Real-Time Feedback Control of the SAGD Process using Model Predictive
Control to Improve Recovery: A Simulation Study

by

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Abstract

Scope of the Work: For over a decade, the oil industry has been moving to "smart fields", which deploy wells with remotely operated valves and permanently installed downhole sensors for real-time pressure and temperature measurements. Real-time data from these "intelligent wells" provide key knowledge about the reservoir performance and enable continuous and automatic production optimization for better economics. In this study, we apply intelligent wells with fiber-optic array temperature sensing to Steam Assisted Gravity Drainage (SAGD) for real-time production optimization using Model Predictive Control (MPC), which is a multivariable constrained control strategy. A linear empirical model is first identified using downhole temperature and well rate data. Based on the linear model and real-time temperature and rate data, an MPC controller manipulates the well rates to control the subcool along a well pair in a SAGD reservoir. We use a multilevel control framework, in which the well settings from long-term optimization using a reservoir model provide the "set points" for MPC.

Procedure: To evaluate the use of MPC for real-time control of subcool in SAGD, we use three-dimensional heterogeneous reservoir models with a single pair of dual tubing string horizontal wells. A set of porosity and permeability realizations are created. Two realizations are selected to represent two different cases of uncertain reservoir models. Further, another realization is created that is considered as the "synthetic" (virtual) reservoir. For each of the two reservoir

models, a proprietary reservoir simulator is used to find the optimum rates and subcool. Then MPC is used to control the subcool along the well pair in synthetic reservoir.

Results, Observations and Conclusions: Using the multilevel control framework, NPV improves by 18.23% and 8.81% in the two cases of reservoir models, over a direct application of the optimum rates. Though the results validate the use of MPC for real-time optimization of SAGD, we faced a couple of issues (which have related practical concerns) in the identification of good linear models and subsequently using them in the MPC controller because of steam breakthrough in the dual tubing string well pair. However, we conclude that identification of good linear models will be feasible if ICVs are used in the injector and producer, which allow for more uniform steam distribution in the injector and differential steam trap control in the producer.

Work's Novelty: A few other works present results for the use of proportional-integral-derivative (PID) control for automatic feedback control of the SAGD variables. However, unlike the MPC strategy, the PID-control strategy is a single-input and single-output control strategy. It acts on each controlled variable in isolation by manipulating a single variable instead of optimizing the whole system as the MPC strategy does.

"What we see depends mainly on what we look for." – John Lubbock

"Science is a way of thinking much more than it is a body of knowledge." – Carl Sagan

To My Father

who encouraged me to look for the right things, be curious about the world around me and have a skeptical inclination.

Acknowledgements

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Abbreviations:

2D	two-dimensional
3D	three-dimensional
ARIX	autoregressive integrated with exogenous input
ARX	autoregressive with exogenous input
ATS	array temperature sensing
BJ	box-jenkins
cSOR	cumulative steam/oil ratio
CWE	cold water equivalent
DTS	distributed temperature sensing
GUI	graphical user interface
FIR	finite impulse response
ICD	inflow control device
ICV	interval control valve
LTI	linear time invariant
MPC	model predictive control
NPV	net present value
OCD	outflow control device
ODE	ordinary differential equation

pdf	probability distribution function
PID	proportional-integral-derivative
RBS	random binary signal
SAGD	steam assisted gravity drainage
SCADA	supervisory control and data acquisition
SOR	steam/oil ratio
STL	stock tank liquid

1. Introduction

In this chapter, we will first consider the challenge in reservoir management of integrated decision making at different time scales. In practice, while the reservoir models are used for overall field development and production planning, the short-term well operating points that are used often disregard the long-term field performance needs. The reason is outlined. However, as digital data takes the center stage in oil fields with the use of *smart-field technologies*, it has enabled enhanced production control and integrated operations. Additionally, through the use of integrated software tools and field controllers, there exists an exciting possibility of implementation of field-wide production optimization in real time—by making use of the real-time data in smart fields. Till now, optimization efforts in oil fields have only been independently focusing on different elements of the production system without a field-wide optimization framework.

We will then discuss Steam Assisted Gravity Drainage (SAGD), which forms the focus of this work. SAGD is a low pressure oil recovery process that uses long horizontal wells for steam injection and oil production. The main challenge in the process is to develop a uniform steam chamber, upon which the oil recovery and the process efficiency hinge. Different technologies, including smart-field technologies, have been used to control the steam chamber formation.

Finally, in the context of the SAGD process, we will consider a multilevel control and optimization framework for real-time feedback control of the process while integrating the long-term production plans from the reservoir models. For the multilevel control, the model predictive control (MPC) strategy is used. Further, in this research a data-driven modelling approach is taken for the real-time production optimization, as data-driven models are well suited for using the high-frequency data in smart fields to make decisions in real-time.

We will frame a hypothesis for this research and state the specific questions that we aim to answer.

1.1. Decision-Making Levels in Reservoir Management

Reservoir management involves the difficult task of addressing conflicting short-term and long-term needs, corresponding to decision-making at different time scales. Long-term decisions (field development planning) include a consideration of the market forces, drainage strategies to be used and infrastructure development. In the mid-term, decisions on production and injection rates and drilling of wells are taken. Short-term decision-making, usually referred to as production optimization in literature, consists of activities related to fine tune well operating points, like decline curve analysis, well tests, well rate allocation and gas lift rate allocation. Saputelli et al. (2005), Nikolaou et al. (2006) and Foss and Jensen (2011) describe these different levels, albeit in slightly different ways. Seldom decisions at these different time scales are made in an integrated manner.

Numerical reservoir simulation has become the central tool in reservoir management. Simulation models have grown very complex and large over the years as more complex reservoirs are being developed and there is a need for more accurate forecasts. The forecasts are used to decide well rates in the medium-term for the highest recovery factors or the best production economics. However, due to the inherent uncertainty in several parameters used in reservoir models and the presence of geological features below model resolution, reservoir performance will vary from that predicted using a reservoir model. E.g., uncertainty in locations and extent of fine-scale geological features like high or low permeability layers and shale barriers, fault intensities and level of heterogeneity can lead to uneven injection and earlier than expected water breakthrough in waterflooding. In order to manage the uncertainty, reservoir models can be updated regularly using history matching to fit past production

data. Closed-loop Reservoir Management (CLRM) has been proposed by different authors. It includes regular and sequential implementation of model-based optimization and history matching. Model-based optimization optimizes well rates or pressures at multiple points of the reservoir life by maximizing or minimizing an economic objective function. Further, to quantify the uncertainty, the optimization exercise can use several realizations to represent the reservoir (robust optimization) and include a risk aversion term in the objective function for optimization. Jansen et al. (2009) do a thorough review of CLRM and illustrate the concept. Van den Hof (2012) is a more recent work that discusses the scope and challenges of CLRM. The works on CLRM show that significant economic benefits can be obtained from the use of these models to optimize production and injection plans. Though there is no case of CLRM being applied in a field, individual elements of it are being rapidly applied.

Because of the inherent uncertainty in and distrust of reservoir model predictions, short-term production control in fields has been largely focused on maximizing short-term returns without any ultimate recovery considerations. The work of Naus et al. (2006) is an example of such a production strategy. However, with the implementation of CLRM to mitigate the uncertainty, the scope of short-term production control can be limited by the reservoir model predictions to avoid overlooking long-term gains. It needs to be noted that even with CLRM, short-term optimization is necessary because different physical constraints need to be managed (e.g., total gas lift gas available). Also, even the history matched models in CLRM can have a large uncertainty in them; Dilib and Jackson (2012) cite some works as examples. History matching may also take up to a year, by which time there is more production data available. Foss and Jensen (2011) describe the adverse effect of such a workflow related time delay on the performance of close-loop reservoir management.

1.2. Smart Fields for Production Optimization

While full field reservoir models are limited to mid/long-term decision-making, for little over a decade, oil industry has continuously made progress on the use of smart-field technologies for short-term production optimization to manage geological uncertainties, increase production from fields and improve economics. The impetus for this comes from the end of "easy oil". Fields being developed today are increasingly complex and riskier with lower profitability. Capital and operating expenditures are also very high coupled with a risky environment that the oil industry field itself in today. To increase success rates, improve economics and improve safety of the personnel, equipment and environment (especially in deepwater drilling), operators are moving towards smart fields (discussed as the "digital oil field", "i-field" or "e-field"). Smart fields represent a new wave of innovation that is changing how business is done through digitization of the industrial world (White 2013). It is underpinned by real time data ("big data"), low-cost remote sensing, advanced computing and improved connectivity between the machines and their operators.

Among other applications of technology, smart fields deploy wells with permanently installed downhole sensors and remotely operated valves. Huge amounts of real-time data from these *intelligent wells*, coupled with data analytics and domain expertise can be used to monitor the production system in real-time (van den Berg 2007; Al-Mulhim et al. 2013). E.g., problems in wells can be identified and well test frequency can be improved. The data can pertain to well rates, pressures and temperatures. Further, along with collaborative work environments (covering the reservoir, wells and production), the real-time data makes integrated operations possible.

Apart from production monitoring, the data can be analyzed using models to optimize the wells and field performance in real-time. Real-time Optimization (RTO) of production system could consist of, e.g., a *Supervisory Control and*

Data Acquisition (SCADA) system to automatically gather real-time well and surface data, analyze the data using integrated well and surface network models to find new optimum operating points and implement the new settings in real-time. For instance, the surface network model could be used to route wells to the correct separator system, debottleneck the production system, optimize the gas lift gas distribution and find the optimum well choke and separator pressure settings (van den Berg 2007).

Different control strategies have been explored to operate the remotely operated valves in intelligent wells for production optimization. The intelligent-well valves provide a greater degree of production control by controlling the inflow from different zones and enabling the continuous adjustment of well operating points. E.g., Naus et al. (2006) maximize daily oil rates in a compartmentalized reservoir by calculating new Inflow Control Valve (ICV) settings using a steady-state wellbore model. The wellbore model includes inflow models for the ICV zones and uses a choke model to represent the ICVs. Every optimization interval, derivative information for relating a change in phase flow rates to a change in ICV setting is re-calculated and an objective function is optimized using *Sequential Linear Programming*. In this control strategy, the inflow models can be periodically updated based on downhole pressure and temperature measurements—such indirect estimation is called *soft-sensing*—combined with regular production tests. The models should be updated when the predicted flow rates and pressures show deviations from the measured values. Dilib and Jackson (2012) employ a simple direct feedback control to choke the ICVs based on downhole multiphase flow measurements. The control strategy is reactive as valve settings are changed only in response to changes in water cut measurements. (On the other hand, the control strategy used by Naus et al. (2006) is proactive as it is based on future output predictions.) The authors however conclude that even such a simple closed-loop strategy can give close-to-optimum economic gains.

We refer to Saputelli et al. (2003) for a concrete definition of the nature of RTO activities. RTO consists of continuously traversing a loop of measurement of data, its analysis using models to calculate new operating points by solving an objective function and lastly control, all executed at the same frequency. Real time is therefore in reference to a certain time scale, which is the longest affordable time between measurement of data and control. E.g., the time scale for RTO of production is much shorter than that for mid-term planning in reservoir management. Saputelli et al. (2003) also pointed out that (as of the writing of their paper) RTO was used in the oil industry merely as a slogan rather than to describe optimization in real time, if there is any optimization at all. In the industry, optimization has been extensively applied to individual parts of the production system. E.g., several works have focused on gas allocation in gas-lift fields. But in these efforts, models have been used for offline optimization once rather than automatic process control using wellhead and field controllers. The authors outline reasons for the slow uptake of real-time production optimization, which includes the need for further development of software tools for data acquisition and control, and further integration in intelligent oil field.

The industry continues to make strides in moving towards this data-centric way of producing oil fields, as a lot of the digital data accumulated from intelligent hardware still remains unused, some even directly thrown away (Perrons and Jensen 2014). The basis of our work is the use of integrated software tools for real-time (hourly–daily) feedback-based optimization of well operating points through a data-driven modelling approach and a multivariable control strategy (MPC). Such automatic feedback control is standard in process control for plant wide optimization, which we explain in Chap. 2.

1.3. Controlling the SAGD Process

With more than a decade of experience, SAGD is a mature process which is commercially used for in-situ recovery of the bitumen reserves of Alberta. It continues to evolve as new technologies are being developed, put into trial and implemented, which focus on improving the efficiency of the process and the oil recoveries. These technologies encompass Interval Control Valves (ICVs), fiber-optic based downhole pressure and temperature measurements, gathering of seismic data for revealing heated zones and real-time optimization of well pads.

The process involves a pair of horizontal wells at the bottom of the reservoir, with steam injected from the top well and oil and steam condensate produced from the bottom well. Steam rising from the injector transfers its latent heat to bitumen and forms an expanding steam chamber with oil and condensate flowing down the sides of the chamber to a liquid pool at the bottom of the chamber. Fig. 1.1 shows an expanding steam chamber in crosswell plane. The dominating heat transfer mechanism is convection in the upper part of the steam chamber (Ito and Suzuki 1999). The steam condensate flowing along the walls displaces oil far ahead of the steam chamber through convective effects. In their analysis, Ito and Suzuki (1999) found peak oil flow appearing as deep as 8 m ahead of the steam chamber interface near the bottom of the reservoir. However, near the production liner, conduction is the mean heat transfer mechanism.
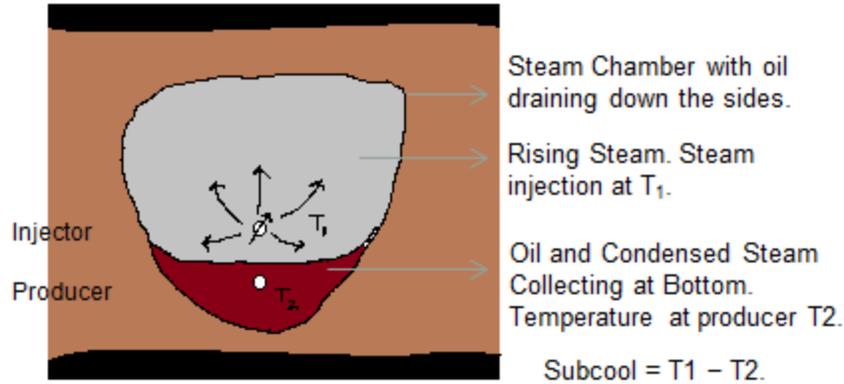
Fig. 1.1: Steam chamber in crosswell plane in SAGD.

1.3.1. Steam Trap for Production Control: Optimum Subcool

To avoid directly drawing steam into the producer in SAGD, the level of the liquid pool needs to be above the producer. This can be ensured by controlling the production temperature such that it's below the steam saturation temperature. Roger Butler was one of the earliest to draw an analogy between controlling SAGD wells this way and the thermodynamic steam trap used in refineries and process industry (Edmunds 2000). For production control by steam trap, there is a question of what an optimum interwell subcool, which is defined as the difference in the temperatures of the injector and the producer, is. As the liquid level drops between the injector and producer, the interwell subcool decreases. When there is no liquid accumulation above the producer, steam breaks through at the producer instead of expanding the steam chamber by heating more bitumen, and the interwell subcool is zero.

SAGD economics depends more than anything on steam utilization, and hence, the operational design focusses on the reduction of cumulative steam/oil ratio (cSOR) over the life of a project. Edmunds and Chhina (2001) performed a series of simulations to analyze the supply (capital and operating) costs for different values of a constant operating steam chamber pressure and varying reservoir quality while the producer was constrained to produce a negligible amount of

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steam (zero subcool). They found cSOR to be a monotonic function of the constant operating steam chamber pressure. A higher constant pressure reduces the number of wells and increases the oil rates, but on the down side, increases the cSOR and the supply costs due to steam. Since steam supply costs due to surface facilities required for treating, boiling, recycling and disposing off water, and fuel costs account for more than half of supply costs, with wells being only responsible for 20 to 30 %, optimization of SAGD lays more emphasis on reducing the pressure and minimizing cSOR rather than on maximizing the oil rates. A poorer quality reservoir and higher gas price further pushes the optimum pressure and cSOR downward. Edmunds and Chhina (2001) found that the range of pressures that minimized the supply costs in their cases was as low as 400–750 kPaa.

Hence, for the two-dimensional (2D) illustration in Fig. 1.1, an optimum subcool will reduce the cSOR and maintain a liquid level a little above the producer. Based on the discussion above, the optimum subcool will be a little lower than the value at which the cSOR is minimized. A further lower subcool ends up drawing too much steam from the injector, which mixes with cooler fluids and condenses before reaching the producer. This decreases the thermal efficiency of the process. On the other hand, a higher than optimum subcool raises the liquid level present above the producer and decreases the oil rate. The delay in oil production leads to slower returns. Additionally, a very high liquid level also reduces the thermal efficiency of the process as some of the latent heat of steam goes towards keeping the oil pool at bottom hot. A range of values from 5 to 40°C has been stated in the literature for optimum subcool. Edmunds (2000) concluded that 20–30 °C subcool was optimum for their 2D model. In their SAGD simulation study of McMurray formation in Hangingstone oil sands area, Ito and Suzuki (1999) found 30–40°C subcool to be the optimum based on minimization of cSOR. Gonzalez et al. (2012) state that in practice, 15–30°C subcool is maintained between the

injector and producer. Optimum subcool will vary depending on the rock and fluid properties.

1.3.2. Heterogeneous Steam Chamber Growth: Reasons and Implications

The 2D analysis in previous section notwithstanding, SAGD well-pair operation is much more complicated in practice. As shown in Fig. 1.2, subcool varies along the long wells used in SAGD. Edmunds (2000) showed that optimum subcool determined from 2D simulation is overly optimistic about oil rates and cSOR. With the combined production stream at the presumed low optimum subcool from 2D analysis, some sections of the well can draw in a lot of steam, while other sections are cooler than the optimum. Gates and Leskiw (2008) did a simulation study using a detailed upscaled geological model of an Athabasca oil sands reservoir in an area near Surmont. Injecting steam at a constant pressure, they used different constant liquid production rate constraints in different simulation runs to note the local subcool values along the well for the simulation period. For the highest production rate that they used that successfully prevented major steam trap failure along the well pair, the local subcool at several intervals was above 60°C for most of the simulation period. Hence, compared to the analysis in Section 1.3.1, defining the optimum operating conditions in SAGD has an added layer of complexity of considering the varying conditions along the well pair. Both steam injection and production get limited by the section of the well pair that is most prone to steam breakthrough. This results in lower oil rates and thermal efficiency compared to a scenario in which the steam chamber develops more uniformly. As we will discuss in Section 1.3.3, dividing the wells into a number of intervals (in which the steam injection and production can be individually controlled) through the use of an intelligent completion provides a solution.
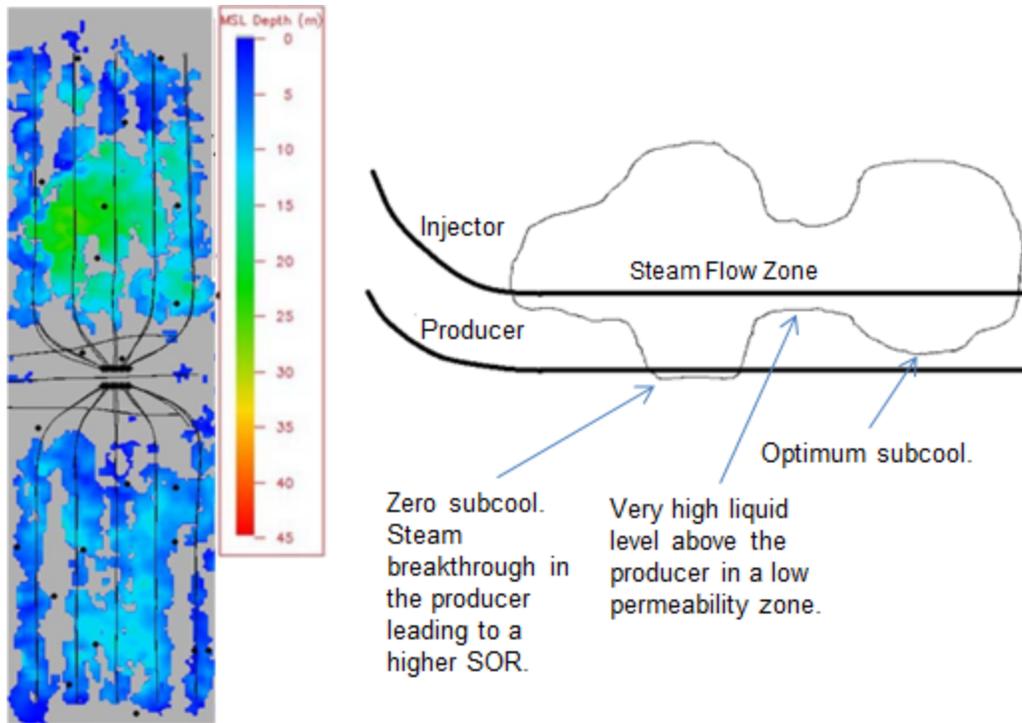
Fig. 1.2: a) Map (left) of steam chamber depth along SAGD wells interpreted from 4D seismic (Suncor 2013); b) Varying subcool along horizontal SAGD wells.

There are several reasons for a heterogeneous steam chamber development. These include heterogeneous porosity, permeability, fluid saturations and oil composition distribution around the wells. Presence of shale and mud layers near the well pair particularly skews the steam chamber. SAGD is known to be susceptible to these heterogeneous conditions due to a combination of high permeability of oil sands, high mobility ratio of steam and the viscosity-temperature relationship of bitumen. Even for two well pairs separated by 100 m, heterogeneity can create very different steam conformance results (Gotawala and Gates 2012). It results in varying injectivities along the well pair, because of which steam will enter into the reservoir preferentially at certain intervals leading to lower subcool, higher temperatures near wellbore and a larger steam chamber size compared to other intervals. There are two such intervals in the illustration of a SAGD well pair in Fig. 1.2. Also, the horizontal sections are drilled within

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certain tolerances. Variations in the injector-producer distance create heterogeneous conditions.

