt to quantify (through the probabilities) the native heterogeneity of the scenario. The definition of “favorable” will be made before the workshop (for example, a favorable reservoir might be one with continuous pay), but the participants will provide the detailed definition.

2.3 Specific Application

Here we discuss how the DT applies to specific hydrocarbon production technologies. The benefit obtained by using sensors fall into three areas:

The sensors. This category includes the accuracy, precision, reliability and cost of the measurements. Evidently, nearly everything that can be measured with conventional logging suites can be measured with sensors (and more): pressure, temperature, phase saturation, flow rate and even some chemical compositions. These measurements, mainly electrical or optical signals, appear to be accurate and precise. The main technical limits are the rate at which (what will ultimately prove to be) large quantities of data can be transmitted, and the range of conditions at which sensors can operate. Given that processes taking place within a reservoir occur slowly, data transmission issues are not as limiting as they would be in other applications. The range of operating conditions (which is a range on sensor packaging) is more severe; currently-available sensors fail at temperatures greater than 175 deg F after a few hours.

Interpretation. While much can be measured with sensors, little is of direct use to a decision-maker. Sensor information must be interpreted with a model, analytical or numerical, that translates what a sensor can measure (e.g. temperature) to what is useful (e.g. downhole flowrate). The translation also allows what is essentially a point measurement to be relevant to a larger volume in the reservoir. Furthermore, the consequences of acting on the sensor information can only be evaluated through a similar model.

Response. Sensors have no use unless there is some way to respond to the interpretation provided by the model. For many applications, the response options are limited. Indeed, for some types of production, there are no choices whatsoever, in which case there can be no value to the sensor. Options usually involve any action that redirects flow: shutting in wells, shutting in zones within a well, opening up wells and zones, redirecting fractures, limiting heat losses.

Each of the above categories is a subject of stand-alone research. For the VOI study all of these are part of assigning worth.

Technologies. We selected several technologies and reservoirs on which to apply VOI analysis. These are summarized in Table 1. The combinations of reservoir type (first column), technology (second), and alternative are intended to cover a range of production encountered in the US. A brief description of each follows.

Reservoir	Technology	Alternative	Basis	Cost Calculation	Ways to Fail	Applicable Sensors
Mature, onshore oil	CO2 flooding	Continued waterflooding	5-spot pattern	Typical CO2 injection	Bypassing Poor injectivity	Flow Temperature <i>Chemical</i> Pressure
Tight gas	Hydraulic fracture	Unfractured vertical well	Single well	Hydraulic fracture cost	Fracture too small Fracture out of zone Poor returns	Seismic <i>Chemical</i> Flow Pressure Temperature Tiltmeter
Deepwater oil	Waterflooding	Continued primary	10 Well Project	5 conversions	Bypassing Poor injectivity Sand production	Flow Temperature Pressure Optical
Heavy oil, tar sands oil	SAGD	Cyclic steam	SAGD well pair	Extension of two horizontal wells	Poor injectivity Uneven breakthrough Sand production Surface eruption	Flow Pressure Temperature Optical Tiltmeter Seismic

Table 1: Reservoir types and production scenarios.

Mature onshore reservoirs. Particularly in West Texas, there is intense activity in CO₂ injection. The purpose of this technology, which is usually applied to a reservoir in the late stages of a waterflood, is to mobilize residual oil saturation by attaining miscibility between the crude and the CO₂. When miscibility (or near miscibility) is obtained, the local recovery of crude is close to 100%. Examples of CO₂ floods include the Means San Andres and the SACROC Units.

Flow rate and pressure sensors could be useful in identifying well pairs between which CO₂ is channeling. Such wells could be shut in if analysis so dictates. Sensors could also identify a zone within a reservoir that is experiencing early CO₂ breakthrough. Chemical sensors could distinguish between CO₂ and water flow. With the right equipment within the well, these zones could be isolated and plugged.

Tight gas. Such reservoirs are defined as those that have an average permeability less than 0.1 md. The hydrocarbon produced from such reservoirs is usually a dry gas. The permeability being so small, these reservoirs require stimulation through massive hydraulic fracturing, the creation of an extensive high-permeability conduit radiating from a producer. Examples of this type of production are wells in the Travis Peak and Barnett Shale Formations.

Fracturing is a mature technology. Nevertheless, fracturing can fail if the fracture moves out of its intended zone, or moves in a direction that tends to short circuit production. These effects can be detected by temperature, pressure and flow rate sensors. With suitable calibration, surface seismic or deflection sensors can also be useful. Another way a frac job can fail is failure to clean-up, or failure to recover enough of the fracturing fluid. Such recovery can be inferred with chemical sensors.

Deepwater production. The newest production area in the US is oil production from water depths greater than 3,000 ft in the Gulf of Mexico. Many of these reservoirs are highly undersaturated meaning that they can produce oil at high rates without significant gas or water production. Sustaining this production once the average pressure falls can be done only with water injection. Waterflooding is an extremely mature technology in onshore reservoirs; however, it is far less common in deep water reservoirs. Examples of this type of production are the Popeye and Green Canyon reservoirs.

As in CO₂ injection, sensors can be used to locate zones that are receiving a large amount of water or wells that are about to experience water breakthrough. Remedial action here consists of isolating and cementing back such zones.

Steam assisted gravity drainage. Designed for extremely heavy or tar sands oil (those with reservoir viscosities greater than one million cp), SAGD consists of drilling pairs of parallel, horizontal wells separated vertically by a few meters. Steam is injected into the upper well, forms a heated zone above it, and oil is produced by gravity drainage into the lower well. Examples of SAGD implementation is the production in the Cold Lake reservoir of northern Alberta and the Tiajuana Field in Venezuela.

SAGD production can suffer from short-circuiting between the injector and producer. This can be remedied again by selective operation of zones. Thermal sensors, maybe even located on the surface, can identify regions of significant heat loss. Finally, pressure sensors can identify the propensity for steam eruptions to the surface. The remedy in many of the circumstances is simply to reduce the steam injection rate.

Value of Information Implementation. We seek a generic way of capturing the response of all of the above technologies in typical reservoir settings. Given the variety of reservoir types, crude types and technologies, this is not easy. And it is certainly true that some of the Table 1 cases only approximately fit the generic representation.

The generic response is shown in Fig. 4.

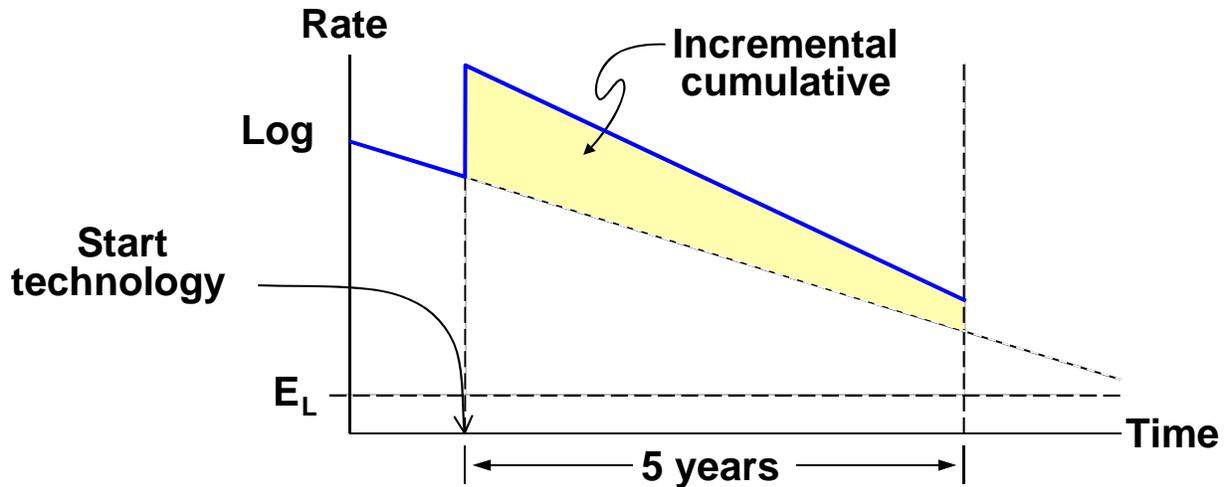


Figure 4: Generic production response.

We assume that the hydrocarbon production rate associated with the technology is declining exponentially, or the rate versus time curve on a semi-logarithm plot is a straight line. The slope of this line is the pre-technology decline rate (dotted line in Fig. 4). Upon implementation of the technology (second column in Table 1 and indicated in Fig. 4) there is an immediate increase in the rate and an immediate resumption of a second decline rate, the post-technology decline rate. The area between the two curves (shaded in Fig. 4) is the incremental cumulative hydrocarbon production, which can be calculated using standard formulas. What determines the incremental production are the rates just before and after implementation of the technology (we represent this as a multiplier or the ratio of the rates on either side of the instantaneous jump) and the respective decline rates. The greater the multiplier, the greater the cumulative production. Also, the larger the pre-technology decline rate, the greater the cumulative production. The smaller the post-technology decline rate, the greater the cumulative production.

The specific values of the quantities discussed above are how we account for specific production. These are values set by expert option. For example, the rate multiplier on SAGD production is likely to be quite large, around 10. For the deepwater waterflood case, the pre-technology decline rate is large, around 40%/year. The post technology decline rate is smaller, say 20%/year, leading to significant incremental production even if the multiplier is not much greater than one.

Uncertainty is added to the procedure by allowing each of the four quantities described above to have two possible values, each with a specified probability of occurrence. For some quantities, such as the pre-technology oil rate in a mature CO₂ flood, the uncertainty is small; the production rate at the start of the technology is known. For other quantities, such as the multiplier for a fractured well, there may be two values that have essentially equal probability.

2.4 Results Summary

Table 2 shows the results of the analysis. Table 2 is an extension of Table 1 wherein the technology decision (column 2) and the value of the sensors over a five year time period (column 3) has been added.

Reservoir	Technology Decision	Value of Sensors
Mature, onshore oil	Implement CO2 Flooding	\$115,506 per pattern
Tight gas	Implement fracturing	\$66,425 per well
Deepwater oil	Implement Waterflooding	\$191 Million per 10 well project
Heavy oil, tar sands oil	Implement SAGD	\$241,306 per 2 well project

Table 2. VOI results.

See Appendix B for the Economic Premises behind the spreadsheets for all scenarios as well as a discussion of the Sensor Probability Tables for each scenario.

Despite the lack of modeling and the subjectivity of the process, Table 2 has interesting results. Specifically,

1. In all cases the new technology (e.g. CO2 flooding as opposed to continued waterflooding) was selected. The VOI is supposed to cause changes of decisions, but this did not happen here. This phenomenon is probably the result of the large (but not unrealistic) hydrocarbon price assumed.
2. Sensors are of most value in considering whether to implement waterfloods in deepwater reservoirs. The value here is, in fact, many times greater than that in any other scenario. The large value is a direct consequence of the large volumes and rates in these types of projects.
3. Sensors are of the least value in tight gas production. Again, the poor showing here is the result of the comparatively small production rates in these projects.
4. Even though the value of the sensors is modest in the heavy oil and mature reservoir projects, their value is still greater than the cost to install the sensors.

The results are consistent with practice. Sensors seem to have the most value in reservoirs having large rates. This experience is consistent with that in the North Sea wherein permanent sensor technology seems to be the most popular. In other words, operators there recognize the value of the sensors without the VOI analysis. This interest is the motivation between the high temperature sensor work discussed in Section 4 of this report. For the same reasons in reverse, sensors are rarely used in fracturing of tight gas reservoirs.

In terms of incremental improvements over current practice, it would seem that the SAGD and mature CO2 projects offer the greatest promise. To our knowledge, there has been no sensor

implementation in CO₂ and the degree of sensor implementation in SAGD projects appears to be declining.

2.5 Future VOI Work

Future work for the value of information group could include 1) formalizing the VOI analysis as a decision tool for industry, this would include providing the VOI tool in CD form to industry; and 2) quantifying and validating the VOI probabilities by developing additional probabilities and values for the decision tree analysis through Monte Carlo analyses on calibrated numerical models and literature review for typical performance data.

3. RESERVOIR SIMULATION MODELING

The reservoir simulation and modeling aspect of the project is intended to show the capability of exploiting sensor information both to better characterize a reservoir and to optimize control of the production system. This work focused on the first of these tasks by developing the codes and methods to exploit initial sets of sensor data and to show that this additional sensor information had an impact in our ability to determine reservoir properties. To achieve this goal the following tasks were performed:

Create two- and three-dimensional (2D and 3D) data sets of two phase flow in a reservoir - Synthetic datasets of observables (pressure, saturation, and velocity) and production data were generated based on up-scaled versions of a cross-sectional reservoir model (model 1 of the SPE 10th Comparative Solution Project). These upscaled models were generated by performing a Haar basis wavelet transformation. The original model was modified to allow oil and gas compressibility and capillary forces because of the interaction of these two phases. The application of wavelets guarantees that the coarser samples preserve some of the macroscopic features of the original data field. A fixed production strategy was adopted with one gas-injecting well located at the leftmost side of the model and a production well at the opposite extreme. This resulted in a realistic datasets to be used in the later optimization studies.

Simulation framework and objective function design - This task consisted of coupling a multiphase parallel reservoir simulator (UT-Austin's IPARS simulator) with two different optimization approaches and a collection of objective functions, with the latter being chosen to demonstrate the impact of sensor information on dynamic reservoir characterization. Two different optimization approaches were carefully chosen for understanding the capabilities of both local and global search space capabilities in reservoir parameter estimation. Moreover, this study permitted investigating the development of a hybrid approach that exploits the strength of both procedures.

Finite difference sensitivity analysis and local optimization - As an initial phase toward developing large scale optimization capabilities within IPARS, we implemented a simple interface to characterize the behavior of parameter estimation constrained by reservoir simulation dynamics. A non-intrusive implementation interface with forward differences was used to calculate the objective function gradient and solved an unconstrained optimization problem with a sequential quadratic programming method (NPSOL). Our goal was to invert for permeability in the entire flow domain by maximizing oil recovery using sparse production observations.

Simultaneous Perturbation Stochastic Approximation - The Simultaneous Perturbation Stochastic Approximation (SPSA) algorithm has received considerable attention for global optimization problems where it is difficult or impossible, as in this case, to compute first order information associated with the problem. This algorithm is a derivative-free (black box) method that does not require intrusive changes to the simulator. SPSA performs random simultaneous perturbations of all model parameters to generate a descent direction at each iteration. The SPSA software for this project was developed at UT-Austin and current enhancements are being implemented (Spall 2003).

Despite the fact that we have used a coarse up-scaled model for initial implementation of the codes during this phase of the project, we can draw some important conclusions and derive further directions for our work: 1) The solutions for pressure and concentration in the reservoir improve as more information is added to the objective function, clearly indicating that sensor information can help to reduce the uncertainty associated with reservoir characterization. 2) Velocity measurement appears to be of additional value in parameter estimation for reducing uncertainty. 3) In order to improve accuracy in permeability estimates one needs to refine the search with local optimization algorithms and sensitivity analysis; this should aid in guiding the search process. 4) The SPSA algorithm was implemented and tested in a matter of a few hours. This makes the procedure attractive for fast implementations. The procedure quickly converged to a minimum but further tuning and enhancements are necessary. 5) Current efforts involve exploiting a multilevel approach, with progressively finer spatial gridding, for estimating thousands of parameters and surrogates to improve permeability estimation and rate of convergence in local search regions.

3.1 Reservoir Simulation Publications

Copies of papers presented from this work are provided in Appendix C. The Abstract and Conclusions are reproduced here.

3.1.1 Assessing the Value of Sensor Information in 4-D Seismic History Matching

H. Klie, A. Rodríguez, R. Banchs and M.F. Wheeler, Assessing the Value of Sensor Information in 4-D Seismic History Matching, 76th SEG International Exposition & Annual Meeting. New Orleans, Oct. 1-6, 2006.

Summary

The main objective of the present work is to numerically determine how sensor information may aid in reducing the ill-posedness associated with permeability estimation via 4D seismic history matching. These sensors are assumed to provide timely information of pressures, concentrations and fluid velocities at given locations in a reliable fashion. This information is incorporated into an objective function that additionally includes productions and seismic components that are mismatched between observed and predicted data. In order to efficiently perform large scale permeability estimation, a coupled multilevel stochastic and learning search method is proposed. At a given resolution level, the parameter space is globally explored and sampled by the simultaneous perturbation stochastic approximation (SPSA) algorithm. The estimation and sampling performed by SPSA is further enhanced by a neural learning engine that estimates sensitivities in the vicinity of the most promising optimal solutions. Preliminary results shed light on future research avenues for optimizing the frequency and localization of 4-D seismic surveys when sensor data is available.

