

Streamline Simulation for Modern Reservoir-Engineering Workflows

M.R. Thiele, Streamsim Technologies and Stanford University, and R.P. Batycky and D.H. Fenwick, Streamsim Technologies

Abstract

In this article, we present a high-level description of streamline-based flow simulation and focus on four areas in which the technology has proved valuable: reservoir-flow surveillance, flow simulation, history matching, and flood management. We highlight the advantages and disadvantages of streamline simulation (SLS) throughout the article and conclude with a look at possible SLS evolution. SLS re-emerged in the early 1990s to alleviate some computational problems faced by finite-difference (FD) simulation when confronted with high-resolution geological models characterized by heterogeneous spatial distributions of static properties. Since then, development and application of SLS has advanced the technology significantly, such that SLS complements conventional-modeling approaches in many reservoir-engineering (RE) workflows.

What Is SLS?

A streamline is defined as a line that is everywhere tangent to the local velocity field at a given instant in time. The smoke lines generated in a wind tunnel and shown in advertisements to demonstrate aerodynamic qualities of cars are a

good representation of streamlines under the assumption of steady state.

Modern SLS used in the oil and gas industry has its roots in the analytical and semianalytical streamline and streamtube methods that date back to the work of Muskat and Wyckoff (1934). Since then, important early contributions were made by several authors (see Datta-Gupta and King 2007 for a reference list). Streamlines also have a long history in the areas of fluid mechanics and groundwater flow, and petroleum literature has drawn heavily from those sources.

In contrast to the early semianalytical streamtube work of the 1970s and 1980s, modern SLS generally is understood to be associated with work published after 1990 and is characterized by six important ideas: tracing 3D streamlines by use of the concept of “time of flight” (TOF) rather than arc length, expressing the mass-conservation equations in terms of TOF, periodic updating of the streamlines in time, solving the transport problems numerically along the streamlines rather than analytically, accounting for gravity effects, and extension to compressible flow. All of these improvements originated from the need to relax the limiting assumptions inherent in the early semianalytical streamtube methods and adapt the method to more-realistic and -complex reservoir scenarios (Batycky et al. 1997).

The distinguishing feature of streamline-based flow simulation is that fluids are transported over a timestep (t to $t+\Delta t$) along streamlines rather than from cell-to-cell as in conventional FD methods. Because streamlines represent an image of the instantaneous velocity field, anything assumed to move with the total velocity field will follow the streamlines until the velocity field is updated to account for its changing behavior in time. The geometry of the streamlines and the velocity at which components travel along each individual streamline result directly from the spatial distribution of the static petrophysical properties (e.g., permeability, porosity, and relative permeability regions) and the volumes produced/injected at the wells. The ability of streamlines to visualize flow is unmistakable, even to the untrained eye.

To trace the streamlines at a particular time t , the total velocity field must be known at that instant. This idea high-

Marco Thiele, SPE, is cofounder of Streamsim Technologies and a Consulting Professor at Stanford University. He earned BS and MS degrees from the University of Texas at Austin and a PhD degree from Stanford University, all in petroleum engineering. Thiele is a recipient of the 1996 SPE Cedrick K. Ferguson Medal, serves on the SPE Books Committee, and is an Associate Editor for SPEREE.

Rod Batycky, SPE, is cofounder of Streamsim Technologies. He earned a BS degree in chemical engineering from the University of Calgary and MS and PhD degrees in petroleum engineering from Stanford University. Batycky is a recipient of the 1996 SPE Cedrick K. Ferguson Medal. Previously, he worked as a reservoir engineer with Shell Canada. Batycky is a Technical Editor for SPEREE and JCPT. He is a registered Professional Engineer in Alberta.

Darryl H Fenwick, SPE, is project leader of the Streamsim/Stanford History Matching Joint Industry Project (JIP) that fast tracks advanced history-matching technology developed at Stanford University to members of the JIP. He earned BS, MS, and PhD degrees, all from Stanford University in petroleum engineering. Fenwick is a Technical Editor for SPEREE.