Even with an ideally uniform geology and interwell spacing, wellbore flow effects will ensure non-uniform steam flow. In a simple SAGD injector well configuration, steam travels through a tubing string landed at the toe, and the annulus, and through the slotted liner into the reservoir. In this configuration, the steam flow is predominantly through the annulus, and there is a significant pressure drop and a decrease in steam quality from the heel to toe. Because of steam's low density and high flow rates, pressure drop in the injector dominates over that in the producer with a high pressure differential at the heel and low values near the toe (Edmunds and Gittins 1993). This pressure drop gets impressed on the reservoir. Parallel flow in the reservoir can't counteract this pressure difference because reservoir transmissibility is only a fraction of the wellbore flow capacities. This leads to a much faster growing steam chamber and a low subcool at the heel whereas a stunted steam chamber and a much higher than desired subcool at the toe. The net result is that the operator is unable to deliver as much steam as desired into the reservoir (because of the risks of steam breakthrough at the heel), a higher cSOR and lower oil rates due to a non-uniform steam chamber. Many operators in Alberta use a dual tubing string inside a slotted liner as shown in Fig. 1.3, with one tubing string landed near the heel and one near the toe of the well, to even out the steam chamber growth (Stone et al. 2014). Even with this configuration, a less than ideal barbell shape steam chamber forms, as illustrated by Bedry and Shaw (2012).
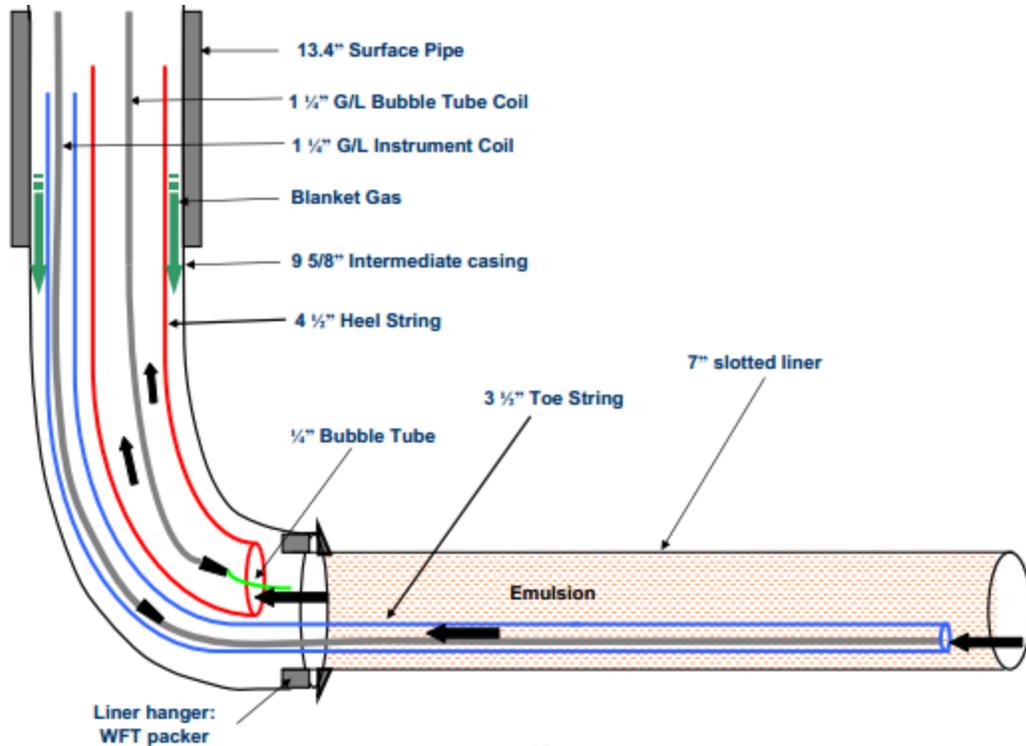
Fig. 1.3: An artificially lifted dual tubing string producer used by ConocoPhillips at its oil sands project in Surmont (ConocoPhillips 2008).

1.3.3. Technologies to Offset Non-Uniform Steam Chamber Growth

In wells with a dual tubing string configuration, the short- or long-tubing string injection and production rates can be decreased in order to control undesired steam chamber growth in some areas. However, this provides limited control over steam placement along the well and steam chamber growth. And with longer wells and more heterogeneity, steam conformance becomes worse.

Different technologies have been used or put on trial to diagnose and control injection conformance and production along SAGD well pairs to counterbalance the adverse effects of heterogeneity (Clark et al. 2010; Gotawala and Gates 2012). These include limited entry perforations (LEPs), inflow and outflow control devices (ICDs and OCDs), ICVs and downhole instrumentation. LEPs have been used by operators to create a more uniform steam injection profile by generating

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supersonic flow conditions as steam flows through a limited number of downhole chokes into the reservoir. Under these flow conditions, the rate depends only on upstream pressure in the well. Hence, reservoir heterogeneity doesn't affect steam placement as much in the case of flow through a slotted liner. A major disadvantage with LEPs is that later in production, the flow rates will become subsonic and the flow rate will depend on the downstream pressure in the reservoir, bringing heterogeneity back into play.

A more complex completion technology that has been used to control the injection/production profiles along wells in SAGD is the inflow and outflow control devices (ICDs and OCDs). (There are variations in the name used for these, e.g., flow control device.) These devices are deployed along the well and work by creating a pressure drop in the fluid flowing in or out through these devices. Through different pressure drops across these devices at different points along the well length, the flow profile can be improved. Two different geometries of these devices are the nozzle type and the helical or baffled pathway type. In the former, a pressure drop is created by forcing the fluid to pass through a constriction before it enters the tubular. In the helical or baffled pathway type, the pressure drop is created through friction instead as the fluid is made to flow through long channels. A still different category of ICDs is the so-called autonomous ICDs. The pressure drop in these ICDs depends on the composition of fluid flowing in, and hence, these devices can adapt to changing flowing conditions. E.g., one model for autonomous ICDs is called the hybrid-geometry autonomous ICDs, which combines flow through a baffled pathway with a series of constrictions present along it as well. The flow pathways in autonomous ICDs are designed so that there is more resistance to flow of water/gas compared to oil. Hence, they can create a more uniform inflow conditions along the producer and prevent steam breakthrough in some intervals in SAGD. Banerjee et al. (2013) discuss the different geometries of ICDs/OCDs, the role of pressure drop through these devices in promoting a more uniform injection and production profile as

well as designing of these devices. They explain that using OCDs in the injector immediately improves the injection conformance compared to the use of a slotted liner. Along with the OCDs in injector, using ICDs in the producer has a "synergistic effect" as it helps create a uniform liquid level above the producer and prevents direct inflow of steam from the producer at any point, leading to a better cSOR as well as higher oil production. These devices can be deployed either in the tubing string or in the liner string. In the former case, a single tubing string containing a few of these flow control devices runs till the toe end of the well. Since only a single tubing string is used compared to a dual tubing string in a slotted liner, using ICDs/OCDs has the added advantage that the liner size is smaller and consequently, so are the casing sizes. And due to the considerations in drilling a smaller wellbore, this enables drilling longer wells. A second option is to deploy the ICDs/OCDs in the liner string. The liner string will then consist of some blank pipes with the rest of the length being made up by the flow devices, equally spaced along the well length. In this configuration, only a heel tubing string is required. Since the whole cross-sectional area of the liner is available to flow, the liner size is further reduced compared to wells with tubing deployed ICDs/OCDs. It also has a further benefit of doing away with the risk of pulling out the tubing string along with the flow devices in case of a workover.

In SAGD, flow conditions along the well pair will change as the steam chamber develops. The steam chamber grows bigger in certain intervals compared to others, which needs a reduction in injection rates in these intervals to normalize the steam conformance. ICDs/OCDs, on the other hand, are designed prior to being run into a well according to the flow profiles along the well, estimated based on reservoir properties, and field data (see below). Hence, a disadvantage with using pre-fixed ICDs/OCDs is that they can't be adjusted with changing flow profiles along the well. Nozzle-type ICDs/OCDs that have adjustable nozzles also exist; however, the workovers that are needed lead to significant downtime, and there are other prohibitive safety considerations as well (Bedry and Shaw 2012).

Other works have focused on the use of reservoir models, with or without the quantification of uncertainty by using multiple Geostatostical realizations, to optimize SAGD variables (Gates and Chakrabarty 2006; Yang et al. 2009, 2011). Yang et al. (2009) optimize injection and production rates by maximizing Net Present Value (NPV) for a real-field three-dimensional (3D) model. Though these optimization efforts are expected to lead to improved operations, there is a significant uncertainty still associated with the field results due to the nature of the SAGD process itself, as Clark et al. (2010) note for the Orion SAGD project.

Intelligent Wells

Intelligent wells with ICVs involve further infrastructure complexity and higher capital investment, but offer the best ability to normalize steam chamber growth and manage uncertainty in field production. An intelligent well completion for SAGD wells would consist of a tubing string, containing a few ICVs and sealed at the end, run to the toe inside a liner. Hydraulic control lines, clamped to the tubing string at the tubing couplings, run alongside the whole string. The ICVs are remotely actuated via these control lines. The valves are sliding sleeves and can be either on/off type or multiple position type. A multiple position type ICV can be choked in increments from a fully open position to a fully closed position. Further, the well would be instrumented with optical fiber-based technology for pressure and temperature measurements. The optical fibers run alongside the tubing string inside capillary tubes. Also, for full control of injection or production along the well length using the ICVs, the tubing string consists of diverters placed in between the valves to isolate the annulus into several intervals. The diverter seals against the annulus and prevents annular flow between the intervals. For designing the diverters, the high-temperature downhole conditions that occur in SAGD are an important factor. Unlike packers, which anchor to the casing, the diverters need to allow tubing movement during thermal changes without compromising the seal with liner. Diverter elements should allow the

hydraulic control line and capillary tubes to pass through them while at the same time maintaining the seal with the liner. The ICVs, hydraulic control fluid, downhole instrumentation and diverters all need to be designed so that they can withstand the high temperatures encountered in SAGD.

While ICDs/OCDs are passive devices, ICVs are active control devices. They allow the injection profiles to be changed throughout the life of the well pair. Further, the use of ICVs along with the zonal isolation achieved using diverters enables differential steam trap control to individually maintain a liquid level above the producer in all the intervals throughout production. Hence, using ICVs has the dual benefit of improved steam conformance and differential steam trap control, which improves cSOR and increases oil production rates.

Two fiber-optic technologies for downhole pressure and temperature measurements are the fiber-optic pressure and temperature gauges, and Distributed Temperature Sensing (DTS). In the oil industry, DTS is by far the most commonly used downhole fiber-optic monitoring technology (Jacobs 2014). The uptake of this technology by operators has been accelerating as technological advancements have made it reliable and durable. And as the industry moves towards more complex and risky fields, fiber-optic monitoring technologies give the operators confidence in developing them. The operators gain key knowledge about the reservoir through the use of these technologies—even if deployed in a few of the wells in a field—which helps them manage their injection and production plans better. Also, along with remotely controlled downhole valves, these technologies can be used in controlling flow into well segments in real-time.

The DTS system consists of a hair thin fiber-optic cable run in the well. The cable goes to a box called the interrogator unit at the surface. The interrogator has a laser which sends light pulses through the fiber-optic cable made of silica at rates as high as upwards of 10,000 times a second. The light loops through the cable and is received back by an optical receiver in the interrogator, where the optical

signal is converted into electronic signal and processed for noise. DTS can give accurate temperature measurements every meter of the well. For fiber-optic pressure and temperature gauges, a fiber-optic cable runs in the well and terminates at the location where a gauge is mounted on the tubing string. The temperature sensor is integrated with the pressured sensor and is meant for both providing a temperature measurement and applying a thermal correction to the pressure measurement. The technological advancements that have enabled wider application of these technologies include improvements in glass chemistry that have improved the silica fibers to be able to withstand harsh downhole environments. In the high temperatures encountered in SAGD, an earliest problem with the fiber-optic cables had been *hydrogen darkening*—we refer to Jacobs (2014)—which soon made the interrogator unable to make useful measurements due to distortion or darkening in the signals because of hydrogen atoms (from oil produced) that enter into the silica fibers. The darkening increases with time and temperature. Recently, companies that provide these monitoring technologies have been able to mitigate and manage this problem, through both use of chemically resistant materials in the cable and advances in laser technology, paving the way for more widespread use of fiber-optic monitoring in SAGD. Further, increase in computer processing speed and efficient algorithms mean that the data from downhole fiber-optic technologies can be interpreted fast-enough for monitoring the well conditions in real-time.

In SAGD, using data from DTS and fiber-optic pressure and temperature gauges, we can know how conditions along the well are changing with production and infer the steam chamber shape. These changes can be monitored in short-term and injection and production plans accordingly modified. Temperature data from downhole optical fibers during shut-in is a good indication of near-wellbore temperatures (see below for a field study by Clark et al. (2010)). Near-wellbore temperature profile reveals injection conformance and production profiles. Pressure data from downhole pressure sensors during injection or transient

pressure analysis during shut-in of the injector is used to calculate injectivities in different intervals. An interval which has high temperature and high injectivity relative to other intervals takes a disproportionate amount of the steam injected. This results in low total steam injectivity (due to steam breakthrough concerns) and lower oil production rates. Also, it increases the steam chamber size in the interval and hence, further distorts the steam injectivity along the well and worsens steam conformance. To normalize the steam chamber, injection in these intervals should be decreased while continuing to monitor injectivity along the well and temperature profile.

For real-time analysis of conditions along a SAGD well pair, Gonzalez et al. (2012) contend that an Array Temperature Sensing (ATS) fiber-optic system with multiple temperature measurement points along the wellbore and at least one pressure point is suitable. In comparison, DTS provides very high-resolution temperature data less apt for real-time analysis. They describe an integrated software tool to monitor, evaluate and control temperatures and pressures in horizontal sections of the injector and producer (inflow of the system) as well as monitor and optimize the artificial lift system (outflow) in real-time while integrating information on wellhead rates and temperatures. The system is thus used to control the subcool along the well pair by changing the injection and production rates. For optimizing the SAGD process using the system described in this work, temperature and pressure measurement points are needed in both injector and producer.

Clark et al. (2010) present the design and early field results for the field trial of an intelligent completion system in a SAGD injector in Orion field in the Cold Lake Oil Sands Area. They state that, based on the modeling works of the likes of Gotawala and Gates (2009), differential steam trap control using ICVs can lead to a 5–10% increase in recovery and 20–40% reduction in cSOR depending on the level of heterogeneity in the reservoir. In the case of Orion field, greater than expected geological heterogeneity was leading to a variable performance between

the well pairs. The producer temperature data (obtained using DTS), production performance data and seismic maps showing heated zones indicated that using ICVs for steam conformance improvement and differential steam trap control would improve the performance in field. It was decided to initially use an intelligent completion in the injectors, and later a completion would also be developed for deployment in the artificially lifted producers to achieve full control. For the trial, they chose the injector in a well pair which had enough baseline data for a comparison with the ICV test results later, producer equipped with DTS, and poor cSOR and lower oil production rates compared to other well pairs. The completion in the injector was pulled out and the intelligent well completion shown in Fig. 1.4 was installed.
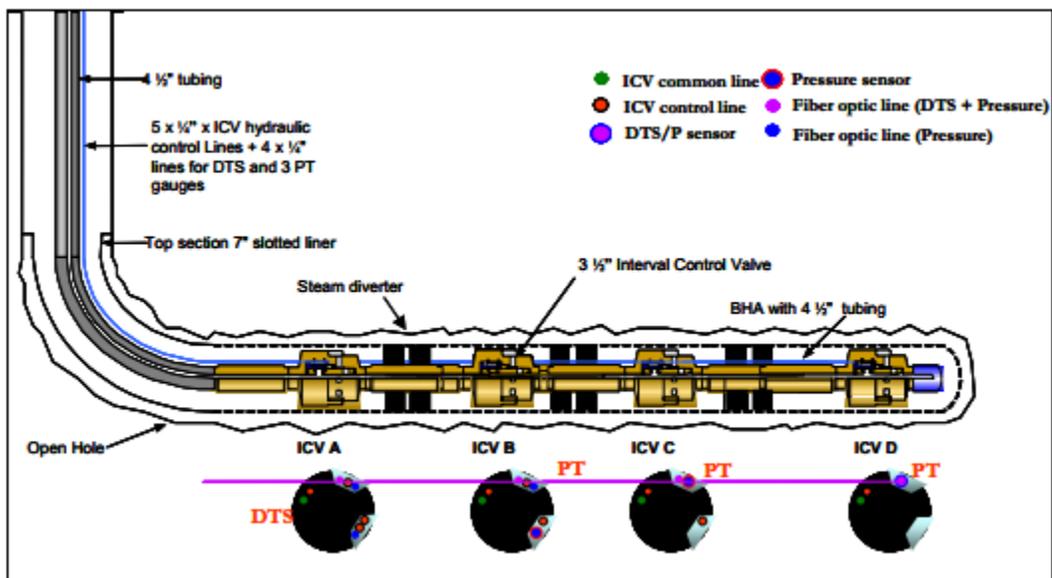
Fig. 1.4: Intelligent well completion tested in Orion field (Clark et al. 2010). The diagram shows steam diverters, ICVs, ICV control lines and downhole instrumentation.

The wells in the field are approximately 750 m long. Four on/off type ICVs are used in the trial injector to divide it into four intervals: A (heel), B, C and D (toe). The ICVs were designed and tested up to temperatures of 265°C and pressures of

20,600 kPa. Each ICV is attached to two hydraulic control lines. There is one control line per ICV to open it, and a common control line closes all the ICVs, making it a total of five control lines. Having a common control line to close all the ICVs avoids the complexity and expense of additional control lines. With this configuration, n ICVs require n + 1 control lines. (However, the authors note that this control configuration soon reaches the space limitations inside the well and wellhead if the well length is increased and more ICVs are used. For higher number of ICVs, a "multiplexed control system" is needed.) The control lines are connected to a manifold at the surface, and a hydraulic control panel is used to open and close the valves. A custom designed diverter was used, which had a special assembly that allowed the control lines and fiber-optic cables to pass through it safely without needing to splice them. This was important for reliable operation of DTS and considerably reduced the completion complexity and time. In each of the intervals B, C and D, a pressure and temperature gauge is mounted on a custom-made gauge carrier just below the ICV valve. The gauges selected for the completion had a temperature rating of 260°C. A fiber-optic cable running inside a capillary tube transmits pressure and temperature information from the sensors to the surface. Pressure in interval A is measured through the nitrogen-filled annulus. The capillary tube that carries a fiber-optic cable to interval D also consists of a DTS system for monitoring the temperature profile along the well.

After the completion was installed, it was tested to check the functioning of the equipment, gather data on the completion performance under steam injection conditions and fine-tune the well operating procedures. First the downhole instrumentation was validated. Then the well operation was tested. The test conditions included injection with all valves closed, all valves open and only one valve open. It was demonstrated that the ICVs functioned reliably up to pressures of 4600 kPa and temperature close to 260°C. Diverters provided good annular isolation under pressure differentials up to 800 kPa. Data from DTS and the pressure and temperature gauges were critical in understanding the equipment

performance and well response. DTS gave good accuracy and resolution under the testing conditions. The gauges showed good reliability and stability. The testing phase resulted in a lot of good data for carrying out the trial of intelligent completion.

After the well function testing, there was a further phase of testing over a month to collect baseline data about the current steam chamber and injection profile characteristics. Steam was injected into each of the intervals individually over a number of days; based on the pressure data from the downhole pressure gauges and injection rates, an injectivity index for each interval was estimated. Further, DTS data was collected over a number of 24-hour periods after both the injector and producer were shut in. After an initial period of rapid cooling and transient effect during these shut-ins, the temperature profile from DTS provided a good indication of the near-wellbore temperatures. Intervals A and B had low injectivities and lower near-wellbore temperatures for both injector and producer, indicating that these intervals had smaller steam chamber size and had low production rates. On the other hand, intervals C and D had good injectivities and higher near-wellbore temperatures. The injectivities and temperature profiles from DTS agreed well with a seismic thermal map interpreted from 2D seismic lines taken just before the installation of the intelligent completion in the injector. These observations also corresponded with the geological information available: a large fraction of the injector and producer well lengths in the heel region lied in low vertical permeability zones.
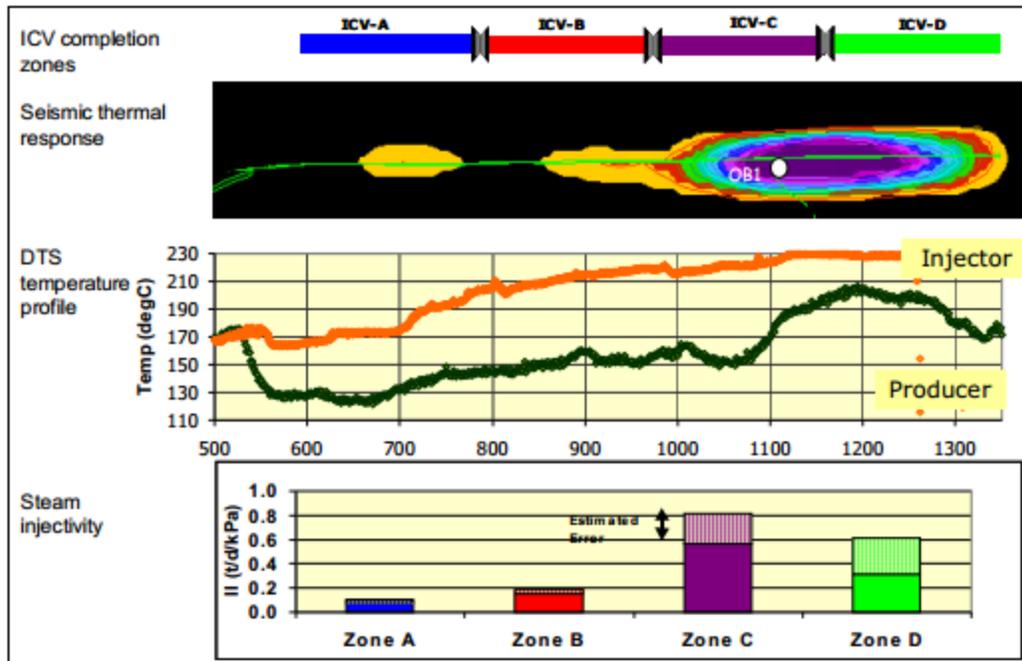
Fig. 1.5: Seismic thermal map (top), DTS temperature profile and steam injectivities (bottom) for the trial well pair in Orion field (Clark et al. 2010). Heel region (intervals A and B) shows little steam chamber growth.

To create a more uniform steam chamber, and hence improve injection conformance and increase the total steam injectivity in the injector, an injection plan was formulated that aimed to selectively inject into intervals A and B. The injection plan consisted of cycles of injection, with each cycle composed of

- Three week of injection into intervals A and B.
- One week of injection into all intervals.
- 24-hour shut-in for DTS measurements.

The intermediate injection into the whole well in each cycle was meant to keep the toe intervals in the well pair warm, and maintain the steam chamber size in those intervals. The authors report the well-pair performance after two cycles of injection. After two cycles, an improvement in injectivities in intervals A and B between 30% and 70% was seen. Pressure measurements revealed that there was

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an increasing communication of the heel intervals with the steam chamber in the toe intervals. Based on the shut-in DTS temperature profile, temperatures near the injector increased by 10–20°C in the heel intervals. Temperature hadn't yet increased much around the producer indicating that oil production from heel intervals hadn't improved much. cSOR improved by 20% after just the two cycles, while the oil production rate remained around the same, compared to the well-pair performance a few months prior to the installation of intelligent completion. The improvement in cSOR is likely because of the fact that there is less steam directly flowing from the injector to the producer in the toe region. A number of additional cycles of injection were further planned to see if ultimately uniform steam conformance could be achieved. It was planned to continue monitoring the well through shut-in DTS temperature profiles, changes in injectivity and production performance of the well pair. The injection cycles could be accordingly modified to injection periods. Further, if a significant communication of steam injected in heel interval with the steam chamber in toe intervals, injection be only in interval A instead of both A and B. Seismic data at some later point would also help confirm the steam chamber growth.

According to the authors, the focus for further technology development work in the field includes increasing the temperature rating of the ICVs and development of multiple position ICVs, which will allow better control of injection and profiles without having to shut in certain intervals.

Manual Well Control

In practice, using the technologies described above, wells are controlled manually in SAGD to transfer the heat uniformly and control the steam chamber growth, while handling constraints like steam treatment capacity and well artificial lift constraints.