Conclusions and Further Remarks

Despite the fact that we have employed a coarse model for the preliminary phase of the project, we can draw some important conclusions:

1. The history matching is improved as more information is added to the objective function, clearly indicating that sensor information can help in reducing the uncertainty associated with reservoir characterization.
2. It is possible to match the production results using only production data in the objective function. However, this does not necessarily yield reliable permeability estimations because of the inherent ill-posedness of the inversion process.
3. Time-lapse 4-D seismic measurements provide global insight into the history matching process that neither production data nor localized sensor information on fluid properties is able to reproduce.
4. The combination of SPSA and ANN is very attractive for parameter estimation purposes, especially when the problem complexity makes derivative computation unfeasible. Moreover, this type of hybrid approach may be convenient when models and data are subject to dynamic changes as the understanding of the reservoir increases.

Ongoing efforts are currently directed toward developing a deeper analysis of the value that sensor information has in 4-D seismic history matching. To that end, the research team is currently exploiting both multilevel and surrogate model approaches for enhancing the estimation when thousands of parameters are involved.

3.1.2 A Learning Computational Engine for History Matching

R. Banchs, H. Klie, A. Rodríguez, A Learning Computational Engine for Seismic History Matching, X European Conference on Mathematics of Oil Recovery (ECMOR), EAGE, Amsterdam, Netherlands, Sept. 4-7, 2006.

Abstract

The main objective of the present work is to propose and evaluate a learning computational engine for history matching, which is based on a hybrid multilevel search method. According to this method, the parameter space is globally explored and sampled by the simultaneous perturbation stochastic approximation (SPSA) algorithm at a given resolution level. This estimation is followed by further analysis by using a neural learning engine for evaluating the sensitiveness of the objective function with respect to variations of each individual model parameter in the vicinity of the promising optimal solution explored by the SPSA algorithm.

The proposed method is used to numerically determine how additional sources of information may aid in reducing the ill-posedness associated with permeability estimation via conventional history matching procedures. The additional sources of information considered in this work are related to pressures, concentrations and fluid velocities are given locations in a reliable fashion, which in practical scenarios might be estimated from high resolution seismic surveys, or directly obtained as in situ measurements provided by sensors. This additional information is incorporated, along with production data, into a multi objective function that is mismatched between the observed and the predicted data. The preliminary results presented in this work shed light on future research avenues for optimizing the use of additional sources of information such as seismic or sensor data in history matching procedures.

Conclusions

According to the preliminary results presented in this work, the proposed method promises to provide a very attractive framework for parameter estimation via history matching, especially when the problem complexity makes derivative computation unfeasible and when computational times strongly limit the search performance. As already discussed, ANN models aid at better understanding the search space in the vicinity of a promising solution by means of a sensitivity analysis. This kind of analysis provides valuable information about the relative contributions of each model parameter and multi objective function component to the overall history matching process.

Despite the fact that we have employed a coarse model for this preliminary phase of the project, we can draw some important conclusions:

1. The history matching can be improved as more information is added to the objective function. It was shown how additional information components can actually help in reducing the uncertainty associated with reservoir characterization.
2. It is possible to match the production results using only production data in the objective function. However, this does not necessarily yield reliable permeability estimations because of the inherent ill-posedness of the inversion process.
3. The combination of SPSA and ANN is very attractive for parameter estimation and analysis purposes, especially when the problem complexity makes derivative computation unfeasible. Moreover, this type of hybrid approach may be convenient when models and data are subject to dynamic changes as the understanding of the reservoir increases.

Ongoing efforts are currently focused on a deeper analysis of the value that sensor information and high resolution seismic data have in history matching. To that end, the research team will continue evaluating the proposed framework by incorporating both travel-time and amplitude related seismic information, as well as sensor data.

3.1.3 A Multiscale and Metamodel Simulation-Based Method for History Matching

A. Rodriguez, H. Klie, S.G. Thomas, M.F. Wheeler, A Multiscale and Metamodel Simulation-Based Method for History Matching, X European Conference on Mathematics of Oil Recovery (ECMOR), EAGE, Amsterdam, Netherlands, Sept. 4-7, 2006.

Abstract

This paper presents a novel framework for history matching based on the concept of simulation based optimization with SVD parameterization, guided stochastic search sampling, Multiscale resolution wavelet and incremental Metamodel (surrogate model) generation. Hence, the primary focus of this work is to mitigate the computational burden of large-scale history matching. Numerical experiments show that viability of the method for addressing realistic problems.

Conclusions

We can draw the following conclusions from the present work:

1. The SVD and wavelet transform parameterization of spatial coefficients into eigenimages of different level resolution show important potentials to reduce the over parameterization (ill-posedness) and cost associated with the history matching problem.
2. The eigenimages basis can accommodate different levels of resolutions for which we can associate different degrees of geological knowledge or uncertainty. Thus, the parameter estimation can be incrementally conducted in respond to this degree of knowledge.
3. We realized that the SPSA algorithm is efficient and provides high flexibility in implementing different parameterizations and functional transformations to the original parameter space without modifications to the original simulation model.

Ongoing efforts are currently focused on generating a family of different eigenimages basis (via statistical realizations) to both incorporate uncertainty and a wider range of possible estimations. This will allow us for obtaining a better reservoir characterization in the absence or event of poor a priori models.

3.2 Future Reservoir Simulation Work

Future Work for the reservoir simulation team could include:

- 1) Reservoir and well control/management: The majority of this work would be devoted to developing a control strategy for well management in an attempt to maximize recovery. We would first implement direct sensitivities capabilities for a control problem for single phase flow in 3D. Furthermore, a control strategy for a multiphase simulation will be developed. A range of control variable types will be evaluated, including velocities and completion intervals. For the large number of variables, we will make use of the adjoint approach for calculating sensitivities to address the computational efficiency issues.
- 2) Parameter Estimation: The parameter estimation work would be completed using the multilevel SPSA and surrogate technique by incorporating additional information such as fluid flow details, petrophysical information and seismic data. As we demonstrated in the initial parameter estimation phase, additional information would significantly improve the solution of the parameter estimation problem. The value of the information would be quantified for each source of additional information in terms of levels of quality of the final solution. In addition to the SPSA method, we would investigate other solution techniques.
- 3) Evaluation of models for VOI: The value of information (VOI) would be quantified numerically by varying the amount of sensor information for the control problem. We wouldl conduct numerical studies for a range of different reservoir datasets and investigate the use of data.

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4.0 NEXT-GENERATION SENSORS

The next generation sensors section of the project involved the determination of whether sensors can survive long-term (5+ years) in hostile borehole environment. These new sensors can be adapted to an already existing well monitoring system designed using electronic components and assembly practices developed at Sandia and Honeywell for aircraft engine monitoring. Unfortunately, existing aircraft engine sensors are specific to aircraft functions and most will not satisfy well monitoring requirements. Work is needed to determine 1) what are the environmental parameters seen by the sensor, 2) what sensors are currently available or will require development and 3) can the sensors be packaged to survive. Assessment of the packaging capabilities has begun by bounding the range of environments that might be encountered in production wells, including temperature, pressure, and corrosion, and developing concepts for device interfaces (both electrical and optical) for down hole sensing of flow, pressure, temperature, tilt, and vibration. This environmental range includes; pressures, 2000 - 12,000 psi; temperatures up to 200° -250° C; flow rates - Crude oil, 10 barrels per day (stripper well) to 1,000 barrels per day; natural gas, 1 - 100 Mcf/d ; viscosities, 5 – 2 cp and densities (fluid), 790-973 kg/m³. This effort includes identifying the failure modes of these packaged interfaces and sensor devices in these environments and providing design guidelines and desirable design approaches to overcome or eliminate these failures.

Fortunately, Sandia has a long history of eliminating failure modes found in most electronic packaging applications needed for extreme environments. Sandia has pre-existing solutions for metal migration, intermetallic growth, pressure seals, hydrogen effects and chloride stress cracking. This is a short list of some of the oil industries' largest reliability issues resulting in well monitoring equipment failures. For sensors, there is a second level of reliability concerns dealing with sensor measurement drift. Obviously, well monitoring sensors will require long-term stability or at least a low cost means of in-situ recalibration.

Customized high temperature micro electro mechanical systems (MEMS) such as pressure sensors, accelerometers, seismometers, and flow sensors, could be extremely valuable in monitoring reservoirs over extended periods of time. In the Microelectronics Development Laboratories (MDL) at SNL there is a strong and mature surface micromachined polysilicon based technology to fabricate such tailored devices. One of the devices designed in the polysilicon surface micromachining based technology under previous funding is a pressure sensor that will be discussed later. Released parts from this project are being used to develop and characterize a high-temperature, high-pressure packaging solution.

Pressure sensing is perhaps the most common wellbore measurement. Pressure or changes in pressure can tell us a lot about what's happening in the reservoir. For example: falling bottom hole pressure during production tell us something about the reservoirs porosity. This information could result in a needed change in production rates. However, to be valuable, the pressure sensor must remain accurate. Conventional MEMS pressure sensors use a silicon diaphragm and Wheatstone bridge. Here extreme care in the design must be achieved in order to match CTEs and diaphragm bonding points or the device will drift with time & temperature as the materials age. Even at 125C, these aging processes are significant in existing commercial grade MEMS pressure sensors.

Other MEMS-like accelerometers use a moving mass, normally of dense metal. The moving mass can be detected with extreme accuracy by monitoring changes in capacitance between the metal mass and a stationary conductor. However, the springs used to return the mass to a normal position will weaken or droop over time. Work on new materials, as highly doped SiC, is currently ongoing to reduce or eliminate this problem.

4.1 Advances in Sensor Applications

The development and application of advanced technology is vital to the modern industry task of finding and developing oil and gas resources with a goal of improving ultimate hydrocarbon recovery. Reservoirs are covered with thousands of feet of rock that makes it difficult to "observe and monitor" the production. But the development of three-dimensional (3D) seismic imaging, coupled with significant increases in computational power allow the industry to develop fairly accurate models of the subsurface. Some of these types of models were discussed and used in Section 3. New and better technology has made it possible to economically develop large oil and gas deposits offshore. Drilling oil and gas wells in thousands of feet of water adds significantly to the complexity, cost, and potential risks. However, technological innovations have enabled the industry to overcome the added challenges. Wells are routinely drilled in 5,000 feet (1,525 m) of water and, after penetrating the sea floor, these well bores extend thousands of feet below the ocean floor.

Innovations in technology are expanding the depth for exploration. Subsurface temperatures and pressures increase with depth, so that a depth is eventually reached that is beyond the capabilities of conventional equipment. But industry has worked diligently to develop equipment made from innovative structural titanium alloys that can withstand the high temperatures and high pressure (HT/HP) in very deep wells. The electronics and sensors needed to guide and monitor drilling and other operations providing feedback on what is encountered down hole have been insulated to withstand HT/HP. As a result of these innovations, the industry now can develop fields with temperatures of 400° F (204° C) and pressures of 16,000 psi (11,000 N/cm²).

The VOI analysis suggests that electronics and sensor technology will allow more oil or gas to be extracted from each type of reservoir as the sensor systems are designed and fabricated to withstand HT/HP environments. Newer sensors among other advances such as stimulation technologies, treatment fluids and enhanced recovery techniques, enable more efficient production of oil and gas.

One particular area of technological innovation is MEMS sensors tailored to HT/HP environments. A pressure sensor designed in the polysilicon surface micromachining based technology is shown in Figure 5. The preliminary design, fabrication and characterization of these devices were done on an externally funded project. We are able to leverage this project as these devices and concepts would be useful for reservoir characterization technologies.

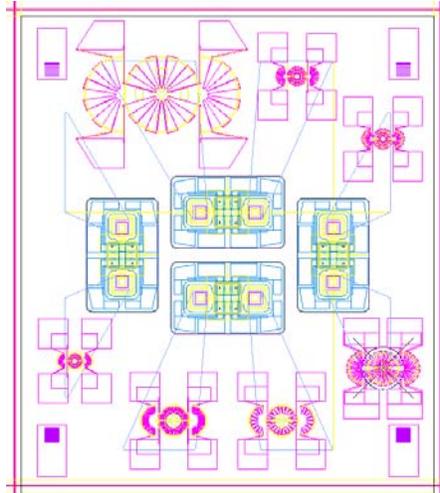


Figure 5: AutoCAD layout of the piezoresistive polysilicon based integrated pressure sensor fabricated in SwIFT (Surface micromachined with integrated fluidics technology)-lite technology

The design uses a Wheatstone bridge with two reference and 2 active resistors. As the silicon nitride membrane is deflected with applied pressure, resistance of the polysilicon resistors changes. The bridge configuration with reference resistors built into the same substrate allows temperature compensation and increased signal level over a single resistor measurement. Simulation for the pressure sensitivity for the designs was performed before design layout to predict the output over the required pressure range. A sample output from the simulation, with the (exaggerated) deflection and stress levels is shown in Figure 6.

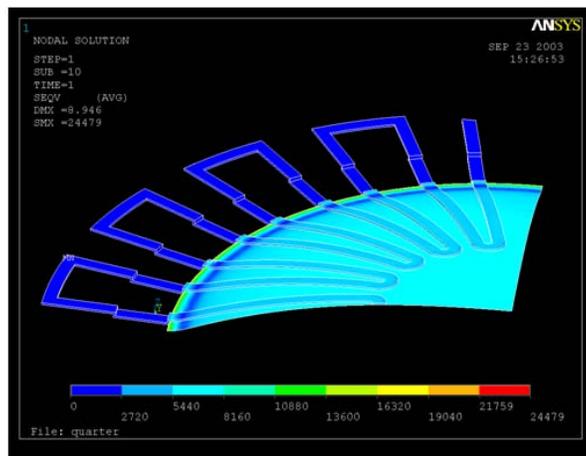


Figure 6: Modeling of the polysilicon piezoresistive (Wheatstone bridge) pressure sensor.

The device was fabricated using both the MDL and CSRL facilities. The backside etch for fluid inlet was done in CSRL while the front side processing was done in the MDL. The film stack associated with the front side are thermal oxide, low stress silicon nitride, and doped polysilicon which are all deposited, patterned and etched on a 6" single crystal Silicon substrate using standard microelectronics based processes. The fabricated device has no metal on bond pads to reduce fabrication steps and to get Si die for down stream unit processes optimization. A cross section of the final unit is shown in a schematic in Figure 7.

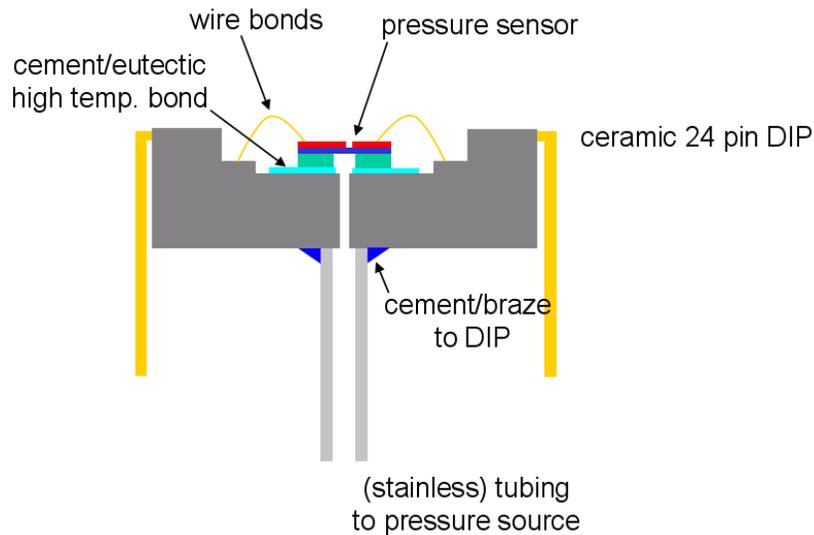


Figure 7: Schematic cross section of the packaged pressure sensor unit.

Figure 8 shows an optical micrograph of the fabricated device along with the pressure versus voltage output. These devices were designed to operate in 0-25 psi range.

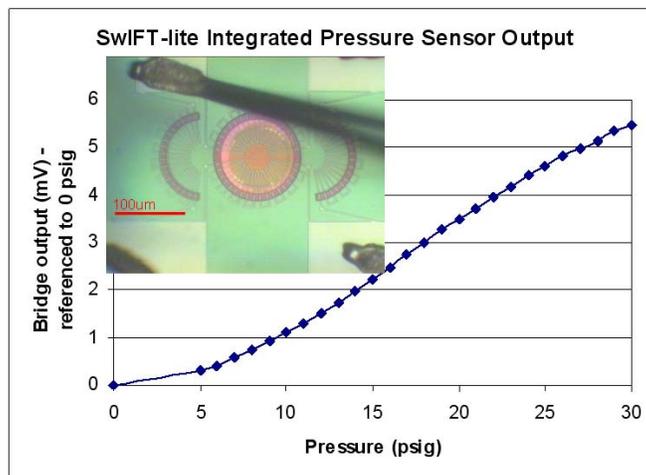


Figure 8: Measured bridge output voltage vs. applied pressure.