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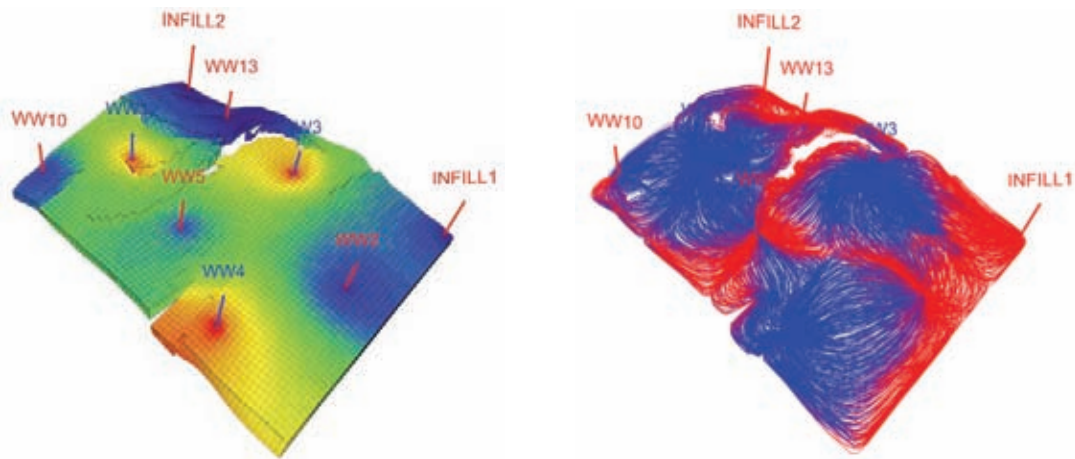


Fig. 1—The dual-grid approach in SLS: (left) The static Eulerian grid is used to calculate the velocity field by use of the pressure field and Darcy’s law; (right) the dynamic Lagrangian grid (streamlines) is used to transport components from an upstream to a downstream location over a timestep, Δt .

lights the first key characteristic of SLS: It is a dual-grid approach. A traditional Eulerian (static) time-invariant grid is used to calculate the total velocity field, while a Lagrangian (dynamic) time-variant grid is used to transport components from an upstream to a downstream location along streamlines. **Fig. 1** shows the 3D pressure field (left), calculated assuming spatially varying static petrophysical properties and well conditions. Once the pressure field is known, the spatial velocity field is constructed by use of Darcy’s law and the streamlines (right) traced in 3D. By displaying water (blue) and oil (red) saturations along each streamline, fast- vs. slow-fluid paths are clearly recognizable.

Reservoir-flow simulation involves constructing a spatial and temporal distribution of pressure(s) and fluid compositions, given a static petrophysical description, an initial state of the reservoir, and the temporal injection/production of fluid volumes. SLS accomplishes this by first solving the pressure on the static Eulerian grid with a conventional FD approach, then constructing the total velocity field from the newly obtained spatial pressure distribution, the static petrophysical description, and Darcy’s law and finally tracing the streamlines that form the Lagrangian grid. The streamlines are assumed to remain fixed for a period Δt , and components are transported along this grid from t to $t + \Delta t$. At this point, the new state of the system (pressures and compositions) at $t + \Delta t$ is known and the process is repeated

until the desired final simulation time is reached. How many times the streamlines are updated (i.e., the number of Δt ’s) is user defined, although there are guidelines and numerical constraints to ensure a sufficiently accurate solution. Large changes in well rates, or new wells coming on line, for example, typically force an update of the streamlines (**Fig. 2**).

One way to frame SLS is the concept of overall sweep efficiency, E , as a product of the volumetric sweep, E_V , times the displacement efficiency, E_D ,

$$E = E_V \times E_D \dots \dots \dots (1)$$

The volumetric sweep efficiency of an injection well is the reservoir volume contacted by the streamlines associated with that well, while the displacement efficiency is given by the transport equation(s) solved along individual streamlines. This points to one of the most appealing characteristics of SLS: breaking up the original 3D domain into a series of 1D independent objects along which the relevant transport equations are solved, then reassembling the 3D solution by mapping back from the streamlines to the original static grid. This breakup and reassembly for each timestep to generate the new distributions of compositions and pressures can be numerically efficient and at the same time can provide useful insight into the displacement process.