Manual control, however, considers relationships between the variables in isolation instead of in an integrated manner. SAGD is a complex dynamic process with many interacting variables. When trying to control subcool along the well pair, based on real-time data, for uniform steam injection (and hence, better steam conformance), subcool will depend on both injection and production rates. A change in the injection rate changes the interwell subcool, which changes the inflow at producer. At the same time, the inflow at producer also depends on the outflow settings (artificial lift). Hence, both inflow and outflow relationships need to be considered at the same time (Gonzalez et al. 2012). With manual monitoring, it becomes more difficult to do so as the number of wells increase. Further, changing the injection rate at, say, heel will also affect the subcool at toe, which is coupled to the subcool at heel through the wellbore. Hence, all real-time downhole pressure and temperature data needs to be integrated with real-time surface production rate measurements to effectively control the process. As Patel et al. (2014) have elaborated on, manual control of wells and management of system constraints can be effective only in case of a few wells, up to 5–10 of them.

Additionally, Edmunds (2000) concludes from his 2D subcool analysis that "there is no unique, quasi–steady state solution of the steam trap problem; rather there are only solution trajectories, whose future evolution depends not just on the boundary conditions of the moment but all past history as well." So, the relationships between injection/production rates and interwell subcool are time varying as the steam chamber grows from ramp-up to plateau to wind-down phase in SAGD. This is a further complication for SAGD well control.

1.4. Hypothesis

Section 1.2 ends on the note that intelligent oil fields provide an opportunity for real-time feedback-based production optimization. Section 1.3.3 discusses how

intelligent wells in SAGD enable better production control for a more uniform steam chamber growth and higher recovery, but that manual control of wells doesn't consider all the variables and constraints of the system at the same time. We could compare this situation with a chemical plant, where there can be thousands of process variables, which also have inequality constraints. In such plants, MPC, which is an advanced multivariable constrained process control technique, is widely used for automatic feedback and feedforward control of multiple variables while handling constraints. The hypothesis for this research follows from this and other discussion previously:

RTO of SAGD using the data from instrumented wells will lead to significant efficiency gains, improve recovery and mitigate uncertainty inherent in the best reservoir model predictions. The MPC strategy is suitable for integrating all downhole and surface real-time data for controlling the process.

As the industry continues to make a transition to smart fields, this simulation study aims to add to the literature by evaluating the capability of advanced process control in optimizing production. One approach for RTO using the MPC strategy is to use the high frequency data from downhole sensors to build simple data-driven linear dynamic models for implementing the control strategy (Nikolaou et al. 2006; Essen et al. 2011; Essen et al. 2013). Specifically in our work, a simple linear model, built using regression from temperature and rate data from wells to capture the dynamic input-output relationships, is used in the MPC strategy to control the subcool along a SAGD well pair.

Further, to take both long-term and short-term reservoir management needs into account, the MPC of subcool along the wells is integrated with well settings obtained from long-term optimization done using a reservoir model, as part of a multilevel control and optimization framework. Fig. 1.6 is a simple illustration of the oilfield management framework we considered. Such a hierarchical

decomposition of operations exists in the process control industry for integrated optimization of plant operations (Seborg et al. 2004). We refer to Saputelli et al. (2003), who expound on the field operations hierarchy for RTO in oil fields. The different layers in the framework shown in Fig. 1.6 have different timescales for decision-making. The timescales are indicated in the figure. The upper layers pass down decisions related to design and/or operations to lower levels as goals (or *set points*) to be followed. At the same time, data from the lower levels are used for feedback-based decision-making at upper levels.
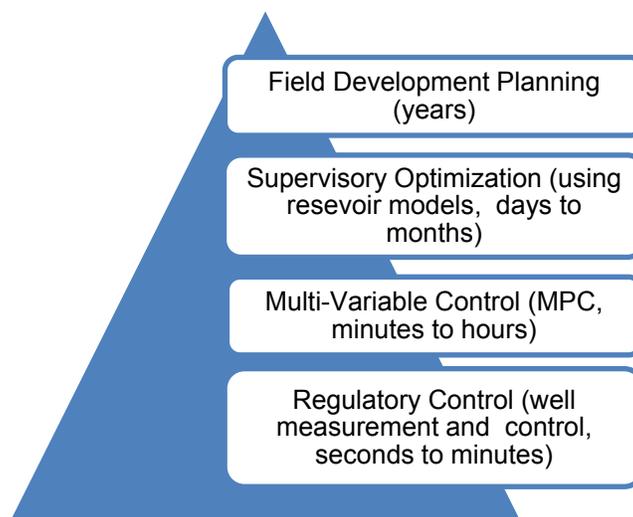
Fig. 1.6: Multilevel oilfield management framework for real-time operations. Saputelli et al. (2003) expound on the multilevel framework.

Regulatory control, which is the lowermost level in Fig. 1.6, involves direct feedback control of individual chokes and valves to control pressures, rates and temperatures. At the multivariable control level (MPC), a centralized SCADA system coordinates the wells and surface network by calculating new operating points. The operating points are calculated every few hours based on the current data on the controlled variables (which, in our case, is the subcool along the SAGD well pair) from well measurements, which are made every few minutes at the regulatory level. The operating points (pressures and rates) calculated are

implemented at the regulatory level by, e.g., acting on the wellhead valves every few minutes. Supervisory optimization (mid-term optimization) refers to the use of reservoir simulation models and optimization routines for scheduling an injection and production plan. **The optimized injection and production plan provides set points (targets) for the MPC level below.** The uppermost level is for asset level decisions.

1.4.1. Research Questions

The questions we seek to answer in this research are as follows:

- How much of an improvement in process efficiency can be expected by using advanced process control (MPC) to control subcool along a dual tubing string SAGD well pair in contrast to direct application of optimized rates from an uncertain reservoir model?
- Can a linear model be effectively identified, using real-time data from surface and downhole sensors, for controlling a dual tubing string SAGD well?

1.4.2. Relation to Other Works on SAGD Well Control

A few other works have used proportional-integral-derivative (PID) control strategy for automatic feedback control of the SAGD variables. However, unlike the MPC strategy, which is a multivariable control strategy, the PID-control strategy is single-input and single-output. It acts on each controlled variable in isolation by manipulating a single variable instead of optimizing the whole system as the MPC strategy does.

Stone et al. (2014) modeled a dual tubing string configuration to study whether PID controllers can be used for injection tubulars to achieve a certain interwell subcool and better steam conformance. They considered a second small case with the injector and producer each having three tubing strings to see if a mid-tubing string could further improve the results. They used 3D models with a single

SAGD well pair and simple heterogeneity patterns—a combination of vertical and horizontal lower permeability streaks near the wells with the rest of the model having a homogenous absolute permeability. The permeability patterns have varying complexity to be able to assess what impact heterogeneity would have on the performance of PID control. A "multisegment well model", which treats the well as a network of nodes and pipes, is used to accurately simulate the multiphase flow in wellbores, and gas lift is modeled using accurate vertical lift performance tables. In the study, the PID-control strategy is used to control the *heel subcool* by manipulating the short-tubing string injection rate, and *toe subcool* by manipulating the long-tubing string injection rate directly. Heel subcool is calculated as the difference between the steam saturation temperature corresponding to the average pressure in the segment of the injector annulus spanning from the heel to the middle of the well and the average temperature of inflowing fluids in the segment of the producer from the heel to the middle of the well. Similarly, toe subcool is calculated based on the toe half of the well pair. However, the production well constraints in this study aren't controlled and remain constant: "Constraints on the production tubulars were set at switchover so that flow into each was roughly equal but otherwise they were not controlled throughout the simulation." The parameters for PID control are selected based on a number of simulations. They are selected such that the controller would be responsive to a sudden temperature rise at the production well because of steam breakthrough. Target for PID control for both heel subcool and toe subcool is 20°C. Though PID control was seen to increase the efficiency of the process in the study, it was found that the heel half of the reservoir was heating up faster and once steam broke through around the heel, PID control was unable to achieve the target for toe subcool. Toe subcool remained much higher than the target after the steam breakthrough around heel. An interesting observation from the work was that in the case of more heterogeneous patterns, PID control was able to reach the subcool target more quickly. Gotawala and Gates (2009) used a similar control strategy, but with ICVs along the injector, and PID control individually

manipulates the injection pressures in the different intervals along injector. They used a 3D model with a single well pair, and a Geostatistical realization for the porosity, permeability and saturation distribution. The properties used are typical for an Athabasca reservoir. In the simulator, line heaters are used to heat the region around the injector and producer in the circulation phase, which lasts 3 months. The PID-control performance is compared with a base case without any control. In the base case, for the production phase in SAGD, both horizontal wells are modeled as line sources (which can be considered equivalent to using a slotted liner and a tubing string at the heel to inject or produce the fluid). The horizontal well length used is 700 m. A constant injection pressure is used, and a maximum steam rate constraint is used for the producer. For the PID-control case, six ICVs along the injection well trajectory are modeled as six separate wells, each modeled as a line source. Total well length in this case is 720 m. Production well constraints remain constant throughout simulation. A subcool target of 25°C is defined for the six ICV intervals. Subcool for an interval is calculated by taking the average temperature along the interval in the injector and subtracting from it the average temperature for the interval in the producer. Each interval starts with the same pressure as in the base case. Thereafter, to control the subcool, new injection pressure controls are implemented at intervals of 1 month using the PID-control strategy. SAGD is simulated for a total 2 years, which is the time it was taking for the steam chamber to reach the overburden. PID control lead to a much better steam conformance. A cold interval is seen in the base case in the interval where there is a low permeability streak above the well pair. This cold interval was eliminated with PID control, which manipulates the individual interval pressures for a more uniform steam injection along the injector trajectory, as shown in Fig. 1.7. At the end of 2 years, cSOR slightly improved and oil production increased by 29% with PID control compared to the constant pressure base case. According to the authors, the improvement in cSOR is more significant in the beginning part of the operations. One of the conclusions that the authors draw from this is that PID control is sufficient for steam conformance *near the*

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well pair. However, away from the well pair as: "Interwell subcool control appears to have a more local (in the region surrounding the well pair) impact on steam conformance control." We don't find this argument convincing, at least in the context of the multilevel control framework considered in our work, where optimization using 3D models provide the subcool set points for control (see below).
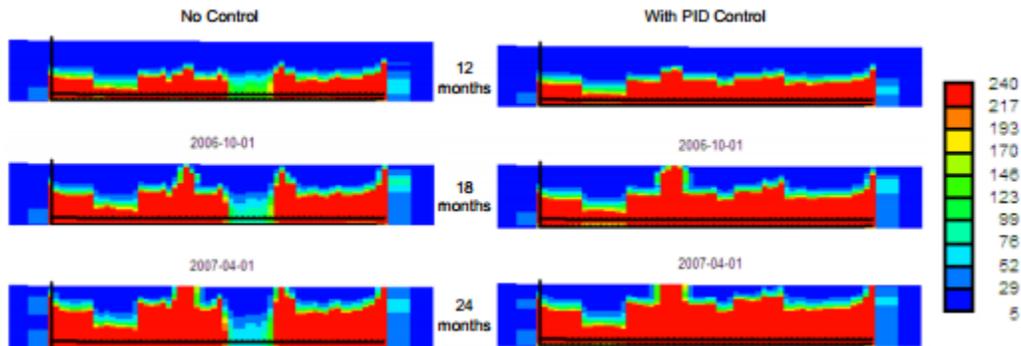
Fig. 1.7: Temperature maps showing steam chamber development in the vertical plane containing a SAGD well pair, in the base case (left), which uses a constant injection pressure with the wells modeled as line sources, and PID-control case, which uses ICVs, at 12 (top), 18 (middle) and 24 months in Gotawala and Gates (2009).

Stone et al. (2010) used simple 3D models with a single SAGD well pair. They used two different models representing two different case studies. Apart from a few lower permeability streaks near the well, permeability remains constant in these models, similar to the work by Stone et al. (2014). The injector and producer, which are 400 m long, consist of a tubing string in a slotted linear and have four ICVs each. A multisegment well model is used to accurately simulate flow through the valves, tubing and annulus. SAGD phase is simulated for around 8 months and the wells have a constant injection and production rate constraints with secondary pressure constraints. In the base case, the ICVs are fully open. Then, they use the PID-control strategy to continuously control the valve apertures. In both injector and producer, the total flow rate in the well is

monitored and an average flow rate for the four intervals is calculated. PID control tries to attain this average flow rate for each of the four intervals, by manipulating the corresponding valve openings, for a more uniform steam chamber development. PID control only showed little improvement over the uncontrolled case. The authors note that PID control was unable to prevent or later reverse a steam breakthrough that occurred at the toe end of the well pair soon after the start of SAGD production phase, which limited its performance. As a result, PID control could only slightly improve the steam injection profile.

Gotawala and Gates (2012) investigated what range of PID parameters is suitable for controlling interwell subcool in SAGD by using downhole valves in the injector. They considered the liquid pool at the bottom of the SAGD steam chamber and developed new heat flow and mass transfer models to study the control characteristics. In the liquid pool model, a constant oil rate was used. Subcool target for PID control was 20°C. In the study, PID control was successfully able to raise the interwell subcool from 0°C (i.e., direct steam production) to 20°C (desired steam trap conditions). Hence, an important conclusion from the study was that PID control can be used for a uniform steam chamber development in SAGD. Even though the analytical model used in this study doesn't consider the effect that heterogeneous flow conditions along the well pair will have on control, unlike the works described above, it shows that wells using downhole control valves that divide the completion into several zones can be effective in controlling the steam chamber.

In all the above works, because variables like subcool values or interval flow rates are individually controlled, optimum operating points obtained from reservoir models and any system constraints, like total steam available, can't be incorporated into production optimization. In our work, inclusion of an additional level of feedback control, MPC, enables optimization of the system as a whole. In this multilevel framework for real-time production optimization, optimum injection/production rates from the reservoir models are used to define the

subcool set points (targets) for the MPC level, based on which the controller calculates the optimum operating points—in our work, the injection and production rates—subject to any constraints. These operating points can then be implemented at the regulatory level of the framework. The rates can be implemented by using PID controllers to manipulate, e.g., well flow valves or the artificial lift's pump current.

1.5. Thesis Outline

In Chap. 2 of this thesis, we will be explaining the significance of multivariable control in process plants using MPC. The focus is on clarifying how it's relevant to the real-time production optimization of SAGD in this research. The relevant control details are covered. MPC is based on the use of a model of the process being controlled. The models are typically linear models built from the input-output data using the theory of system identification. Relevant details on the different types of linear models used in system identification, fundamental differences between these different types and estimation of model parameters are covered in Chap. 3.

Details of the simulation study that we do to illustrate the hypothesis of this research, including the reservoir models used, model-based optimization of well rates, how we choose to identify linear models from the well data and control parameters for MPC, is contained in Chap. 4. The results of the simulation study are presented in Chap. 5.

The final chapter, Discussion and Conclusions, and Recommendations for Future Work, tries to explain the observed results of the simulation study based on an understanding of the dynamics of the SAGD process. The discussion is framed around what the initial expectations from the hypothesis, formulated at the beginning of this research, were and what the simulation study revealed. This is followed by conclusions, which lead to some recommendations for future work.

2. Model Predictive Control

In chemical plants, a process converts the feed into products though chemical and physical operations. The subject of *process control* in chemical engineering deals with the use of computer control systems to maintain the processes in a plant at optimum operating conditions, while satisfying all the safety requirements and the stringent environmental and product quality needs.

In a process plant, there can be several integrated processes and thousands of process variables. The variables can be categorized as inputs, outputs and disturbance variables. The inputs are adjusted or manipulated to control the outputs while compensating for the effects of disturbance variables. The disturbance variables include changes in the operating environment (like temperature or changes in the composition of feed like crude oil) and measurement errors in the outputs.

There are two distinct control strategies: feedback and feedforward control. In a feedback control strategy, the output variables are measured and the inputs are accordingly adjusted to control the outputs. This way, the controller is able to take a corrective action after the disturbances have caused the outputs to move away from their desired values. This is useful when the disturbance variables have an unknown origin or they are unmeasured. When the disturbance variables are measured, a corrective action can be taken by the controller based on these measurements before the outputs are affected. This significantly reduces the effect of the disturbances. This control strategy requires a model of the process that captures how the disturbances affect the process.

MPC is an advance process control technique, which was first developed in the 1970s and later found widespread industrial use, especially in oil refineries and petrochemical plants (Seborg et al. 2004). It incorporates feedback control for

unmeasured disturbances and feedforward control for measured disturbances. It's used for multivariable problems with constraints (Qin and Badgewell 2003; Ljung 1999). This means that in a plant, where there are multiple inputs and multiple outputs, MPC coordinates the changes in inputs required to control the outputs in a desired manner. And it does so while taking care of any inequality constraints on the inputs and outputs, which is a unique capability of MPC. **In the context of SAGD, injection and production rates/pressures can be manipulated at regularly spaced time instants to control the subcool along well pairs while managing constraints like artificial lift constraints and surface constraints, which can include the total steam consumption.**

2.1. Outline of MPC

In any process plant, there invariably are unmeasured disturbances, or plant dynamics that haven't been modeled, which lead the outputs to deviate from their desired targets. This affects the plant efficiency as well as the safety of the plant if any constraints are violated. (In case of an oil reservoir, the unknown dynamics manifest themselves in a heterogeneous geology, which leads to unexpected production results.) Hence, multivariable control like MPC is used to manipulate the inputs based on the information on outputs that is continuously fed back into the controller. Through this feedback action, the controller is able to compensate for any undesired movement in output variables.

To calculate the adjustments in input variables required to control the outputs, MPC uses a *dynamic model* (elaborated in the next chapter) of the process. The dynamic model can be one of the following three kinds (Seborg et al. 2004):

1. An empirical linear or nonlinear model of the process is built by fitting coefficients to input-output data using the theory of system identification. An empirical model is easier to build compared to the other kinds of models. They have a serious disadvantage that they don't perform well when

extrapolated to operating conditions outside of those used in fitting the model coefficients, which are usually restricted.

2. A physical model is built using the principles of physics, chemistry and biology. They are accurate over a wide range of operating conditions, but are also more expensive and time-consuming to build. Also, some of the parameter values can be difficult to know.

3. A semi-empirical or gray-box model combines the advantages of the above two kinds of models.

In MPC, the dynamic model of the process is used to make future prediction of the outputs and an optimization problem is solved to find an optimum sequence of adjustments for each input that will drive the outputs to their set points (or targets). The optimization incorporates any inequality constraints, like upper and lower bounds, on the inputs and outputs. The control calculations are repeated at every sampling instant, when new measurements of the outputs are available, and the input adjustments calculated for the current sampling interval (the interval between two successive sampling instants) is implemented in the process. For control calculations at each sampling instant, current measured output values form the feedback to the controller. Based on the measured output values, the model states (see state-space models in next chapter) are estimated by a *state observer*. Bemporad et al. (2012b, pp. 2-12 to 2-16) cover some of the mathematical details of state estimation.

Qin and Badgewell (2003) define the objectives of MPC as follows:

- Drive outputs to their set points. If there are more outputs than input, and thus, only a limited degree of freedom, some of the outputs can be driven to their set points while keeping the remaining outputs within their constraints.
- Prevent violation of the input and output constraints.
- Prevent excessive adjustments in the inputs.

- Control as many inputs and outputs as possible depending on the sensors and actuators available for the variables.

Fig. 2.1, adapted from Seborg et al. (2004), shows the control calculation for a simple single-input single-output process and the related terminology. Current sampling instant is k (the corresponding time is given by kT_s, where T_s denotes the sampling interval). P is the prediction horizon, the number of sampling intervals for which the output is predicted using the process model available. Output predicted at time t is denoted by $\hat{y}(t|k)$. The corresponding input sequence calculated is also shown, with the input value remaining constant for each sampling period. For optimization, input values are varied by the controller only for the first M sampling intervals, which is the control horizon. After the M sampling intervals, the input is held constant till the end of prediction horizon. The first value in the sequence of optimum input adjustments calculated gets implemented for the current sampling interval and calculations are repeated at the next sampling instant.
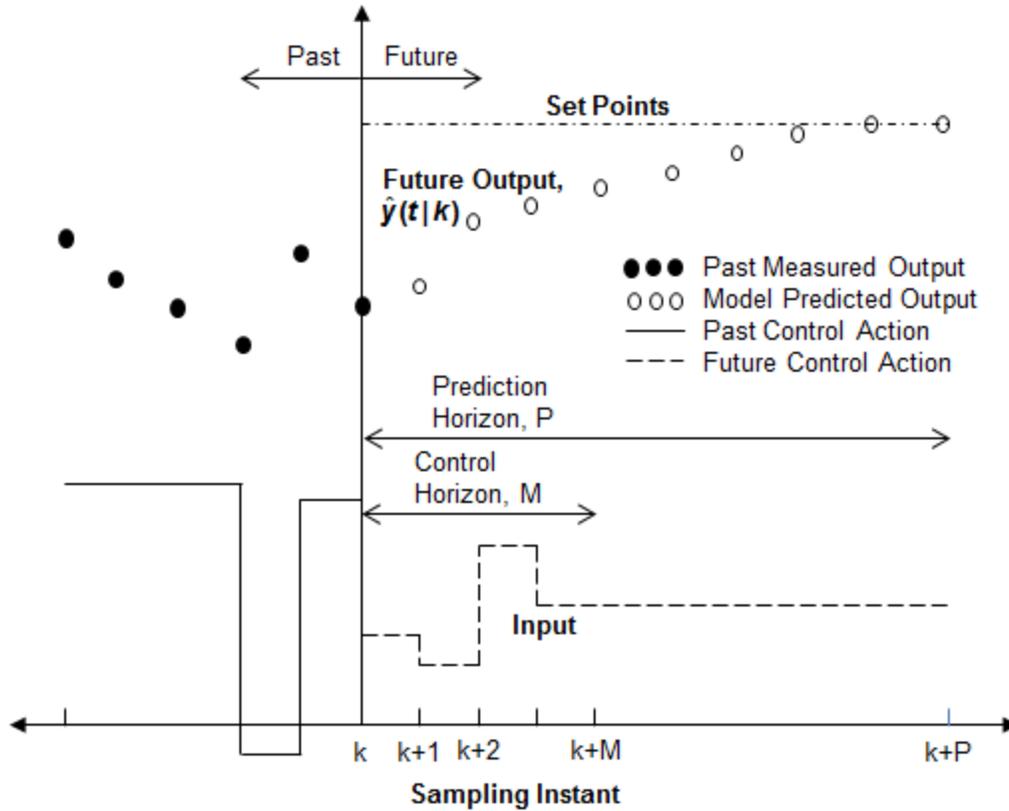
Fig. 2.1: MPC of a single-input single-output system. Adapted from Seborg et al. (2004).