Released parts from this project are being used to develop and characterize a HT/HP packaging solution under this LDRD focusing on reservoir environment requirements. Figure 9 shows the basic ceramic package being used to package the pressure sensors. The package has a recessed area of 8.13×4.44 mm. The pressure sensor die size is 6.75×3 mm so there should be space around the edges for centering or fill without causing the wires from the die to the package to be too long. A laser drilled hole in the package allows for fluid attachment to the back of the sensor. The hole is designed to be 1.77mm in diameter allowing access to four sensors. Using a high temperature epoxy will allow tubing attachment to the back side DRIE (Bosch etched fluid access hole) of the silicon die in the package for testing. Further, to have HT compatible unit, a

HT epoxy has been identified to place the silicon die in this HT package. Initial samples during process optimization of the desired high temperature packaging process will require wire bonding to polysilicon which is a known challenge. Once the majority of the packaging processes are optimized for high temperature stability then fabricated metallized silicon die will be used in the prototype packages.

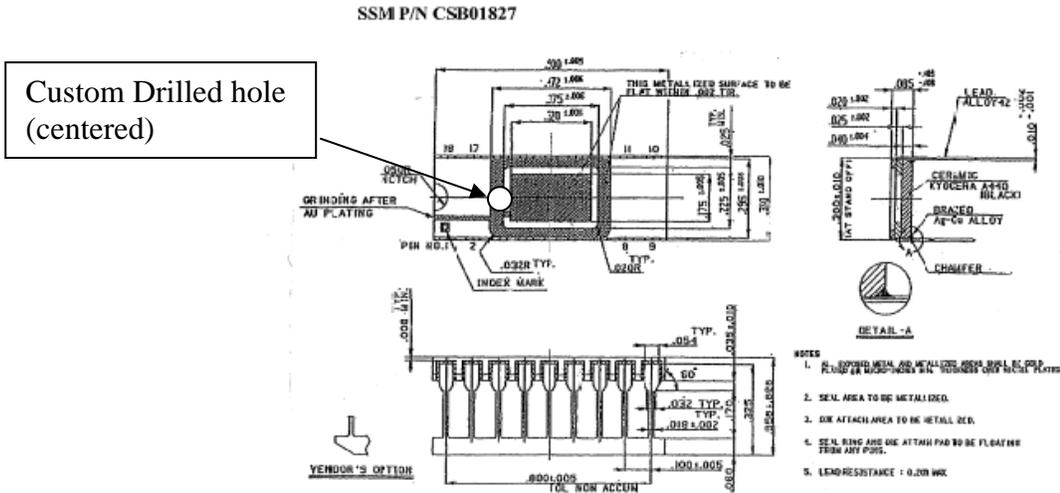


Figure 9: Basic ceramic package

4.2 Problems Associated With Logging: Packaging and Sensors

In this study we focused on the problems associated with oil well logging in production wells. We were concerned with the reliability and packaging of continual use sensors. We investigated possible environments and sensor types in an attempt to determine the most difficult aspects of packaging sensors for long term use in production wells. Our goal was to provide the project with sufficient packaging-related information to allow future research efforts to be focused properly to the issues. Consequently, the primary output of this work is a comprehensive set of issues associated with packaging failures in these deep well scenarios and ideas for how to drive future work.

4.2.1 Packaging Overview

We believe that packaging may represent the most significant technical challenge associated with the application of state-of-the-art sensor technology in down-hole environments under the stringent requirements associated with maintaining sensor operation for extended periods. This real-time monitoring concept nullifies existing strategies for making such measurements which invokes the potentially risky assumption that survival for short periods – just long enough to insert the probe, gather the data and extract – is probably acceptable. Neglecting the almost certain impacts to sensor and package reliability this operational mode implies, representing an entirely different research activity, the real-time usage concept now must address much more basic survival and operational threats. Certainly, any future effort to develop intrinsic, real-time monitoring capability for deep well environments must accommodate packaging and

interconnects as primary and equal activities in the investment and technical tasking aspects. Success will depend on a fully holistic approach to the sensor design that includes packaging and the power/signal transmission aspects – the so called interconnect technology – as equal parts to any efforts expended towards the sensors themselves.

Obviously, there are multiple environmental issues that threaten the integrity of the package and the interconnect technology for sensors in these applications. Our study has indicated that we must focus on the following items to the first order:

1. excessive absolute temperatures
2. thermal cycling, even over moderate changes in temperature,
3. presence of corrosive and/or highly permeable fluids (liquid and gas).

Second order issues are:

1. excessive exposure pressure on the package and interconnect boundary and
2. unanticipated materials interactions in hostile environments.

The reasoning behind these statements will be explored below. The bounding of the environmental factors is crucial to this activity. There are many types of wells that exhibit a wide variety of package-threatening environments. Depths, soil and rock properties and types of extracted media all play a role in determining the specific challenges that a long-term down-hole sensor system will experience.

4.2.2 Well Types Considered

Wells are in many different geologic setting in areas all over the world. We were asked to focus on three primary well types. Wells in tight gas sands, wells drilled in the Gulf of Mexico, and wells drilled in the Permian Basin. Each well location has distinct characteristics and unique environmental concerns but there are also many similarities that impact the reliability of long term sensors.

The Permian Basin is an area of about 250 by 300 miles in West Texas and southeastern New Mexico. The first shallow oil wells in the area were drilled in the early 1920's. Some deep modern wells can be 16,000 feet deep but wells are typically in the range of 3,000-9,000ft deep. The bottom hole temperatures of the deeper wells can reach 390 F (200 C). The bottom hole pressure can range between 1,300-7,000psi depending on depth. Hydrogen sulfide can be present in these wells and will corrode certain materials.

Gulf of Mexico ultra deep wells (water depths greater than 5000ft; Smith, 2002) can range in depth from a couple thousand feet below base mud line (bml) or sea floor to over 20,000ft bml. Bottom hole pressures in these deep wells can be over 9,000psi with bottom hole temperatures over 390 F (200 C). These wells can contain hydrogen sulfide.

Tight gas sands are defined as sandstone formations with permeability less than 0.1 millidarcy. Thousands of tight gas sand wells are in the San Juan Basin in northwestern New Mexico and southwestern Colorado. These wells vary in depth but are usually less than 6,000ft deep and have bottom hole temperatures ranging from 150-300 F (65-150 C). Bottom hole pressures in

these wells (at 6,000ft depth) is approximately 2,600psi. Some of these wells will also have hydrogen sulfide.

Though each of the three well types has unique characteristics there are some things that are challenges for all. Although hydrogen sulfide may not be present in every well hydrogen is present in every well. Instruments going into each well type will also experience similar installation and transportation shocks. Though the bottom temperatures vary slightly from well to well there is a temperature gradient in every well. These similar environments combine with the individual concerns to make each well type a difficult environment for electronic and sensor packaging survivability.

4.2.3 Packaging Challenges

Packaging challenges can be grouped into a few categories, most easily explained by failure mechanism. The most challenging environmental elements thought to cause packaging failures in the environments of oil wells are extreme temperatures, thermal cycling, and hazardous or corrosive gases. Some failures will also arise from high pressure environments as well as materials interaction situations. Occasionally materials that do not interact under normal conditions will react with catastrophic results at elevated temperatures or in certain gaseous or humid environments. These responses are difficult to predict and will require carefully planned experimentation, including detailed reliability life-studies, to address. High physical or electrical shocks can also cause failure in electronics although these are often easier to accommodate through robust package design practices than some of the other environmental characteristics.

Excessive temperatures have been linked to various packaging failures in the IC industry, particularly as chip temperatures rise due to size reductions. At high temperatures, above 150 °C, the main concern is excessive thermally-induced stresses in the packaged sensor. Typical packaging strategies involve the use of adhesives, frequently polymer-based, to bond the sensor device to a package substrate. The resulting sandwich of three materials, in the simplest case, will experience stresses as the temperature is increased (or decreased) away from the bond formation temperature. These stresses can be described and ameliorated through knowledge of the coefficient of thermal expansion (CTE) of the various materials in the stack. CTE mismatches between sensor, die attach adhesive, and substrate are responsible for a large portion of package-related failures in the IC industry. These failures, which can happen at relatively modest temperature excursions, imply that the challenges for the significant temperature changes of a down-hole monitoring sensor suite represent are great. Failure to develop die attach adhesive technology that is not directly tested at in-situ conditions would create an unacceptable level of risk. Some materials are very weak (i.e., significantly reduced yield strength) at high temperatures and can deform or crack under thermal stresses that would not cause failure at room temperatures. Metal bonding, such as solder or eutectic methods, often cause problems at high temperatures due to formation of intermetallic alloys that reduce the yield strength of the bond. Additionally, the rate of corrosion-induced degradation increases with temperature and the reliability effects of these environments have not been well studied.

Thermal cycling accelerates failure mechanisms that are observed at high temperatures. Even slight thermal cycling, such as a 50 degree change, can have drastic effects on the fatigue life of

components relative to what would occur under a steady-state high temperature load. Many polymers are notorious for sensitivity to thermal cycling but the effect is also observed in metal bonds as well. These problems can be compounded when a metal contacts a plastic package. Solder joints can fail from simple expansion and contraction caused by thermal cycling. Also, existing combinations of solder materials and their associated underfill epoxies have not been characterized in these thermal environments. CTE mismatches at elevated temperatures with modest to even low cycling amplitudes will almost certainly have adverse reliability effects. CTE-induced stresses at high temperature will be amplified if thermal cycles around that temperature are experienced.

Hazardous or corrosive gases or liquids can compound other problems. Hermeticity against these fluids at the package boundary will be critical. Hermeticity is a difficult concept at ambient pressures; the issues associated with developing hermetic packages at the extreme pressures a down-hole sensor suite will experience have not even been formulated. The time frame for failure based on a loss of hermeticity (either as a slow chronic problem or as a single event, such as a crack) is not well understood at the conditions of interest. Corrosive fluids, injected into the package at high pressure (assuming the package environment is close to ambient) could possibly cause nearly instantaneous failure.

A particularly prevalent gas in the oil industry is hydrogen. Hydrogen diffusion rates are significant and it has been shown to cause failures in packaging materials in several different modes. Hydrogen embrittlement of metals is one strong failure mechanism that would affect not only the components but also any metallic packaging materials used, such as solder bonds and interconnect wires. This effect essentially reduces the fatigue life of the metals substantially and will lead to low reliability. Hydrogen's ability to rapidly diffuse through otherwise hermetic boundaries presents a significant challenge to packaging designers particularly under elevated pressure environments. In addition, should the interconnect designs include optical signal and power transmission components, such as fiber optics, then the degrading effects of hydrogen on these materials must also be considered. Hydrogen gas is known to not only reduce the fatigue life of fiber materials but also causes gradual variations in the attenuation coefficient prior to failure. This attenuation creep will have adverse effects on the operation of the down-hole sensors and may be difficult to diagnose from information collected on the surface. Temperature gradients along the length of the interconnect; from well-top to well-bottom will only exacerbate the hydrogen diffusion problem.

Hydrogen sulfide, while not as common, is frequently present in oil and gas wells. The primary failure issue for this gas is related to stress cracking of steels caused by the corrosion of the sulfur compound. As with the other corrosive materials, high temperatures increase the rate of attack on the packaging materials and the interconnects. Problems with hydrogen sulfide are also more serious for deep wells due to the increased stress levels associated with sensors in these environments; deeper wells create large gravity loads on the down-hole sensors.

Oil and gas wells are often high pressure environments. Common well pressures are between 13,800 and 39,000 kPa (2,000-10,000 PSI). Some wells reach pressures as high 83,000 kPa (12,000 PSI). It is believed that excessive pressure can also decrease the time to failure for many packaging and potential interconnect materials, although these effects have not been well

studied. Hermeticity strategies for a 12,000 psi environment will require a significant development effort to formulate. Packaging designers will need to investigate the trade-offs associated with pressure equalization within the package (i.e., seal the package at high pressure to equalize with the anticipated environment) with the current standard practice of permitting pressure gradients, although at a substantially reduced magnitude. An additional significant constraint is the probable requirement to allow portions of the fluid surrounding the sensor package to infiltrate the package boundary. For advanced sensors, compositional analysis will be required to increase the efficiency of the exploration and extraction process. The packaging challenges associated with this concept have not been addressed. Active pressure regulation by the package might be required to accomplish this task.

A second order concern for package designs for these applications is shock survivability. It is believed that, other than significant seismic events, most shock experienced by well-logging tools occurs during transportation of the tool rather than while it is inserted into the well. Consequently, package designs for typical transportation-induced shock events are well understood and do not present any significant challenges. However, for long-term down-hole monitoring, seismic events can create shock loads on sensors. Current tool usage patterns – insert, measure, extract – eliminate the need to have the sensors shock hardened. It will be necessary to understand the seismic activity in the region of the wells and design packages accordingly. There is literature regarding shock effects on package that we believe is directly applicable to this problem and so do not believe this issue merits the investment or attention as those mentioned previously.

4.2.4 Example Sensors

There are many sensors available for well logging tools. Some sensors are currently available for purchase and some are still being developed. These include, pressure sensors, temperature sensors, seismic sensors, and combination sensors.

There are many different sensor technologies available for each type of sensor, the interfaces available also vary. Although most of the sensors have electrical interfaces, there are also many sensors with optical fiber interfaces. Many of these interfaces are similar for all sensors. Most of the sensors are packaged in stainless steel. Most of the packages are similar in size and package construction. Many of the packages also fail at 200-250 °C. Reliability testing shows that many of the sensors have similar failure mechanisms. This information would imply that the packages are mostly constructed with the same technology.

4.2.5 Technology Development

We would propose a development activity to address the issues noted in this section in the following specific manner:

1. Design and fabricate a robust environmental test chamber to allow down-hole conditions to be created in a laboratory. The chamber should accommodate excessive pressures and temperatures and allow the introduction of multiple fluids (gas and liquids) to simulate the conditions of the deep wells.

2. Formulate and execute an experimental program using accepted design-of-experiments (DOE) concepts coupled with standard reliability testing strategies (i.e., via acceleration mechanisms) to address the effects of the primary environmental factors noted above on the packaging, interconnect and sensor designs.
3. Develop sophisticated finite element analyses of the package designs and validate them against the data gathered in the chamber. These models can be empirical in nature to accelerate the formulation of design tools. However, the quality of this modeling work will then rely on the ability to achieve deep-well conditions within the chamber to avoid the need to extrapolate the models.
4. Utilize the models to develop a set of design rules that are generally applicable under a variety of well conditions. From these rules, package and interconnect designers can then approach the problems in a manner that is similar to existing methods.

4.3 Next Generation Sensors Future Work

Future work for the next generation sensor team could include identifying gaps in available sensor platform technology to survive the downhole environment and providing preliminary design of individual sensors and robust sensor systems. This could be accomplished through application of an advanced finite element modeling (FEM) capability. FEM models of proposed packaging designs would be developed and studied parametrically to guide engineering efforts for long-term sensor operation down-hole. Solid modeling CAD software would be used to evaluate the designs of the sensor package platform, optical and electrical interconnect cable protection system and the mechanical linkage between the interconnect and the platform. Deliverables for this effort would include: 1) a white paper detailing the platform design strategy and parameter variations to be included in the models (materials, dimensions, shape, etc.), 2) results of parametric FEM study described in deliverable 1, 3) conceptual design of the interconnect protection structure (IPS), 4) FEM model of IPS response to environmental variables, 5) conceptual design of method to link IPS to the sensor platform package, 6) FEM model of the structure response of the IPS/platform linkage region.

An opportunity also exists to validate the FEM modeling developed in using the results of high-temperature accelerated life testing experiments in the Geothermal Research Department (6211). In addition, packaging failures observed in those experiments will be analyzed and discussed from the perspective of future long-term monitoring requirements. Deliverables in this effort would include: 1) FEM model (structural and thermal) of packaging designs used in SNL's Geothermal Department work (both at sensor level and for optical interconnection), 2) detailed explanation of the observed packaging failures, and 3) reliability assessment of packaging strategy based on experimental data.

5.0 CONCLUSIONS

The project objective was to detail better ways to assess and exploit intelligent oil and gas field information through improved modeling, sensor technology, and process control to increase ultimate recovery of domestic hydrocarbons. The model utilized permanent downhole sensor systems (Smart Wells), whose data are fed real-time into computational reservoir models that are integrated with optimized production control systems and.

To meet this objective the project utilized a three-pronged approach 1) a value of information analysis to address the economic advantages, 2) reservoir simulation modeling and control optimization to prove the capability, and 3) evaluation of new generation sensor packaging to survive the borehole environment for long periods of time. A summary of the work is provided below:

The Value of Information decision tree method was developed and used to assess the economic advantage of using the proposed technology.