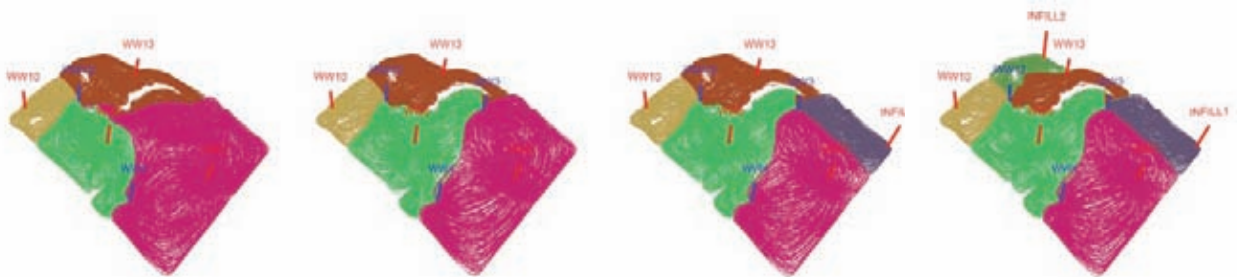


Fig. 2—Streamline change as new wells are brought on line. Here, the streamlines are colored by terminating producers, and the streamline geometries change as new wells are added over time.

Advantages and Drawbacks

Much has been written on the benefits of SLS, such as speed and the ability to process high-resolution grids efficiently. However, understanding the limitations of SLS is equally important for proper application of the technology. Some of the advantages and disadvantages of SLS are discussed next.

The major advantage of SLS compared with other simulation approaches is the information provided by the streamlines themselves. There are two particularly useful sources of data. First, streamlines can outline the drainage and irrigation volumes associated with producers and injectors, respectively. It is possible to know which gridblocks are associated with which well—injector or producer—at any particular time. These regions can be used in well-level assisted-history-matching workflows to decide how to modify static-grid properties to improve the match between simulated and historically observed volumes. Another use can be as a metric to establish the effectiveness of scaleup methodologies. The second data source comes from summing the volumetric flow rates associated with all the streamlines connecting an injector/producer pair. Doing so enables determining the well-rate allocation factors (WAFs) (i.e., the percentage of flow from one well to each offset well with which it communicates). Thus, streamlines offer a simple solution to the challenging problem of trying to associate produced and injected volumes. Well-allocation data are critical to workflows that are based on pattern analysis and are critical to manage floods effectively.

Computational speed and memory efficiency are well-known strengths of SLS. Because the transport problem—usually the more-difficult and computationally involved step in reservoir simulation—is solved efficiently along 1D streamlines and the streamlines are updated at user-defined intervals (timesteps), SLS can be significantly faster than FD methods. The most immediate application of the efficiency of SLS is in the simulation on fine grids with a high level of geological detail. Because streamlines lend themselves to easy parallelization (Batycky et al. 2009), it is also possible to pursue such workflows on standard multicore hardware. For example, a 1.5-million-active-cell waterflood model of the Forties field (UK), with 200+ wells and 40+ years of history, ran in less than 2.5 hours on a 2-CPU quad-core system compared to approximately 6 hours for a single-core run.

However, the improved computational speed and memory efficiency apply to problems that are particularly tailored to SLS: slightly compressible systems in which the principal flow physics is displacement of resident oil by an injected fluid—usually water, miscible gas, or both—in the presence of strongly correlated geological features. These problems are referred to as being convective-dominated (i.e., principally governed by pressure gradients rather than absolute pressure). These cases are traditionally difficult to model with FD methods, and the use of SLS can be an effective complementary approach for a broader RE analysis.

If SLS is best suited for problems dominated by convection, then problems dominated by diffusive-flow physics, such as gas expansion and capillary pressure, are more challenging for SLS. The reason is that diffusive problems do not have a well-defined flow direction—the exact opposite of a streamline. However, such problems are treated effectively and efficiently

by FD methods, underscoring the complementary nature of SLS and FD approaches. Problems that fall in between are more difficult to decide on. Initial depletion of a reservoir that creates a gas cap, followed by repressurization by water injection, is a classic hybrid case. With experience, such problems can be solved sequentially, by use of FD for the expansion and repressurization phases and then by use of SLS.