In the context of control of SAGD in our work, the inputs, the outputs and the feedback of output data for MPC are shown in Fig. 2.2. We consider that the process consists of a single well pair having dual tubing string configuration. The inputs are the short- and long-tubing string injection and oil production rates. Subcool values at the heel and toe, measured in real-time through a downhole ATS system, feed back to the controller.
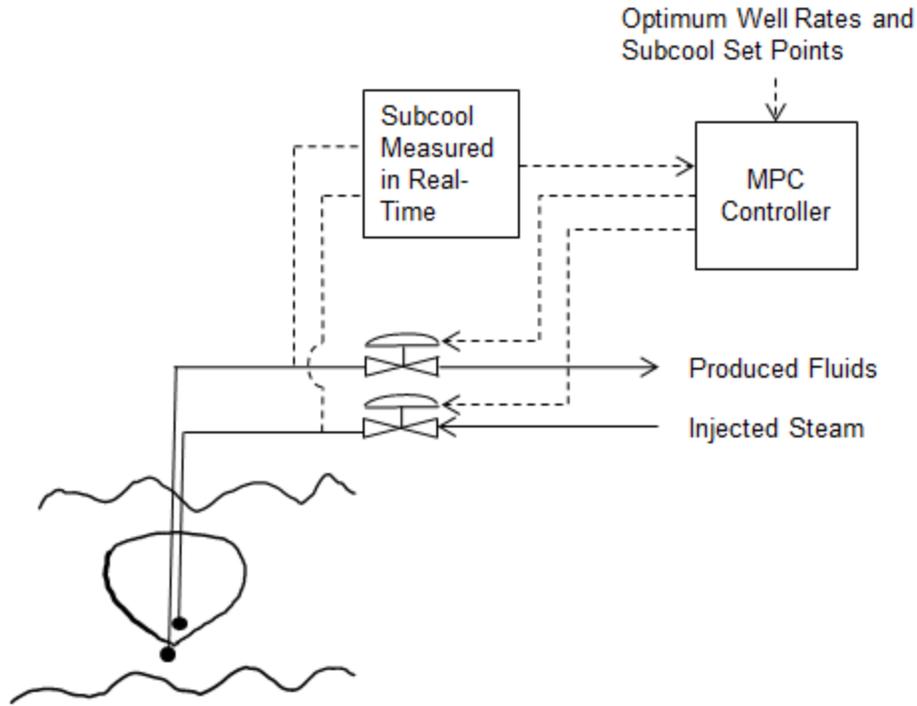
Fig. 2.2: Schematic diagram of MPC of subcool in SAGD.

2.2. MPC Optimization Problem

A simple form of the objective function that is minimized at each sampling instant in MPC is (Bemporad et al. 2012b)

$$J = \sum_{i=0}^{P-1} \left\{ \sum_{j=1}^{n_y} \{w_j^y [\hat{y}_j(k+i+1|k) - r_j(k+i|k)]\}^2 + \sum_{j=1}^{n_u} [w_j^{\Delta u} \Delta u_j(k+i|k)]^2 \right.$$

$$\left. + \sum_{j=1}^{n_u} \{w_j^u [u_j(k+i|k) - u_{jopt}(k+i|k)]\}^2 \right\}. \quad \text{.......................(2.1)}$$

 In the equation, subscript j denotes the jth input or output. $k + i|k$ denotes the value at time $k + i$, with k standing for the current time instant at which the MPC calculations are being done. n_y is the total number of outputs in the process. n_u is

the number of inputs considered for the optimization problem. $\hat{y}_j$ is the predicted value, r_j is the set point and w_j^y is the weight for the jth output. Higher the relative output weight, more is the emphasis that MPC gives for tracking the set points for the output. w_j^u is the weight and u_{jopt} is the optimum value for jth input. Depending on the weight, MPC will try to follow, more or less closely, the optimum input values. For optimization, set points, r_j, and optimum input values, u_{jopt}, need to be provided for the whole of prediction horizon, P. Input rate, $\Delta u_j(k + i|k)$, is defined as the adjustment in input u_j, $\Delta u_j(k + i) - \Delta u_j(k + i)$, at the time instant $k + i$. The corresponding weight for optimization is $w_j^{\Delta u}$. Input rates are included in the optimization to prevent excessive movement of inputs from their optimum values.

MPC finds the values of adjustments, $\Delta u_j(k|k)$, $\Delta u_j(k + 1|k)$, ... $\Delta u_j(k + M - 1|k)$ that minimize J. Minimization of J is subject to following constraints:

$$u_{jmin} \le u_j(k + i \mid k) \le u_{jmax}$$

$$\Delta u_{jmin} \le u_j(k + i \mid k) \le \Delta u_{jmax}$$

$$y_{jmin} \le u_j(k + i \mid k) \le y_{jmax}$$

$$\Delta u(k + h \mid k) = 0 \quad , \dots\dots\dots\dots\dots\dots\dots\dots\dots\text{(2.2)}$$

where $i = 0$, 1, ... $P - 1$ and $h = M$, ... $P - 1$. u_{jmax}, Δu_{jmax} and y_{jmax} are the upper bounds on the inputs, input rates and outputs. u_{jmin}, Δu_{jmin} and y_{jmin} are the lower bounds on the inputs, input rates and outputs. The last constraint signifies that inputs are adjusted only in the first M sampling intervals and thereafter held constant. After optimization, inputs $u_j(k + i) = u_j(k - 1) + \Delta u_j(k|k)$ are used in the process for the current sampling interval.

In a process plant, the set points and optimum input values in MPC objective function J come from an upper layer of optimization. The optimization uses a

steady-state model of the process, traditionally a linear model, along with an economic objective function like net profit to calculate the set points for MPC. In the context of real-time optimization of SAGD production in our work, optimization using the reservoir models gives the set points and optimum input values for MPC.

Optimum input values are included in the optimization function in MPC applications only in a few cases when the number of inputs is greater than the number of outputs. When the number of inputs is higher, there will be more than one way in which output set points can be tracked and hence, optimum values for the additional inputs are also tracked. In the case, when the number of inputs is smaller than number of outputs, tracking any of the inputs will compromise output set point tracking performance. Hence, the inputs are allowed to move freely within their constraints. However, in our work all the inputs are tracked so that all the variables in the SAGD process remain as close as possible to their optimum values.

For the MPC controller in our simulation study, we use the Model Predictive Control Toolbox^{TM} (Bemporad et al. 2012a, 2012b) in MATLAB$^®$, version V7.14 (release R2012a). The toolbox only allows the option of using a *linear time invariant* (LTI) model (i.e., a linear model that doesn't vary with time) for the control calculations. If there are no constraints, the controller uses a fast analytical solution to calculate the optimum sequence of input adjustments at each time instant. With constraints, as present in our work, the Model Predictive Control Toolbox uses a *Quadratic Programming* solver (Bemporad et al. 2012b).

2.3. Controller Design Considerations

In MPC design, a critical part is choosing the weights for the input and outputs. These usually have to be tuned to get the desired control performance. For example, if the controller solely focusses on tracking the output set points, it can

lead to equipment wear due to excessive input movements, or controller instability due to the process dynamics that haven't been correctly captured by the plant model. At the same time, higher weights for the inputs or the input rates reduce the ability of the controller to track the output set points, but will also make it more robust against any instability. In the Model Predictive Control Toolbox, all outputs have a weight of 1.0, all inputs have a weight of 0 and all input rates have a weight of 0.1 by default.

It is general practice to keep the control horizon much smaller than the prediction horizon, $M \ll P$. The length of the prediction horizon is kept around the *settling time* (defined in the next chapter) of the plant. It is necessary to predict this much into the future in the control calculations so that the controller can move the input in the right direction as well prevent future constraint violations. Bemporad et al. (2012b) note that, as a rule of thumb for a *lag-dominant* stable process, control horizon is usually between 3 and 5 sampling intervals, when the sampling interval is approximately $1/5^{th}$ the *dominant time constant* (defined in next chapter). We try to follow this rule in this work. Seborg et al. (2004) state a slightly different convention. (The dominant time constant in a process is the slowest or the largest time constant. The lag is synonymous with the time constant for an input-output relationship. In a lag-dominant process, lag is more than *dead time* (explained in next chapter) in the process.)

3. System Identification

In Section 2.1, we noted that MPC of a process makes use of a dynamic model of the plant to predict its behavior, which demands some elaboration. Dynamic models, as opposed to static models, are used for processes which exhibit unsteady-state behavior. In these processes, the inputs change the internal states of the plant, which in turn decide the output variables. Thus, the current outputs depend on what the inputs/outputs were in the past instead of depending only on the current inputs.

Linear dynamic systems can be modeled by linear ordinary differential equations (ODE):

$$a_n \frac{d^n y}{dt^n} + a_{n-1} \frac{d^{n-1} y}{dt^{n-1}} + \ldots + a_1 \frac{dy}{dx} + a_0 y$$

$$= b_m \frac{d^m u}{dt^m} + b_{m-1} \frac{d^{m-1} u}{dt^{m-1}} + \ldots + b_1 \frac{du}{dt} + b_0 u. \quad \ldots\ldots\ldots\ldots\ldots\ldots(3.1)$$

In this equation, y is the output variable and u is the input variable. Given a set of initial conditions and u as a function of time t, y at any time can be solved for by integrating the equation. The order of the system is n. For physical systems, $n \geq m$, called the *physical realizability condition* (Seborg et al. 2004). Many cases have $m = 0$. The following is a first order system:

$$a_1 \frac{dy}{dx} + a_0 y = b_0 u. \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(3.2)$$

It has a *steady-state gain* of b_0 / a_0. Steady-state gain is defined as the ratio of change in steady-state output value to the change in input, when there is a step change in input from one value to another and the process is allowed to reach a

new steady-state condition,. Hence, the steady-state gain, K, of a system is given by

$$K = \frac{(\overline{y}_2 - \overline{y}_1)}{(\overline{u}_2 - \overline{u}_1)}, \qquad \text{.......................................(3.3)}$$

where $\overline{u}_1$, $\overline{u}_2$, $\overline{y}_1$ and $\overline{y}_2$ denote steady-state values. For a linear system, steady-state gain is constant irrespective of the operating conditions (the inputs used). Further, the time constant, τ, of the system in Eq. 3.2 is a_1 / a_0. Time constant of a first-order system is the time it takes for the output to make 63.21% of the change from $\overline{y}_1$ to $\overline{y}_2$, when the input changes from $\overline{u}_1$ to $\overline{u}_2$. When there is a step change in input by M at time $t = 0$, the output y of a first-order system asymptotically changes to $\overline{y}_2$ as

$$y - \overline{y}_1 = KM(1 - e^{-t/\tau}). \qquad \text{.......................................(3.4)}$$

This is represented in Fig. 3.1. On the horizontal axis, time is plotted in multiples of the time constant τ. It is considered that there is a step change in input by M at time $t = 0$.
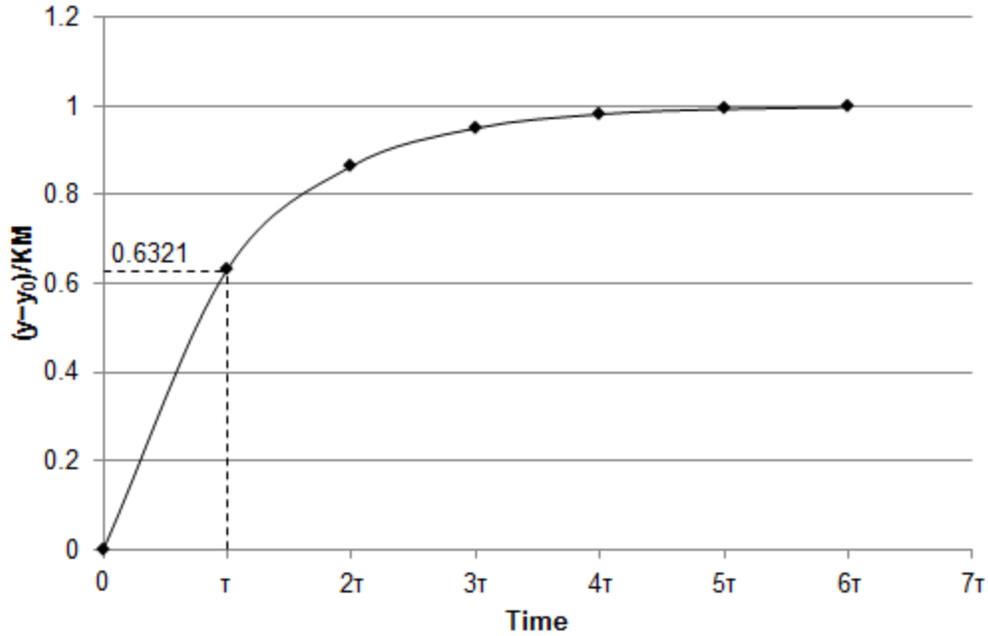
Fig. 3.1: Dynamic behavior of a first-order system.

Time constant, τ, and steady-state gain, K, completely characterize the response of a first order system to a given input. If there are multiple input variables, the individual affects add up. A second order system is equivalent to two first order processes in series. When there is a step change in input from one value to another, the output oscillates to its new steady state. The response is characterized by a time constant, a steady-state gain and a damping coefficient, which characterizes the oscillatory behavior.

Mostly, models that are developed for processes are in discrete time as the data itself is recorded at discrete time instances. (However, continuous-time controllers are also used for processes.) In discrete time, if the input is piecewise constant with the values changing only at regular discrete intervals (sampling instants), a first-order system, similar to the one in Eq. 3.2, can be accurately expressed using a *difference equation* as follows:

$$y(k) + a_1 y(k-1) = b_1 u(k-1), \quad \text{................................(3.5)}$$

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where, k denotes the current sampling instant, $k - 1$ denotes the previous sampling instant and so on. Steady-state gain of the system is $b_1 / (1 + a_1)$. If sampling is done at intervals of 1s, then the time constant of the system in seconds is given by the ratio $- a_1 / b_1$, considering a_1 is negative and b_1 is positive. Note that due to the physical realizability condition, $y(k)$ depends on $u(k - 1)$, but not on $u(k)$. Hence, there is no b_0 term in the equation or equivalently $b_0 = 0$. It has been assumed that the system doesn't have any *dead time*. In reality, after changing an input like a valve opening, it takes some time for it to start affecting the output. This time lag is called the dead time. A dead time can be easily incorporated into Eq. 3.5 by starting from $u(k - d)$ instead of $u(k - 1)$, where d is the time in multiples of sampling interval, T_s, it takes for the effect of any change in $u(k)$ to be observed on $y(k)$.

Eq. 3.5 can also be written in terms of the forward shift operator, q:

$$q^{-1}u(k) = u(k-1) \quad \text{...(3.6)}$$

$$q^{-n}u(k) = u(k-n) \quad \text{...(3.7)}$$

Using q, Eq. 3.5 can be re-written as

$$y(k) + a_1 q^{-1} y(k) = b_1 q^{-1} u(k) \quad \text{..................................(3.8)}$$

$$(1 + a_1 q^{-1}) y(k) = b_1 q^{-1} u(k) \quad \text{...................................(3.9)}$$

$$y(k) = \frac{b_1 q^{-1}}{1 + a_1 q^{-1}} u(k) \quad \text{..(3.10)}$$

or

$$y(k) = \frac{B(q)}{A(q)} u(k). \quad \text{...(3.11)}$$

In Eq. 3.11, $A(q)$ and $B(q)$ are polynomials in forward shift operator, q. B / A is a general form of the *transfer function* from the input u to output y. Note that B polynomial starts from b_1, b_0 being zero for all physical systems. Any dead time can be incorporated by setting the initial few coefficients in the polynomial, b_0, b_1, b_2, ... to zero.

Another kind of discrete-time dynamic models is the *finite impulse response* (FIR) model or a related form, the *step response model*. These models are equivalent to a difference equation like Eq. 3.5, but have many more parameters to represent the system dynamics.

The unsteady-state behavior of linear dynamic processes as described above is called *process dynamics*. We refer to Seborg et al. (2004) for further treatment of process dynamics as well as process control, including development of transfer functions (using Laplace transforms, which express the differential equations representing linear dynamic processes in an algebraic form for easier analysis and generalize the behavior of a process), dynamic behavior of different linear processes, and the design and analysis of controllers based on the linear dynamic models,.

In MPC applications, the dynamic models used are typically empirical (built by fitting to data) linear models in the form of difference equations, as show in Eqs. 3.8 through 3.11, or step response models (Seborg et al. 2004).

In this chapter, vectors and matrices are be denoted by bold notation.

3.1. Stochastic Processes in Real-World Applications

The concepts of random variables and stochastic processes in statistics are briefly discussed in this section before continuing with the discussion of linear dynamic models. This discussion has been taken from Nelles (2001, pp. 739–756) and will be useful when we move to the discussion of the different linear dynamic model

structures in Section 3.3. As mentioned in the introduction to Chapter 2, all real world processes have unmeasured disturbances, which will corrupt the outputs in a random way (see below). If, in different experiments, same input values are used for the process, the output values will be a little different each time. The effect of these disturbances can be modeled by including a stochastic component (a disturbance model) in a model of the process (see Section 3.3). Ideally with the inclusion of this stochastic component, the difference between the actual measured output and the predicted output will be *purely random* because all information about the disturbances has been captured by the disturbance model (further elaborated below and Section 3.5).

The stochastic component used to model the disturbances makes use of a random variable. In statistics, a random variable x can be completely characterized by its probability density function (pdf), which relates probability density, $p(x)$, to x. Every time an experiment is done, it yields one realization of the random variable. The probability that the realization will be within a range of values is given by the area under the pdf for the given range. Also, from the pdf, the mean and variance of the random variable can be determined:

$$\text{mean}\{x\} = \mu_x = E\{x\} = \int_{-\infty}^{+\infty} x p(x) dx \,. \quad \text{.........................(3.12)}$$

$$\text{var}\{x\} = \sigma_x^2 = E\{(x - \mu_x)^2\} = \int_{-\infty}^{+\infty} (x - \mu_x)^2 p(x) dx \,. \quad \text{...............(3.13)}$$

where E is the expectation operator, which forms the basis of all statistical calculations. σ is the standard deviation, which is a direct measure of the width of the pdf. An important kind of probability distribution is Gaussian or normal distribution, which has practical importance. For a given mean μ and standard deviation σ, Gaussian distribution is given by

$$p(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-(x-\mu)^2 / 2\sigma^2} \quad \text{....................................(3.14)}$$

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For a Gaussian distribution, the probabilities that a realization will lie in the intervals $\mu \pm \sigma$ (one-sigma interval), $\mu \pm 2\sigma$ (two-sigma interval) and $\mu \pm 3\sigma$ (three-sigma interval), which is given by the area under the pdf in the respective intervals, are 68.3%, 95.4% and 99.7%. The higher the value of σ, larger is the interval around mean with higher probabilities and wider is the pdf.

For more than one random variable, a joint pdf can be defined. E.g., for two random variables x_1 and x_2, the joint pdf is denoted by $p(x_1,x_2)$. (For more information, we refer to Nelles (2001).) Further, for two random variables, x and y, we can define the correlation ($\text{corr}\{x,y\}$) and covariance ($\text{cov}\{x,y\}$) between the two. Both these measures describe the degree to which the two random variables are related to each other and are in fact identical when the means of the two random variables are zero.

$$\text{corr}\{x,y\} = \text{corr}_{xy} = E\{x.y\} \quad \text{.................................(3.15)}$$

$$\text{cov}\{x,y\} = \text{cov}_{xy} = E\{(x - \mu_x).(y - \mu_y)\} \quad \text{.......................(3.16)}$$

For more than two random variables, a covariance matrix can be defined that contains covariance values for all pairs of the random variables. The values along the diagonal of this matrix are the variances of the variables.

In a process, the disturbances evolve over time. A random variable that is also function of time, k, is called a stochastic process, $x(k)$. The pdf is now also a function of time, $p(x,k)$. A noise signal is a stochastic process. An experiment can be done each time to produce a realization of the noise signal. In general, statistical properties like mean and variance are now defined as functions of time as follows:

$$\text{mean}\{x(k)\} = \mu_x(k) = E\{x(k)\} = \int_{-\infty}^{+\infty} xp(x,k)dx \quad \text{.................(3.17)}$$

$$\text{var}\{x(k)\} = \sigma_x(k) = E\{(x(k) - \mu_x(k))^2\} = \int_{-\infty}^{+\infty} (x(k) - \mu_x(k))^2 p(x,k)dx$$

$$= \int_{-\infty}^{+\infty} (x(k) - \mu_x(k))^2 p(x,k)dx . \quad \text{...............................(3.18)}$$

It is useful to consider to some definitions here. A stochastic process is called *stationary* if the probability distribution $p(x,k)$ remains constant with time, k. In other words, $p(x,k_1) = p(x,k_2)$, for all k_1 and k_2. For most real-world application, it is reasonable to make the assumption that the disturbances are stationary (which means that the mean remains constant). In some applications, noise could be drifting or non-stationary, e.g. in a *random walk*. Another example is the output of a sensor that depends on the temperature of the sensor, which increases monotonously from the time sensor starts taking measurements (Nelles 2001). In such a case, the disturbance model needs to account for the non-stationary noise characteristics.

In practice, apart from stationarity, a further assumption is made for most applications that the stochastic processes are *ergodic*. For a stationary process that is ergodic, statistical properties like mean and variance can be found out by averaging a signal over time, instead of averaging over realizations. Because in reality there is only one realization available for a stochastic process from measurement, the simplifying assumption of ergodicity makes the calculation of statistical properties possible by using the expectation operator over time for the single realization. Ergodicity assumes that as $k \rightarrow \infty$, the realization contains all the information about the underlying pdf of the stochastic process. (For an example of a stationary stochastic process that is not ergodic, consider the simple case of a stochastic process whose value remain constant with time k for every realization, i.e. $x(k) = c$, where c is a constant. Using the expectation operator over realizations of the stochastic process for any time k gives the properties of the distribution $p(x,k)$. However, the same is not true for averaging over time for a single realization.) A stochastic process that is ergodic is also stationary by definition because using the expectation operator over time naturally implies that the properties are time-independent. If a realization of an ergodic stochastic

process is measured at times $k = 1, 2, ... N$, mean and variance can be calculated as

$$\mu_x = E\{x\} \approx \frac{1}{N}\sum_{k=1}^{N} x(k) = \bar{x} \quad \text{.................................(3.19)}$$

$$\sigma_x^2 = E\{(x - \bar{x})^2\} \approx \frac{1}{N-1}\sum_{k=1}^{N} (x(k) - \bar{x})^2 = s^2 . \quad \text{...................(3.20)}$$

In these equations, x has been used with the expectation operator instead of $x(k)$ to represent the stochastic process as the averaging, following from the assumption of ergodicity, takes place over time, k, itself to calculate the statistical properties. Symbol $\bar{x}$ for mean signifies this. In Eq. 3.20, using $N - 1$ instead of N in the denominator gives an unbiased estimation.

(We make a brief note about *estimators* here. An estimator, such as those given by Eqs. 3.19 and 3.20, determines the values of a small number of parameters, given by the vector $\boldsymbol{\theta}$, based on a large number of measurements, N. Each time the estimator is used on a set of measurements, it will give one realization of the parameters. Hence, an estimator will have a probability distribution given by $p(\boldsymbol{\theta}, N)$. The distribution depends on the number of measurements N used for estimation. $\boldsymbol{\theta}$ denotes estimated parameter values. Particularly the mean and the covariance matrix of the distribution are considered. An estimator is called unbiased if the estimated mean values of the parameters are equal to their true value for any size of the data set used to make the estimates, N. Further, an estimator that is unbiased is called consistent if, as the number of measurements approaches infinity, $N \rightarrow \infty$, the estimated mean values of the parameters approach their true value. Further, a property worth noting for estimators is that most of them have a Gaussian distribution as $N \rightarrow \infty$, in which case the mean and covariance matrix of the distribution characterize it completely (see Eq. 3.14 for a univariate Gaussian distribution).