Value of Information findings and conclusions:

- The procedure developed for VOI studies appears to be a practical means of ascertaining the value associated with a technology, in this case application of sensors to production. The procedure acknowledges the uncertainty in predictions but nevertheless assigns and monetary value to the predictions. The best aspect of the procedure is it builds consensus within interdisciplinary teams. Another important aspect is that the value of the sensors is only useful in regard to a specific decision.
- Sensors have the most benefit by far when applied to the decision to waterflood deepwater reservoirs. This is because the associated production rates are so very large that small improvements have a large net value. On a percentage basis, the improvement is not as large but it is still the largest net value among the technologies considered.
- Sensors would have the least impact on the decision to use horizontal wells versus hydraulic fracturing.
- All of the technologies considered appear to benefit from application of sensors at current hydrocarbon prices. Recovery technologies tend to become uneconomic (and would be shut down) prior to sensors losing value.

The reservoir simulation and modeling aspect of the project was developed to show the capability of exploiting sensor information both for reservoir characterization and to optimize control of the production system.

Reservoir Simulation and Modeling findings and conclusions:

- History matching is improved as more information is added to the objective function, clearly indicating that sensor information can help in reducing the uncertainty associated with reservoir characterization. However, production data alone is insufficient to yield

reliable permeability fields. Seismic data, particularly so-called 4D seismic data, substantially improves the process. The combination of SPSA and ANN is very attractive for parameter estimation, especially when the problem complexity makes derivative computation unfeasible. Moreover, this type of hybrid approach may be convenient when models and data are subject to dynamic changes as the understanding of the reservoir increases.

- The SVD and wavelet transform parameterization of spatial coefficients into eigenimages of different levels of resolution and show important potentials to reduce the over parameterization (ill-posedness) and cost associated with the history matching problem. The eigenimages basis can associate different degrees of geological knowledge or uncertainty. Thus, the parameter estimation can be incrementally conducted in response to this degree of knowledge.

The next generation sensors aspect of the project evaluated sensors and packaging survivability issues. Our findings indicate that packaging represents the most significant technical challenge associated with application of sensors in the downhole environment for long periods (5+ years) of time.

Next Generation Sensor and Packaging Development

- The greatest challenges for sensor design include extreme temperatures, temperature fluctuations, and hazardous and/or corrosive gases and fluids.
- Our findings indicate that packaging represents the most significant technical challenge associated with application of sensors in the downhole environment for long periods (5+ years) of time. These issues can be addressed through development of technologies such as:
 - Design and fabricate a robust environmental test chamber to allow down-hole conditions to be created in a laboratory.
 - Develop sophisticated finite element analyses of the package designs and validate them against the data gathered in the chamber.
 - Utilize the models to develop a set of design rules that are generally applicable under a variety of well conditions.

This work has been a joint effort with Sandia National Laboratories and UT-Austin's Bureau of Economic Geology, Department of Petroleum and Geosystems Engineering, and the Institute of Computational and Engineering Mathematics.

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APPENDIX A: WORKSHOP
Valuing Real-Time Sensor Technology Workshop
 June 12-13, 2006
 The University of Texas
 Brons Conference Room
 Chemical and Petroleum Engineering Building

AGENDA

June 12, 2006

0830	Welcome and introductions	Larry W. Lake (LWL)
0900	The SNL/UT collaboration	Scott Cooper
0930	Objectives of workshop	LWL
1000	VOI and hydrocarbon production	LWL
1100	The VOI process	Bob Gilbert
1200	Lunch - presentation by Dr. David J. Goggin, Chevron	
1330	Technology 1 discussion Technology description review Economics of technology Spreadsheet	All
1630	Adjourn	

June 13, 2006

08300	Discussion of previous day	LWL
0900	Technology 2 discussion Technology description review Economics of technology Spreadsheet	All
1200	Lunch	
1330	Technology 3 discussion Technology description review Economics of technology Spreadsheet	All
1500	Technology 4 discussion Technology description review Economics of technology Spreadsheet	All
1630	Final comments	LWL

ATTENDEES

Name	Affiliation
Allen, Jesse	Kerr-McGee
Cooper, Scott	Sandia
Elbring, Greg	Sandia
Gilbert, Bob	UT-Civil Engineering
Goggin, David	Chevron
Hite, Roger	Consultant
Jennings, Jim	UT-BEG
Lake, Larry W.	UT-PGE
Lorenz, John	Sandia
MacDonald, Robert	Platt Sparks
Normann, Randy	Sandia
Nunez, Emilio	UT-CPARM
Pizarro, Jorge	Petrobras
Waggoner, John	Schlumberger
Webb, Tom	Shell

APPENDIX B: VOI SPREADSHEET DETAILS

B 1.0 Economic Premises

General

- All analysis is done on a Before Federal Income Tax (BFIT) basis.
 - The BFIT cash flow is simplified as follows:
 - $CF_{BFIT} = \text{Sales Revenue} - \text{Royalty} - \text{Production/Severance Taxes} - \text{Direct Variable Production Costs} - \text{Direct Fixed Costs} - \text{G\&A}$.
 - Discounting
 - We recognize that cash flows are spaced throughout the 5-year horizon of analysis. To keep the model simple, and to avoid biasing the valuation to users with high or low discount rates, we did not discount the flows (i.e. discount rate = 0%). The main impact of this approach is that the value of sensor figures that we compute are actually maximum values.
-

Mature CO2 Case

- Commodity Price
 - The net selling price is determined by taking the market price and subtracting 25% to reflect Royalty, production taxes, and G&A. The spreadsheet has been modified to reflect this in two places as noted in the spreadsheet. See Economics Tab, Row 1. Other costs are then subtracted. Other possible scenarios are 100, 70, 40, 10 \$/bbl market price.
- FIXED COST and OPEX
 - Fixed Cost: The fixed costs derive from the Experts' assessment that fixed costs will increase with increasing oil price (inflation). We agreed on a formula which yields the economic limit in barrels for different prices (see cell EconomicsB10). This is then used to compute fixed costs using the current market price (EconomicsG1).
 - Variable Cost: CO2 cost per MCF comes from /Experts and does not vary with oil price.

Finally, for both of these costs, the Experts said there would be efficiencies to be gained if sensors were installed. So, for the sensor case, we assume 10% savings in fixed cost and 10% less CO2 consumption. The CO2 unit is cost is held constant, we alter the volume.

Deepwater Waterflood

In this scenario, we employ the same structure as other scenarios regarding the effects of the technology—that we observe an increase in rate, a decrease in decline rate, or both. In the case of deepwater waterflooding however, the objective is typically to extend the plateau of oil production. So our approach of rate/decline analysis serves as a proxy for this underlying objective. In the spreadsheet, we have computed a variable called “Number of Years of Extended Plateau” to provide a reality check on the impact of the technology. This computation is entered in the Basic Decision Tree to the far right, and is made as follows:

$$\text{Years Extended Plateau} = (\text{WF incremental oil, bbls}) / (\text{Initial Rate, bbls/yr})$$

- Commodity Price
 - The net selling price is determined by taking the market price and subtracting 18% to reflect Royalty and G&A costs. The spreadsheet has been modified to reflect this in two places as noted in the spreadsheet. Other costs are then subtracted.
 - Suggest scenarios be run for: 100, 70, 40, 10 \$/bbl market price.
- FIXED COST and OPEX
 - Fixed Cost: The incremental fixed cost for the waterflood is based on the number of new injectors that are drilled plus the installation of new waterflood facilities on the topsides. It was decided at the workshop to take this approach for the fixed costs, that is, we do not give up significant detail by aggregating all of the incremental fixed costs in this fashion.
 - Variable Cost: The variable cost is computed based on a \$/bbl lifting cost for oil+water; the default value is \$8/bbl. The water-to-oil ratio is specified by the user. The spreadsheet reflects a default value of 2, but this variable could be the basis of a sensitivity analysis.

All of these costs are the same whether sensors are installed or not. Unlike the CO2 case, there was no consensus that fixed or variable costs would be less in the presence of sensors.

Tight Gas

- **Commodity Price**
 - The net selling price is determined by taking the market price and subtracting 25% to reflect Royalty, production taxes, and G&A. The spreadsheet has been modified to reflect this in two places as noted in the spreadsheet. Other costs are then subtracted.
 - Suggest scenarios be run for: 12, 10, 8, 6 \$/mcf market price.

- **FIXED COST and OPEX**
 - **Fixed Cost:** The fixed costs derive from setting the economic limit in terms of production volumes. Similar to the Mature CO₂ case, the Experts' assessment is that fixed costs will increase with increasing gas price (inflation). Unlike the Mature CO₂ case, the economic limit volume is constant across all prices. This is then used to compute fixed costs using the current market price.

The other component of fixed cost is the cost of the fracture job, which is entered by the user.
 - **Variable Cost:** There are no variable costs in this case.

All of these costs are the same whether sensors are installed or not. Unlike the CO₂ case, there was no consensus that fixed costs would be less in the presence of sensors.

SAGD

- Commodity Price
 - The net selling price is determined by taking the market price and subtracting 25% to reflect Royalty, production taxes, and G&A. There is also a discount factor for oil quality set by the user. The spreadsheet has been modified to reflect this in two places as noted in the spreadsheet. Other costs are then subtracted.
 - Suggest scenarios be run for: 100, 70, 40, 10 \$/bbl market price.

- FIXED COST and OPEX
 - Fixed Cost: The fixed costs derive from setting the economic limit in terms of production volumes. Similar to the Mature CO₂ case, the Experts' assessment is that fixed costs will increase with increasing oil price (inflation). Unlike the Mature CO₂ case, the economic limit volume is constant across all prices. This is then used to compute fixed costs using the current market price. I changed cells in Basic Decision Tree to reflect referencing the market price.

The other component of fixed cost is the cost of the new horizontal wells for SAGD. These well depths and \$/m costs are entered by the user.

- Variable Cost: The variable cost is computed based on the technical inputs for the steamflood and using a long term gas contract price of \$5/mcf.

All of these costs are the same whether sensors are installed or not. Unlike the CO₂ case, there was no consensus that fixed or variable costs would be less in the presence of sensors.

B 2.0 Discussion of Sensor Probability Tables

B 2.1 Mature Reservoir with Waterflood or CO₂ Injection

This scenario considers a typical Permian Basin mature oil reservoir currently under waterflood. The reservoir management choice is to continue the waterflood or to initiate CO₂ injection. In addition to this basic reservoir management choice, we also considered the choice of installing an array of sensors in every injector and producer to measure a vertical profile of injection or production rate, pressure, temperature, and in the case of production wells, water cut and CO₂ content. This information should help reservoir surveillance engineers determine which intervals are taking the most water, which intervals are producing the most fluid, and which producing intervals have the highest water cut. With this additional information reservoir engineers might be able to shut off intervals that have been swept by waterflood or CO₂ and divert injection to previously unswept intervals, improving oil production rate and/or arresting the rate of oil production decline.

The sensor probability tables provide approximate quantification of the potential improvement in the oil production rate or reduction of the decline rate that improved reservoir management might be able to achieve due to additional information provided by the sensors. There are two sensor probability tables, one for the waterflood option (Table B-1), the second for the CO₂ injection option (Table B-2).

Continuation of waterflood			With sensors			
	Initial production rate	Decline rate over	25	25	5	5
	(bbl/day/pattern)	next 5 years (%/year)	5	15	5	15
Without sensors	25	5	1	0	0	0
	25	15	0.1	0.9	0	0
	5	5	0.04	0.16	0.8	0
	5	15	0.02	0.04	0.1	0.84

Table B-1. Sensor probability table for a typical mature Permian basin reservoir under continued waterflood.

Implement CO ₂ injection			With sensors			
	Initial production rate	Decline rate over	15.6	15.6	5.2	5.2
	(bbl/day/pattern)	next 5 years (%/year)	5	15	5	15
Without sensors	15.6	5	1	0	0	0
	15.6	15	0.2	0.8	0	0
	5.2	5	0.2	0.2	0.6	0
	5.2	15	0.1	0.2	0.2	0.5

Table B-2. Sensor probability table for a typical mature Permian basin reservoir with a new CO₂ injection program.

Each table is a four-by-four array of estimated probabilities that the additional information provided by sensors would lead to a change between the four possible combinations of two initial production rates and two decline rates. Considering only two states for rate and decline rate, a favorable and unfavorable state for each, is of course a very crude discretisation of the broad spectrum that each might attain for any given reservoir, but this simplification was nevertheless chosen to keep the table of probabilities at a manageable size. The two initial rates for the CO₂ option represent factors of three and one times the expected value for the waterflood initial rate. The decline rates for the waterflood and CO₂ options are equal.

The tables are organized so that entries on the diagonal quantify the probability that neither the initial rate nor the decline rate changes because of sensor information. The lower-left triangle of each table generally contain cases where a favorable change occurs in the oil rate, the decline rate, or both. The upper-right triangle generally contains cases where unfavorable changes occur. The single case with a favorable initial rate change but an unfavorable decline rate change is in the lower triangle (third row, second column) and the single case with the reverse outcome, an

unfavorable initial rate change but a favorable decline rate change is in the upper triangle (second row, third column). The probabilities along each row of the table sum to one.

The panel of Experts decided that the information provided by the sensors would not lead to a worsening of the initial oil rate or the decline rate in either the waterflood or CO₂ options (except for the case of an initial rate improvement coupled with an unfavorable decline rate change, discussed below). Thus, the upper-right triangle of both tables are filled with zeros. The upper-left corner entry of each table is one, indicating that if the initial rate and decline are already optimal before the installation of sensors, then the new sensor information will neither improve nor worsen the reservoir performance.

For the waterflood option (Table B-1) the Experts decided that targeted injection or production profile modifications indicated by the new sensor information might lead to improved sweep of previously bypassed oil between wells, which in turn might lead to a long-lasting oil rate increase. However, the probability of this occurring seems small because of the infrequent vertical compartmentalization in typical Permian Basin reservoirs, so the two table entries representing an oil rate improvement with no decline rate change were assigned a small but non-zero probability of 4%. It seems even less likely that both the oil rate and decline rate would improve, so the lower left corner of the table was assigned a probability of 2%.

The Experts considered it more likely that targeted injection and production profile modification could reduce water production, leading to an improvement in the decline rates. Thus the panel assigned somewhat larger probabilities (10%) to the two cases of decline rate improvement without a change in initial oil rate. However, they decided that the most likely improvement (16% probability) would be a temporary oil rate increase, followed by a steep decline, due to improved sweep of bypassed oil in small areas near each injector and producer. The remaining entries on the diagonal of the table were set to obtain a sum of one on each row.

Similar arguments were applied to estimate the CO₂ sensor probabilities (Table B-2), except somewhat larger probabilities of reservoir performance improvement were assigned because sensor-inspired injection and production profile modifications might improve sweep in previously water-flooded intervals in addition to the improvements that might occur in a waterflood only.

B 2.2 Deep-Water Reservoir with Primary Production or Waterflood

This scenario considers a typical Gulf of Mexico deep-water sandstone oil reservoir produced from offshore facilities with a small number of relatively expensive wells. The reservoir management choice is to continue with primary production or to install a waterflood for pressure maintenance. A wide variety of sensors and controls were considered, but the panel decided that the most likely benefit in this reservoir setting would be to extend plateau production by detecting zones of early water-breakthrough and shutting them off, and by identifying previously undrained areas of the reservoir for targeted recompletions or sidetracks. These reservoir performance improvement mechanisms could work for both primary production, with water encroachment from an aquifer, and for waterflood with water encroachment from injection wells.

Although the potential reservoir-performance improvement the panel considered was an extended time of plateau production, not a rate increase, it was nevertheless decided to approximate the total oil-volume benefit with rate increases and decline rate improvements to maintain consistency with the other three reservoir scenarios. The two sensor probability tables for primary production and the waterflood are shown in Tables B-3 and B-4 respectively. The decline rates are the same for each table. The waterflood initial oil rates were set to four times and two times the expected value of the primary production initial oil rates.

Continuation of primary production			With sensors			
Initial production rate (bbl/day/well)		Decline rate over next 5 years (%/year)	5000	5000	2000	2000
			15	35	15	35
Without sensors	5000	15	0.97	0.01	0.01	0.01
	5000	35	0.2	0.78	0.01	0.01
	2000	15	0.05	0.1	0.84	0.01
	2000	35	0.02	0.05	0.2	0.73

Table B-3. Sensor probability table for a typical deep-water Gulf of Mexico reservoir under continued primary production.

Implement waterflood			With sensors			
Initial production rate (bbl/day/well)		Decline rate over next 5 years (%/year)	17600	17600	8800	8800
			15	35	15	35
Without sensors	17600	15	0.97	0.01	0.01	0.01
	17600	35	0.3	0.68	0.01	0.01
	8800	15	0.05	0.1	0.84	0.01
	8800	35	0.02	0.05	0.3	0.63

Table B-4. Sensor probability table for a typical deep-water Gulf of Mexico reservoir with a new water injection program.