The biggest drawbacks of SLS may come from its two core architectural features: the dual grid and the assumption that streamlines are independent of each other. The dual grid requires repeated mapping of the solution variables—pressure and overall compositions—between the static Eulerian and the dynamic Lagrangian grid, which leads to a method that is inherently not mass conservative. Additionally, the independence between streamlines does not favor capturing physics that is transverse to the main direction of flow, such as might be the case with gravity (driven by density gradients), transverse-capillary-pressure (driven by saturation gradients), diffusion (driven by concentration gradients), compressibility (in all directions), and transverse-thermal (temperature gradients) effects. These difficulties can be alleviated with an operator-splitting approach, which solves the convective part along the streamlines and the diffusive part on the Eulerian grid. Nevertheless, it remains a sequential approach to capturing nonlinearities in the flow, which might not always be appropriate. In fact, modern SLS can be considered a sequential multigrid method to solve nonlinear partial-differential equations, with the special feature that one grid is dynamic and streamline-based.

The authors' experience with SLS over the last 15 years has been that all real-world reservoir problems exhibit characteristics that do not align perfectly with the assumptions in SLS. Whether SLS can still be of benefit depends strongly on the questions being asked from the model, the assumptions engineers are willing to make, and ultimately the time available for a reservoir study. Without exception, however, it has been found that SLS provides useful insights into the dynamic behavior of a reservoir and can be inserted successfully into most traditional engineering workflows.

SLS-Based Workflows

SLS has found its way into many areas of RE. Four specific examples illustrate how SLS can aid RE workflows. Workflows are stepwise application processes used to solve RE problems. The examples are not meant to be exhaustive, and many other applications of SLS exist that the reader is encouraged to explore in published literature.

Flood Surveillance. Flood surveillance is the pairwise association of produced- and injected-well volumes from observed production/injection data and usually does not involve flow simulation. Flood surveillance relies on WAFs—the percentage of total flow at a producer that can be attributed to an offset injector. Traditionally, WAFs for a producer are estimated by use of a fixed geometric pattern derived from the injectors nearest to it and the angle open to flow. For large multiwell floods, geometric-pattern definitions and WAF calculations are time consuming and critically exposed to the strengths and weaknesses of the engineer undertaking the study. Except for the most regular of five- or nine-spot patterns, it

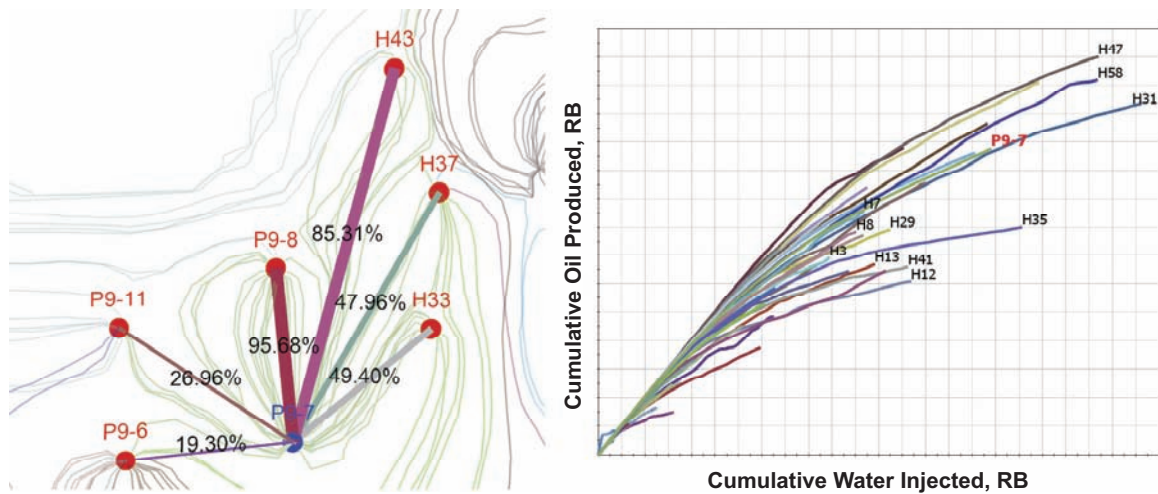


Fig. 3—(left) Streamlines and flux-pattern map used for determining WAFs for the pattern centered on Injector P9-7, and (right) a traditional conformance graph for all the injectors in the field calculated from the WAFs for all injectors over all times. RB=res bbl.

is unlikely that any two engineers will determine the same patterns for a field, much less the same WAFs. This is one reason that pattern-level surveillance is rarely practiced.