Similar to Eqs. 3.15 and 3.16 for two random variables, correlation and covariance can be defined for two stochastic processes:

$$\text{corr}\{x,y,k_1,k_2\} = \text{corr}_{xy}(k_1,k_2) = E\{x(k_1).y(k_2)\} \quad \text{...............(3.21)}$$

$$\text{cov}\{x,y,k_1,k_2\} = \text{cov}_{xy}(k_1,k_2) = E\{(x(k_1)-\mu_x).(y(k_2)-\mu_y)\} \;. \quad \text{.......(3.22)}$$

The properties depend on time k_1 for the stochastic process $x(k)$ and k_2 for the stochastic process $y(k)$. They measure how much the measurement $x(k_1)$ is correlated to the measurement $y(k_2)$. If the two stochastic processes are stationary, dependence on time k ceases and only the lag, $\Delta k = k_1 - k_2$, between $x(k)$ and $y(k)$ matters:

$$\text{corr}\{x,y,\Delta k\} = \text{corr}_{xy}(\Delta k) = E\{x(k_1).y(k_1-\Delta k)\} \quad \text{................(3.23)}$$

$$\text{cov}\{x,y,\Delta k\} = \text{cov}_{xy}(\Delta k) = E\{(x(k_1)-\mu_x).(y(k_1-\Delta k)-\mu_y)\} \;. \quad \text{.......(3.24)}$$

Further, with the assumption of ergodicity, the following give unbiased estimates of correlation and covariance:

$$\text{corr}_{xy}(\Delta k) \approx \frac{1}{N-\Delta k} \sum_{k=1+\Delta k}^{N} x(k).y(k-\Delta k) \quad \text{......................(3.25)}$$

$$\text{cov}_{xy}(\Delta k) \approx \frac{1}{N-\Delta k-1} \sum_{k=1+\Delta k}^{N} (x(k)-\overline{x}).(y(k-\Delta k)-\overline{y}), \quad \text{............(3.26)}$$

where $\overline{x}$ and $\overline{y}$ are the estimated mean values. Correlation of a stochastic process with itself, $\text{corr}_{xy}(\Delta k)$, is called auto-correlation. As can be expected, auto-correlation is highest at zero lag, $k_1 - k_2 = 0$, and usually it will decrease with increasing lag. It is symmetric with respect to positive and negative values of Δk.

One kind of a stochastic process that is of great practical significance is the *Gaussian white noise*. The term Gaussian refers to the nature of probability

distribution of the stochastic process at any time k, $p(x,k)$. "White" tells that the auto-correlation for the stochastic process at any non-zero lag, $\Delta k \neq 0$, is zero. Hence, the noise value at a time instant k_1, $x(k_1)$, has no correlation with the value at any other time k_2, $x(k_2)$. This means that if a measurement of white noise is made at one time instant, it provides no information on what the value could be at some other time instant. White noise is hence purely random. In practice, noise that is observed is correlated. However, any such noise can be generated by passing white noise though a dynamic *filter*, as it done in the development of the general linear dynamic model structure in Section 3.3.

In a process, the measured output y can be thought of as composed of a deterministic component y_u, which is the undisturbed process output because of the input u, and a stochastic component, noise n, as shown in Fig. 3.2. Noise n summarizes the effects of all process disturbances. (Note that disturbances in reality can both enter directly at the output as well as affect the internal process variables). y is the output predicted by a model of the process based on estimated parameters θ. The difference in measured output and predicted output is given by the error e. In order to estimate the model parameters θ, an objective function can be defined in terms of e and minimization of this objective function will give the parameters (see Section 3.5). If the model is able to accurately capture the process dynamics as well as the correlation in noise n, the error e should be white noise. In other words, the difference between the process and the model is purely random. Further, in Fig. 3.2, because n is a stochastic process, both y and e are stochastic processes as well. Hence, the estimated parameters are themselves random variables, given by $p(\theta)$. Analyzing the mean and the covariance matrix of the estimated parameters gives insights about the quality of the estimated model.
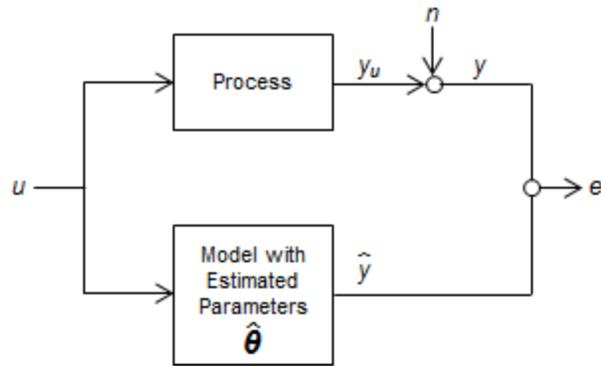
Fig. 3.2: Effect of stochastic processes on the measured output in a process.

3.2. Overview of System identification

The parameter values in a difference equation like Eq. 3.11 used to model a linear dynamic system can be estimated by using regression to fit them to the plant's input/output data. The theory of linear system identification deals with the identification of linear dynamic models, i.e., building a model from the input-output data from the process. For identification, a couple of things need to be considered which we note in this section before going into further details in later sections focusing on an intuitional understanding of the subject.

Data that is sampled for system identification is divided into two parts. An initial part is used for the actual model estimation. The latter part is used for *model validation*, in which the model is used to fit the data to validate its performance. This is necessary as validation must be on some future data that is separate from the data that is used to estimate the model itself. For model estimation, a rule of thumb in system identification is to keep the estimation period at least five times the time constant of the process. Further, the data is *detrended*—a linear trend is removed from the data so that its mean and overall slope are 0—before identification (Huang 2012). As will become clear in Section 3.3, the model structures used for linear system identification don't have a constant term. As a result, if the data is not detrended, the identified model orders increase by one.

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For estimating a model from the data, following questions have to be considered:

a) What should be the model structure?
b) What should be the model orders?

Section 3.3 discusses the different linear dynamic model structures that are used in system identification. As discussed in Sections 3.3 and 3.5, different model structures have different noise assumptions leading to differing model complexities. E.g., the *autoregressive with exogenous input* (ARX) and *state-space* models discussed in these sections offer simple structures. For linear system identification, one should first start with a simple model like the ARX (Ljung 2012b). This provides an idea about the model orders that are needed. If the model performance is not satisfactory with respect to modeling the noise in output, one should then go for more complex model structures because more complex models are more difficult to estimate from the data as explained in Section 3.5. Further, a more complex structure doesn't translate into more accuracy as there will be more uncertainty in the estimated parameters and more data is required for estimation. Apart from using the simplest model structure possible, model orders should also be kept as low as possible.

We stress the fact that in reality processes are not linear. Hence, linear system identification is truly only a method for approximating the process dynamics. This is significant for how linear system identification is done, some of which was explained above, with more details in the following sections. (Note that before even using linear system identification, process dynamics are analyzed to see is a linear model is enough. If no, then nonlinear system identification is done, which, as the name suggests, uses nonlinear models.)

As noted in Chap. 2, in this work we use the Model Predictive Control Toolbox for MPC calculations. The software only accepts state-space models. Hence, the linear models identified this work are first converted to state-space models (see Section 3.3).

In addition to the discussion that follows, the works of Ljung (1999) and Söderström and Stoica (2001) are good references for a detailed mathematical treatment of system identification.

3.3. Difference Equation Model Structures

The difference equation previously stated in Eq. 3.11 can be completed by including a stochastic component for modeling the disturbance in output and generalizing the structure such that all the standard difference equation structures used in system identification can be derived from it (Nelles 2001; Ljung 1999; Ljung 2012b). A general difference equation structure for system identification is as follows:

$$y(k) = \frac{B(q)}{F(q)A(q)}u(k) + \frac{C(q)}{D(q)A(q)}v(k), \quad \text{......................(3.27)}$$

which can be written in a compact form as

$$y(k) = G(q)u(k) + H(q)v(k). \quad \text{...............................(3.28)}$$

In this equation, $G(q) = B(q) / (F(q)A(q))$ is the input transfer function. $v(k)$ is Gaussian white noise with mean 0 and variance σ^2 (which is determined during identification along with the parameters in polynomials). The correlated noise or disturbance signal in output is generated by passing white noise through a filter:

$$n(k) = H(q)v(k). \quad \text{..(3.29)}$$

$H(q) = C(q) / (D(q)A(q))$ is called the noise transfer function because it relates white noise $v(k)$ to output $y(k)$. As depicted in Fig. 3.3, the filter $G(q)$ modifies the frequency characteristics of $u(k)$ and filter $H(q)$ acts on the noise $v(k)$ to produce the output. The polynomial $A(q)$, which is present in both $G(q)$ and $H(q)$, represents common denominator dynamics for the process and the disturbance.
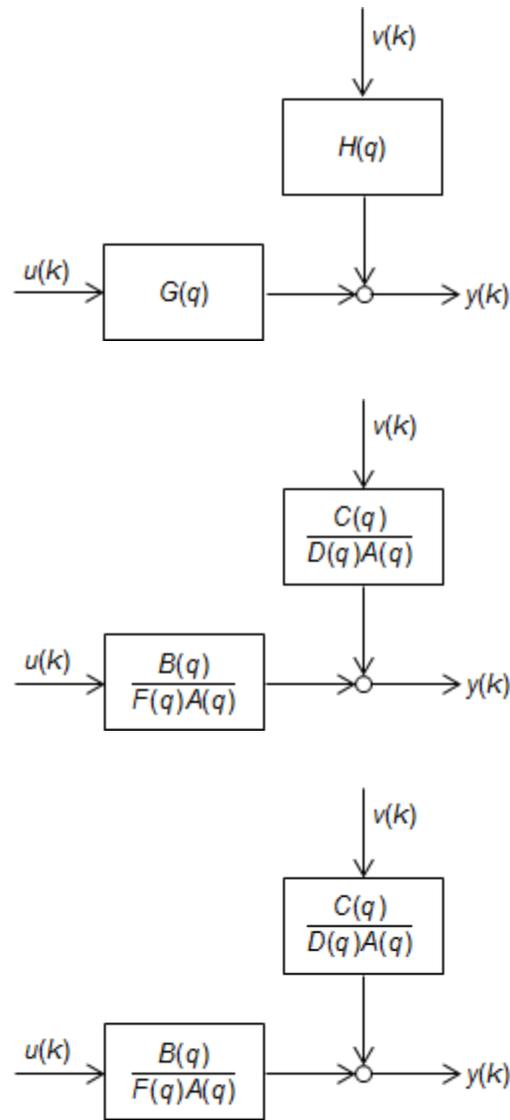
Fig. 3.3: General difference equation model structure in system identification.

In Eq. 3.27, the roots of the numerator polynomials in $G(q)$ and $H(q)$ are called the *zeros* of the model. The roots of the denominator polynomials are called the *poles*. Poles are related to the output side of the equation and zeros are related to the input side. E.g., in Eq. 3.5, the number of poles is the number of sampling intervals between the most recent output appearing in the equation, $y(k)$, and the oldest output, which is $y(k-1)$. Hence, the number of poles is one (which is same as number of unknown coefficients on the output side). Similarly,

considering the input side of the equation, the number of zeros is zero (the number of coefficients on the input side being equal to number of zeros plus one). Poles associated with $F(q)$ in Eq. 3.27 are related to the process dynamics whereas poles associated with $D(q)$ are related to the disturbance dynamics. The number of poles and zeros determine the orders of the system. They can be thought in the same vein as m and n in Eq. 3.1.

To model drifting disturbances (see Section 3.1), a *noise integrator*, $1 / (1 - q^{-1})$, can be added to the disturbance model:

$$y(k) = G(q)u(k) + \frac{H(q)}{1-q^{-1}}v(k). \quad \text{.................................(3.30)}$$

This can be interpreted as follows:

$$(1-q^{-1})y(k) = (1-q^{-1})G(q)u(k) + H(q)v(k) \quad \text{......................(3.31)}$$

$$y(k) - y(k-1) = G(q)(u(k) - u(k-1)) + H(q)v(k) \quad \text{.................(3.32)}$$

$$\Delta y(k) = G(q)\Delta u(k) + H(q)v(k). \quad \text{..............................(3.33)}$$

Hence, the effect of drifting disturbance on the output can be modeled by considering the differences in input data (Δu) and output data (Δy) instead of the input and output data directly for system identification (Huang 2012).

In practice, the model structures that are used for system identification are simpler forms of the generalized form given in Eq. 3.27. The most commonly used linear dynamic model is the ARX model (Nelles 2001):

$$y(k) = \frac{B(q)}{A(q)}u(k) + \frac{1}{A(q)}v(k). \quad \text{..............................(3.34)}$$

The ARX model has identical process and disturbance denominator dynamics given by the polynomial $A(q)$ (Fig. 3.4). This simple structure leads to the model's popularity. It is applied even for processes with more complex

disturbance dynamics, given the signal-to-noise ratio is good (Ljung 2012b). (Signal-to-noise power ratio is the ratio of the variance of the signal to that of the noise.) This is further elaborated in Section 3.5.
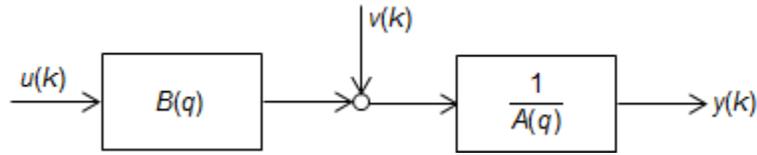
Fig. 3.4: The ARX model.

For drifting disturbances, the ARX model can be modified as follows to give the *autoregressive integrated with exogenous input* (ARIX) model:

$$y(k) = \frac{B(q)}{A(q)}u(k) + \frac{1}{A(q)(1-q^{-1})}v(k). \qquad \text{(3.35)}$$

The following are the structures of *autoregressive moving average with exogenous input* (ARMAX), *autoregressive autoregressive with exogenous input* (ARARX) and *autoregressive autoregressive moving average with exogenous input* (ARARMAX) models. The ARARMAX model is rarely used in system identification.

ARMAX $$y(k) = \frac{B(q)}{A(q)}u(k) + \frac{C(q)}{A(q)}v(k) \qquad \text{(3.36)}$$

ARARX $$y(k) = \frac{B(q)}{A(q)}u(k) + \frac{1}{D(q)A(q)}v(k) \qquad \text{(3.37)}$$

ARARMAX $$y(k) = \frac{B(q)}{A(q)}u(k) + \frac{C(q)}{D(q)A(q)}v(k) \qquad \text{(3.38)}$$

The ARMAX model extends the ARX structure by adding numerator dynamics, given by polynomial $C(q)$, to the disturbance model. This is a better

representation of processes in which the disturbance enters at the input (Ljung 2012b).

The four autoregressive models described above fall into the category of equation error models. They are called equation error models because the noise $v(k)$ enters before the filter $1 / A(q)$ (as shown in Fig. 3.4 for the ARX model), which also modifies the frequency characteristics of $u(k)$.

The nomenclature for equation error models derives from the time series models used in economics (Nelles 2001). A time series model is equivalent to Eq. 3.27 without any input $u(k)$; and the denominator of $H(q)$ can be represented by a single polynomial $D(q)$. Hence, a time series model is purely stochastic with only a noise model. A time series model with only a denominator polynomial is called an autoregressive (AR) model:

$$y(k) = \frac{1}{D(q)} v(k). \quad \text{..}(3.39)$$

If it has only a numerator polynomial, it is called a moving average (MA) model:

$$y(k) = C(q)v(k). \quad \text{..}(3.40)$$

Combining AR and MA models, one arrives at the autoregressive moving average (ARMA) time series model:

$$y(k) = \frac{C(q)}{D(q)} v(k). \quad \text{..}(3.41)$$

In system identification, this terminology extends directly to equation error models and it has become standard since it was first used by Ljung (1999).

Another class of difference equation models is the output error models (Nelles 2001). The distinctive feature of these models is that there is no common denominator dynamics for the process and the disturbance. Hence, these models are used for processes in which the disturbance directly affects the output as

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measurement noise. Output error models do not follow the nomenclature for equation error models.

In the simplest form of an output error model, white noise $v(k)$ directly adds to the true output:

$$y(k) = \frac{B(q)}{F(q)} u(k) + v(k).\ \dots\dots\dots\dots\dots\dots\dots\dots\dots\text{(3.42)}$$

On the other hand, the *Box-Jenkins* (BJ) model provides complete flexibility to model the disturbance in output by passing white noise $v(k)$ through an ARMA filter as

$$y(k) = \frac{B(q)}{F(q)} u(k) + \frac{C(q)}{D(q)} v(k).\ \dots\dots\dots\dots\dots\dots\dots\text{(3.43)}$$

The disturbance dynamics is parameterized completely independent of the process dynamics. Such a model is useful when the disturbance enters primarily at the output as measurement noise.

The FIR model mentioned previously is also classified as an output error model:

$$y(k) = B(q)u(k) + v(k).\ \dots\dots\dots\dots\dots\dots\dots\dots\text{(3.44)}$$

Compared to other models discussed above, FIR model doesn't have any *output feedback* (in other words, output $y(k)$ doesn't depend on past outputs but depends only on past inputs) because $A(q) = D(q) = F(q) = 1$. An FIR model has many more parameters (as contained in $B(q)$) compared to the other models; however, it is useful for describing processes that have unusual dynamics that can't be adequately described by other models, all of which have lower orders.

For identifying the dynamic models described above from input-output data, we need to specify the number of poles and zeros corresponding to all the polynomials in a model, which determines the number of coefficients that need to be estimated. The estimated poles and zeros of the input transfer function $G(q)$

have significance in model analysis. The estimated poles and zeros (which are complex numbers) can be plotted with a confidence interval (e.g., a confidence interval of one standard deviation; the confidence interval can be calculated based on the mean and variance of the estimated model parameters and assuming they have a Gaussian distribution.). If a pole-zero pair, plotted along with their confidence intervals, overlaps, this means that they could be cancelling each other and the orders of the model chosen could be reduced. In case of a pole-zero cancellation, lower orders should be tried. Further, e.g. with the ARX model, if trying lower orders leads to a degradation of the model performance when it's used for validation, this could mean that the cancelling poles (which are also common to the disturbance) might be helping in modeling the disturbance, and therefore a model with more complex disturbance dynamics should be tried, an ARMAX or BJ model. This is elaborated further by Ljung (2012b, pp. 8-60 to 8-63).

Apart from the input-output models described above, we also briefly touch upon another kind of dynamic model, called the state-space model (Ljung 2012b). Dynamic models of processes that are derived from first principles can be a set of ODEs, instead of single ODE or difference equation discussed earlier. A state-space model is a compact representation for a dynamic model that is a set of ODEs. State-space models use a *state vector* $\boldsymbol{x}$, which contains the *state variables*, and the model order n is given by the dimension of this vector. Compared to the input-output models, the only user input required for estimation of a state-space model is n. The discrete-time state-space structure for a single input and a single output is given as follows. In the state-space structure, there is only a delay of one sampling interval, and no representation of dead time is needed.

$$\boldsymbol{x}(k+1) = \boldsymbol{A}\boldsymbol{x}(k) + \boldsymbol{B}u(k) + \boldsymbol{K}v(k) \quad \text{..........................(3.45a)}$$

$$y(k) = \boldsymbol{C}\boldsymbol{x}(k) + Du(k) + v(k) \quad \text{...............................(3.45b)}$$

$$x(0) = x_0 \quad \text{..(3.45c)}$$

In the equations, $x(k)$ is the state vector at time k, A is a constant matrix, B, C and K are constant vectors (C being a row vector), D is a constant and x_0 gives the initial conditions. For an example of continuous-time state-space model of a simple physical system, we refer to Seborg et al. (2004, pp. 96).

All the input-output models can also be written in their equivalent state-space form. Setting $K = 0$ in the set of Eqs. 3.45 gives the OE model of Eq. 3.42. State-space models are especially suited for multi-input multi-output (MIMO) processes (Nelles 2001).

3.4. Identification of MIMO Models

In the description of different linear model structures in the previous section, it was assumed that the process only has one input and one output. In case of a MIMO process, A, B, C, D and F are arrays of polynomials instead, and $u(k)$ and $y(k)$ represent vectors of input and outputs respectively in Eq. 3.27. The inputs are u_i, $i = 1:n_u$, and the outputs are y_i, $l = 1:n_y$. As an example, A is an n_y-by-n_u array of polynomials. The following table summarizes the dimensions of different arrays.

Table 3.1: Description of polynomials in difference equation model structures.

Array	Dimension	Polynomial Description
A	n_y-by-n_y	Polynomial $A\{i,j\}$ describes how output y_j affects output y_i.
B, F	n_y-by-n_u	Polynomials $B\{i,j\}$ and $F\{i,j\}$ describe the relationship between input u_j and output y_i.
C, D	n_y-by-1	Polynomials $C\{i\}$ and $D\{i\}$ describe how noise v_i disturbs output y_i.

The first coefficient (corresponding to q^0) of polynomials along A's diagonal is 1, which can also be noted from Eqs. 3.10 and 3.11. Further, the non-diagonal polynomials in have their first coefficient as 0 because output y_j can't instantaneously affect output y_i. The first coefficient of all polynomials in C, D and F is also equal to 1. Further, extending what was noted for Eq. 3.5, each input/output pair can have a separate delay which is specified by setting the initial few coefficient in the corresponding polynomial $B\{i,j\}$ to zero.

For a MIMO model, the number of poles or zeros corresponding to a polynomial array can be specified as a matrix having same dimensions as the array. E.g., the orders of polynomials in A can be assigned by a n_y-by-n_u matrix or they can all be given the same order. Further, noise integration can be individually added for each output in order to model non-stationary disturbance in an output.

In general, as the number of inputs included in the model of a process increases, the model performance becomes better; however, for outputs it becomes more difficult to model multiple outputs simultaneously as the number of outputs increases (Ljung 2012b). With more outputs, the number of parameters required to define the couplings between outputs increases and the model performance typically deteriorates. E.g., in the ARX model, array A has parameters that couple

the outputs. If there are two outputs y_1 and y_2, $A\{1,2\}$ .describes how $y_1(k)$ is depends on $y_2(k − 1)$, $y_2(k − 2)$, ... (Note that the first coefficient of polynomial $A\{1,2\}$ is zero as $y_2(k)$ can't instantly effect $y_1(k)$.) Also, because A is a n_y-by-n_u array, the number of polynomials in A increases as n_y^2.

If there are no couplings between the outputs and there is no output feedback in a process, it is better to construct a MIMO model as a combination of multiple multiple-input single-output models (Ljung 2012b).

3.5. Optimal Predictor

The explanation in this section is mostly with respect to the ARX model.

An ARX model can be used in two ways. It can be used for *simulation* or *prediction* (Nelles 2001). In simulation, for given inputs $u(k)$, where $k = 0, 1, ...$ n, the outputs at these times are calculated. In prediction, to estimate the output at k, all the past inputs are known as well as the *measured* output values up to $k − l$ are used, where l is the prediction horizon. Hence, in simulation, no information on outputs is available. Past output values used to calculate the current outputs are themselves the result of previous calculations. On the other hand, in prediction, information on past outputs is used. Usually, $l = 1$ for prediction, which is called one-step prediction.

