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Production Optimization—A Moving-Horizon Approach

M. Nikolaou, SPE, U. of Houston, and A.S. Cullick and L. Saputelli, SPE, Halliburton Digital and Consulting Solutions

Abstract

Designing fluid injection policies to optimize the production of a hydrocarbon reservoir has attracted considerable interest in recent years. Production policies can emerge from numerical optimization analyses, the solutions for which are most frequently based on optimal control theory. In this paper we argue that (a) a simpler alternative to the optimal control approach may be used, and (b) we present a moving-horizon formulation alternative. We illustrate the proposed approach through several examples.

Introduction

The increasing availability of real-time downhole measurements and remotely activated valves in an oil-field has made field-wide optimization of operations in real time a distinct possibility.[1] While the term real-time optimization (RTO) is certainly not new and RTO is practiced in elements of drilling or production operations [2, 3], the extent to which RTO is now feasible has increased dramatically. At the same time, the increased scope of RTO of oil-field operations entails significant complexity and creates challenges related to"

- Conceptual development: e.g., what is "real time"? What should be optimized? What are associated work flows?
- Technological realization: e.g., what hardware and software should be used? When? Where?
- Practical implementation: e.g., what is the expected and actual return on investment?
- Management: e.g., who is responsible for the development, implementation, operation, and maintenance?[4]

RTO technologies have been advanced, either within the oil and gas industry or in related industries, such as oil refining. While it would certainly be beneficial to further develop technologies for field-wide RTO, it would also be useful to identify existing technologies suitable for the task, streamline such technologies for use in the oil-field, and ensure that such technologies are used prudently and ultimately add value.[5 6] Because elements of field-wide RTO can be manifest in many activities related to production optimization[7, 8], one may be overwhelmed by the multitude of approaches and breadth of scope of field-wide RTO. Putting field-wide RTO in a concrete framework offers clear development and implementation benefits, in that it can catalyze progress by suggesting the path to long-term benefits that might not be immediately obvious from incremental improvements from individual projects.

Building on previous work that established the multi-scale nature of RTO and focused on decision making at the time-scale of days to weeks[9], we are concentrating in this work on decision making at coarser time-scales, e.g., months, with application to optimizing the production of a hydrocarbon reservoir by proper injection of fluids. Capitalizing on significant new capabilities for bottom-hole measurements and remote valve manipulation, a number of authors have convincingly pointed out that sizeable economic benefits can result by proper selection of fluid injection policies (for a thorough recent review see Brouwer's Ph.D. Thesis [10]). Such policies can be designed by solving a numerical optimization problem, usually for the net present value (NPV) of a project or for total oil recovery. The numerical solution of such an optimization problem has attracted considerable attention. The approach most frequently taken is based on optimal control theory. In this work we provide a critical assessment of recent work in this area, identify complexity issues, and suggest approaches toward complexity reduction based on the concept of moving-horizon optimization. In particular, we argue that (a) simpler alternatives to the optimal control approach may be used and (b) the formulation of a selected optimization problem may significantly affect how efficiently that problem can be solved. We illustrate the proposed approach through a number of examples.

Real-Time Optimization under Uncertainty

What Is "Real-time"? The term "real-time optimization" refers to the use of measurements of a process at a certain frequency to enable decision-making at the same frequency. Such optimization would ideally be performed continuously, by collecting all available data in real time and continuously solving an all-encompassing optimization problem. The solution of that problem would indicate what decisions must be made at an instant and acted upon until new process measurements arrive at a subsequent instant at which the decision making process would be repeated. However, the overwhelming complexity and inherent uncertainty of such a task immediately render it impractical. Indeed, blending decision making at the scale of oil-field development over a number of years with decisions made minute by minute by an automatic flow controller is a daunting task.

To address this issue, the overall real-time optimization problem for an oil-field can be decomposed into a hierarchy of multiple levels, each level corresponding to a different time scale, as shown in Fig.1 [2, 11, 12, 13]. At each level, optimization is performed at an appropriate frequency, i.e. time scale. It should also be mentioned that in addition to time scale, other significant differences exist among various levels of the multi-level hierarchy of Fig.1. For example, each level entails different space scales [14, 15] (e.g., optimization of production of several wells vs. flow regulation in a pipe), uncertainty and risk (e.g., reservoir properties used by a simulator early stages of field development vs. effect of choke characteristics on flow), decision making and optimization paradigms (e.g., global optimization [16, 17, 18, 19] vs. PID control algorithms), and extent of automation of decision making tasks (e.g., business development decisions vs. control action for flow regulation). There is a vast amount of published work related to specific elements of each level of the multi-level hierarchy of Fig.1. Fig.1 makes it clear that the term “real-time” is level-specific. It is commensurate with the time scale of the corresponding level. At each level, real-time optimization refers to a feedback scheme. Decisions passed downward from a certain level to an underlying level are updated at the time scale of the decision passing level. The underlying level follows the decisions passed to it from above at its own time scale, namely “almost instantly” in comparison to the time scale of the overlying level.

The feedback scheme of Fig.1 encompasses a broad class of optimization and control paradigms, ranging from optimization for field development and production planning and scheduling, to second-by-second feedback control of flow rate through valve adjustment. For example, decision making at the upper levels of Fig.1 may involve various optimization paradigms concentrating on explicitly stated economic objectives [20], whereas decision making at the lower levels may be automated and focus on engineering objectives, such as *via* standard PID controllers.

The hierarchy of Fig.1 is not unique to hydrocarbon production operations but has broad applicability. As a notable example, such a hierarchy of real-time optimization of operations has been practiced by the oil refining industry for more than two decades, with great success. [21]

As is the case for any feedback loop, the scheme depicted in Fig.1 can only be functional if several indispensable elements are available.

Measurements. New downhole instrumentation is offering important capabilities in this area. The potential to use other real-time information, such as 4D-seismic data, could also have significant impact.

Manipulations. Remotely activated downhole valves offer obvious control capabilities.

Decision Making Algorithm (Control Law). Any such algorithm uses measurements to produce manipulations by explicitly or implicitly postulating:

- Objectives and constraints
- A model describing how manipulated variables (process inputs) affect controlled variables (process outputs)
- A description of uncertainty, e.g. process modeling uncertainty or kind and uncertainty of external disturbances

Human-machine Interaction. Human-machine interaction may include explaining to computers what is desired (e.g., set-points, economic objectives, constraints) and monitoring system operation. In fact, humans can play an important role as decision makers in various places of the hierarchy in Fig.1 and may well be elements of related feedback loops. Assisting humans at this task, technologies such as visualization, monitoring, data analysis, modeling, and numerical optimization are important enablers. For example,

- Visualization can help humans recognize a problem or opportunity for value creation. It is also important for collaboration that is essential to making better decisions.
- Monitoring enables production teams to recognize when wells and equipment are drifting from their design efficiencies. Such observations are important not only from a simple performance perspective but also for anticipating potentially costly failures and taking corrective actions to prevent them.
- With the myriad of data that digital oil fields are bringing in to data historians every second, analysis tools can convert these data to information, diagnoses, and knowledge. These tools span a broad spectrum including conventional engineering tools as well modeling and pressure transient analysis, tools based on multivariate statistics, artificial intelligence, and dynamic systems.