Because streamlines connect sources and sinks, the bundle of streamlines connecting an injector and a producer necessarily quantifies the volumetric flux between the two. This is a significant improvement over the guess-work associated with geometric WAFs. Also, because streamlines change over time with well-rate changes, so will the WAFs. Most importantly, SLS changes the concept of a pattern from being a fixed predefined geometric object to being a dynamic injector-centered element. A pattern becomes an injector and its connected producers at a particular moment in time. The pattern is dynamic because the connections change over time and there will be no influx or efflux from such a pattern (Batycky et al. 2008).

To determine the streamlines, it is necessary to calculate the velocity field. To do so, requires as a minimum a static Eulerian grid with associated petrophysical properties, well locations, and historical injected/produced volumes. The static model can range from a simple one-layer homogeneous “pancake” to a 3D faulted grid with spatially varying properties. Because WAFs reflect the connectivity of the reservoir, assumptions about faults or other spatial properties will necessarily affect the calculation of the WAFs. In the authors’ experience, major flow units and gross geologic properties are important and should be included, but small-scale properties, such as interwell permeabilities, have a much smaller effect on well-pair WAFs. This is because the WAFs are, largely, a function of well locations and voidage rates, which, implicitly, account for the geology and the connectivity of the reservoir; wells would not be producing/injecting at the given rates if the reservoir would not allow it.

A streamline-based reservoir-surveillance model is not a flow-simulation model. Streamlines are used only to calculate well-pair connectivity. There is no transport step involved along the individual streamlines. This restriction makes it computationally light, but it also precludes the model being used for forecasting. Once the WAFs are calculated, they

can be represented with a flux-pattern map*, a convenient abstraction to show the volumetric flux between well pairs and its relative strength. The streamline-derived WAFs then can be used to generate a conventional conformance graph: offset oil production vs. volume injected for each injector (pattern). **Fig. 3** shows a close-up of the streamline-derived WAFs for Injector P9-7 and the conformance graph determined from the WAFs for all the injectors (patterns) in the field. As an example, the offset oil rate associated with the injection at Injector P9-7 is prorated according to the WAFs for that time period as follows:

$$Q_o^{P9-7} = 0.19 \times Q_o^{P9-6} + 0.27 \times Q_o^{P9-11} + 0.96 \times Q_o^{P9-8} + 0.85 \times Q_o^{H43} + 0.48 \times Q_o^{H37} + 0.49 \times Q_o^{H33} \dots \dots \dots (2)$$

The oil volume produced by the pattern, Q_o , over that time period is the oil rate times the time period for which that pattern is assumed to hold. Summing all volumes for all pattern configurations over time for Injector P9-7 gives the conformance curve for that pattern (injector). The elegance of a streamline-based reservoir-surveillance model is the ease with which the reservoir engineer can perform a pattern analysis.

Flow Simulation. A flow-simulation model differs from a reservoir-surveillance model in that there is a fluid-transport step along each streamline, and, thus, it can be used for modeling past and future performance. Typically, SLS models are introduced when the equivalent FD versions are computationally too costly, as might be the case in workflows involving optimizing or screening full-field models with detailed geological descriptions, hundreds of wells, and many years of history. Given the large uncertainties inherent in the model parameters—particularly geological parameters—many would argue that estimating the range of uncertainty by use of SLS is more valuable than a single, costly full-physics FD simulation.

*FPMMap is protected by US Patent 6,519,531.