When the ARX model, given by Eq. 3.34, is used to represent a process, output $y(k)$ can be simulated for a given input sequence $u(k)$ using

$$y(k) = \frac{B(q)}{A(q)} u(k).$$ ....(3.46)

In this equation, $y(k)$ denotes simulated output ($y(k)$ denoting actual measured output). For simulation, there is no need of using the disturbance model

$H(q) = 1 / A(q)$ in Eq. 3.34. However, note that for estimation of the ARX model itself, $H(q)$ is necessary to estimate an accurate input transfer function $G(q)$.

To see how the output might be different with noise, white noise $w(k)$ with an appropriate variance can nonetheless be added to Eq. 3.46:

$$y(k) = \frac{B(q)}{A(q)} u(k) + \frac{1}{A(q)} w(k) . \quad \text{...............................(3.47)}$$

However, $w(k)$ will be different from the actual noise in the process, $v(k)$. Hence, the error in simulated output, given by $y(k) - y(k)$, will be less in Eq. 3.46 compared to Eq. 3.47.

In the following, the term prediction is used to mean one-step prediction. Unlike simulation, in prediction, information about disturbances in the previous output values can be used in making an estimate of the output at sampling instant k, denoted by $y(k \,|\, k - 1)$. An *optimal predictor* can be designed for prediction as

$$y(k) = t_1 u(k - 1) + t_2 u(k - 2) + ... + t_{n_t} u(k - n_t)$$

$$s_1 y(k - 1) + s_2 y(k - 2) + ... + s_{n_s} y(k - n_s), \quad \text{......................(3.48)}$$

which leads to

$$y(k \,|\, k - 1) = S(q)u(k) + T(q)y(k) . \quad \text{..........................(3.49)}$$

In the ARX model, white noise $v(k)$ filters through $1 / A(q)$ before adding to the output. The function of filter $T(q)$ in Eq. 3.49 is to extracts information about the correlated disturbances $n(k)$ in the past outputs $y(k)$ to predict $y(k \,|\, k - 1)$. For the ARX model, it can be derived that in the optimal predictor $S(q) = B(q)$ and $T(q) = 1 - A(q)$ (Nelles 2001):

$$y(k \,|\, k - 1) = B(q)u(k) + (1 - A(q))y(k) . \quad \text{.........................(3.50)}$$

For the ARMAX model, the optimal predictor is

$$y(k \mid k-1) = \frac{B(q)}{C(q)} u(k) + \frac{C(q)-A(q)}{C(q)} y(k). \quad \text{................(3.51)}$$

For the simplest OE model (Eq. 3.42), white noise adds to the output without any filtering. Hence, the disturbances in the past outputs are uncorrelated or purely random. Because there is no information available about the disturbances in the outputs, the optimal predictor for the simplest OE model is the same as simulation (Nelles 2001):

$$y(k \mid k-1) = \frac{B(q)}{F(q)} u(k). \quad \text{....................................(3.52)}$$

The prediction is based only on previous input values (the calculation also uses the calculated predicted output values at previous time instants). This can seem counter-intuitive at first sight that the previous output values are not included in the optimal predictor. However, for a process in which white noise simply adds to the output, Eq. 3.52 will lead to minimum prediction error.

The error in prediction, $e(k) = y(k) - y(k \mid k-1)$, is called the residual. Consider that for a process, the assumptions of the ARX model are satisfied: white noise enters before the common denominator dynamics $A(q)$ as shown in Fig. 3.4. (Though in reality, if the disturbance enters the process early, it will also have some numerator dynamics. Furthermore, disturbances that directly affect the output are much more common.) Let's say the true process is given by

$$y(k) = \frac{B(q)}{A(q)} u(k) + \frac{1}{A(q)} w(k), \quad \text{.............................(3.53)}$$

$w(k)$ being white noise with mean 0. The identified model of the process is

$$y(k) = \frac{B(q)}{A(q)} u(k) + \frac{1}{A(q)} v(k). \quad \text{.............................(3.54)}$$

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The optimal predictor for the ARX model is

$$y(k\,|\,k-1) = B(q)u(k) + (1-A(q))y(k). \quad \text{.........................(3.55)}$$

The prediction error can be obtained by subtracting $y(k)$ from both the sides of Eq. 3.55 and manipulating the equation:

$$e(k) = y(k) - y(k\,|\,k-1) = A(q)y(k) - B(q)u(k). \quad \text{.................(3.56)}$$

$e(k)$ is the error in prediction based on the process model in Eq. 3.55. When the model equals the process, i.e. $A(q) = A(q)$ and $B(q) = B(q)$, the prediction error

$$e(k) = A(q)y(k) - B(q)u(k). \quad \text{..................................(3.57)}$$

Multiplying Eq. 3.53 by $A(q)$, we see that $e(k) = w(k)$. The residuals $e(k)$ are white.

Hence, **if the assumptions about the process are correct** (in the above example, assumptions are those of the ARX model), **the optimal predictor leads to white residuals**. The whiteness of the residuals is one criterion for a good identified model, i.e. auto-correlation of the residuals $e(k)$ for any non-zero lag Δk is zero. The correlation should lie within some confidence interval around zero. This is the *whiteness test* for an identified model. Along with whiteness test, an identified model should also pass the *independence test*. For any positive lag Δk, there should be no correlation between residual $e(k)$ and input $u(k - \Delta k)$. Presence of a correlation indicates that the identified model doesn't completely describe how input $u(k - \Delta k)$ affects output $y(k)$. Correlation for negative lags doesn't necessarily have to be zero. We refer to Ljung (2012b, pp. 8-25 to 8-26) for a little more elaboration.

We note that for the optimal predictor, for prediction at $t = 0$, a set of initial conditions need to be known: $u(-1)$, $u(-2)$ ... $u(-n_t)$, and $y(-1)$, $y(-2)$ ... $y(-n_s)$. These initial conditions are typically set to zero as the error that is introduced

decays exponentially with time unless the system is unstable (Nelles 2001). In the case of simulation using an identified model (Eq. 3.46), since no information on outputs in used, simulated output can be completely different from the true output if the initial conditions are different. Hence, the initial conditions should be estimated first before using the model for simulation.

Prediction Error Method

For determining the parameters in system identification, very commonly the prediction error is minimized (Nelles 2001). An objective function to be minimized can be defined in terms of the prediction error. For a Gaussian noise (as $v(k)$ is assumed to be in Eq. 3.28), an optimum objective function is the squared sum of errors (Nelles 2001). If measurements are made for N time instants, then for an ARX model with $nb - 1$ zeros and na poles, the prediction errors $e(k)$ can be written in terms of the unknown coefficients as

$$e(k) = A(q)y(k) - B(q)u(k), \quad \text{.................................(3.58)}$$

or

$$e(k) = y(k) + a_1 y(k-1) + a_2 y(k-2) + \ldots + a_{na} y(k-na)$$

$$-b_1 u(k-1) - b_2 u(k-2) - \ldots - b_{nb} u(k-nb), \quad \text{.......................(3.59)}$$

where $k = na + 1,\ na + 2,\ \ldots$ N. (Note that for $k \leq na$, $e(k)$ can't be calculated without knowing initial conditions.). Eq. 3.59 is linear in parameters b_1, b_2, ... b_{nb}, and a_1, a_2, ... a_{na}. Hence, for minimization of the squared sum of error

$$J = \sum_{k=na+1}^{N} e(k)^2, \quad \text{...(3.60)}$$

the least squares technique for linear optimization can be applied. This convenience for calculation of parameters is the reason why ARX is the most widely used linear model. Out of the equation error models and the OE models

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with output feedback (Eqs. 3.42 and 3.43), only the ARX model is linear in parameters. The ARMAX model, e.g., has the following prediction error, which can be derived by subtracting $y(k)$ from both the sides of Eq. 3.51 and manipulating the equation:

$$e(k) = y(k) + a_1 y(k-1) + a_2 y(k-2) + \ldots + a_{na} y(k-na)$$

$$-b_1 u(k-1) - b_2 u(k-2) - \ldots - b_{nb} u(k-nb)$$

$$-c_1 e(k-1) - c_2 e(k-2) - \ldots - c_{nc} e(k-nc). \quad \text{.....................(3.61)}$$

Since the prediction error $e(k)$ depends on the previous prediction errors—$e(k-1)$, $e(k-2)$, ...—the equation is "pseudo-linear" in parameters and requires either nonlinear optimization or some form of an iterative optimization approach (Nelles 2001). On the contrary, the OE model in Eq. 3.42—which along with the ARX and ARMAX models is amongst the most commonly used linear dynamic models (Nelles 2001)—is nonlinear in its parameters. The nonlinearity arises from the fact that output prediction at time instant k, $y(k)$, depends on the following terms containing previous output predictions, $f_1 y(k-2)$, $f_2 y(k-2)$, ..., as can be seen in Eq. 3.52. f_1, f_2, ... are the parameters in polynomial $F(q)$.

Apart from minimizing a one-step prediction, an *l*-step prediction error could also be minimized for identifying a model. This can be necessary, e.g., when the model will be used for MPC with a prediction horizon P. In this case, it is best to minimize the prediction error P steps ahead. However, as the prediction horizon increases, estimation of parameters become more computationally involved and hence, even for MPC application, usually one-step prediction is minimized (Nelles 2001). Further, parameter estimation can also be done focusing solely on model simulation.

Since most processes in reality satisfy the noise assumption of the OE model in Eq. 3.43, identification of an ARX model usually leads to a biased and non-

consistent (see Section 3.1 for the definitions of biased and non-consistent estimators) estimation of model parameters. Different approaches exist to correct for the non-consistent estimation, including alternatives to the prediction error methods described above (Nelles 2001). Despite these troubles, the ARX model is widely used because of its predictor properties, given the disturbances are small enough. The ARX predictor is stable as it has no feedback (prediction error $e(k)$ doesn't depend on the previous prediction errors). Hence, the ARX predictor remains close to the process output even if the process itself is unstable. In contrast, the simple OE predictor in Eq. 3.52 will result in increasing prediction errors with time if the noise assumptions aren't satisfied or the process dynamics aren't completely modeled (due to the nonlinear behavior of the process).

3.6. Input Excitation for Identification

For system identification, the input-output data should contain relevant information about the dynamics of the process if a representative model has to be identified (Nelles 2001). Let's say, for a single-input single-output first-order process, the process is in its steady state and the input and output are constant. Using this data (and given that some other set of nominal steady-state conditions are known), only one parameter, the gain of the process, can be accurately known as the data contains no information about the unsteady-state behavior of the process. For system identification, the only way to properly excite the dynamics is through the input signal. Hence, the choice of an input signal is very important in system identification.

Because processes in reality exhibit certain degree of nonlinearity, a fundamental principle for input design is that for choosing the frequency contents of the input signal, the intended use of the model should be considered (Huang 2012; Nelles 2001). The power spectrum of a signal shows how the power (which corresponds to variance) of the signal is distributed over a range of frequencies contained in

the signal. The identified model will be of a higher quality for those frequencies that are strongly excited by the input signal compared to other frequencies. If the input signal is a sine wave, then the model will have a very good performance at the frequency of the sine wave used while compromising its quality at other frequencies. If only a set of frequencies are important for model identification, then an addition of sine wave having exactly those frequencies is the best choice for an input signal. If the modeling effort focuses on steady-state operating conditions, then very low frequencies in the input signal are enough. In fact, if only steady-state gain needs to be known, then a step input is the ideal choice as it leads to an excellent estimation of the gain.

If the model will be used in a controller, as in MPC, it should especially be accurate around the *Nyquist frequency*. (In angular terms, radians per unit time, Nyquist frequency is given by π / T_s, where T_s denotes the sampling interval length. Nyquist frequency is thus half of the sampling frequency at which control actions will be implemented.) For the sampling interval, a rule of thumb in system identification is to use a sampling interval of one-tenth to one-fifth the time constant, τ, of the process (Huang 2012). Using a larger sampling interval neglects the high frequency dynamics and requires a longer estimation time. A much smaller sampling interval poses control related and other practical problems. (Also, it is interesting to note that since models structures used for identification, like the ARX model, are only approximations of reality, using a very high sampling frequency (i.e., a very small sampling interval) nevertheless leads to large errors in the high frequency range (Nelles 2001)). Regarding the frequencies in the input signal, for a first-order liner system, a rule of thumb is to use a bandwidth from 0 to p / τ, where $p > 1$. A value from 2 to 3 is considered enough for p. In the System Identification Toolbox[TM] (Ljung 2012a, 2012b) in MATLAB, the function *idinput* (see below) is used to design input signals with specific amplitudes and bandwidth. The function takes the bandwidth of the signal as one of the input arguments. One way the bandwidth is defined for using *idinput*

is by expressing it as a fraction of the Nyquist frequency. In terms of a fraction of the Nyquist frequency, the bandwidth recommended above for input signal design for system identification then is 0 to $pT_s / \pi\tau$ (Huang 2012).

As explained in Sections 3.1 and 3.2, the effect of disturbances in a process appear in the output $y(k)$ as noise $n(k)$. For a good model of the process to be identified, the signal-to-noise power ratio should be maximized. Since noise $n(k)$ itself can't be influenced, the only opportunity to affect the signal-to-noise ratio is the input signal. The process will have certain limits on the input, a minimum (u_{min}) and a maximum (u_{max}). The input signal should be varied in this whole range to maximize its power (Nelles 2001). However, in reality, if the plant is in operation, the input can't be varied a lot from its optimized value in order because of process efficiency etc. Further, the plant can't be pushed to its limits because of safety concerns. However, within these constraints, the guidelines of system identification should be followed. Very nonlinear processes have a different consideration (Huang 2012). If a linear dynamic model is identified for a very nonlinear process, it will be accurate around the operating point at which it is identified. The linear model, in other words, linearizes the nonlinear process around that operating point. Hence, the input amplitude for system identification should be relatively small in such a case. A larger magnitude will improve the signal-to-noise ratio, but will introduce more error into the identified linear model.

A signal suitable for identification is the random binary signal (RBS). The input moves between two levels in a random manner. All frequencies are equally excited in a given bandwidth. Fig. 3.5 shows a pair of input and output in the case of a dual tubing string SAGD well operation. The input, short-tubing string injection rate, is an RBS signal with a bandwidth of 0–0.063, expressed as a fraction of Nyquist frequency, corresponding to $p = 2$, $T_s = 0.25$ day and $\tau = 2.5$ days. A pseudorandom binary signal (PRBS) looks similar to an RBS

signal and is statistically random; however, as the name suggests, it is generated by a completely deterministic process.
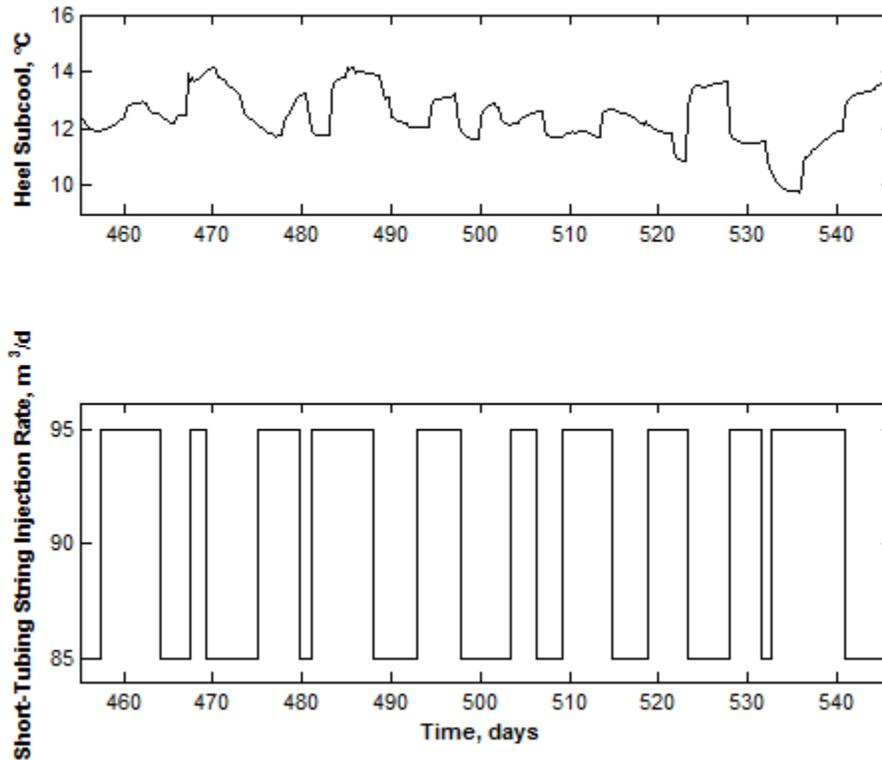
Fig. 3.5: Example of an RBS signal.

These signals can be generated by the function *idinput* in the System Identification Toolbox. It has the following syntax: $u = idinput(N, type, band, levels)$. When N is a scalar, the signal generated, u, has N discrete regular time intervals; hence u is a column vector with N entries. The argument *type* for defining the type of signal can be *'rbs'* or *'prbs'*, among other options. The argument *band* is a row vector with two entries: the lower and upper bounds of the input signal's bandwidth. The two frequencies are expressed as fractions of Nyquist frequency for signal type *'rbs'*. The argument *levels* is a row vector with two entries that specifies the lower and the higher levels of the input

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signal. For signal type *'prbs'*, a scalar *N* and given *band* and *levels*, *idinput* generates the same signal every time.

Söderström and Stoica (2001, pp. 96–100) describes commonly used input signals for system identification.

4. Simulation Study: Models and Procedure

4.1. Numerical Models

We study the scope of real-time feedback control for production optimization of SAGD using a *synthetic reservoir* (we will be using *synthetic reservoir* interchangeably with *reservoir* from here) having a pair of dual tubing string wells. The synthetic reservoir is a heterogeneous 3D reservoir model built in the thermal reservoir simulator STARS$^{®}$, version 2013.10 (STARS 2013). Also, two 3D *reservoir models*, picked from an ensemble of 100 porosity and permeability realizations, are considered as two different cases of an uncertain reservoir model used in reservoir management to evaluate production plans. The two reservoir models are used to find the optimum injection and production rates for SAGD (see Section 4.3). The subcool calculated from the reservoir models corresponding to these optimum rates gives the set points for real-time production optimization of SAGD in the reservoir using MPC. Section 1.4 explains this multilevel optimization and control framework in more details.

The two reservoir models have a $32 \times 28 \times 25$ ($I \times J \times K$) cartesian grid. The model dimensions are $42 \text{ m} \times 1000 \text{ m} \times 26 \text{ m}$. In the I direction, the grid block lengths are 3 m, 23 blocks of 1 m and 8 blocks of 2 m. In the J direction, the grid consists of 2 blocks of 50 m, 30 m, 2 blocks of 10 m, 20 blocks of 35 m, 3 blocks of 50 m. (There are 2 blocks of 10 m in the middle so that the tubing string lengths could be kept identical in the reservoir models and synthetic reservoir; see grid dimensions of synthetic reservoir below and Section 4.2.). In the K direction, the model is divided into 2 blocks of 1 m, 1.5 m, 4 blocks of 1 m, 1.5 m, 17 blocks of 1 m. Wells are in the layers $k = 3$ and $k = 8$ in blocks with $i = 1$, the top

well an injector and bottom a producer for SAGD. Both these well extend from $j = 4$ to $j = 25$. Hence, the total well length is 720 m. The models are symmetry elements constituting half of the actual reservoir volume. The plane of symmetry passes through the middle of the $i = 1$ blocks. To model the symmetry element correctly, the FRAC keyword in STARS is used so that the well indices and rates are internally halved by the simulator. Further, the $i = 1$ blocks (and the refined blocks within these blocks; see Section 4.2) are halved by using the VAMOD keyword.

The reservoir model properties were sourced from Gates and Chakrabarty (2006), who choose properties to reflect a low to medium quality Athabasca reservoir. Average horizontal permeability is around 4200 md and average porosity is around 0.22. Vertical to horizontal permeability ratio is 0.25. The endpoint data for gas-liquid and oil-water relative permeability tables used in the models are given in Table 4.1. Three phase relative permeability is calculated using Stone's Model II (STARS 2013). A bitumen viscosity table was generated using the empirical linear viscosity model developed by Khan et al. 1984. The reservoir models don't have any water/gas zones. Other parameter values for the models are summarized in Table 4.1.

Table 4.1: Fluid and Rock Properties used in simulation models.