It should be stressed that tools used at any level should be used in a way that eventually produces actionable decisions, to ensure value creation. The actionable decision principle is applicable whether dealing with a control system automatically adjusting valves and chokes or with a work flow manager who leads an organization through a process.

What Is Optimized? As already stated, optimization will ideally attempt to optimize an entire asset continuously

- using all available information up to that point
- predicting future outcomes with certain confidence
- making decisions that would produce optimal future outcomes
- implementing such decisions until the next decision making point in time

If there were complete information about the behavior of a system into the future, optimization would not have to be performed continuously. But uncertainty is always present in future predictions, thus rendering feedback-based, continual decision-making necessary. In addition, what is currently uncertain will be less uncertain in the future, as additional data are collected. For example, the optimal production plan for an oil-field could be computed at the beginning of production. However, uncertainty in reservoir parameters, market conditions, or unforeseen upsets during production should be accounted for early on, and the optimal plan should be continually revised as new data from actual production become available within reasonable time. As another example, the optimal choke opening which ensures that flow rate is at a certain value could be easily computed *a priori*, if there were no uncertainty in equipment condition, fluid properties, pressures, etc. Re-computation and re-adjustment of the choke opening (e.g., by an automatic feedback controller every few seconds) would ensure that the flow rate is at or close to its target.

Current uncertainty as well as its future reduction can be accounted for by the Dynamic Programming *formulation* of the optimization problem [11], which at time t can be expressed as

$$\underbrace{J\left(\mathbf{x}(t);\mathbf{u}(t \text{ to } \infty)\right)}_{\substack{\text{Optimal value of objective}\\ \text{from } t \text{ to } \infty\text{, starting at } \mathbf{x}(t)}} = \max_{\mathbf{u}(t \text{ to } t+dt)} E[\underbrace{\phi\left(\mathbf{x}(t);\mathbf{u}(t \text{ to } t+dt)\right)}_{\substack{\text{Uncertain value of objective}\\ \text{from } t \text{ to } t+dt\text{, starting at } \mathbf{x}(t)}} + \underbrace{J\left(\mathbf{x}(t+dt);\mathbf{u}(t+dt \text{ to } \infty)\right)}_{\substack{\text{Optimal value of objective}\\ \text{from } t+dt \text{ to } \infty\text{, starting at } \mathbf{x}(t+dt)}}] \tag{1}$$

where $J\left(\mathbf{x}(t);\mathbf{u}(t \text{ to } \infty)\right)$ is the optimal value of the time-additive (uncertain) objective function (e.g., NPV) $\sum_{\theta=t}^{\infty}\phi\left(\mathbf{x}(\theta),\mathbf{u}(\theta \text{ to } \theta+d\theta)\right)$ from time t to infinity (practically a large number), with the system starting at state $\mathbf{x}(t)$, assumed to be known at time t (e.g., $\mathbf{x}(t)$ is the set of pressures and saturations of an oil reservoir); $\mathbf{u}(t)$ is the input or decision variable at time t (e.g., the flow rates of injectors and/or producers); $\phi\left(\mathbf{x}(t);\mathbf{u}(t \text{ to } t+dt)\right)$ is the additive part of the objective function from time t to time $t+dt$ and is uncertain because of external disturbances; and $J\left(\mathbf{x}(t+dt);\mathbf{u}(t+dt \text{ to } \infty)\right)$ is the optimal value of the time-additive objective function from time $t+dt$ to infinity, with the system starting at state $\mathbf{x}(t+dt)$, assumed to be known at time $t+dt$, but uncertain at time t.

The state $\mathbf{x}(t)$ of the system at time t follows the dynamic equation (e.g., captured by a reservoir simulator)

$$\mathbf{x}(t) = f\left(\mathbf{x}(t-dt),\mathbf{u}(t-dt),\mathbf{d}(t-dt)\right); \tag{2}$$

where $\mathbf{d}(t)$ is a stochastic disturbance (e.g., deviations of injection rates from desired values, equipment problems), introducing uncertainty to the system.

While, in principle, the above equations (1) and (2) would be applicable for $dt \to 0$, in practice they are applied for a finite dt, commensurate with the time scale of each level in Fig.1. It is such a value of dt that dictates the context within which the term "real-time" is understood, namely dt quantifies the time intervals at which equation (1) should be solved, as new information comes in and $\mathbf{x}(t)$ is updated.

The Curse of Dimensionality and Getting Around It with a Moving Horizon. An explicit solution of the problem posed by equation (1) is impossible in all but a few special cases. The well known reason is that the value of $J\left(\mathbf{x}(t);\mathbf{u}(t \text{ to } \infty)\right)$ depends forward-recursively on the subsequent value of $J\left(\mathbf{x}(t+dt);\mathbf{u}(t+dt \text{ to } \infty)\right)$. Given that the latter is not known as a function of $\mathbf{x}(t+dt)$ in a closed form, one could use a collection of values $J\left(\mathbf{x}_i(t+dt);\mathbf{u}(t+dt \text{ to } \infty)\right)$ at distinct points $\mathbf{x}_i(t+dt)$ and solve equation (1) for all of them. But, in turn, $J\left(\mathbf{x}_i(t+dt);\mathbf{u}(t+dt \text{ to } \infty)\right)$ depends on the subsequent value of J at time $t+2dt$ through equation (1). Therefore, one would have to be able to evaluate $J\left(\mathbf{x}_i(t+2dt);\mathbf{u}(t+2dt \text{ to } \infty)\right)$ at distinct values $\mathbf{x}_i(t+2dt)$. The preceding argument would have to be repeated for t going to infinity. This would create an explosion of combinations, i.e. number of paths to consider for optimization from time t, as depicted in Fig. 2**.**

To avoid this so-called "curse of dimensionality", heuristic alternatives have been applied. One that has found widespread success in practice is based on a concept that is known as *moving* or *receding horizo*n in the process control literature or *rolling horizon* in the planning and scheduling literature. The idea is based on the following heuristics:

- Rather than performing the optimization suggested by equation (1), which accounts for reduction of uncertainty in the future, one neglects the fact that uncertainty will be reduced in the future due to availability of updated information, and formulates the problem as (cf. equation (1))

$$\max_{\mathbf{u}(t \text{ to } \infty)} E\left[\sum_{\theta=t}^{\infty}\phi\left(\mathbf{x}(\theta),\mathbf{u}(\theta \text{ to } \theta+d\theta)\right)\right] \tag{3}$$

- Note that in the above optimization the fact that the future state $\mathbf{x}(\theta)$ of the system, which is unknown at time t, will be known at each future time $\theta>t$ is neglected.
- Because predictions into the future are increasingly uncertain, the summation in equation (3) is confined up to a finite terminal time (i.e. up to the end of a finite time horizon), beyond which the optimization is meaningless. In addition, because the further one looks into the future, the more difficult it becomes to make reliable high-frequency predictions; thus, values of the input $\mathbf{u}$ are decided upon less frequently as θ increases within the horizon.