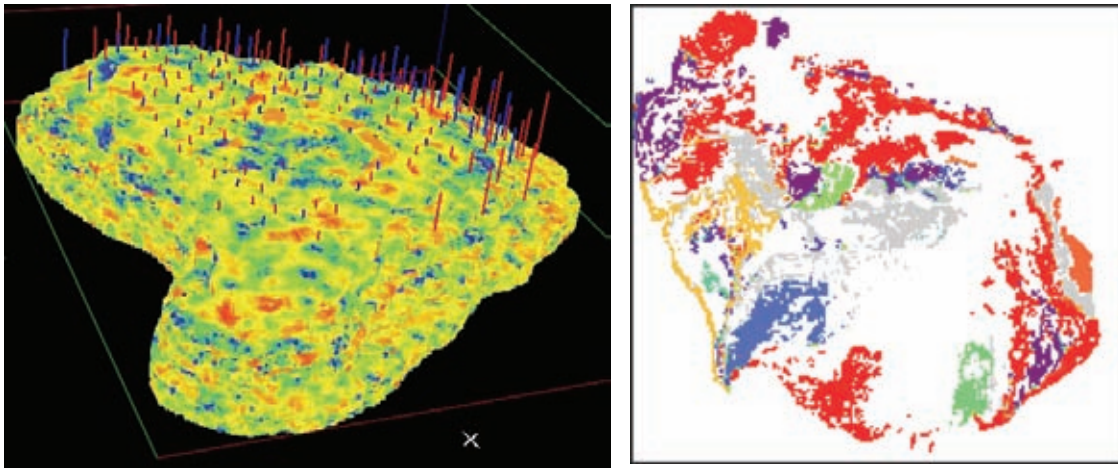


Fig. 4—(left) Original permeability distribution and (right) example of areas identified by streamlines to be modified to improve well-level history matches (Batycky et al. 2007).

As models increase in size, number of wells, and/or flow complexity, the speed advantage offered by SLS can be substantial. A good example is full-field miscible-gas-injection models. These models are difficult and costly to run under FD simulation, but can be effectively simulated on standard computational platforms within the “overnight” time criterion by use of SLS. This method avoids having to divide a model into sectors and bypass the issue of setting the flux across the boundaries, which often is the only way to run an FD model. The Judy Creek field in Alberta, Canada, is such an example (Batycky et al. 2007). The flow model contains approximately 623,000 active cells, 300 wells, and 46 years of history, with water injection starting soon after initial production and miscible-gas injection introduced over the last 20 years. The run time of the final history-matched model used for engineering work is approximately 5.2 hours on standard off-the-shelf hardware.

With speed and efficiency comes the possibility of finer models with improved geological descriptions. In turn, this leads to higher resolution of in-situ fluid distributions, which is critical when trying to find infill locations to drain bypassed oil or evaluate the viability of enhanced-recovery strategies. Speed also allows more-exhaustive sensitivity runs across the traditional input parameters [e.g., relative permeabilities, fluid pressure/volume/temperature (PVT) properties and contacts, and aquifer location and strength]. As those familiar with reservoir-flow simulation will attest, sensitivity runs are an important part of the model-building phase. Gaining an understanding of the dynamic response of the model early on can provide significant help later on when the model is history matched and used for forecasting purposes.

Despite its reputation of being a “simpler” simulation approach, the expertise required to set up and run an SLS model properly does not differ significantly from that needed to run traditional FD models. SLS needs the same input data as traditional FD models—a static grid populated with rock properties, PVT data, well locations, and production data. As such, the model-building phase can be as tedious and involved as that for an FD model.

History Matching. Well-level history matching is probably one of the more challenging and time-consuming tasks faced by reservoir engineers. The industry has reached a consensus that the most important element in history matching is the proper geological description of the reservoir. The term “geological description” is used broadly here to include the spatial distribution of parameters such as facies, permeability, porosity, and relative permeabilities, as well as fault locations and their transmissibilities.

If history matching is approached as a pure optimization problem, then hundreds and possibly thousands of flow simulations may be required to find a match. Thus, the speed of SLS can be used to determine an optimal solution more rapidly. A more recent approach to history matching, however, is to consider it a data-integration problem (Caers 2005). As such, the challenge is to use all available data sources—seismic, core, outcrop, well-test, and production data—in constructing the static geological model. Streamlines can help with this task. First, streamlines outline the drainage region associated with individual wells. This step provides a flow-based outline of regions of the reservoir that have the highest probability of changing the production response of the wells of interest. Second, because fluids are transported along streamlines, streamline-based history-matching algorithms can determine whether fluids need to flow faster or slower—and by how much—to improve the production signals at a particular well.