Property	Value
Initial Reservoir Pressure	1700 kPa at reference depth, reference depth is 500 m at the center of blocks $k = 25$
Initial Reservoir Temperature	11°C
Average Horizontal Permeability	4200 md
Average Vertical Permeability	1100 md
Average Porosity	0.22
Irreducible Oil Saturation for Water Injection, S_{oirw}	0.20
Irreducible Water Saturation, S_{wcon}	0.20
Residual Oil Saturation for Gas Injection, S_{org}	0.005
Connate Gas Saturation, S_{gcon}	0.05
Relative Permeability to Oil at Connate Water and Zero Gas Saturation, k_{rocw}	0.992
Relative Permeability to Water at $S_w = 1 - S_{oirw}$ in the Water/Oil Table, K_{rwiro}	0.1
Relative Permeability to Gas at Connate Liquid, K_{rgcw}	1
Molecular Weight of Bitumen Component	480 g/mol
Methane Liquid Component Viscosity, $\mu_L = avisc \times \exp(bvisc/T_{abs})$	$avisc$ = 0.000974 cp, $bvisc$ = 3696.1 K
Bitumen Liquid Component Viscosities, $\ln \ln \mu(cp) = A + B\ln T_{abs}$	A = 22.815, B = -3.5784
Methane K-value Correlation, $K = \dfrac{k_{v1}}{P}e^{\frac{k_{v4}}{T+k_{v5}}}$	k_{v1} = 5.4547×10^5 kPa, k_{v4} = −879.84°C, k_{v5} = −265.99°C

Bitumen Thermal Conductivity	1.15E+04 J/(m.d.$^{\circ}$C)
Rock Thermal Conductivity	6.6E+05 J/(m.d.$^{\circ}$C)
Rock Heat Capacity	2.6E+06 J/(m^3.$^{\circ}$C)
Overburden Thermal Conductivity	6.6E+05 J/(m.d.$^{\circ}$C)
Overburden Heat Capacity	2.6E+06 J/(m^3.$^{\circ}$C)

To select the two reservoir models, we create 100 porosity and permeability realizations using Gaussian simulation conditioned to synthetic wellbore data. The porosity and permeability statistics are kept similar to that in the 2D model used in Gates and Chakrabarty (2006). To do that, we create three geological units with distinct porosity/permeability statistics. Average porosity and permeability increase from the bottom geological unit (layer $k = 1$ and $k = 4$) to the top geological unit (layers $k = 11$ and $k = 25$). The hundred realizations were simulated for 6 years and 7 months using nominal well constraints and ranked using NPV. Fig. 4.1 shows the NPV histogram. From the distribution, the P10 and P80 realizations form the two reservoir models used in the study. Fig. 4.2 shows the I-direction permeability values in J-K plane containing the wells ($i = 1$) for the P10 reservoir model. Fig. 4.3 shows the full 3D model. In Figs. 4.2 and 4.3, the scale along the well direction is smaller by a factor of 17 compared to the perpendicular directions to conveniently show the entire grid dimension in the well direction.
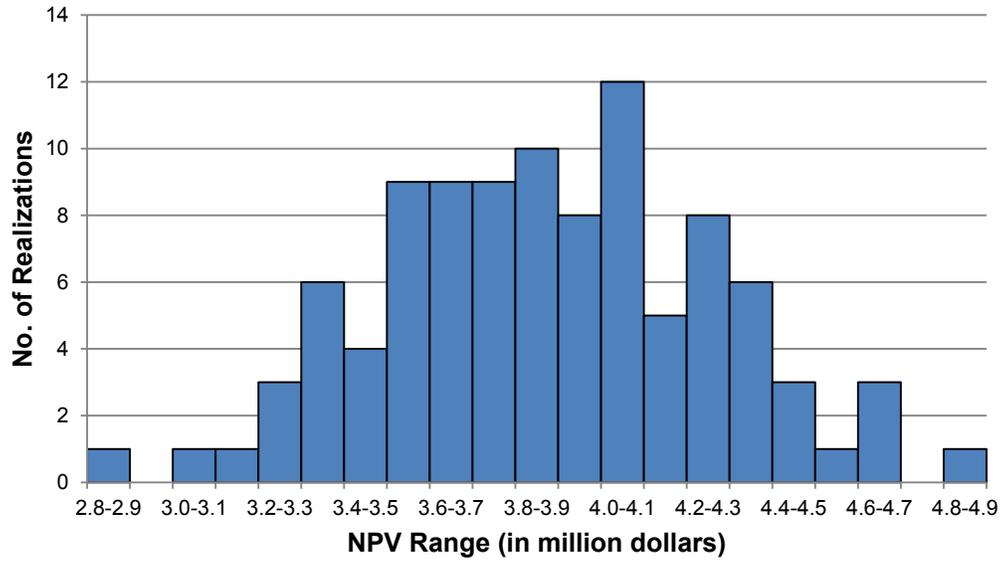
Fig. 4.1: NPV histogram for the 100 realizations used to select P10 and P80 reservoir models.
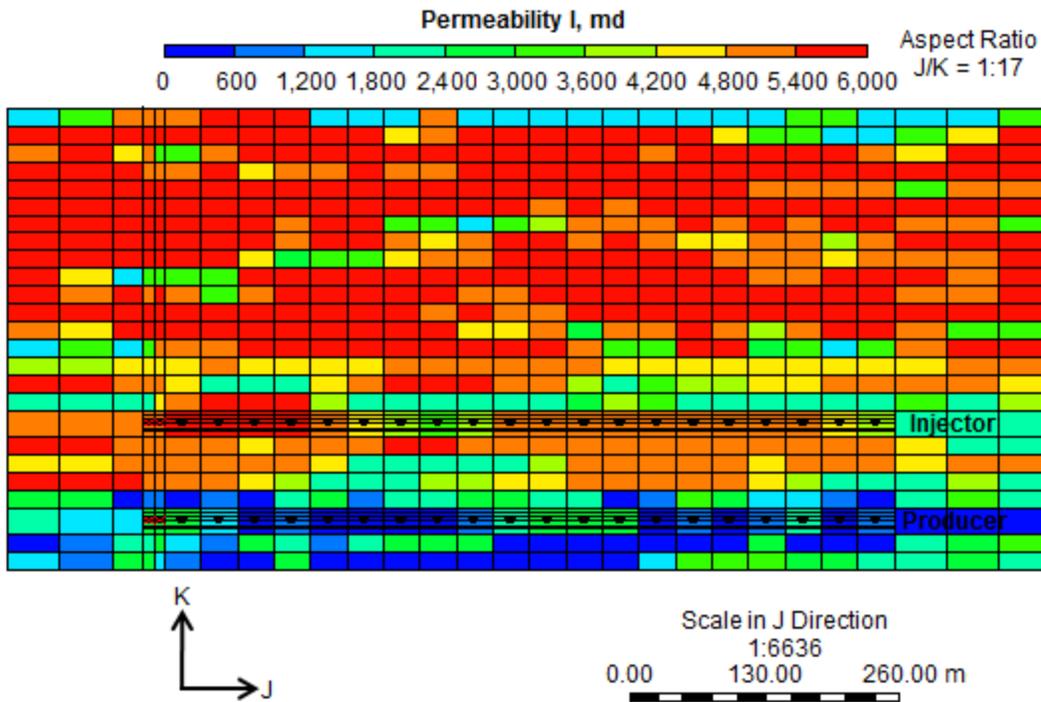
Fig. 4.2: *J-K* cross section of P10 reservoir model containing the wells. The map shows *I*-direction permeability values of the grid blocks in millidarcies.
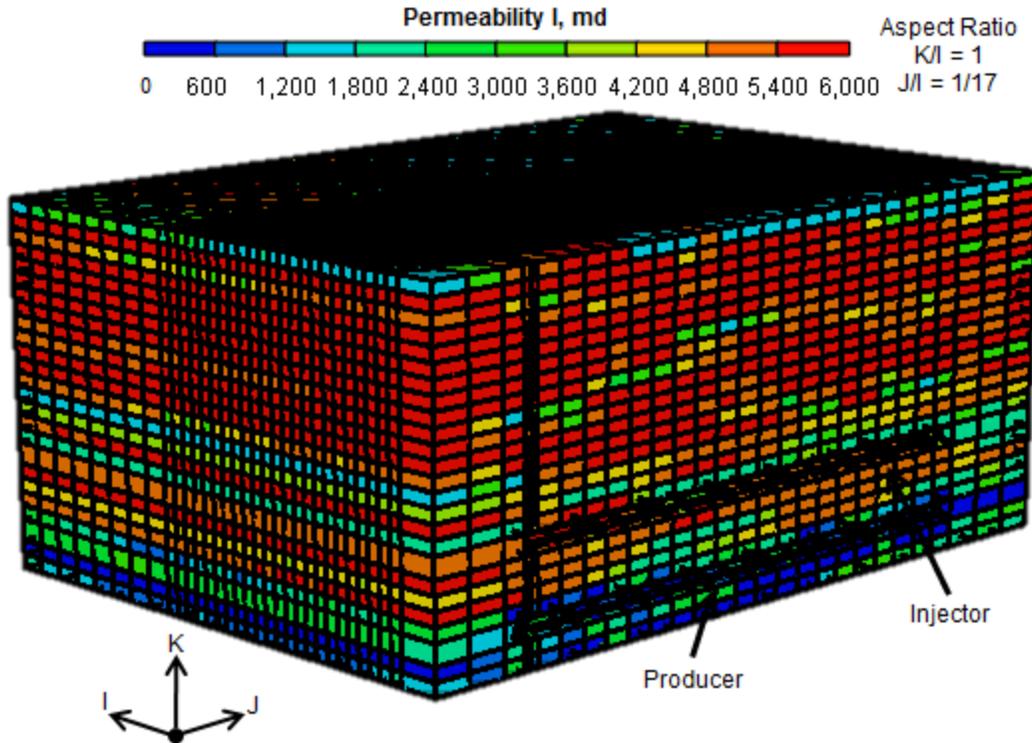
Fig. 4.3: The P10 reservoir model showing the *I*-direction permeability values.

The synthetic reservoir used in the study is selected from a separate ensemble of 23 realizations conditioned to the same wellbore data as the 100 realizations used for the reservoir models. However, these 23 realizations are different in that the grid block dimensions in *J* direction are smaller. In *J* direction, the grid divided into 15 blocks of 10 m, 40 blocks of 17.5 m and 15 blocks of 10 m. So it's a $32 \times 70 \times 25$ ($I \times J \times K$) Cartesian grid. In the new coordinates, the injector and producer extend from $j = 14$ to $j = 55$ in layers $k = 3$ and $k = 8$ respectively. (Well locations are identical with the reservoir models.) The 23 realizations are ranked based on their NPV (when simulated using nominal well constraints) and the synthetic reservoir is chosen approximately as the P60 realization. The synthetic reservoir is also different from the reservoir models in that a smaller maximum time step size of 0.1 day is used compared to 0.25 day for reservoir model. The synthetic reservoir also has convergence tolerance for material balance error $1/10^{th}$ of the reservoir model. These differences are created to

replicate the differences between reservoir model predictions and real field performance in reality, and to be able to judge the performance of MPC in mitigating the uncertainty in reservoir models.

4.2. Well Configuration and Modeling

Long horizontal wells used in SAGD lead to non-uniform temperature profile and steam flow along the wellbore because of the combined effects of reservoir heterogeneity, frictional pressure drop and heat losses by conduction. The accuracy with which these effects and the dynamic nature of SAGD are captured by simulation models depends on the use of accurate well models. We model the wells in our simulation study as Flexible Wellbores in STARS, which is an advanced well modeling capability that discretizes the wellbore and solves the wellbore equations simultaneously with the reservoir equations. This feature in STARS allows modeling of up to three tubing strings inside an annulus. Packers and ICDs/OCDs can also be included.

Further, as noted before, the wells in the simulation study have a dual tubing string configuration. The dual tubing string in injector enables control of steam injection into the heel and toe ends of the well, and the dual tubing string in producer enables a differential steam trap control at the two ends of the well.

Also, the well containing blocks are refined into hybrid grid blocks. Each of these blocks has 3 radial and 4 angular divisions to accurately model fluid flow around the wellbore. The innermost radial division contains the well; the innermost block doesn't have any angular divisions.

The well dimensions that we use are summarized in Table 4.2. Other properties related the wells including heat capacity and thermal conductivity of the wells, relative roughness for pressure drop calculations and the maximum Nusselt number allowed for heat transfer calculation are set to their defaults in STARS.

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Table 4.2: Well dimensions used in our simulation study.

Parameter	Value
Horizontal Well Length	720 m
Liner Location	j = 4 to j = 25 in Reservoir Models j = 14 to j = 55 in Synthetic Reservoir
Liner Perforations	j = 6 to j = 25 in Reservoir Models j = 16 to j = 55 in Synthetic Reservoir
Short Tubing String Location	j = 4 to j = 5 in Reservoir Models j = 14 to j = 15 in Synthetic Reservoir
Long Tubing String Location	j = 4 to j = 25 in Reservoir Models j = 14 to j = 55 in Synthetic Reservoir
Packer Location	j = 5 in Reservoir Models j = 15 in Synthetic Reservoir
Liner ID/OD	0.219 m/0.241 m
Cement Thickness	0 m
Tubing ID/OD	0.076 m/0.089 m

4.3. Model-Based Optimization of Well Rates

For the P10 and P80 reservoir models, we use CMOST®, version 2012.10 (CMOST 2012), for optimizing the well rates in SAGD production phase. CMOST's DECE (Designed Exploration and Controlled Exploration) optimization method is used (Yang et al. 2009). DECE combines experimental design technique with an evolutionary algorithm to find the optimum parameter values from the given candidate values.

Complete simulation period consists of 4 months of circulation phase, from January to April 2013, and 6 years and 8 months of SAGD production phase,

from May 2013 to December 2019. The first 8 months of the production phase are left out of optimization because of the relatively long simulation run times for this period. The results for RTO using MPC that we report in this thesis also only concern the remaining 6 years of production from 2014 to 2019. In the two reservoir models, for the production phase, the short and long tubing strings in the injector have the maximum steam injection rate in Cold Water Equivalent (CWE) as the primary well constraint. Further, a secondary well constraint of maximum injection pressure of 9000 kPa is used. (Note that the simulator tries to operate a well so that its primary constraint is satisfied; if it can't be satisfied because a secondary constraint is being violated, then that secondary constraint is used for operating the well.) The short and long tubing strings in the producer have the maximum steam production rate as their primary constraint. In STARS, a maximum steam production rate constraint specifies the total volume of water phase that is produced as vapor under downhole conditions, expressed in CWE. Secondary constraints used for the producer strings are a minimum BHP of 102 kPa and maximum production rate of 300 m^3/d of STL.

In CMOST, we specify the primary constraint values for injector and producer as the optimization parameters. The different optimization intervals are January–June 2014 (2014-1), July–December of 2014 (2014-2), January–June 2015 (2015-1), July–December 2015 (2015-2), January–June 2016 (2016-1), July–December (2016-2), 2017, 2018 and 2019. Within each of these optimization intervals, the values of optimization parameters remain constant for optimization. (Note that for the first 8 months of SAGD production, the primary well constraints are fixed at 90 m^3/d and 70 m^3/d steam injection rates in CWE for short and long tubing strings respectively in the injector and 1 m^3/d and 7 m^3/d maximum steam production rates in the short and long tubing strings respectively in the producer. The same constraints are also used for the wells in synthetic reservoir for this period.) The candidate values (these are the values that CMOST will try) for optimization parameters in each optimization interval are chosen based on the

pressures observed during SAGD production in test simulations and the general trend of optimized rates found in the works of Gates and Chakrabarty (2006) and Yang et al. (2011). Gates and Chakrabarty (2006), who used a heterogeneous 2D model, used a genetic algorithm to optimize steam injection pressures in 13 time intervals over a total SAGD simulation period of 6 years. (At the producer, the steam trap constraint in STARS was used, and a steam trap subcool of 5°C was implemented). In the optimized profile that they found, shown in Fig. 4.4, injection pressure was high at the beginning of SAGD production phase, when all the heat is going to the bitumen formation. The pressure peaked again just before the steam chamber hit the overburden, which according to the authors of the work can be thought of as "overcoming thermal inertia". After hitting the overburden, as the steam chamber laterally expanded, the pressure continuously decreased to reduce heat losses to the overburden. Yang et al. (2011), who used a 2D model with three well pairs, also found a similar injection profile from optimization. They used a maximum pressure constraint for the injector and maximum steam rate constraint for the producer, both of which were optimized.
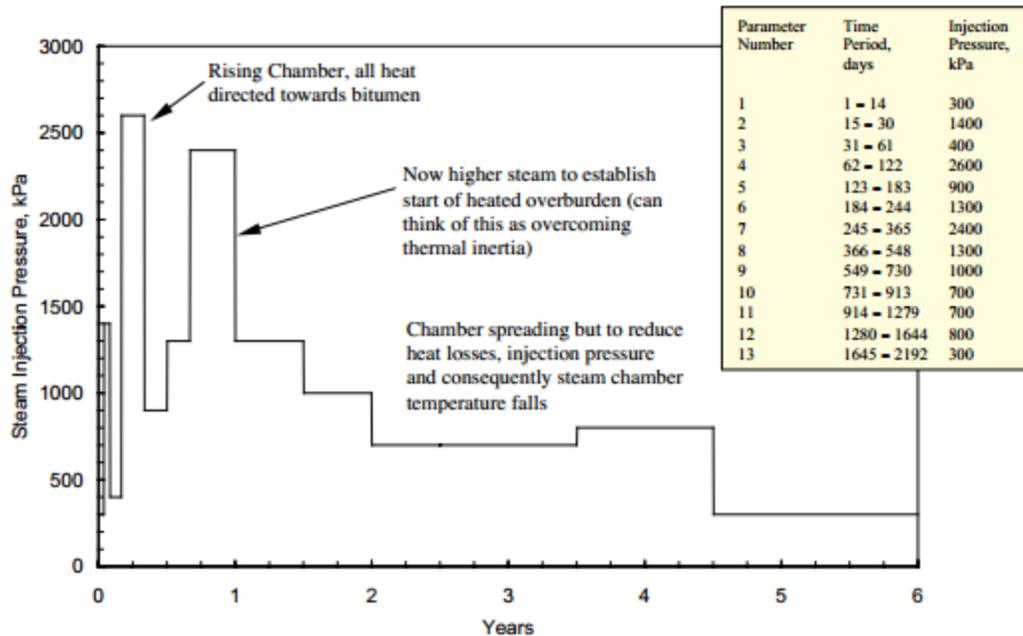
Fig. 4.4: Optimum steam injection pressures in 13 time intervals for the 2D model used in Gates and Chakrabarty (2006).

The candidate values that we use in this work for the optimization parameters in each optimization interval in the case of P10 reservoir model are shown in Table 4.3. Table 4.4 shows the values for P80 reservoir model. The optimized values found by CMOST are underlined in the two tables. The P10 model was the first to be optimized. The optimum values found in the P10 case helped us in choosing a more narrow range of candidate values for the optimization parameters in P80 case. The range of candidate values for an optimization parameter was approximately centered around the optimum value found in the P10 case. As a result, as can be seen in the figures in the next section, the results of CMOST optimization in the P80 case are better than the P10 case.

Table 4.3: Candidate values for optimization using P10 reservoir model. Optimum values found by CMOST are underlined.

Optimization Parameters	Optimization Intervals								
	2014-1	**2014-2**	**2015-1**	**2015-2**	**2016-1**	**2016-2**	**2017**	**2018**	**2019**
Heel Injection Rate (m³/d)	70 80 <u>90</u> 100 110 120	70 80 <u>90</u> 100 110 120	<u>70</u> 80 90 100 110 120 140	70 80 90 <u>100</u> 110 120 140	70 80 90 <u>100</u> 120 140 150 160	70 80 90 100 120 <u>140</u> 150 160	50 60 70 80 90 <u>100</u> 120	<u>50</u> 60 70 80 90 100	<u>40</u> 50 60 70 80 90 100
Toe Injection Rate (m³/d)	70 80 <u>90</u> 100 110 120	70 80 90 <u>100</u> 110 120	70 <u>80</u> 90 100 110 120 140	70 <u>80</u> 90 100 110 120 140	<u>70</u> 80 90 100 120 140 150 160	70 80 90 100 120 <u>140</u> 150 160	50 60 <u>70</u> 80 90 100 120	50 60 70 <u>80</u> 90 100	40 <u>50</u> 60 70 80 90 100
Heel Maximum Steam Rate Constraint Value (m³/d)	1 1.5 2 2.5 3 <u>4</u> 5 7	1 1.5 2 2.5 3 <u>4</u> 5 7	1 1.5 2 2.5 3 <u>4</u> 5 7	1 1.5 2 2.5 3 <u>4</u> 5 7	1 1.5 2 <u>2.5</u> 3 4 5 7	1 1.5 2 2.5 3 4 5 7	1 1.5 <u>2</u> 2.5 3 4 5 7	1 1.5 2 2.5 3 4 <u>5</u> 7	1 1.5 2 2.5 <u>3</u> 4 5 7
Toe Maximum Steam Rate Constraint Value (m³/d)	<u>2.5</u> 3 4 5 6 6.5 7 7.5 8	2.5 3 4 <u>5</u> 6 6.5 7 7.5 8	2.5 3 4 5 6 6.5 <u>7</u> 7.5 8	2.5 3 4 <u>5</u> 6 6.5 7 7.5 8	2.5 3 4 5 <u>6</u> 6.5 7 7.5 8	2.5 3 4 <u>5</u> 6 6.5 7 7.5 8	2.5 3 4 5 6 6.5 7 <u>7.5</u> 8	2.5 3 4 5 6 6.5 7 <u>7.5</u> 8.0	2.5 3 4 5 6 <u>6.5</u> 7 7.5 8

Table 4.4: Candidate values for optimization using P80 reservoir model. Optimum values found by CMOST are underlined.

Optimization Parameters	Optimization Intervals								
	2014-1	**2014-2**	**2015-1**	**2015-2**	**2016-1**	**2016-2**	**2017**	**2018**	**2019**
Heel Injection Rate (m³/d)	70 80 90 100 110 120	70 80 90 100 110 120	50 60 70 80 90 100	80 90 100 110 120 130	80 90 100 110 120	120 130 140 150 160	80 90 100 110 120	40 50 60 70	40 50 60
Toe Injection Rate (m³/d)	70 80 90 100 110 120	80 90 100 110 120 130	60 70 80 90 100 110	60 70 80 90 100 110	50 60 70 80 90	120 130 140 150 160	50 60 70 80 90	60 70 80 90 100	40 50 60 70
Heel Maximum Steam Rate Constraint Value (m³/d)	2 3 4 5	2 3 4 5	2 3 4 5	2 3 4 5	1 2 3 4	1 2 3 4	1 2 3 4	3 4 5 6	2 3 4 5
Toe Maximum Steam Rate Constraint Value (m³/d)	1 2 3	4 5 6 7	5 6 7 8	4 5 6 7	5 6 7 8	4 5 6 7	5 6 7 8	5 6 7 8	5 6 7 8

For the P10 reservoir model, optimized cSOR is found to be 3.34. For the P80 model, it is 2.97.

4.4. Economic Parameters for Optimization

We use NPV as the objective function for optimization of well rates in the reservoir models using CMOST. Calculation of NPV involves the discounting of daily cash flow over a period of time. We use the following simple formula for its calculation:

$$NPV = \sum_{t_1}^{t_N} \frac{Q_o r_o - Q_w r_w}{(1+D)^{t_k - t_{ref}}} . \qquad ....(4.1)$$

Here, t_1 is the starting time for calculating cash flow in days, t_N is the ending time in days. Q_o is the oil produced in a day, r_o is the oil price, Q_w is the steam injected in CWE in a day, r_w is the steam generation cost and D is the discount factor. t_k goes from t_1 to t_2. t_{ref} is the time to which all cash flow is discounted . For the reservoir models, NPV is calculated from 01-01-2014 to 01-01-2020. Cash flow is discounted to the start of 2014. Oil price used is 8 $/bbl and steam generation cost is fixed at 50 $/bbl CWE. A discount factor of 0.1 a year is used.