Both sensor probability tables are organized like those of the previous Permian Basin scenario with reservoir performance improvement generally represented in the lower-left triangle, performance decreases in the upper-right, and unchanged performance on the diagonal. Unlike the Permian Basin scenario, the panel decided that there is a small probability (1%) that the installation of sensors and controls in a well might cause damage that is too expensive to fix, leading to a permanent loss of production. Thus both tables have non-zero entries in the upper triangle.

For the primary-production option (Table B-3) the Experts decided that the most likely performance improvement (with an estimated 20% probability) would be a reduced decline (row two, column 1, and row four, column three) and extended plateau because of sensor-inspired water-production shut off and recompletions or sidetracks to produce undrained portions of the reservoir. The other forms of performance improvement were assigned smaller probabilities. The

waterflood sensor table (Table B-4) is the same as for primary production, except the probability of arresting the decline without increasing the initial rate was increased from 20% to 30% because during a waterflood there are opportunities for control in injectors in addition to the opportunities for control in producers.

B 2.3 Tight Gas Well with Hydraulic Fracturing

In this scenario we are considering a vertical well in a typical North-American tight gas formation. For consistency with the other three scenarios the panel included a reservoir management choice of doing nothing or stimulating the well with a hydraulic fracture, even though the preferred alternative will always be to stimulate the well with or without sensors. The sensor suite would include pressure, temperature, flow profiles, geophones, tilt meters, and possibly “smart proppants” that create small explosions for detection by the geophones. The panel decided that the primary benefit of these sensors would be to provide more detailed information on the effectiveness of the hydraulic fracture, not to improve the performance of the current well, but to allow better planning of fracturing in subsequent wells.

Unfractured vertical well			With sensors			
	Initial production rate	Decline rate over	500	500	30	30
	(MCF/day/well)	next 5 years (%/year)				
Without sensors	500	20	1	0	0	0
	500	40	0	1	0	0
	30	20	0	0	1	0
	30	40	0	0	0	1

Table B-5. Sensor probability table for a typical unfractured vertical well in a tight gas reservoir.

Vertical well with hydraulic fracture			With sensors			
	Initial production rate	Decline rate over	2602.5	2602.5	69.4	69.4
	(MCF /day/well)	next 5 years (%/year)				
Without sensors	2602.5	40	0.9	0.05	0.025	0.025
	2602.5	60	0.15	0.75	0.05	0.05
	69.4	20	0.1	0.15	0.7	0.05
	69.4	40	0.1	0.15	0.2	0.55

Table B-6. Sensor probability table for a typical hydraulically fractured vertical well in a tight gas reservoir.

The two sensor probability arrays are shown in Tables B-5 and B-6. The initial production rates for the hydraulic fracturing option were set to 75 and 2 times the expected value for the unstimulated initial rates. Two of the decline rates were increased for the fractured-well table

because fracturing can accelerate the production with larger initial production rates followed by more rapid declines, but not increase the reservoir volume.

The purpose of the sensors is to provide information on hydraulic fractures. Thus, they can have no effect on the performance of an unfractured well and Table B-5 has only ones on the diagonal and zeros elsewhere. Table 6 includes small probabilities in the upper triangle to account for the possibility that information from the sensors might lead to over-confidence in the design of subsequent hydraulic fractures, fracturing too close to water zones, in turn leading to water production and lost gas productivity. Larger probabilities were assigned to the lower triangle to account for better hydraulic fractures and improved well performance, but the largest probabilities were assigned to the diagonal to represent no change.

B 2.4 Heavy-Oil Reservoir with Cyclic Steam or Steam-Assisted Gravity Drainage

In this scenario we are considering a typical North-American heavy-oil reservoir currently under cyclic steam injection in vertical wells. The reservoir management choice is to continue the cyclic steam process or to initiate a steam-assisted gravity drainage (SAGD) program in injector-producer pairs of new horizontal wells. The panel decided that the most useful downhole sensors for this scenario would be temperature profiles to map formation heating near each well. However, more useful measurements might include surface time-lapse seismic to map heating throughout the reservoir and surface temperature arrays to map heat losses through the overburden. With knowledge of reservoir heating and heat losses from the sensors it might be possible to optimize steam injection for more even heating, less heat loss, and more efficient oil recovery.

The two sensor probability tables for cyclic steam injection and SAGD are shown in Tables B-7 and B-8 respectively. The decline rates are the same for each table. The SAGD initial oil rates were set to 3 times and 1.5 times the expected value of the cyclic steam initial oil rates.

The panel decided that the information provided by the sensors could not lead to worsening of reservoir performance, so the upper-right triangle of each table was filled with zeros. For the cyclic-steam option it was decided that because no new wells are drilled an initial-rate increase was not possible. However, sensor-inspired optimization of steam injection might arrest the decline. Thus probabilities of 20% were assigned to the two table entries corresponding to a decline-rate reduction. All other entries in the lower-left triangle were set to zero.

Continuation of cyclic steam process			With sensors			
			150	150	30	30
Initial production rate (bbl/day/project)		Decline rate over next 5 years (%/year)	10	20	10	20
Without sensors	150	10	1	0	0	0
	150	20	0.2	0.8	0	0
	30	10	0	0	1	0
	30	20	0	0	0.2	0.8

Table B-7. Sensor probability table for a typical heavy-oil reservoir under continued cyclic steam injection.

Implement steam-assisted gravity drainage			With sensors			
	Initial production rate (bbl/day/project)	Decline rate over next 5 years (%/year)	93.6	93.6	46.8	46.8
			10	20	10	20
Without sensors	93.6	10	1	0	0	0
	93.6	20	0.4	0.6	0	0
	46.8	10	0.2	0.2	0.6	0
	46.8	20	0	0.2	0.4	0.4

Table B-8. Sensor probability table for a typical heavy-oil reservoir with a new steam-assisted gravity drainage program.

Similar arguments were applied to the SAGD sensor probability table, except (1) the probabilities of a decline-rate decrease were doubled because the additional wells in SAGD might provide more opportunities to optimize reservoir heating, and (2) 20% probabilities were assigned to three entries with initial rate increases because the additional wells provide a rate-increase opportunity. The probability of both a rate increase and a drop in decline rate was set to zero.

APPENDIX C: PUBLISHED PAPERS

Copies of papers published and presented by the Reservoir Simulation work are provided in this Appendix.

C 1.0 Assessing the Value of Sensor Information in 4-D Seismic History Matching

H. Klie, A. Rodríguez, R. Banchs and M.F. Wheeler, Assessing the Value of Sensor Information in 4-D Seismic History Matching, 76th SEG International Exposition & Annual Meeting. New Orleans, Oct. 1-6, 2006.

Assessing the Value of Sensor Information in 4-D Seismic History Matching

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Summary

The main objective of the present work is to numerically determine how sensor information may aid in reducing the ill-posedness associated with permeability estimation via 4-D seismic history matching. These sensors are assumed to provide timely information of pressures, concentrations and fluid velocities at given locations in a reliable fashion. This information is incorporated into an objective function that additionally includes production and seismic components that are mismatched between observed and predicted data. In order to efficiently perform large-scale permeability estimation, a coupled multilevel, stochastic and learning search methodology is proposed. At a given resolution level, the parameter space is globally explored and sampled by the simultaneous perturbation stochastic approximation (SPSA) algorithm. The estimation and sampling performed by SPSA is further enhanced by a neural learning engine that estimates sensitivities in the vicinity of the most promising optimal solutions. Preliminary results shed light on future research avenues for optimizing the frequency and localization of 4-D seismic surveys when sensor data is available.

Introduction

The continuous growth of computing power, sensor and communication technology is bridging gaps in understanding several fields in the geosciences. Specialized sensors are capable of measuring at a high local resolution, fluid and rock properties (see e.g., Lumley, 2001, Versteeg et al., 2004, Hornby et al., 2005, and references therein). These advances, in conjunction with 4-D time-lapse seismic studies, are revealing enormous potentials to reduce the uncertainty in both reservoir characterization and production scenarios. Meanwhile, new stochastic optimization and statistical learning methods are arising as promising tools to find nontrivial correlations between data measurements and responses and to develop optimal reservoir exploitation plans (van der Baan and Jutten, 2000, Nikravesh, 2004, Klie et al., 2004, Spall, 2004, Keane and Nair, 2005).

The main objective of the present work is to numerically assess the value of sensor information in 4-D seismic history matching. To that end, we will assume that reliable sensor information may be available at any time and at any reservoir location. Despite the fact that this analysis may explore far beyond customary industrial practice, our main motivation is to evaluate, from a numerical standpoint, the potentials that sensor technology may have in reservoir characterization. This work involves a comparative analysis of different sensor-based objective functions and the introduction of a new methodology to eventually tackle large-scale parameter estimation problems. The set of objective functions evaluates the impact that the addition of sensors for pressure, concentration and fluid flow velocity has in the quality of the permeability estimation. This allows us to relate detailed changes in fluid flow and seismic traveltimes to permeability field distribution.

The proposed 4-D seismic history matching methodology consists of the use of a multilevel approach to gradually perform parameter estimation from low to high resolution levels. The combination of global stochastic searches with local estimations via artificial neural networks (ANNs) provides means to perform sensitivity analysis and further refinements to the parameter estimation process. The whole methodology comprises the integration of multiphase flow simulation, petrophysics (via Biot-Gassmann's theory) and traveltime seismic modeling in the evaluation of the objective function. An important component of the whole methodology is illustrated on a coarse but realistic 2-D data-set. Preliminary results reveal that sensor-based reservoir characterization may provide important guidelines as to how time-lapse 4-D seismic studies should be effectively performed.

A Sensor-based Seismic History Matching Methodology

The proposed methodology consists of the use of a multilevel approach to gradually perform parameter estimation from low- to high-resolution levels. We restrict our attention to permeability although the proposed framework could also be employed for other reservoir parameters of interest, such as porosity, PVT data, stress and fracture distribution. An initial upscaling process is carried out via wavelet transformations, and the downscaling propagates the best permeability estimation from coarser to finer simulation grids. As the resolution is increased, the amount of computation is systematically decreased in order to achieve further efficiency. This is illustrated in Figure 1.

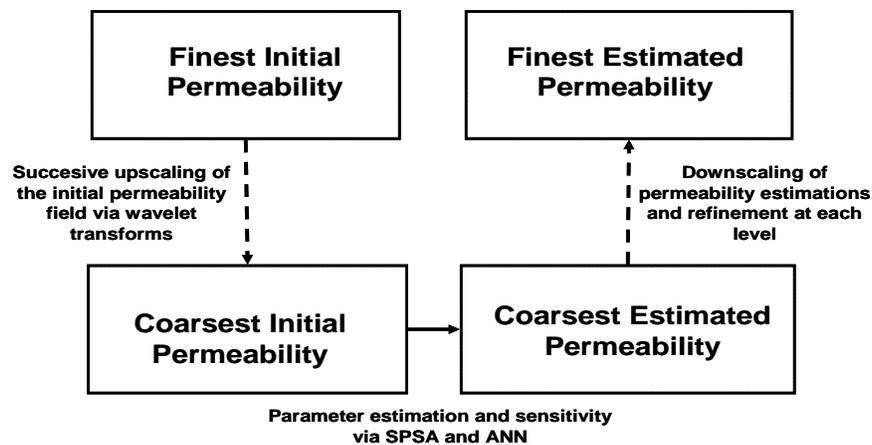


Figure 1. Multilevel approach for permeability estimation.

Starting from the coarsest grid, the parameter estimation is first carried out with the simultaneous perturbation stochastic approximation (SPSA) algorithm (Spall, 2003) with different initial guesses. This not only augmented the chances for finding a global optimal solution, it also allows for a rich sampling of the parameter space. Moreover, the search performed by the SPSA algorithm guides the sampling toward promising regions containing a global solution (“hot spots”). We provide more details on the SPSA algorithm below. Due to the size of the coarse grid, thousands of computations are affordable in a few hours. Based on the mapping between parameters and the objective function, we generate an artificial neural network (ANN) that allows us to perform sensitivity analysis and further refine the solution of the optimization. Therefore, points evaluated by the ANN are validated against the simulator. If these evaluations lead to a better optimizer, then the final estimation is used as an initial guess for the next finer resolution permeability grid. In this way, the ANN acts as a surrogate model or metamodel for the simulation model. Figure 2 illustrates this process for a given permeability resolution level.

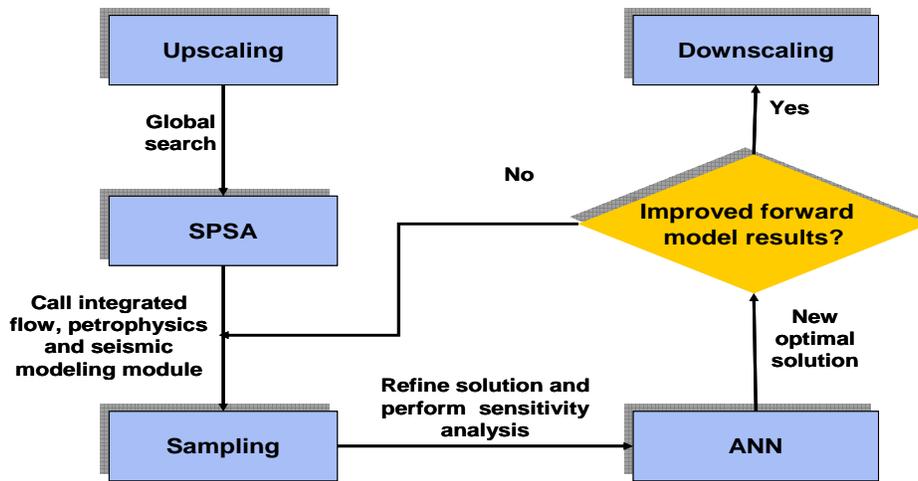


Figure 2. Permeability estimation at each resolution level.

The simulation model consists of the integrated functionality of independent multiphase flow, petrophysics and seismic models. The flow component is provided by the Integrated Parallel Accurate Reservoir Simulation (IPARS) framework (Wheeler, 1998). The petrophysics model follows the Biot-Gassman theory, which describes seismic velocity changes resulting from changes in pore-fluid saturations and pressures. Given the resulting seismic velocities, it is possible to perform wave propagation modeling through the porous media. In the first stage of the present effort, we are momentarily disregarding amplitude effects and, instead, reporting on traveltme measurements generated by a raytracer algorithm. Therefore, the simulation model allows us to evaluate a collection of objective functions of the form:

$$\Phi(\mathbf{p}, \mathbf{c}, \mathbf{u}, \mathbf{q}, \boldsymbol{\tau}) = \sum_{i=1}^T \left[\left\| \mathbf{w}_{p,i} (\mathbf{p}_i^d - \mathbf{p}_i) \right\|_2 + \left\| \mathbf{w}_{c,i} (\mathbf{c}_i^d - \mathbf{c}_i) \right\|_2 + \left\| \mathbf{w}_{u,i} (\mathbf{u}_i^d - \mathbf{u}_i) \right\|_2 \right] + \sum_{i=1}^T \left[\left\| \mathbf{w}_{q,i} (\mathbf{q}_i^d - \mathbf{q}_i) \right\|_2 + \left\| \mathbf{w}_{\tau,i} (\boldsymbol{\tau}_i^d - \boldsymbol{\tau}_i) \right\|_2 \right],$$

where p , c and u denote pressure, concentration and velocity vectors at discrete times, respectively. Here, q represents data at production wells, i.e. bottom hole pressure, gas/oil ratio and cumulative production. The variable τ stands for the travelttime vector. Superscript d indicates measured data. The weight operators, w_x , include scaling factors and allow for the flexible selection of sensor, production and seismic measurements. Note that the above formulation may include measurements at selected locations and at discrete times throughout the simulation interval $[0, T]$.

Simultaneous Perturbation Stochastic Approximation

The simultaneous perturbation stochastic approximation (SPSA) algorithm has received considerable attention for global optimization problems where it is difficult or impossible to compute first order information associated with the problem. SPSA performs random simultaneous perturbations of all model parameters to generate a descent direction at each iteration. Despite the random character of the procedure, the expected value of the computed direction is the deterministically steepest descent direction. One of the most attractive features of the SPSA algorithm is its simplicity, flexibility and low computational cost. This algorithm only requires one or, at most, two function evaluations per iteration independently of the parameter space size in order to generate a stochastic descent direction. This means that the method does not require further modifications to the simulation model (i.e., a black-box approach). This is very convenient due to the size of the parameter space and the complexity of the current simulation model. Promising SPSA results have already been reported in several engineering and scientific scenarios (Spall, 2003).