The final optimization problem can be further simplified as

$$\max_{\mathbf{u}(\theta_i)} E\left[\sum_{\theta_i=t}^{t+T}\phi\left(\mathbf{x}(\theta_i),\mathbf{u}(\theta_i \text{ to } \theta_i+d\theta_i)\right)\right] \tag{4}$$

where the time points $\{\theta_i\}$ are increasingly less densely spaced as θ_i goes from t to $t+T$.

Once the optimization in equation (4) is performed at time t, only the optimal input $\mathbf{u}_{\text{opt}}(t \text{ to } t+dt)$ out of the sequence of optimal inputs over the horizon is implemented until the next decision-making time point $t+1$. At $t+dt$, new information is collected and used to formulate and solve the new optimization problem.

$$\max_{\mathbf{u}(\theta_i)} E\left[\sum_{\theta_i=t+1}^{t+1+T} \phi\left(\mathbf{x}(\theta_i), \mathbf{u}(\theta_i \text{ to } \theta_i + d\theta_i)\right)\right]. \tag{5}$$

The procedure is repeated at subsequent times, $t+2dt, t+3dt, \ldots$, as illustrated schematically in Fig. 3**.** Note that the shift of the summation indices from equation (4) to equation (5) manifests the concept of *moving horizon*. Note also that because the moving-horizon strategy always uses the latest measurements to formulate a corresponding optimization problem it is a feedback strategy.

Naturally, the moving horizon idea is explicitly or implicitly applicable to many levels of the hierarchy in Fig.1, including planning, model predictive control (MPC), or regulatory control. In this work we concentrate on the upper levels in Fig.1, as discussed below.

At this point it should be made clear that the moving-horizon idea involves the following parameters.

- The sampling period, i.e. frequency at which measurements are taken.
- The frequency of decision making.
- The time length of the moving horizon.

Note also that the system model used at each time step t (equation (2)) can be updated (history-matched) on the basis of the latest observed data available (Fig. 3).

Solving the Optimization Problem in a Moving Horizon. Within a single moving-horizon window, the optimization problem to solve, i.e., equation (4) subject to constraints is a standard one. A standard approach toward solution is based on optimal control theory, of which the most elaborate example is Pontryagin's Maximum Principle (PMP)[22]. PMP augments the original system states by creating a co-state (adjoint) vector of the same dimension as the state vector. The co-states satisfy a set of differential or difference equations that can be directly constructed from the original system equations. Then the optimal values of the decision variables can be found by maximizing, subject to constraints, the Hamiltonian function *at each time point* (hence the term "Maximum Principle"). While this maximization is relatively simple if the states and co-states are known, knowing the states and co-states is not. As a result, PMP reformulates the original problem as one which is conceptually appealing by being mathematically concise. However, the PMP formulation is numerically as difficult to solve as the original one. From a reservoir simulation viewpoint, the co-state equations are of comparable complexity to the reservoir simulation equations and must be solved in concert with the latter repeatedly. In addition, numerical solutions based on the PMP formulation may easily converge to a local optimum; or they may have difficulty converging given that the problem may be non-convex.

As an alternative to optimal control, one can solve the optimization within the moving horizon window by using direct methods for global optimization, such as genetic algorithms and variants, e.g. scatter or tabu search. While such algorithms are probabilistic in nature and can be inefficient, they are very easy to program, requiring only a function evaluation from the reservoir simulator. Furthermore, they can be easily run in parallel over a network of computers, and solutions are not trapped in local optima.

Results

The three examples illustrate the moving-horizon optimization methodology on small reservoir models with a few wells. They compare conventional control practice, e.g., reactively shutting in zones to high water-cut, with use of proactive optimal zonal controls. The reservoir simulator and the economic net present value (NPV) calculator are treated as black-box functions by the global optimizer. A full description of the optimizer, the reservoir simulator, and the optimization workflow is found elsewhere[26]. All computations were performed on desktop computers using the Windows operating system. For each example, a discounted cash flow calculation was performed to obtain a net present value (NPV), using a discount rate of 12%, a tax rate of 35%, assumed operating costs, and constant oil and gas prices.

Example 1. Example 1 is adapted from Chapter 6.2 of Brouwer's Ph.D. thesis[10]. The reservoir is primarily low-permeability with one high-permeability streak that runs parallel to the direction of flow, as shown in Fig. 4. There are two horizontal wells, a smart injector (left) and a producer (right). Each well is has forty-five independent injection or production perforations. The economic data for this study are shown in Table 1. We compare water injection and production managed by "reactive control" (that is when a production well exceeds a water-cut threshold, it is shut-in) with results from "ideal control" (that is when the reservoir properties are completely known with the optimization conducted over the full time horizon).

Reactive control: This is conventional oil-field practice, i.e. reacting to high water-cut from producing zones by shutting-in the zone or the well. Water injection is targeted at constant flow rates. Production zones that exceed a water-cut threshold are shut in

Ideal control: This scenario provides the theoretically maximum NPV that would be obtained in a single optimization with no modeling uncertainty. The decision variables are annual injection flow rate targets for each of the forty-five injection intervals over an entire 12-year period. Each injection rate is constrained by an upper bound.

A summary of the production strategies employed along with resulting NPV is shown in Table 2. Saturations for the two cases are shown in Fig. 5 through Fig. 8**.** The NPV increases from \$12.9 million to \$16.6 million. Flow control of each interval in the horizontal wells with the optimizer clearly improves the water sweep with less unrecovered mobile oil.

Example 2. Example 2 is a one-quarter 5-spot configuration with one water injector and one oil producer (Fig. 9). The reservoir has an upper, high-permeability layer and a lower low-permeability layer, separated by an impermeable layer. Each vertical well is perforated at each of the two producing layers. Remotely activated valves are available at each permeable layer, so that injection or production can be remotely adjusted. The challenge for this problem is caused by the contrast in permeability between the upper and lower layers.