Fig. 4 shows areas outlined by the streamlines for which changes in permeability and porosity would improve well-level matches for the Judy Creek field. The colors can be interpreted as probabilities: red indicating the probability of higher permeability, blue of lower permeability. The static properties then can be modified accordingly, but always constrained to other data to retain a geologically consistent model.

However, there are several points that complicate this approach. As the properties change, so will the drainage regions, the streamlines responsible for the signal mismatch, and the resulting areas identified as needing modifications. Therefore, the workflow is necessarily iterative, with no

guarantee of convergence. In addition, there is always the question of whether the starting geological scenario is even correct. Trying to perform a well-level history match by starting from a flawed geological scenario (e.g., wrong correlation structure, facies distribution, structure, or training image) remains problematic. In the authors' experience, a certain sign of a wrong starting point is excessive changes in static properties, indicating that the algorithm is trying to compensate beyond what is reasonable. Finally, how much resolution is there in the production data and the numerical model to allow the methodology to work? A frequently occurring example is trying to match breakthrough times between wells with only a few numerical gridblocks separating them, or giving 50-year-old production volumes the same weight as more-recently acquired data.

The authors' experience has been that streamline-based assisted history matching can modify the static geological model to account for production data, and at the same time supply useful diagnostic metrics that can help the reservoir engineer make decisions that otherwise would have been much more difficult to justify. In a very practical sense, SLS enables well-level history matching on large reservoir models with hundreds of wells and long production histories by use of much shorter cycle times than with traditional methods.

Flood Management. The primary reason for history matching is to build models that can be used with confidence for forecasting and planning purposes. For example, this technique might apply to a brownfield producing at a high water cut and clearly in need of improved sweep efficiency. Engineers can achieve this by recompleting or sidetracking existing wells, converting wells, drilling infill wells, rebalancing injection/production rates, initiating/improving an enhanced-recovery operation, or by a mix of all these options. Regardless of the option selected, effective management of mature floods is principally an optimization problem, and being able to rely on the speed and efficiency of the numerical simulator is helpful.

As in history matching, however, the real advantage from SLS comes from the novel data available, specifically the ability to relate produced-oil volumes to injected (usually water) volumes on an individual-well-pair level. The difference from the surveillance workflow, where the oil volumes were simply prorated by use of the WAFs, is that the transport step is now solved along each streamline associated with the bundle connecting a well pair over a timestep, Δt . Thus, each connection in the FD map can be associated with simulated effluent-oil volumes. Knowing the effluent-oil volumes on a well-pair level enables determining the injection efficiency (IE) for that connection: the ratio of oil volume produced to the injected volume (usually water). Being able to determine such a metric down to an individual well pair is unique to SLS. It can be used to identify sweep imbalances at the well-pair level such as watering out of a producer because of a specific injector. Well-pair IEs also can be used for proactive management of a flood on an individual-pattern basis by diverting injected volumes from inefficient connections to efficient ones through well-rate changes (Thiele and Batycky 2006). The IE of each injector (pattern) can be summarized by a crossplot that displays offset oil production vs. water

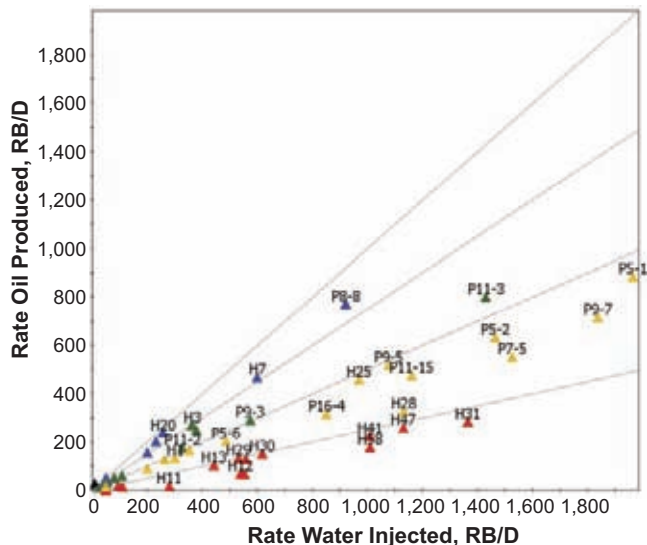


Fig. 5—The IE crossplot displays the offset oil production as a function of water injection for each injector (pattern) in the field. It is a powerful representation of the state of a flood and is the starting point for a targeted management strategy to improve recovery.