The Neural Learning Engine

The ANN implementation of the present work considers a multilayer perceptron architecture under the supervised learning framework. Supervised learning implies the existence of a "teacher" or "adviser" entity, which is responsible for quantifying the network performance. In many practical applications, this reduces to the availability of a set of input data for which the expected output data is known. This input data, along with its corresponding output data, constitutes the training data set for the multilayer perceptron. Such a training set should be split into three sets: training, test and cross-validation; which should be used in both experimentation phases: the first one regarding the ANN parameter calibration, and the second one regarding the final training of the ANN for the application under consideration. The training of the multilayer perceptron considered here is implemented by using the classical back-propagation algorithm, which is based on the error-correcting learning rule derived from the optimal filtering theory. In the application developed here, the ANN engine is used with a double objective in mind. The first one has to do with capturing the intrinsic complexities of the mismatch objective function with respect to variations of the permeability field values in a given neighborhood of suboptimal reservoir parameters. This will enable performance of fast sensitivity analyses of each individual model parameter with respect to the overall system response, which will provide useful information about the specific locations where multiple scale refinements are required. The second objective regards the ability to provide an efficient and smooth estimator of the mismatch objective function in a given neighborhood of suboptimal reservoir parameters, which will lead to more robust and faster parameter estimation.

Numerical Examples

Computational experiments were performed on a coarse grid representation of model 1 of the SPE 10th Comparative Solution Project (Christie and Blunt, 2001). The main objective of this preliminary set of experiments was to evaluate the implications that sensor technology may have in complementing 4-D seismic history matching in a rather exhaustive fashion. The original permeability field is shown in Figure 3 and consists of a cross-sectional reservoir model with $1 \times 100 \times 20 = 2000$ gridblocks. The size of each grid block is $25 \times 25 \times 2.5 \text{ ft}^3$. The reference coarse permeability field, consisting of $1 \times 10 \times 2 = 20$ gridblocks, is obtained by successive upscaling using the Haar wavelet (Daubechies, 1992). The original reservoir model was slightly modified to allow for oil and gas compressibility and capillary forces due to the interaction of these two phases. A fixed production strategy was adopted with one gas injecting well located at the leftmost side of the model and a production well at the opposite side. Sensor measurements were assumed to be a) inactive, b) active along the wellbore, c) active midway between the two wells and along the wellbore and, d) active at every grid cell. Sensors were able to provide timely (i.e., at each simulation step) measurements of pressures, concentrations and flow velocities. A cross-well raytracing modeling was performed every 90 days for this well configuration. An initial guess for the parameter estimation was generated by means of the singular value decomposition (SVD) that considered only the first three resolution components (out of 2000) from the fine grid reference data. In this way, some of the features of the original permeability field were somewhat captured. Each iteration of the SPSA algorithm involved two function evaluations, where each of them implied the execution of a coupled flow, petrophysics and seismic simulation model for $T = 1000$ days (~ 3 years) on a different permeability field configuration. The SPSA algorithm was able to converge to the desired tolerance ($1.e-5$) in less than 1000 iterations.

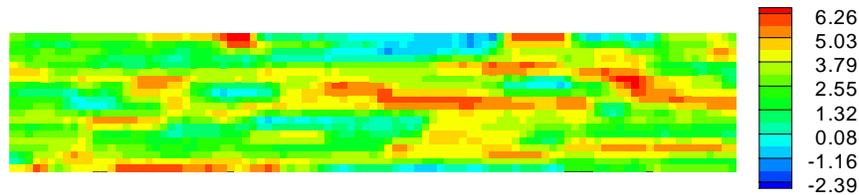


Figure 3. Original high resolution permeability field.

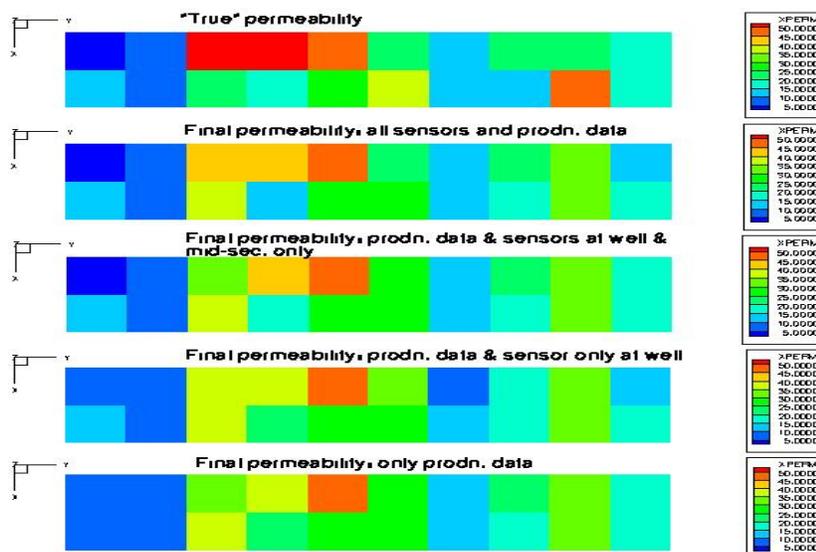


Figure 4. Permeability estimation as sensor observations are added into the inversion process.

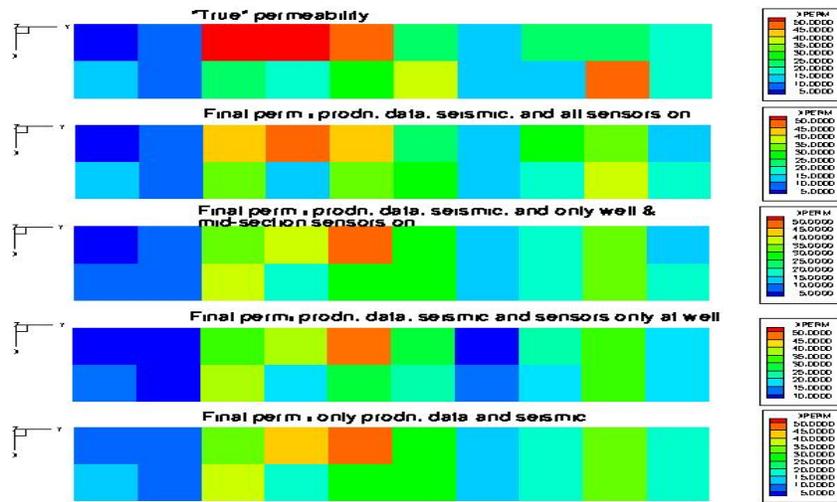


Figure 5. Permeability estimation as sensor observations are added with seismic observations into the inversion process.

In all cases considered, well production data (oil production rates, GOR and cumulative oil production) were matched reasonably well (not shown here). Only a slight mismatch error was noticeable when the inversion was performed solely on production measurements. Figure 4 shows the permeability estimation using different degrees of sensor information without the use of seismic information. Clearly, the more sensors are added the higher the quality of the permeability estimation. However, in spite of considering the hypothetical situation of having sensors everywhere, the reference permeability is never recovered. In general, the estimation presents more difficulties in adjacent cells showing higher contrasts.

Figure 5 presents the permeability estimation with the inclusion of seismic measurements. The estimations display a similar global trend as in Figure 4. Nevertheless, the inclusion of seismic measurements introduces some important estimation enhancements as panels from both figures are compared one by one. We can see that the permeability estimation based on both production and seismic data is comparable to using both production and sensor data from the wellbore. As more sensors are added, we can observe how the quality of the estimation improves in the locality of the sensor. This shows that sensor data have a local resolution effect in contrast to the global effect that seismic and production data have in the estimation process. A comparison was also made for pressures, concentrations and flow velocities at different gridblocks, showing a similar trend. We note that concentrations were harder to obtain than pressures and flow velocities harder to obtain than concentrations in the estimation process.

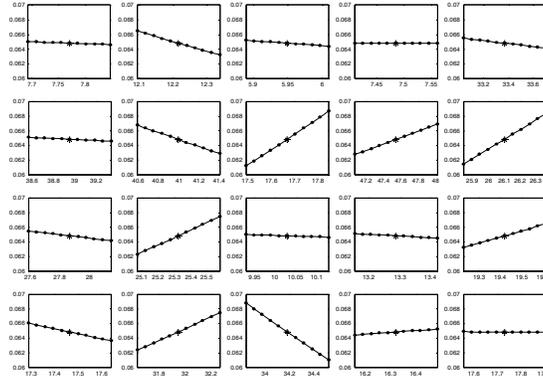


Figure 6. Sensitivity results using the ANN.

Figure 6 depicts the sensitivity results obtained from the ANN in the case that the estimation relies only on production and seismic data (no sensor information). Each panel (numbered in a row-wise fashion) corresponds to a computational gridcell. We can see that cells 2, 7, 8 and 9 in each horizontal layer are the most sensitive ones. This implies that further refinement of the estimated solution in those cells can be obtained by means of a local optimization procedure (e.g., Newton or quasi-Newton method). Moreover, the degree of sensitivity may suggest that additional information in those cells would be of value for further constraining the search space and, thereby enhancing the quality of the estimation. In fact, the more sensors that are added into the estimation the less steep the sensitivity curves are. This illustrates how additional information tends to smooth out the search space.

Conclusions and Further Remarks

Despite the fact that we have employed a coarse model for this preliminary phase of the project, we can draw some important conclusions:

1. The history matching is improved as more information is added to the objective function, clearly indicating that sensor information can help in reducing the uncertainty associated with reservoir characterization.
2. It is possible to match the production results using only production data in the objective function. However, this does not necessarily yield reliable permeability estimations due to the inherent ill-posedness of the inversion process.
3. Time-lapse 4-D seismic measurements provide global insight into the history matching process that neither production data nor localized sensor information on fluid properties is able to reproduce.
4. The combination of SPSA and ANN is very attractive for parameter estimation purposes, especially when the problem complexity makes derivative computation unfeasible. Moreover, this type of hybrid approach may be convenient when models and data are subject to dynamic changes as the understanding of the reservoir increases.

Ongoing efforts are currently focused on a deeper analysis of the value that sensor information has in 4-D seismic history matching. To that end, the research team is currently exploiting both multilevel and surrogate model approaches for enhancing the estimation when thousands of parameters are involved.

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C 2.0 A Learning Computational Engine for Seismic History Matching

R. Banchs, H. Klie, A. Rodríguez, A Learning Computational Engine for Seismic History Matching, X European Conference on Mathematics of Oil Recovery (ECMOR), EAGE, Amsterdam, Netherlands, Sept. 4-7, 2006.

A LEARNING COMPUTATIONAL ENGINE FOR SEISMIC HISTORY MATCHING

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1. Introduction

Learning technologies have helped oil industry exploration and production in finding nontrivial correlations between data measurements and responses (see e.g., van der Baan and Jutten, 2000; Nikraves, 2004). Nevertheless, these efforts have been primarily incorporated in an isolated fashion within the oil industry practice. On the other hand, the continuous growth of computing power, sensor and communication technology is bridging the gap between several fields in geosciences for the common goal of reducing uncertainty for achieving better subsurface understanding and producing more reliable decisions (see e.g., Lumley, 2001; Versteeg et al., 2004; Hornby et al., 2005, and references therein). Time-lapse seismic for history matching is also a relevant example of how this technology is making possible to further constrain the parameter search space and produce better reservoir characterizations.

The present work is concerned about jointly learning from production observations and other additional sources of information, and being able to relate detailed changes in the observed data into valuable permeability distributions. Furthermore, the present research aims at determining the value these additional sources of information have in the overall history matching process. More specifically, we investigate how information contained in state variables such as pressure, concentration and flow velocities may aid at improving the quality of the overall parameter estimation. To that end, we proposed a hybrid methodology based on the coupling of a neural network estimation engine (ANN) with the simultaneous perturbation stochastic approximation (SPSA) algorithm to be able to perform an efficient minimization of the output error criteria and guidance of the self-learning process. The optimization framework includes a multi-scale approach to gradually perform the estimation from low to high resolution levels (Rodriguez et al., 2006).

The proposed ANN implementation considers a multilayer perceptron architecture under the supervised learning framework that is trained by means of the classical back-propagation algorithm. Regarding the simulation model, the methodology comprises the full integration of multiphase flow simulation into the mismatch history matching function. The concept of using ANN with stochastic optimization (via SPSA) for intelligence amplification in history matching is illustrated on a realistic 2D data-set. Although the proposed framework could also be

employed for other reservoir parameters of interest, such as porosity, PVT data, stress and fracture distribution; for simplicity reasons we restrict our attention to permeability.

The structure of the present paper is as follows. First, we provide a brief description of the optimization framework, emphasizing the formulation of the multi-objective function, parameterization and the integrated flow simulation model. Section 3 presents a brief description of the SPSA algorithm. Section 4 describes the ANN approach and its role for performing sensitivity analysis of the multi-objective mismatch function. Section 5 shows the numerical experiments and section 6 presents the conclusions and further research avenues of this work.

2. Optimization Framework

2.1 Fundamentals

The current methodology is based on a multi-scale treatment of the parameter space (Rodriguez et al., 2006). This is achieved by decomposing the log of the original permeability (or porosity) field in a summation of different *eigenimages* that are obtained by the singular value decomposition (SVD). Each of these *eigenimages* represents a resolution level of the original parameter space whose relevance (or energy content) is controlled by the associated singular value. Thus, the problem is parameterized in terms of singular values and the determination of each one of them provides a level of resolution in the parameter space.

The second step is to generate further resolution levels with the successive application of wavelet transforms on each *eigenimage*. Due to the linear character of wavelet transforms, the value of the parameters to estimate can be preserved at different scales. This allows for obtaining good estimations for higher parameter values (those associated with low-resolution levels) in an inexpensive computationally manner. In this way, the number of estimated variables increases as finer resolution levels are progressively included.

At each resolution level, we use the simultaneous perturbation stochastic approximation (SPSA) method to perform a broad search for the optimal solution. The SPSA algorithm produces a systematic sampling on the parameter space which is richer in a neighborhood of the optimal solution. This sampling can be used to construct a metamodel (i.e., surrogate model) based on the response surface. In our particular case, the sampled points are training points for an artificial neural network (ANN). Despite that there are other methods for constructing metamodels (Keane and Nair, 2005), the ANN can capture complex and nonlinear multivariate relations in the presence of noise. Figure 1 illustrates how the SPSA and ANN are coordinated to enhance the parameter estimation process.

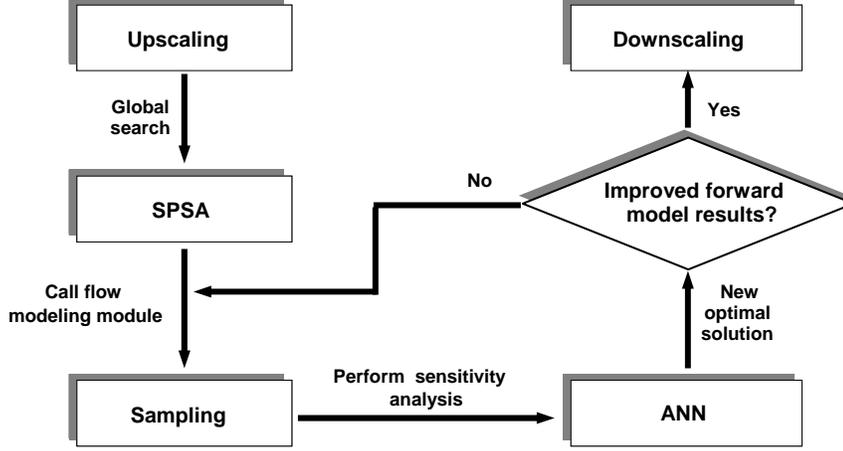


Figure 1. Parameter estimation at each resolution level.

2.2 Integrated Multiphase Flow

The forward model comprises a multi-scale flow reservoir simulator. The flow component is given by the IPARS (Integrated Parallel Accurate Reservoir Simulator) framework. An attractive feature of IPARS is that it allows for the coupling of different models in different subdomains and supports message passing for parallel computations on structured multi-block meshes in two and three space dimensions (M.F. Wheeler and M. Peszynska, 2002).

2.3 Objective Function

The complete objective function accommodates several components that account for mismatch values of simulated production, and the three state variables of pressure, concentration and flow velocities, with respect to field measurements:

$$F(p, c, u, q) = \sum_{i=1}^T \left(\|W_{pi} (p^d - p(q))\|_2 + \|W_{ci} (c^d - c(q))\|_2 + \|W_{ui} (u^d - u(q))\|_2 \right) + \sum_{i=1}^T \left(\|W_{qi} (q^d - q(q))\|_2 + \|W_{qi} (q - q_{prior})\|_2 \right), \quad (1)$$

where p, c and u denote the pressure, concentration and flow vectors at discrete times, respectively. Here, q represents data at production wells, i.e. bottom hole pressure, gas/oil ratio and cumulative production. Superscript d indicates measured data. The last term represents the constraint given by the model parameters θ based on some *a priori* information. Recall that these model parameters are singular values and result from the parameterization of the original reservoir parameters. The weight operators, W_* , include scaling factors and allow for the flexible selection of each different measurements at specific experimental setting. These operators integrate the definition of covariance operators. The above formulation includes measurements at selected locations and at discrete times throughout the simulation interval $[0, t]$.