The following production strategies over a 10-year time horizon are compared:

1. *No control:* Water is injected at a well constant flow-rate target. The water entering each layer is determined by its kh.

2. *Reactive control:* Water is injected at constant flow-rate targets as in (1), but production at a perforation-interval that exceeds a water-cut threshold is shut in.

3. *Moving-horizon control with individual upper bounds on injection rate targets:* The decision variables are the flow rate targets for each of the two injection zones set at the beginning of each year for six years. Thus, there twelve decision variables for each optimization of the moving horizon window. Fig. 10 has the moving horizon optimization template for the six-year windows of time, i.e. the time horizon. Each flow rate target is bounded individually and is held constant for one year. The algorithm performs an optimization at the beginning of each year to maximize NPV for production from the beginning of that year, discounting the cash flow from the end of the 10th year. At the end of each six-year window, the final values for injection rate targets are held constant until the end of the 10th year. After an optimization is completed, the first value in the sequence of optimal future injection rate targets is implemented for a year. At the beginning of the following year, it is assumed that new data have been collected, and the optimization is repeated. This recursive cycle continues until the end of the 10th year, simulating field production over 10 years.

   To make the simulation more realistic, it is assumed that a discrepancy exists between the reservoir model used by the optimizer and the "actual" reservoir. That discrepancy is realized in the form of different permeability values, which are assumed to be updateable with new data from the field each year. The optimizer uses initial estimates in the first year; and for every subsequent year, it revises the estimates, as a result of an assumed history match. The assumed model permeability values are shown in Fig. 11 for the upper layer, asymptotically approaching the true reservoir permeability of 400 md. The lower layer model permeability is adjusted by only a few md over the period.

4. *Moving-horizon control with upper bound on total injection rate target:* This is similar to the preceding strategy, with the following difference: the total water injection rate target is constrained, rather than individual layers.

5. *Ideal case:* This scenario provides the theoretically maximum NPV that would be obtained in a single optimization with no modeling uncertainty. The decision variables are annual injection flow rate targets over the entire 10-year period. The total injection rate is constrained by an upper bound.

A summary of the production strategies employed over a 10-year period along with resulting NPV and oil recovery values are shown in Table 3. Fig. 12 compares the cumulative production and injection profiles for the field. Figs. 13, 14, and 15 compare the oil and water cumulative profiles for individual reservoir layers. The moving horizon approach shows improved NPV, as compared with reactive control and also compares quite well in the NPV for an ideal optimization, that is, with no uncertainty. The moving horizon has somewhat less oil production at ten years than reactive control, but the water-handling efficiency is so much improved that the NPV is much higher by comparison. For reactive control, the water in the high-permeability layer breaks through quite quickly, so the zone is shut off, whereas the optimization manages the water production in the high-permeability layer at a low rate. The moving horizon with individual injection zonal targets is better than the moving horizon with an overall well target.

Example 3. Example 3 is a 2-D model adapted from the 10th SPE Comparative Solution Project [23] as discussed in reference 24. The reservoir model has $60\times220\times1$ cells of dimensions $20\times10\times170$ ft, and the properties correspond to layer 61 of the SPE model. The porosity and permeability spatial distributions are very heterogeneous, forming a somewhat channel-like geometry, as shown in Fig. 16. The well locations are in an approximate five-spot pattern with a vertical injector near the center and four vertical producers near the model's corners. Economic data are shown in Table 4. Note that the price for produced water handling was deliberately selected to be artificially high, following Reference 10. The following production strategies over a 4.5-year period were considered.

1. *Reactive control:* Water is injected at constant flow rate targets. Production wells that exceed a water-cut threshold are shut.

2. *Moving-horizon control with individual upper bounds on injection rate targets:* Fig. 17 has the moving horizon optimization workflow. The decision variables are the flow rate targets for the water injection well for each month over the horizon time window. Each flow rate target is individually bounded and is held constant for a month. The algorithm proceeds by performing an optimization at the beginning of each year, to maximize NPV for production from the beginning of that year up to the end of year 4.5. The maximization is performed with respect to water injection rate targets over a horizon of up to two years (25 months). The 25th value of the optimal injection rate target is held constant until the end of year 4.5. After an optimization is completed, the first 12 values in the sequence of optimal injection rate targets are implemented for a year. At the beginning of the next year,

it is assumed that new data have been collected and are the basis for an improved optimization. Then the optimization is repeated. The cycle continues until the end of year 4.5. It is assumed that no discrepancy exists between the reservoir model used by the optimizer and the actual reservoir.

3. *Ideal control:* This scenario provides the theoretically maximum NPV that would be obtained in a single optimization with no modeling uncertainty. The decision variables are injection flow rate targets, selected every month over the entire 4.5-year period, i.e., 54 values in total.

A summary of the production strategies employed over a 4.5-year period along with resulting NPV and oil recovery values are shown in Table 5. The moving horizon NPV compares well with the NPV for ideal control. The resulting fluid saturation at the end of the production period for moving horizon control is shown in Fig. 16. Figs. 18, 19 and 20 show the improved oil production and water handling efficiency, as compared with reactive control. The moving horizon and ideal control methods show similar fluid profiles.

Conclusions and Discussion

In this paper we emphasized that production optimization and efficiency is an element of oil-field-wide optimization, a task that spans many interconnected space and time scales, each scale entailing appropriate decision making paradigms. We focused on production optimization by designing optimal waterflood policies. We proposed a moving-horizon optimization paradigm, an approach that has found widespread success in other industries, such as oil refining. The moving-horizon formulation allows the incorporation of uncertainty. In addition, it allows a variety of numerical optimization techniques to be used for computation of optimal profiles in each horizon. While the latter task has been attempted primarily by employing optimal control theory, we demonstrated that standard global optimization algorithms, such as genetic algorithms and variants, offer attractive alternatives, i.e., (a) they search for the global optimum; (b) they are extremely easy to program, as opposed to optimal control theory, which requires a simulation effort comparable and in addition to that of reservoir simulation; and (c) they can be easily run in parallel over widely available PC clusters. The computational time requirements are comparable to those of serially run algorithms based on optimal control; the approach requires no effort for the set up and programming of the adjoint equations [10]; and the optimizer does not become trapped in local solutions.

The examples demonstrated the upside potential of a real-time proactive optimal control policy when applied to producing projects, as compared with only reacting to well performance.

It is clear that the work presented in this paper can be refined in a number of ways, such as the following:

- Explicitly introduce uncertainty in the moving-horizon optimization [25]. The description and quantification of uncertainty will be important for both how realistic the moving-horizon optimization problem is and how efficiently it can be solved.
- Use proxy models [1,26,27] to partially replace the reservoir simulator, to reduce simulation time.
- Parametrize the decision variables (e.g., waterflood flow rates) in a more efficient manner, to reduce the size of the moving-horizon formulation.