injection (Fig. 5). The IE crossplot is an invaluable snapshot of the performance of each injector and the overall state of a (water)flood. It is a metric that allows for a step change in reservoir management.

Other Applications

Four workflows for which SLS is being used with success were presented. Other important RE areas also benefit from streamlines and are mentioned briefly in the following. Also, the reader is encouraged to read the details in published SPE literature.

Scaling up is one clear application. Speed and efficiency allow running fine-scale reference solutions, which often are difficult or even impossible to obtain with FD models. In addition to comparing the match between fine- and coarse-scale responses of bottomhole pressure and water cut, streamlines offer the metric of well drainage and irrigation volumes. Properly scaled-up models should necessarily preserve these volumes between fine and coarse grids.

Modeling uncertainty is another application for SLS. Quantifying the sensitivity of input parameters—particularly geological variability—on forecasted oil production requires many simulations. Such probabilistic workflows benefit from fast proxies, particularly when the emphasis is on the difference between model responses rather than on the absolute response of each individual model.

Challenges still exist when trying to solve complex displacement processes, such as miscible-gas injection, thermal recovery, in-situ combustion, and enhanced-oil-recovery methods in general. Again, SLS offers an alternative formulation because these processes depend on improving sweep in one way or another along streamlines. The natural decoupling of displacement-efficiency calculations along streamlines and the volumetric sweep imposed by well locations, rates, and gross geological features allow improved

engineering by showing how geology and flow interact to displace bypassed oil. Application of SLS to polymer flooding is an example. Excellent results for miscible-gas injection and recent encouraging results for thermal recovery point to the potential of SLS in this area.

Modeling fluid flow in fractured media has proved difficult, extremely CPU intensive, and very sensitive to fracture locations, density, and connectivity. Here, SLS has provided an alternative to conventional simulation, particularly in the early stages of static-model building.

In closed-loop management, there is continuous feedback among data collection, reservoir monitoring, simulation, and decision making. Reduced-order proxies are very important here because of the real-time aspect and the volume of data associated with such workflows. Use of SLS in these workflows is expected in the future.

Looking to the Future

Beyond obvious extensions that will improve the usability of SLS in the workflows mentioned in the preceding section, there are areas where SLS could be a strong catalyst for change. End users are concerned primarily with making good decisions with the aid of flow simulation. The actual methodology used is much less of a concern to them. Future flow simulation could become more of a hybrid approach,


allowing users to switch between FD methods and SLS—possibly even automatically and unbeknown to the user—and moving toward a fit-for-purpose approach. Such a tool would have a profound effect on good decision making and, ultimately, on optimal exploitation of reservoirs.

The industry has long recognized the importance of quantifying uncertainty. As a result, computational resources are being directed more toward simulating large ensembles of models rather than adding ever-increasing levels of detail and physics to a single representation of the subsurface. For multimillion-dollar capital investments, it is far more important to acknowledge the possibility of catastrophic outliers and invest in reducing uncertainty by guided data acquisition than to tweak a single reality to excess. SLS could bring these workflows into sharper focus within the next 5 years.

Finally, interdisciplinary teams have proved to be a successful model in most companies, with each member bringing the depth of knowledge essential for the decision-making process. Such teams work together and are successful because knowledge is shared in a form that empowers the entire team. The proper display of streamlines and streamline-derived data, such as WAFs, drainage and irrigation volumes, and TOF maps, makes for powerful visual aids that are very important in fostering discussions, cross checking results, and helping teams to make timely reservoir-management decisions related to improving the performance of the reservoir.

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