3. Global Optimization via SPSA

The SPSA algorithm has received considerable attention for global optimization problems where it is unfeasible to compute function gradients. SPSA performs random simultaneous perturbations of all model parameters to generate a descent direction at each iteration. Despite

the random character of the procedure, the expected value of the computed direction is the deterministically steepest descent direction. The SPSA for equation (1) is defined by the following recursion:

$$\theta_{k+1} = \theta_k - a_k g_k(\theta_k), \quad (2)$$

where a_k is a positive scalar that monotonically decreases with respect to k , and $g_k(\theta_k)$ is a stochastic approximation to the gradient given by a simultaneous perturbation of all elements of θ_k , that is,

$$g_k(\theta_k) = \frac{1}{2} [\Phi(\theta_k + c_k \Delta_k) - \Phi(\theta_k - c_k \Delta_k)] \Delta_k^{-1}, \quad (3)$$

where c_k is also a positive scalar that monotonically decreases with respect to k , Δ_k is a vector consisting of $\{-1, 1\}$ values randomly generated with a Bernoulli distribution and Δ_k^{-1} stands for the component-wise reciprocal of each of the entries of Δ_k . The parameters a_k and c_k form a monotonically decreasing sequences with respect to k that are chosen to ensure asymptotic convergence of the algorithm; for more details and pointers on SPSA see (Spall, 2003).

One of the most attractive features of the SPSA algorithm is its simplicity, flexibility and low computational cost. As can be seen from (3), the algorithm only requires one or, at most, two function evaluations per iteration independently of the parameter space size in order to generate a stochastic descent direction for (2). This means that the method does not require further modifications to the simulation model (i.e., a black-box approach). This is very convenient due to the size of the parameter space and the complexity of the current simulation model.

4. The Learning Neural Network Engine

4.1 Fundamentals

The ANN implementation used in this work considers a multi-layer perceptron architecture under the supervised learning framework (Haykin, 1994). Supervised learning implies the existence of a "teacher" entity responsible for quantifying the network performance. In many practical applications, this reduces to the availability of a set of input data for which the expected output data is known. In the case under consideration, this data is numerically generated by the SPSA while exploring a specific region of the objective function close to a promising optimal solution.

These parameter space samples, along with their corresponding objective function values, constitute the training data set for the ANN model. Such a training set should be split into three sets: training, test and cross-validation, in order to calibrate the multi-layer perceptron parameters, as well as for the final training of the ANN model. The training of the ANN is implemented by using the classical back-propagation algorithm, which is based on the error-correcting learning rule derived from the optimal filtering theory (Haykin, 1991).

In the application developed here, the ANN engine is used for constructing an efficient and smooth estimator of the mismatch objective function in the given neighborhood of optimal reservoir parameters, which will allow for capturing the intrinsic complexities of the mismatch objective function with respect to variations of the model parameter values in a more robust and faster manner.

4.2 Sensitivity analysis

According to the proposed methodology, the ANN engine allows for capturing the mismatch objective function variations with respect to model parameter values in the given neighborhood of the promising optimal solution already explored by the SPSA. This will enable the performance of a fast sensitivity analysis of each individual component of the multi-objective function defined in (1) with respect to variations of each individual model parameter. Figure 2 illustrates the overall process of SPSA space exploration and the subsequent multi-objective function sensitivity analysis.

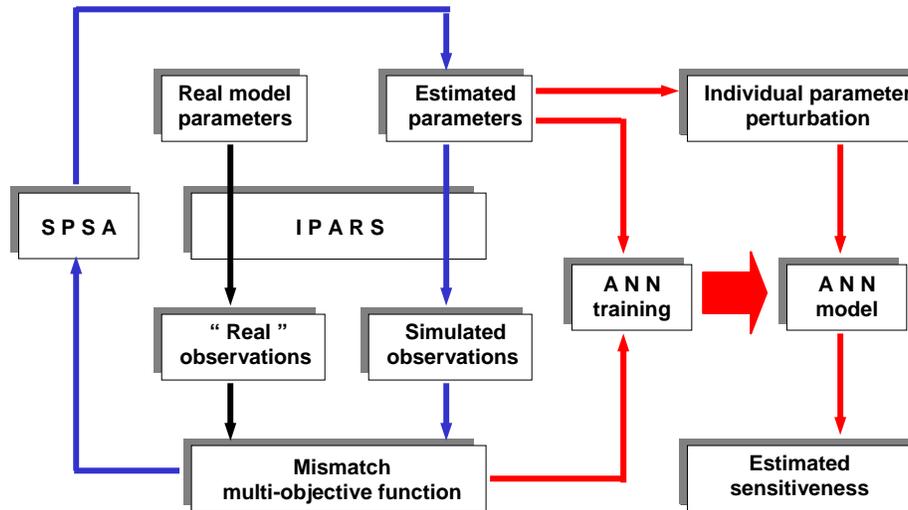


Figure 2. SPSA space exploration and multi-objective function sensitivity analysis.

The performance of this type of sensitivity analysis provides very useful information about the relative impact that each specific information component of the objective function has on the overall history matching process. In a similar way, it also provides valuable information for performing further resolution refinements to the parameter model in a more efficient and appropriate manner.

Two important considerations must be taken into account. First, special attention should be paid to the sampling process performed by SPSA in order to ensure collected samples to provide a good representation of the parameter space and then guarantee an appropriate ANN model training. Hence, several runs of SPSA within the same neighborhood might be necessary to ensure a good parameter space representation. Second, special care must be taken when performing the sensitivity analysis since the ANN representation is only valid inside the core region explored by the SPSA. According to this, the sensitivity analysis should be restricted to model parameter variations within the valid area of representation.

6. Experimental Results

Computational experiments were performed on a coarse grid representation of a cross-sectional reservoir model consisting of 20×100 grid-blocks. The size of each grid-block was $25 \times 25 \times 2.5 \text{ ft}^3$. A reference coarse permeability field, consisting of $5 \times 25 = 125$ grid-blocks, was obtained by successive upscaling using the Haar wavelet. Figure 3 shows the fine and resulting coarse

permeability field. The main objective of this preliminary set of experiments was to evaluate the implications that additional information provided by state variables such as pressure, concentration and flow velocities have in complementing production data history matching.

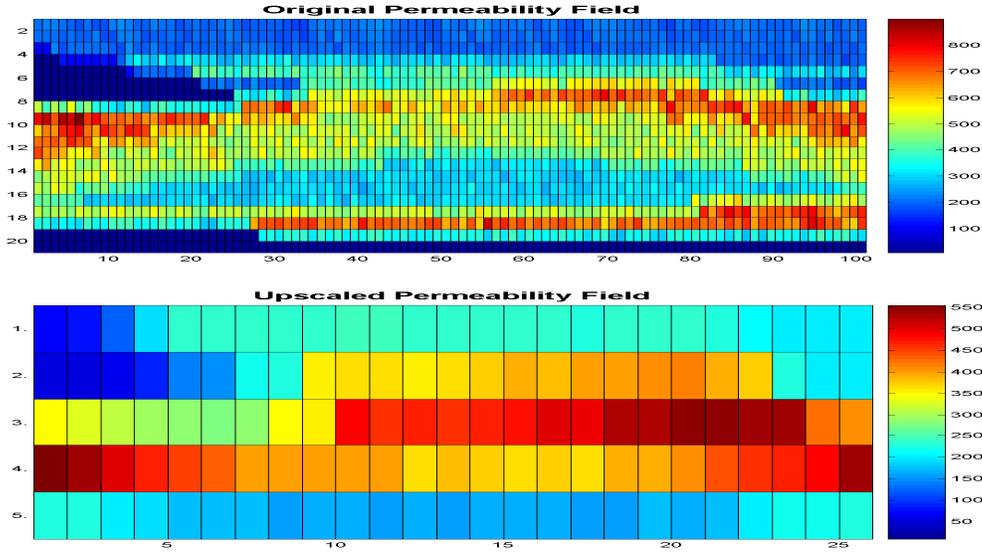


Figure 3. Original permeability field (top) and upscaled version (bottom).

The original reservoir model was slightly modified to allow for oil and gas compressibility and capillary forces due to the interaction of these two phases. A fixed production strategy was adopted with one gas injecting well located at the leftmost side of the model and a production well at the opposite side. In the experimental setting considered here, state variable measurements were assumed to be available midway between the two wells and along the wellbore. Timely (i.e., at each simulation step) measurements of pressures, concentrations and flow velocities were considered. An initial guess for the parameter estimation was generated by means of the singular value decomposition (SVD) that considered only the first three resolution components (out of 20) from the fine grid reference data. In this way, some of the features of the original permeability field were somewhat captured.

Each iteration of the SPSA algorithm involved two function evaluations, where each of them implied the execution of the flow simulation model for $t = 1000$ days on a different permeability field configuration. The SPSA algorithm was able to converge to the desired tolerance ($1.e-5$) in 674 iterations. Once convergence was achieved, the ANN model was trained by using the sample points generated by the SPSA algorithm. An ANN architecture of two hidden layer with 8 and 4 processing units, respectively, was empirically selected. Afterwards, ANN-based models were trained for each multi-objective function component individually: production, pressure, concentration and flow velocity. An additional ANN-based model was trained for the combined contribution of the three non-production information components.

A sensitivity analysis was performed for each multi-objective function component and the combined non-production component with respect to the individual variations of each of the four resolution model parameters. Table 1 presents the resulting percentage variations for each

objective function component when perturbing each of the model parameters from -0.5% to $+0.5\%$ of its final SPSA convergence value. Each percentage variation reported in table 1 actually corresponds to the mean value of 30 independent ANN model simulations, for which a confidence interval is also provided by means of the corresponding standard deviations.

Table 1: Percentage variations of objective function components with respect to model parameter variations of 1%.

Information	Component	Parameter 1	Parameter 2	Parameter 3	Parameter 4
Production	Production	56.76 ± 8.45	17.70 ± 1.69	0.54 ± 0.11	2.32 ± 0.31
Non-production	Pressure	80.47 ± 1.97	0.95 ± 0.09	0.39 ± 0.02	0.22 ± 0.02
	Concentration	37.29 ± 2.75	16.47 ± 0.92	0.67 ± 0.06	2.23 ± 0.15
	Fluxes	23.49 ± 2.01	10.95 ± 0.49	0.49 ± 0.03	1.09 ± 0.10
	Combined	45.27 ± 3.05	11.29 ± 0.61	0.34 ± 0.05	1.47 ± 0.12

Some interesting observations can be drawn from table 1. First of all, notice that all objective function components are sensitive the most to variations of the first low-resolution parameter, and much less sensitive to variations of the higher-resolution parameters. It is also very interesting the fact that all evaluated function components seem to be totally insensitive to model parameter 3. This observation has been independently confirmed by (Rodriguez et al., 2006). Thus, resolution parameter 3 does not provide any valuable information for the permeability model under consideration.

Another important observation has to do with the fact that although the production component of the multi-objective function seems to be more sensitive to model parameter variations than the combined non-production data component, it is evident from the sensitivity analysis that non-production data also should be able to provide useful information for model parameter optimization. Indeed, notice that confidence intervals are generally smaller for the non-production related components. This suggests that these information components can help reducing the overall uncertainty associated to the history matching process.

Finally, it is of special interest the behavior of the pressure component of the multi-objective function, which exhibits the largest sensitiveness with respect to the lowest resolution parameter, while being practically insensitive to all other three parameters. This seems to suggest that pressure measurements are the most fundamental component for determining basic geological structures whereas fluxes and concentrations (or saturations) play a bigger role in capturing details of the reservoir.

7. Conclusions

According to the preliminary results presented in this work, the proposed methodology promises to provide a very attractive framework for parameter estimation via history matching, especially when the problem complexity makes derivative computation unfeasible and when computational times strongly limit the search performance. As already discussed, ANN models aid at better understanding the search space in the vicinity of a promising solution by means of a sensitivity analysis. This kind of analysis provides valuable information about the relative contributions of

each model parameter and multi-objective function component to the overall history matching process.

Despite the fact that we have employed a coarse model for this preliminary phase of the project, we can draw some important conclusions:

5. The history matching can be improved as more information is added to the objective function. It was shown how additional information components can actually help in reducing the uncertainty associated with reservoir characterization.
6. It is possible to match the production results using only production data in the objective function. However, this does not necessarily yield reliable permeability estimations due to the inherent ill-posedness of the inversion process.
7. The combination of SPSA and ANN is very attractive for parameter estimation and analysis purposes, especially when the problem complexity makes derivative computation unfeasible. Moreover, this type of hybrid approach may be convenient when models and data are subject to dynamic changes as the understanding of the reservoir increases.

Ongoing efforts are currently focused on a deeper analysis of the value that sensor information and high resolution seismic data have in history matching. To that end, the research team will continue evaluating the proposed framework by incorporating both travel-time and amplitude related seismic information, as well as sensor data.

Acknowledgements

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C 3.0 A Multiscale and Metamodel Simulation-Based Method for History Matching

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A MULTISCALE AND METAMODEL SIMULATION-BASED METHOD FOR HISTORY MATCHING

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Abstract

This paper presents a novel framework for history matching based on the concept of simulation based optimization with SVD parameterization, guided stochastic search sampling, multiscale resolution wavelet and incremental metamodel (surrogate model) generation. Hence, the primary focus of this work is to mitigate the computational burden of large-scale history matching. Numerical experiments show the viability of the method for addressing realistic problems.

1. Introduction

Parameter estimation for reliable reservoir characterization has been and is still one of the most consuming and challenging tasks in reservoir engineering (see e.g., Shah et al, 1978; Abacioglu et al., 2001; Grimstad et al., 2003; Zhang et al., 2005). The main issue is to be able to estimate a large number of reservoir parameters (e.g., permeability, porosity) from a relative small set of observations. Besides the severe ill-posedness induced by this fact, the cost of running realistic simulations is too high and overwhelming for obtaining opportune and effective decisions.

The main objective of the present work is to describe a novel history matching methodology that combines multiscale and metamodel approaches in order to achieve fast and reliable estimations. The multiscale component is given by a two-fold procedure that parameterizes the original parameter estimation problem in terms of a reduced set of coefficients (singular values). That is: (1) generate an eigenimage decomposition of the original parameter field by means of the singular value decomposition (SVD) (Horn and Johnson, 1994) followed by (2) the application of the wavelet transformation to each eigenimage (Droujinine, 2006). This decreases the cost of parameter estimation process since convergence is incrementally achieved at the resolution level of interest while preserving the locality of the information contained in each eigenimage. The metamodel component consists of building a faster and simpler multivariate approximation (surrogate model) of the original simulation model (Keane and Nair, 2005). Given sufficient sampling in a given region or set of parameters of interest, the metamodel can be constructed by interpolating the response surface associated to the parameter space. In our particular case, metamodeling provides the means to combine global (derivative-free) optimization and local (derivative-based) optimization methods to reduce the number of computation-intensive simulations as well as increasing the accuracy of our estimations.

We consider that the combination of multilevel, metamodeling and an optimization method such as the stochastic perturbation stochastic approximation (SPSA) (Spall, 2003) provide several potential advantages which include: (1) flexibility, since the present methodology is independent of the simulation model considered which may range from a very simple (e.g., single-phase or streamline simulator) to a very complex one (e.g., compositional coupled with chemical and geomechanics capabilities); (2) robustness, since there are possibilities to explore larger portions of the parameter space which may lead to a global optimal solution; (3) efficiency, since the construction of high-fidelity metamodels provide fast ways to perform sensitivity analysis, parameter estimation refinement and even uncertainty analysis restricted to the domain of interest (Keane and Nair, 2006); and (4) parallel scalability, several levels of granularity can be computationally exploited without apparent bottlenecks such as independent function evaluations (simulations), stochastic gradient computations and optimization runs with different parameter scenarios (realizations).

The present paper is structured as follows. In the next section, we provide a detailed discussion of our optimization approach. In section 3 we show, in particular, numerical results illustrating the capabilities of the multiscale approach. Concluding remarks and further research directions are highlighted in the last section.

5. Description of the Multiscale and Metamodel Framework

2.1 Objective Function

Denoting the model parameters by m , the parameter estimation problem can be stated as the minimization of the mismatch between the vector of observed data d and the vector of predicted data by the simulation model $f(m)$. This mismatch is quantified by an objective function Φ defined in a weighted least squares sense

$$\Phi(m) = (d - f(m))^t C_d^{-1} (d - f(m)). \quad (1)$$

Here, the observation covariance matrix C_d represents the errors in the data. In our particular case, we assume that the model parameters depend on location such as permeability, porosity, rock compressibility, initial or boundary conditions. The vector of measurements d may be obtained at different locations and time intervals.