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Nomenclature

BHP – bottom-hole pressure
COP – cumulative oil produced
CWI – cumulative water injected
CWP – cumulative water produced
D - day
h – thickness
J – general objective function form
k – permeability
md – milliDarcy, permeability
NPV – net present value
Q (q) – rate
STB – stock tank barrels

Subscripts:
o – oil
w – water
g – gas
max - maximum

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Table 1 – Economic data for Example 1

Variable	*Value*
Oil price, $/STB	30
Water operating expense, $/STB	2
Water injection expense, $/STB	0.5
Discount rate, %	15

Table 2 – Production scenarios for Example 1. Producers: BHP = 4000 psi, Qmax = 10000 STB/D

Mode of Operation	*Constraints on water injection flow rates (in STB/D)*	*NPV* ($ MM)	*COP* (MSTB)	*CWP* (MMSTB)	*CWI* (MMSTB)
Reactive control	Water injectors: Qmax = 10,000, Wells with water cut > 0.90 are shut in	12.9	667	1.5	2.1
Ideal control (Perfect model)	Injectors: Qmax < 2000 Wells with water cut > 0.90 are shut in	16.6	777	1.4	2.1

Table 3 – Production scenarios for Example 2

Mode of Operation	*Constraints on water injection flow rates in STB/D*	*NPV*	*Recovery*
No control	Constant flowrate targets for both injection layers: Qmax_upper = 3000, Qmax_lower = 3000	$5.7 MM	28.7%
Reactive control	Constant flowrate targets for both injection layers: Qmax_upper = 3000, Qmax_lower = 3000 Shut in production wells with Water cut > 0.85	$6.5 MM	29.7%
Moving-horizon control 1	Optimized flowrate targets for both injection layers: Constraints: Qmax_upper < 3000, Qmax_lower < 3000	$7.2 MM	28.8%
Moving-horizon control 2	Optimized flowrate targets for both injection layers: Constraint: Qmax_upper + Qmax_lower < 6000	$6.7 MM	28.7%
Ideal case (Perfect model)	Optimized flowrate targets for both injection layers: Constraint: Qmax_upper + Qmax_lower < 6000	$7.3 MM	28.8%

Table 4 – Economic evaluation data for Example 3 (SPE 10) [28].

Variable	*Value*
Oil price, $/STB	30
Water operating expense, $/STB	40
Water injection expense, $/STB	3
Discount rate, %	0

Table 5 – Production scenarios for Example 3 (SPE 10)

Mode of Operation	*Constraints on water injection flow rates (in STB/D)*	*NPV* ($ MM)	*COP* (MMSTB)	*CWP* (MMSTB)	*CWI* (MMSTB)
Reactive control	Water injector: Qmax = 5000, Producer: BHP = 3000 psi Shut in production wells with Water cut > 0.42	55.5	2.5	0.24	3.3
Moving-horizon control	Injector: Qmax < 6000 Producer: 500 < BHP < 4000 psi	77.3	3.2	0.30	2.2
Ideal case (Perfect model)	Injector: Qmax < 6000 Producer: 500 < BHP < 4000 psi	81.4	3.1	0.14	1.8

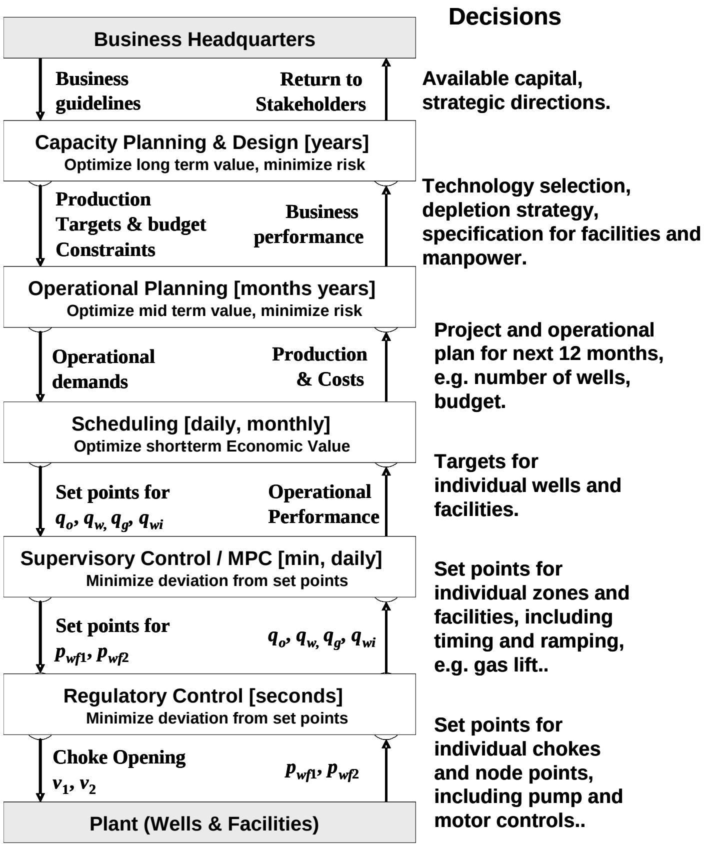

Fig.1—A multi-level hierarchy of oil-field decision making tasks at different time scales. Feedback loops between levels consist of (a) passing data from a lower level to an overlying level, (b) processing data and making a decision over a time period at the overlying level, (c) passing the decision as objectives and constraints to the underlying level, and (d) almost instantly following the decision at the underlying level.

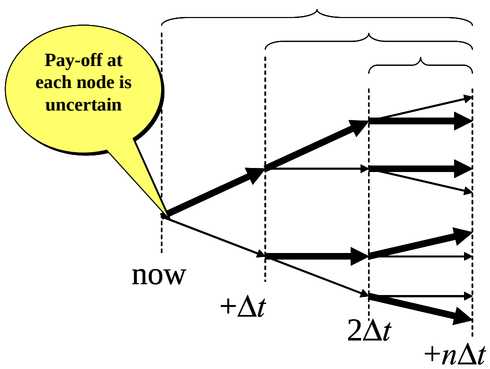

Fig. 2—Combinatorial explosion in dynamic programming

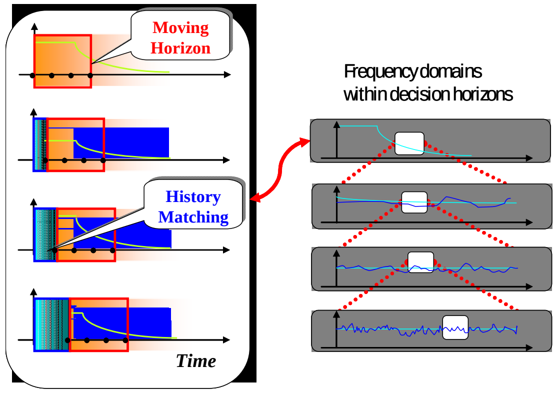

Fig. 3—Moving horizon for real-time reservoir management, within the context of the hierarchy in Fig.1. At lower levels of decision hierarchy, the frequency of observations increases.

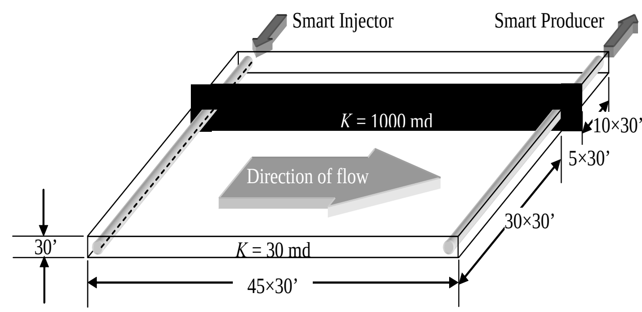

Fig. 4—Example 1 reservoir and well model. The smart injector and smart producer each have 45 individual control points.

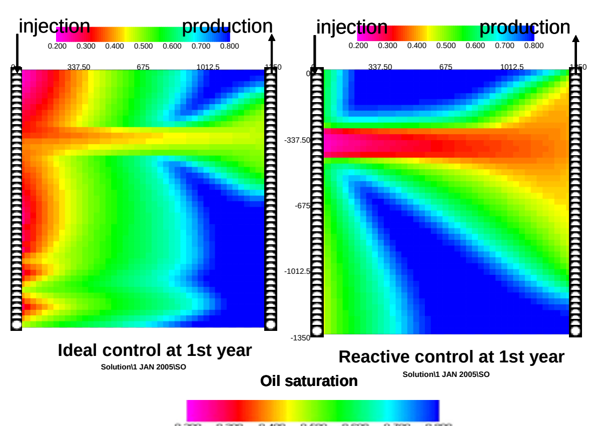

Fig. 5—Example 1 oil saturation after 1-year of water injection, illustrating improved sweep with well control.

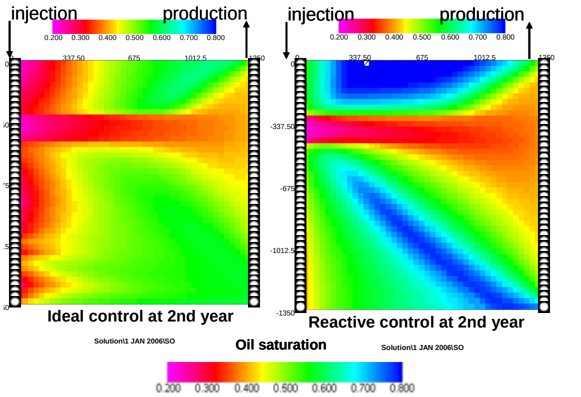

Fig. 6—Example 1 oil saturation after 2nd-year of water injection, illustrating improved sweep with well control.

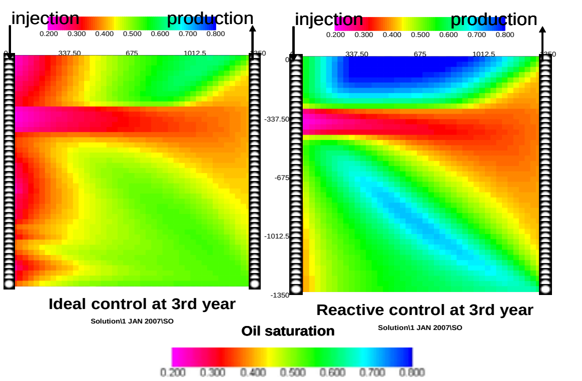

Fig. 7—Example 1 oil saturation after 3rd-year of water injection, illustrating improved sweep with well control.

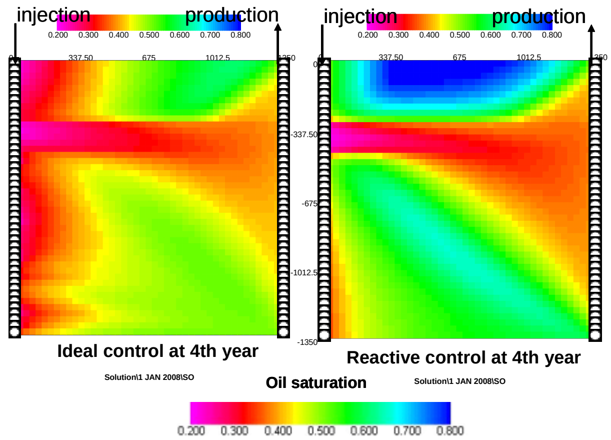

Fig. 8—Example 1 oil saturation after 4th-year of water injection, illustrating improved sweep with well control.

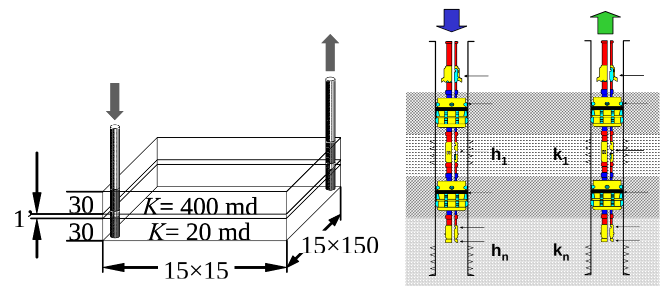

Fig. 9—Example 2 reservoir and well configuration.