2.2 Eigenimage Decomposition

Let us assume that the vector of model parameters m is given by a 2-D permeability field $K \in \mathbb{R}^{nh \times nv}$. Moreover, to avoid high-local variations of permeability we define $Y = \log(K)$. We remark that the methodology to be described is also applicable to the 3-D case without major inconveniences. The initial stage of the framework consists of a multiscale treatment of Y through the singular value decomposition (SVD) (Horn and Johnson, 1994) followed by a wavelet transformation of each of the components resulting from this decomposition. Thus, Y is decomposed in the following way:

$$Y = U\Sigma V^t = \sum_{i=1}^r \sigma_i u_i v_i^t = \sum_{i=1}^r \sigma_i Y_i, \quad (2)$$

with $U \in \mathbb{R}^{nh \times nh}$, the columns of which are composed by the horizontal covariance matrix YY^t , $V \in \mathbb{R}^{nv \times nv}$, the columns of which are composed by the vertical covariance matrix Y^tY , and $\Sigma \in \mathbb{R}^{nh \times nv}$, is a rectangular matrix with diagonal entries $\sigma_1 \geq \sigma_2 \geq \dots \geq \sigma_r > 0$, where $r = \min(nh, nv)$ and σ_i is the i th singular value of Y .

The i th eigenimage of Y is given by Y_i and forms an orthogonal basis. Clearly, the contribution of the i th eigenimage to the construction of Y depends on the magnitude of σ_i . The error that results from the partial reconstruction can be shown to be equal to the summation of the discarded singular values, thus, providing an indicator of the number of eigenimages required to reconstruct the original field within a prescribed threshold error.

2.3 The Wavelet Transform and Generation of Multiple Scales

Since its emergence, wavelet transforms have been used in many reservoir engineering applications showing important potentials for multiscale parameter estimation (Lu and Horne, 2000; Sahimi et al., 2005). The linear property of the wavelet transform preserves the singular values when applied to each eigenimage, that is, if W_2 is the 2-D wavelet transform then

$$W_2 \{Y\} = \sum_{i=1}^r \sigma_i W_2 \{Y_i\}. \quad (3)$$

Moreover, since each eigenimage is expressed as the outer product of left and right singular vectors we can express the 2-D wavelet transformation in terms of the 1-D wavelet transform W_1 ,

$$W_2 \{Y\} = \sum_{i=1}^r \sigma_i (W_1 \{u_i\})(W_1 \{v_i\})^t. \quad (4)$$

This fact is not only computationally convenient for the application of the wavelet transform itself. The possibility of leaving the singular values unaffected allows for performing estimations at different resolution levels when successively wavelet transforms are applied in each resulting eigenimage. This means that the coarser the eigenimage the higher the features that we may be able to resolve from the original permeability image. In other words, the parameter space generally *shrinks* towards higher singular values as we perform further upscaling. We will see that this has important implications not only on the reduction of floating point operations but also on the way that the optimization should be conducted to further refine the estimation.

2.4. Parameterization

The parameterization consist of solving (1) in terms of the singular values s_i . That is, we construct the matrix operator $R \hat{\mathbf{I}}_i^{(nh \times nv) \times r}$ that depends on the (upscaled) singular vectors u_i and v_i such that

$$m = \exp(R\hat{m}), \quad (5)$$

where $\hat{m} = (s_1, s_2, K, s_r)'$ and m has the permeability field ordered in vector form. It is worth to add, that the number of singular values to estimate is generally smaller than r .

2.5. Stochastic Optimization and Sampling

The SPSA algorithm is a viable global optimization approach when it is unfeasible to compute function gradients (Spall, 2003). SPSA performs random simultaneous perturbations of all model parameters to generate a descent direction. The SPSA for equation (5) is defined by the following recursion for the parameter vector \hat{m}

$$\hat{m}_{k+1} = \hat{m}_k - a_k g_k(\hat{m}_k), \quad (6)$$

where a_k is a positive scalar that monotonically decreases with respect to k , and $g_k(\hat{m}_k)$ is a stochastic approximation to the gradient given by a simultaneous perturbation of all elements of \hat{m}_k , that is,

$$g_k(\hat{m}_k) = \frac{1}{2} \left[\Phi(\hat{m}_k + c_k \Delta_k) - \Phi(\hat{m}_k - c_k \Delta_k) \right] \Delta_k^{-1}, \quad (7)$$

where c_k is also a positive scalar that monotonically decreases with respect to k , Δ_k is a vector consisting of $\{-1, 1\}$ values randomly generated with a Bernoulli distribution and Δ_k^{-1} stands for the component-wise reciprocal of each of the entries of Δ_k . The parameters a_k and c_k form a monotonically decreasing sequences with respect to k that are chosen to ensure asymptotic convergence of the algorithm (for more details and pointers on SPSA see Spall, 2003).

2.6 Metamodeling and Incremental Refinement of the Parameter Estimation

Construction of the metamodel involves a judicious experimental design (i.e., a fairly representative sampling strategy), a parameter space reduction and a rigorous validation procedure to assess its accuracy. Their construction is usually done through multidimensional regression analysis, radial basis functions (e.g., kriging) or neural networks (Keane and Nair, 2005). Metamodeling allows us for mitigating and focusing the simulation effort in those regions of the parameter space that better define the physical behavior of the reservoir. We have already reported on the use of artificial neural networks (ANN) to increase the accuracy of the estimation provided by the SPSA algorithm (Banchs et al., 2006; Klie et al., 2006)

The metamodel is initially built by means of the points densely sampled by the SPSA algorithm on a given region (“*hot spot*”) of the parameter space. The quality of the metamodel is gradually improved by increasing the sampling points as the metamodel estimations are compared against those produced by the simulator. The analytical structure of the metamodel allows to perform these estimations with a local optimization method (such as Newton or nonlinear conjugate gradient iteration) that efficiently finds an optimum solution in a few number of steps. The sampling is stopped when the metamodel is capable to reproduce the reservoir simulator response within a predefined tolerance.

The optimal solution computed at a given resolution level is used as an initial point for the next higher resolution level after applying the inverse wavelet transform. The procedure is repeated with a decreasing number of function evaluations as the grid resolution level is increased.

3. Numerical Results

The permeability field used for the simulations is shown in Figure 1. It consists of a cross-sectional reservoir model with $1 \times 100 \times 20 = 2000$ gridblocks. The size of each grid block is $25 \times 25 \times 2.5$ ft³. We considered an oil-water model system with a water injection well located at the leftmost side of the model and a production well at the opposite side. To perform the permeability estimation, the production life of the reservoir is analyzed on a span of 1000 days.

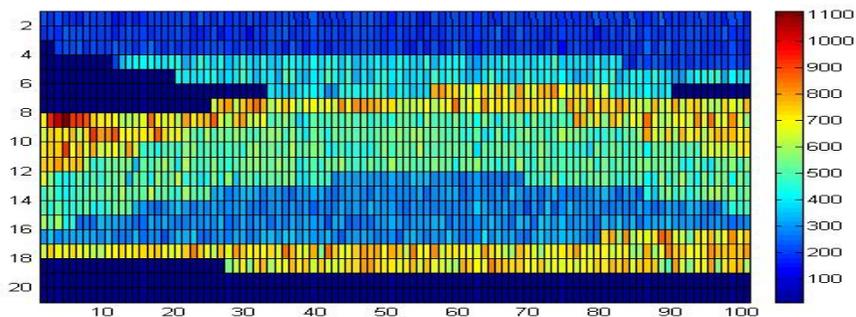


Figure 1. Permeability field used in the simulations.

In order to obtain an initial representation of the reservoir, we perturbed different scales (eigenimages) of the original reservoir model by a 10% of Gaussian noise. In Figure 2 we show the first four eigenimages resulting from the decomposing the log of the permeability field with SVD (the remaining 16 are not shown). From this figure it is possible to observe the relevant features captured by the different terms in the expansion. Notice for example that the first eigenimage at the top left corner represents the broader features of the permeability field; the next images capture details that correspond to finer scales. We found that only 8 eigenimages were sufficient to reproduce the most relevant scales of the perturbed permeability field.

Once the basis of eigenimages has been computed, the problem reduces to determine the optimal set of weights σ_i that minimize the objective function. To that end, we chose an initial guess for the weights that yield the image shown in figure 3. Despite the fact that the weights do not seem to be very far from the actual values, the image produced is very different from the image corresponding to the real permeability field. Next, we use the SPSA algorithm to compute the optimal weights. We compare two different procedures that we distinguish below as case 1 and case 2.

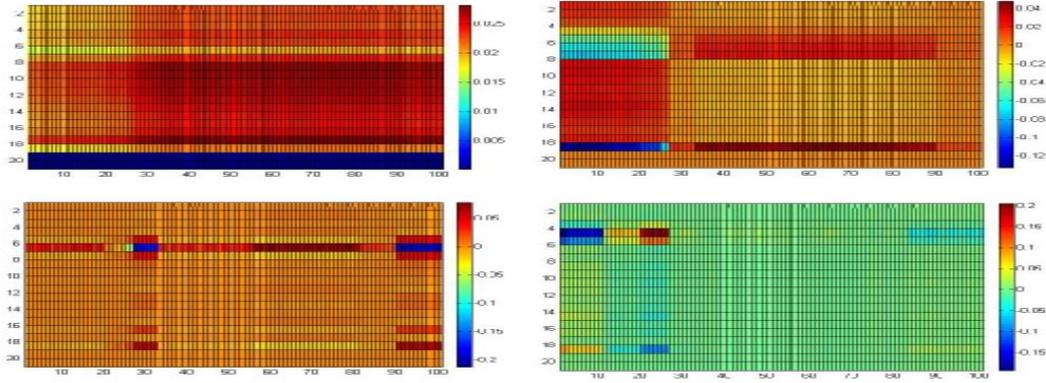


Figure 2. First four eigenimages (ordered from top left to right bottom) corresponding to the log of the permeability field shown in Figure 1.

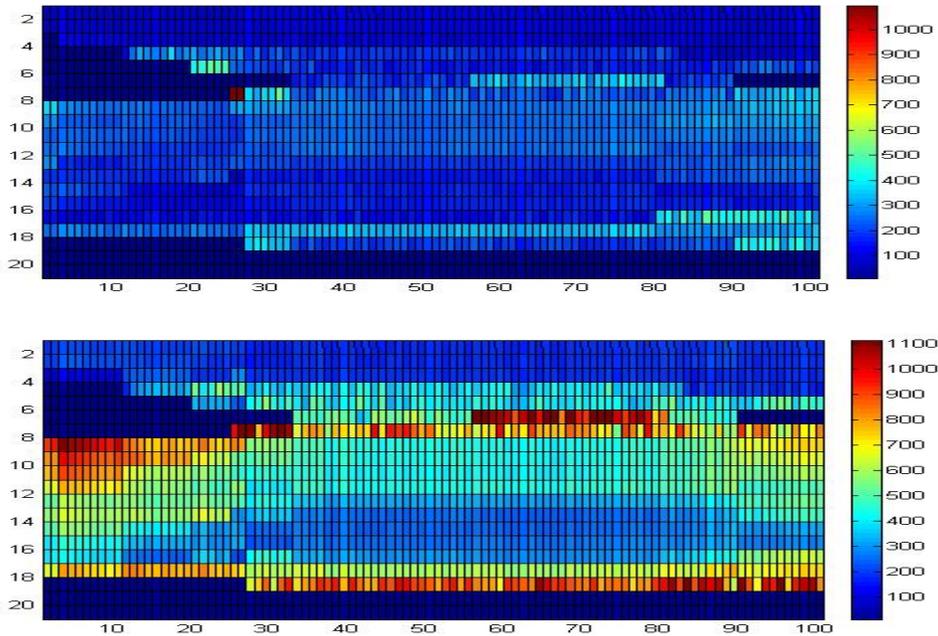


Figure 3. Initial guess permeability (top) and solution for case 1 (bottom).

Case 1. In this case the estimation is performed starting with one term in the expansion to obtain an estimate for σ_1 along a fixed number of 10 SPSA iterations after which a second term is added in a way that the value for σ_1 continues to be improved and σ_2 is estimated. The procedure is repeated until the desired number of terms in the expansion has been added and the corresponding weights are satisfactorily estimated within a given tolerance. Figure 4 shows the evolution of the objective function throughout the whole process, the corresponding first seven σ values in the expansion are shown in table 1. From Figure 4 we can obtain an idea of the relative sensitivity of the objective function to the different weights in the expansion. The procedure described took a total of 140 function evaluations (simulations) corresponding to approximately 35 hours of CPU time.

Case 2. With the objective to reduce the CPU time involved in the estimation procedure, we introduce a multiscale algorithm based on the coarsening of the SVD expansion using a wavelet transformation as it has been discussed above to obtain a $1 \times 25 \times 5$ upscaled system. We then start with an initial guess at the coarse level that included only two terms with $\sigma_1 = 100$ and $\sigma_2 = 10$.

After 100 SPSA iterations at this coarse level we obtained optimal values of $\sigma_1 = 232$ and $\sigma_2 = 40$. These values are used as an initial guess of the permeability field at the fine level. We start with a three-term expansion to adjust σ_1 and σ_2 and get an estimation for σ_3 and, as before, we added a new term every 10 SPSA iterations.

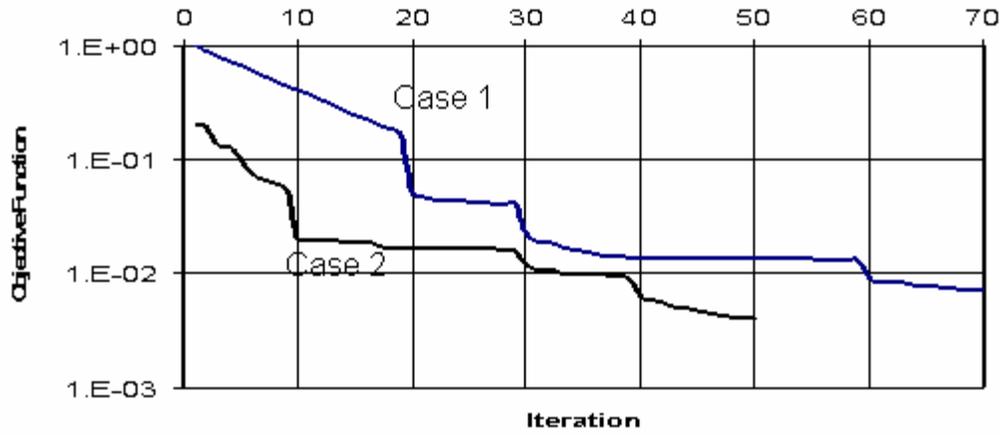


Figure 4. Behavior of the objective function as the parameter estimation proceeds.

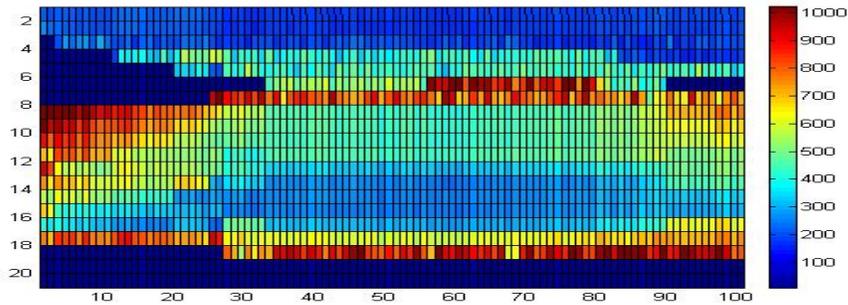


Figure 5. Permeability field obtained after the procedure described in case 2.

The behavior of the objective function is shown in Figure 4 where it is clear the improvement with respect to case 1. Figure 5 shows the resulting estimated permeability field. It clearly shows a better agreement with the reference permeability field than that obtained with case 1. Table 1 shows the eigenimage weights along with the number of function evaluations and CPU time. We can additionally conclude that case 2 did not only lead to a better estimation than case 1, but also in a more efficient fashion. The time of 25h does not include about 1h of CPU time involving approximately 200 fast function evaluations in the coarse space.

Table 1. Parameter estimation based on the cases 1 and 2 described in the text.

σ	1	2	3	4	5	6	7		
Best	235	35	14	10	6.2	4.4	3.8	Eval.	CPU
Case 1	243	20.7	14.2	11.8	5.62	6.38	5.09	140	35 h
Case 2	242	44	16.3	11.75	5.44	6.24	5.03	100	25 h

6. Conclusions

We can draw the following conclusions from the present work:

8. The SVD and wavelet transform parameterization of spatial coefficients into eigenimages of different level resolution show important potentials to reduce the over-parameterization (ill-posedness) and cost associated with the history matching problem.
9. The eigenimage basis can accommodate different levels of resolutions for which we can associate different degrees of geological knowledge or uncertainty. Thus, the parameter estimation can be incrementally conducted in respond to this degree of knowledge.
10. We realized that the SPSA algorithm is efficient and provides high flexibility in implementing different parameterizations and functional transformations to the original parameter space without modifications to the original simulation model.

Ongoing efforts are currently focused on generating a family of different eigenimages basis (via statistical realizations) to both incorporate uncertainty and a wider range of possible estimations. This will allow us for obtaining a better reservoir characterization in the absence or event of poor *a priori* models.

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