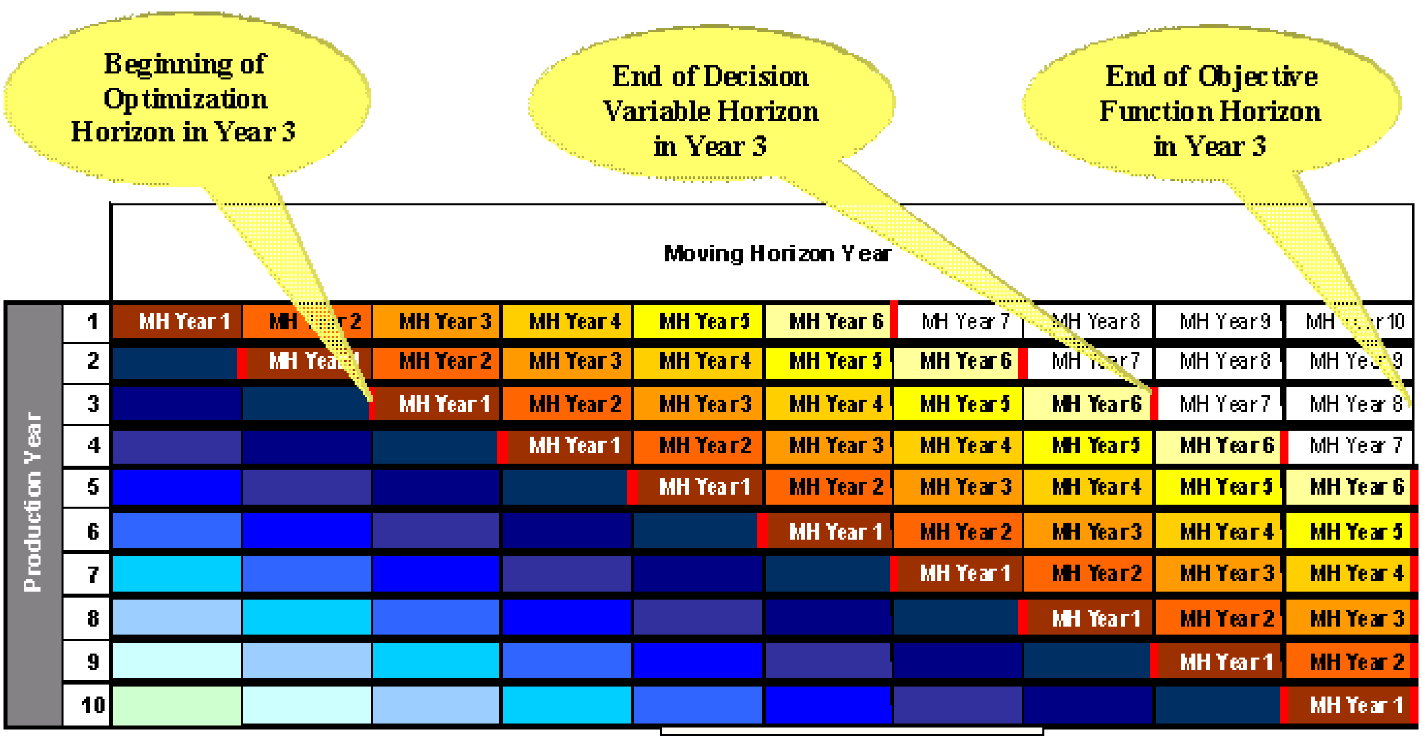

Fig. 10—Moving horizon (MH) strategy for Example 2. Each time window (horizon) is six years. An optimization of downhole zonal injection is performed from beginning of each six-year horizon to end of 10-year period, given previous years' history.

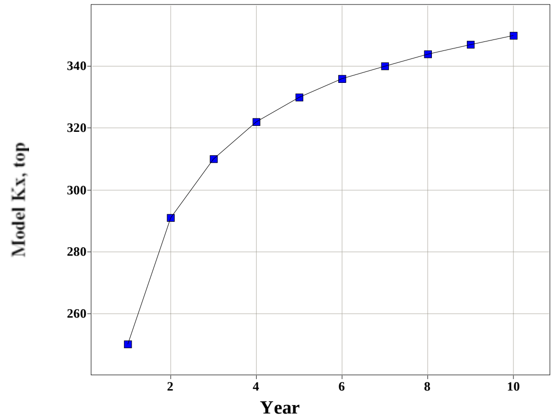

Fig. 11—Example 2 evolution of reservoir model permeability of the upper high permeability later estimate for moving horizon model updates.

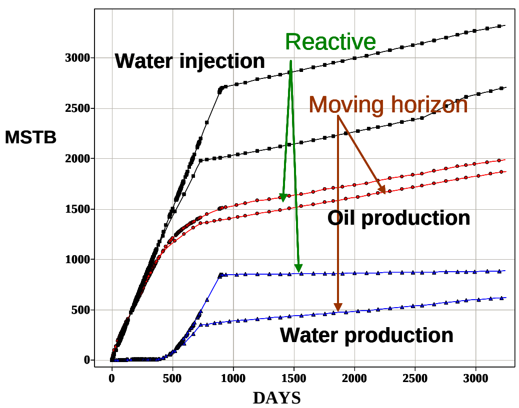

Fig. 12—Example 2 production and injection for reactive control and moving horizon control for each permeability layer.

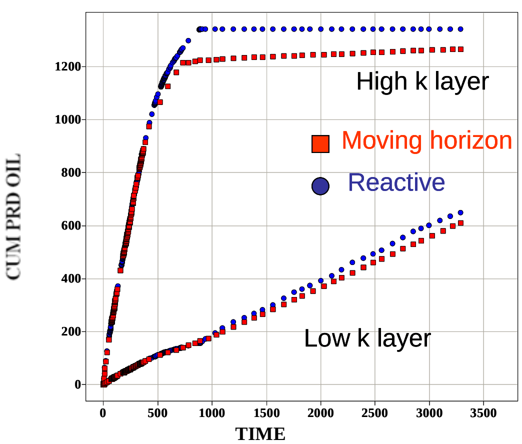

Fig. 13—Example 2 Cumulative oil production (CUM PRD OIL MSTB) by layer for reactive control and moving horizon control for each permeability layer.

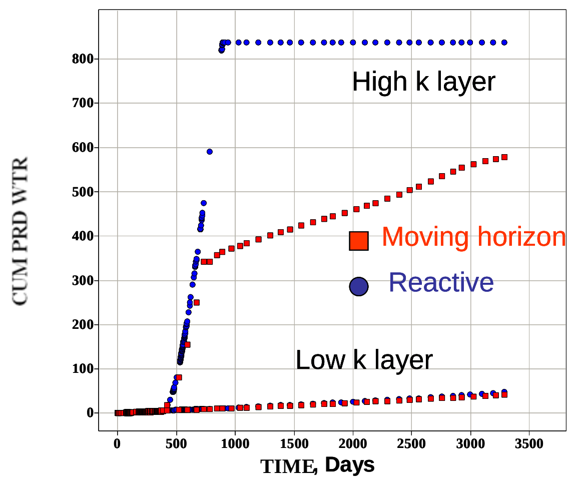

Fig. 14—Example 2 Cumulative water production (CUM PRD WTR MSTB) by individual permeability layer for reactive control and moving horizon control.

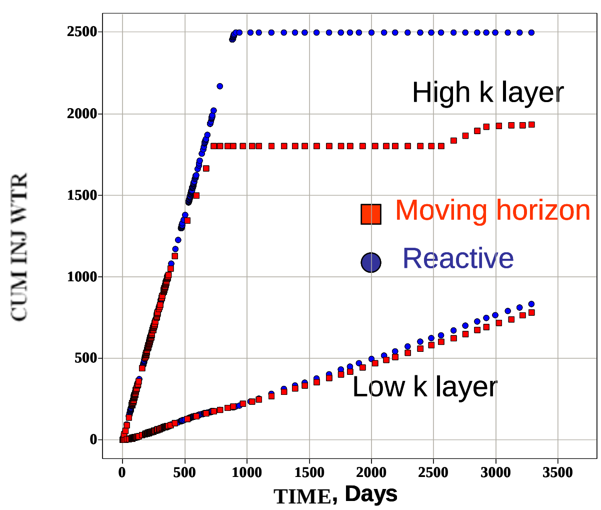

Fig. 15—Example 2 Cumulative water injection (CUM INJ WTR MSTB) by layer for reactive control and moving horizon control for each permeability layer.

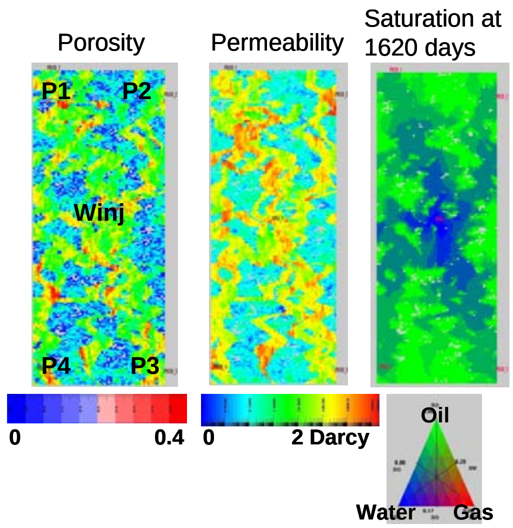

Fig. 16—Example 3 – comparative solution model SPE 10. Saturation is shown for water injection at 1620 days for the ideal control case. The producing wells are labeled P1, P2, P3, P4.

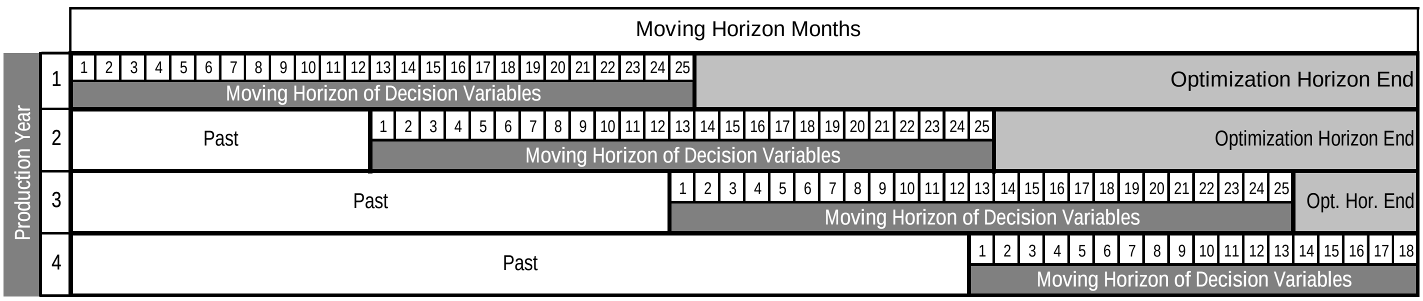

Fig. 17—Example 3 SPE 10 model moving-horizon controls strategy.

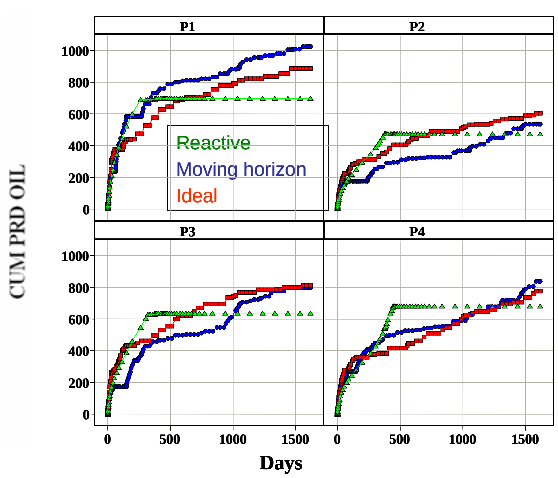

Fig. 18—Example 3 - comparative solution model SPE 10. Cumulative produced oil (CUM PRD OIL, MSTB) profiles for reactive control, moving horizon control, and ideal control cases for each well. See Table 5 for the field cumulative results.

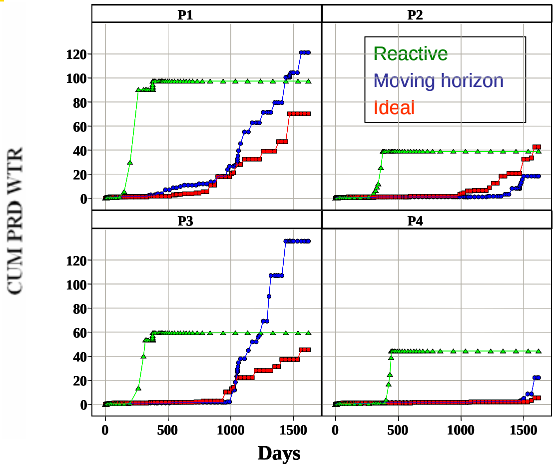

Fig. 19—Example 3 - comparative solution model SPE 10. Cumulative produced water (CUM PRD WTR, MSTB) profiles for reactive control, moving horizon control, and ideal control cases. See Table 5 for the field cumulative results.

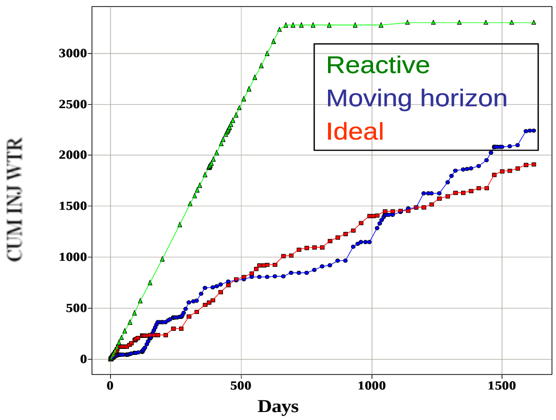

Fig. 20—Example 3 - comparative solution model SPE10. Cumulative injected water (CUM INJ WTR, MSTB) profiles for reactive control, moving horizon control, and ideal control cases. See Table 5 for the field cumulative results.