Fig. 4.5 shows the CMOST objective function evaluations (the jobs) for the P10 reservoir model. Fig. 4.6 shows the objective function evaluations for the P80 reservoir model. Each job is a simulation of the reservoir model for the optimization period (6 years from 2014 to 2019) using a given set of optimization parameter values. Simulation of the 6 years of production roughly took between 1 hour and 1.5 hours (considering the fact that in the two CMOST runs, we ran two jobs concurrently most of the time). Further, a job restarts from a previous job, instead of simulating the whole 6 years, if an initial set of optimization parameters values being used for the job is identical to that of the previous job, which helps cut the simulation time. Certain jobs in the CMOST runs, which took an unusually large time to simulate, were terminated when the run time reached a set maximum amount (as many as 8 hours). Objective function isn't evaluated for these jobs. In the P10 case, the CMOST run consisted of a total of 1452 jobs and lasted a little more than 3.5 months with an Intel$^®$ Core^{TM} i7-2600 3.40 GHz processor and 12 GB RAM, whereas in the P80 case, 1476 jobs needed around 3 months.
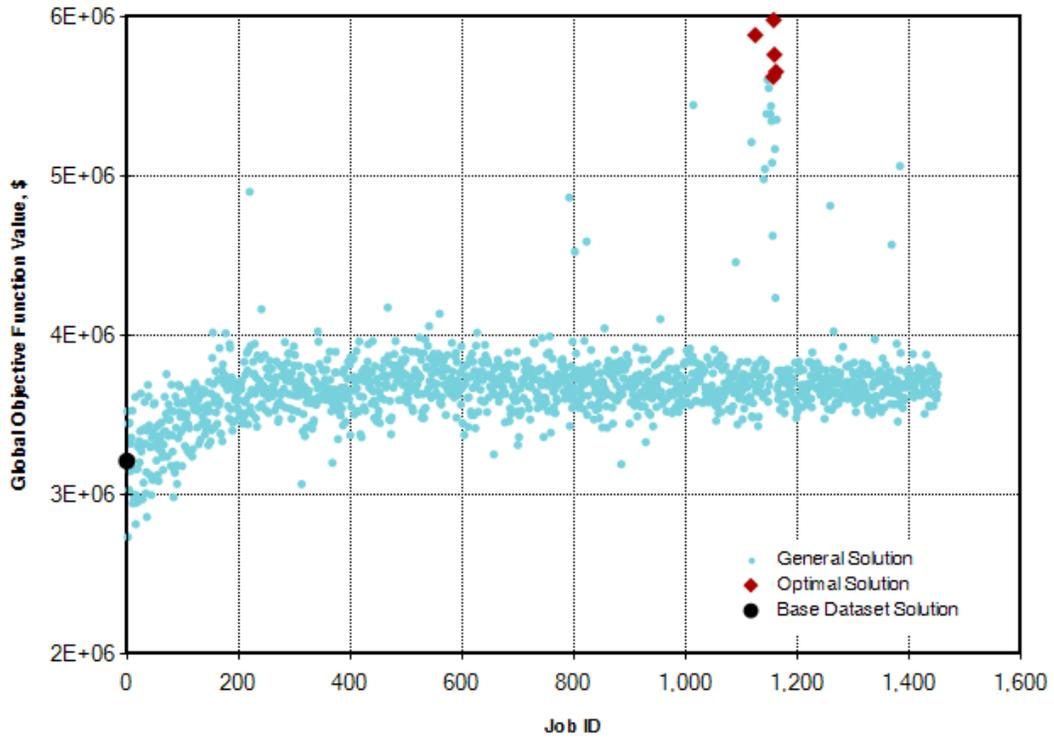
Fig. 4.5: Evolution of objective function (in dollars) in CMOST for the P10 reservoir model. Objective function value is plotted along y-axis, and job number is along x-axis.
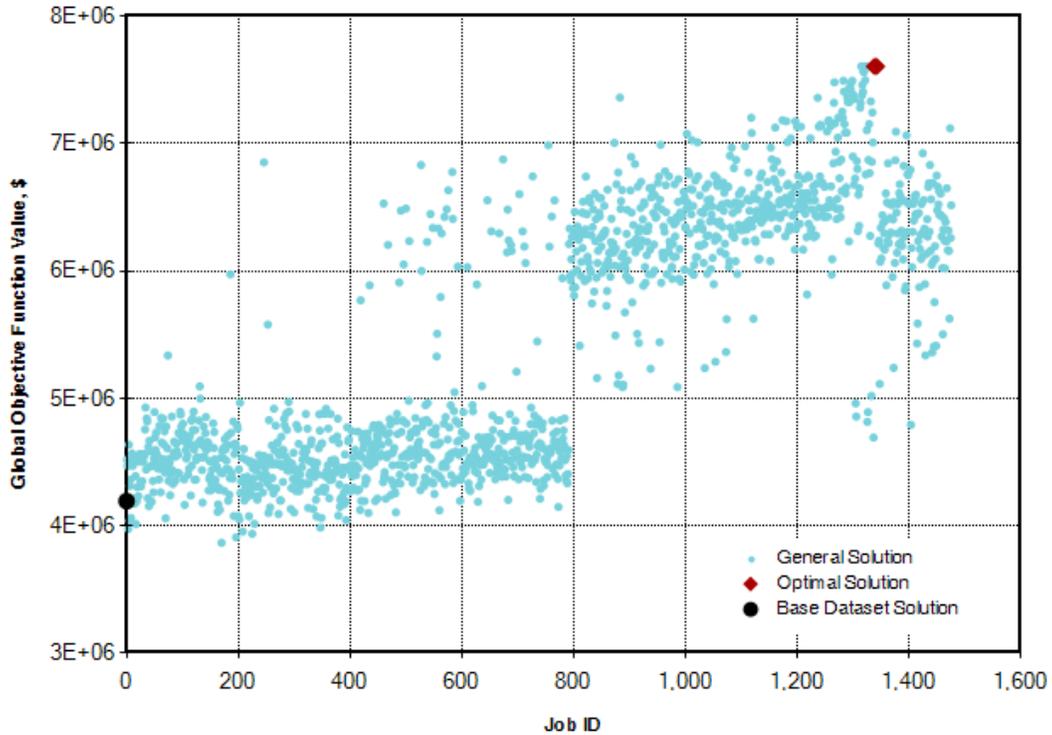
Fig. 4.6: Evolution of objective function (in dollars) in CMOST for the P80 reservoir model. Objective function value is plotted along y-axis, and job number is along x-axis.

4.5. Interwell Subcool Control

(In the remainder of the thesis, we refer to the short-tubing string rates in a dual tubing string well as heel rates and the long-tubing string rates as toe rates for the sake of brevity.)

A workflow created in MATLAB integrates STARS, Results Report®, version 2013.10 (Results Report 2013), the System Identification Toolbox and the Model Predictive Control Toolbox to control the subcool along SAGD well pair in synthetic reservoir. The inputs that are manipulated for controlling the process are the heel/toe steam injection and oil production rates. Hence, these (the heel and toe rates) are used as the primary well constraints in the synthetic reservoir

created in STARS (the secondary well constraints remain the same as the reservoir models). To control subcool along the well pair, the primary well constraint values in synthetic reservoir are changed every sampling interval to reflect the rates calculated by the MPC controller. (We note that instead of the oil production rate, total production rate would have been a better choice for input because in practice, choke settings are varied to control the production rate.)

The controlled variables are the heel subcool and the toe subcool. For control purpose, the heel subcool in synthetic reservoir is defined as the average of temperatures in the innermost hybrid refined blocks in the injector well blocks from $j = 16$ to $j = 35$ (i.e., the heel half of the well pair after the packer) less the average of temperatures in the corresponding innermost hybrid refined blocks in the producer well blocks. Toe subcool is defined similarly based on the well blocks from $j = 36$ to $j = 55$ (i.e., the toe half of the well pair after the packer). The heel subcool and toe subcool set points for MPC are calculated from the reservoir models for the same well intervals ($j = 6$ to $j = 15$ for heel subcool and $j = 16$ to $j = 25$ for toe subcool in the two reservoir models).

Fig. 4.7 shows how the MATLAB workflow used for identification and control in our simulation study works.
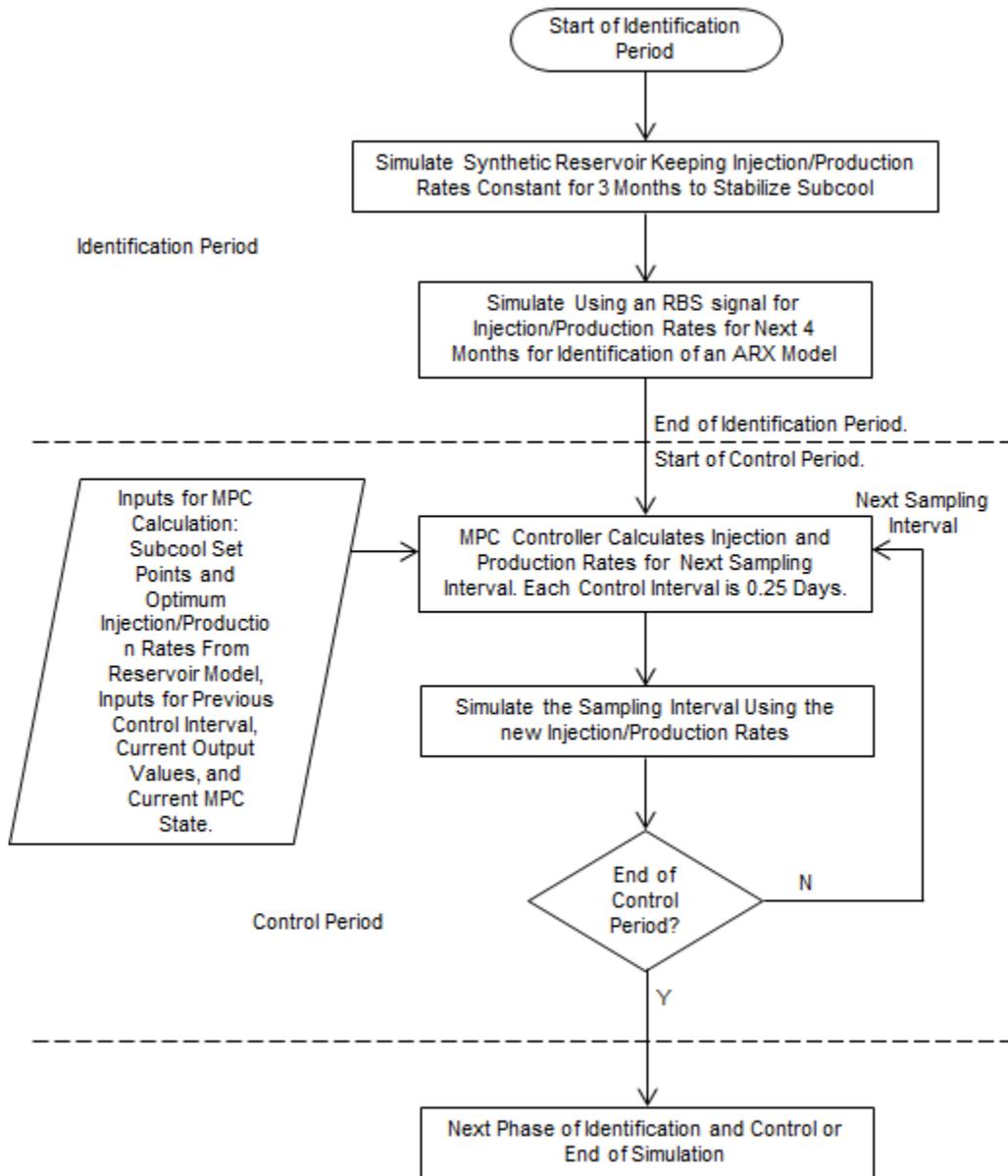
Fig. 4.7: A schematic representation of the MATLAB workflow used for identifying linear models and controlling the SAGD wells in synthetic reservoir.

Because SAGD is a time-varying process, multiple identification periods are required for the system identification model to correctly represent the input-output relationships, which is necessary for a stable control performance. In our simulation study, we demarcate two *identification plus control periods*—the first such that it is roughly till the point in time when the steam chamber hits the

overburden and the second, after this event—each consisting of a control period preceded by an identification period based on which an ARX model is identified, which is then used for MPC of subcool along the well pair in reservoir. We chose the ARX model because there is no disturbance in our synthetic process—SAGD in the synthetic reservoir. The signal-to-noise ratio is zero and this allows us to use the simple ARX model rather than a more complex linear dynamic model structures like the BJ model, in which the disturbance dynamics are modeled fully independently of the process dynamics.

In both the P10 and P80 reservoir model cases, the first identification plus control period is the first three years from 2014 to 2016, and the second is the latter three years from 2017 to 2019. We choose the second identification plus control period to start from 2017 based on the optimum rate profiles for the reservoir models. As can be noted from Table 4.3 and Table 4.4 as well as the figures in Chap. 5, the optimum injection rates peak in the second half of 2016, which signifies that the steam chamber hits the overburden in this period. Starting the second identification plus control period after the steam chamber hits the overburden ensures that the rates are more similar for the period. That way, an ARX model identified in the beginning of the period will have a better predictive ability over the whole period.

The only difference between the P10 and P80 reservoir model cases is that the actual identification period, which prepares the data for identification, starts from January 2014 in the former whereas in the latter, it starts from July 2014, followed by a control period till the end of 2016. The first 6 months of 2014 are left out of identification and control in the P80 case as the optimum toe oil rate obtained from the reservoir model (corresponding to the optimum maximum steam rate constraint value obtained from CMOST) for this period is zero. (Note that this will happen if the long tubing string in the reservoir model is shut in by the simulator because the secondary constraint value can't be satisfied.) Table 4.5

contains the starting and ending points for the identification and control periods, with the point of time in simulation mentioned in parentheses.

Table 4.5: Identification and control periods. Any differences in the P80 case are noted.

Periods	Start	End
First Identification Period	01/01/2014 (365 days) for P10.	01/08/2014 (577 days) for P10.
	01/07/2014 (546 days) for P80.	01/02/2015 (761 days) for P80
First Control Period	01/08/2014 (577 days) for P10.	01/01/2016 (1461 days) for P10.
	01/02/2015 (761 days) for P80.	
Second Identification Period	01/01/2017 (1461 days)	01/08/2017 (1673 days)
Second Control Period	01/08/2017 (1673 days)	01/01/2020 (2556 days)

Prior to running the MATLAB workflow represented in Fig. 4.7 for our simulation study, we simulated the synthetic reservoir a number of times to determine how to best identify an ARX model. The input-output data (injection rates, oil rates, heel subcool and toe subcool) recorded from these simulations was divided into two identification plus control periods, just as planned for the simulation study, and for each of the periods, an initial part of the data was used to estimate an ARX model, and the rest was used to validate the identified model. A number of simulations were required as we found it very difficult to identify a model that performed reasonably well in validation—we will come back to the

issues in identification and control and identify the causes in Section 6.1. Hence, we used a trial-and-error approach to design the identification phase.

Based on the trial simulations of synthetic reservoir, we decided to keep the identification periods 7 months long in our simulation study, which is also evident from Table 4.5. The first 3 months of the 7 months, injection rates and oil production rates are held constant at the corresponding average values of optimum rates obtained from the reservoir model for the 7 months. The remaining 4 months, RBS signals with zero mean are superimposed on the average rates; an ARX model is identified based on the input-output data from these 4 months only. (Precisely the RBS signals start after the first 2 days of this 4-month period so that the identification data has a short steady state-like part in the beginning.) Note that in the reservoir models, the well constraints values that were varied for optimizing the NPV were the maximum steam injection rates and the maximum steam production rates. However, in the synthetic reservoir, wells are operated by specifying the steam injection rates and oil production rates (these values are manipulated by the MPC controller for optimizing the production). Hence, the RBS signals for identification in synthetic reservoir are also for the steam injection and oil production rates. In the identification periods, the optimum oil rates (corresponding to the constant optimum steam injection and steam production rates during the period) and hence the subcool exhibit a transient behavior for the first 3 months, when they are seen to fluctuate a lot. We noted during the trial simulations that keeping the oil production rates constant in these 3 months to prepare the data for identification leads to acceptable validation results for the identified model. This explains our choice of an initial 3 months of constant rates in the identification periods.

For identification of a linear model of a nonlinear process about an operating point, the choice of amplitude of the identification signal is a trade-off between a good signal-to-noise ratio and a close-to-linear process response (see Section 3.6). Large changes in the signal increases the error in identified model because of the

system nonlinearity. On the other hand, using a small amplitude leads to a low signal-to-noise ratio in the measurements. However, as noted before, signal-to-noise ratio isn't an issue in our simulation study. We choose amplitudes which are just large enough to cause a clear change in the subcool. (We ran four small simulations using the P10 reservoir model for the first 4 or 7 months of 2014, in each of which a step change in one of the four primary constraint values (maximum steam injection rate and maximum steam production rate) was introduced after the first 2 months to observe the effect on the heel subcool and toe subcool compared to a base case in which the constraint values are constant throughout.) For identifying the ARX models in our simulation study, for the RBS signals for injection rates and oil production rates, we choose amplitudes of 5 m^3/d (so there are step changes of 10 m^3/d) and 1 m^3/d respectively for the first identification period in 2014 and 15 m^3/d and 1 m^3/d respectively for the second identification period in 2017. We choose a much higher amplitude for the injection rate RBS signals in second identification period as the response of subcool to changes in injection rates is much smaller in second identification plus control period. This is further explained below; it is also evident in the plots of inputs and outputs with MPC and without MPC given in Chap. 5.

For an acceptable model performance, the linear models are identified separately for the two outputs, and the two MISO models are combined to form a single MIMO model for use in the MPC controller. For the first identification period, the modified form of the ARX model structure that includes noise integration, the ARIX model (given by Eq. 3.30 in a SISO case), is used for identification of a model for heel subcool. And for the second identification period, the ARIX model is used for both heel subcool and toe subcool. The need for using the ARIX model was identified in the trial simulations that we did using the synthetic reservoir. While looking into the validation results for the heel subcool model identified in the first identification period, we observed that the heel subcool data shows a drifting character. This prompted us to try the ARIX model, which vastly

improved the model quality to give a validation performance that was marginally reasonable such that we could use it in the MPC controller in our simulation study. This is shown in the figures that follow. We surmise that the improvement in performance is because the drifting nature of the output gets modeled as noise, which otherwise introduces big errors into the identified models.

In the MATLAB workflow that we use in this work, the function *arx* is used to build the MISO models, specifying the property values appropriately for integrating noise, if required. Further, the function *idpoly* is used to combine the MISO models into a single MIMO model, specifying each element of the D array as $1 - q^{-1}$ to integrate noise, if required, for the corresponding output (see Eq. 3.30 and Section 3.4).

The plots in Figs. 4.8 and 4.9 (which are for first, 365–1461 days, and second, 1461–2556 days, identification plus control periods respectively) represented by a solid black line show heel subcool and toe subcool data recorded during two different trial simulations of synthetic reservoir. In these simulations, the optimum well settings from P10 reservoir model were used. During the identification periods outlined in Table 4.5 for the P10 case, the injection and oil production rates were initially held constant and then RBS are superimposed, as described previously. For the rest of the simulation, rates corresponding to the optimum well settings from the P10 reservoir model were directly used. For system identification, we chose a sampling interval of 0.25 day (see below); hence, for simulating the synthetic reservoir, the primary constraint values were specified at intervals of 0.25 day so that the input-output data for identification could be recorded at these intervals from the simulation. Further, in each of the two identification plus control periods, models—a model each for the heel subcool and toe subcool—are identified using the identification period input-output data recorded from the synthetic reservoir, and simulated to observe the match with the subcool data for the whole identification plus control period to validate the models. Plots represented by a dashed line in Figs. 4.8 and 4.9 show the

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simulation results for identified models. The figures were obtained from the graphical user interface (GUI) of System Identification Toolbox. Before an identified model is simulated (or predicted) in the GUI, the initial conditions are estimated to minimize the prediction error. Note that no noise is added to the model output for simulation; i.e., the stochastic component in the identified model is disregarded (see Section 3.5).
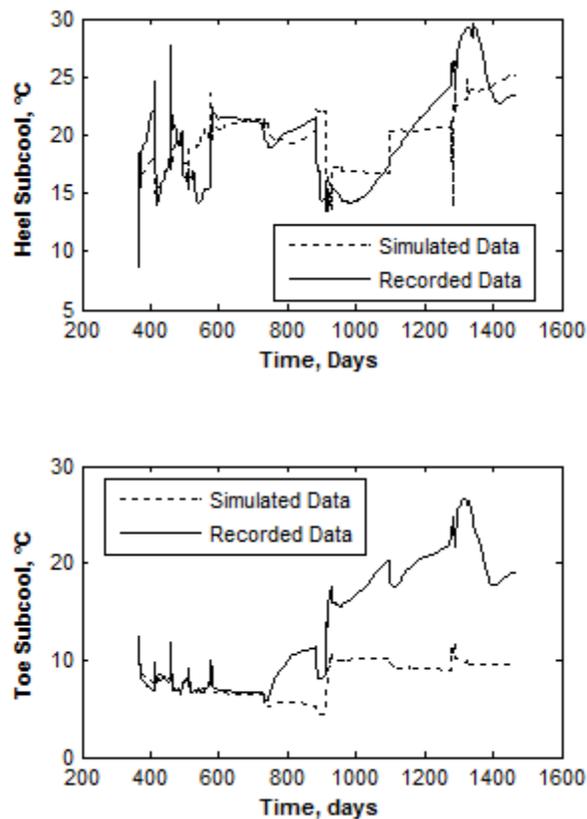
**Fig. 4.8: Simulation performance of models identified for heel subcool (top) and toe subcool, represented by a dashed line, against data recorded from a trial simulation of synthetic reservoir, for the first identification plus control period.**
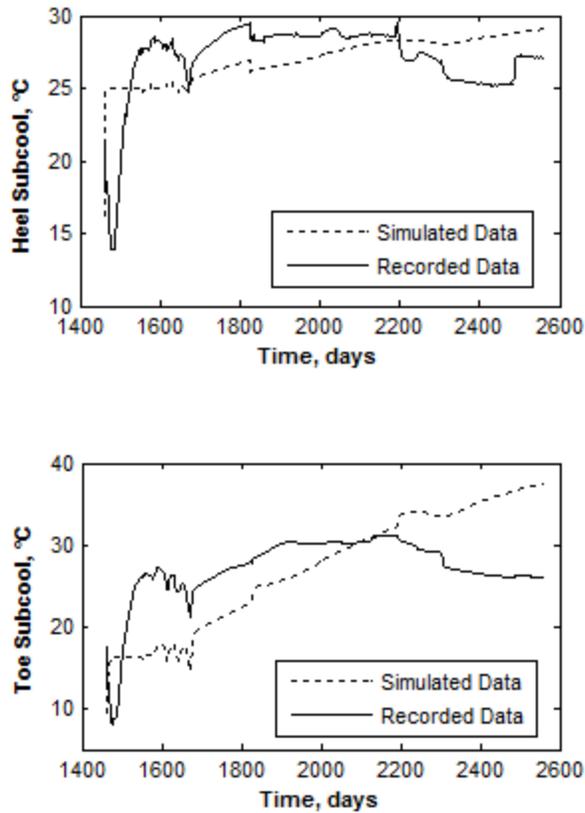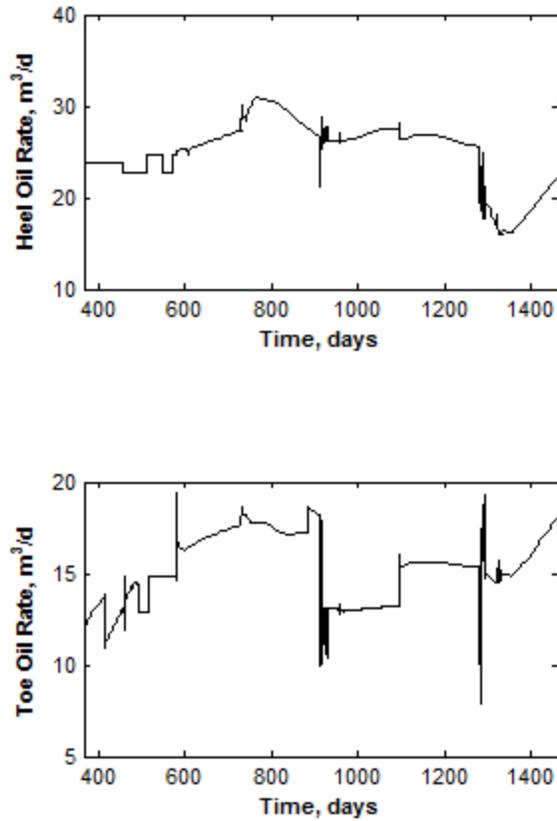
Fig. 4.9: Simulation performance of models identified for heel subcool (top) and toe subcool, represented by a dashed line, against data recorded from a trial simulation of synthetic reservoir, for the second identification plus control period.

Corresponding to the subcool data in Fig. 4.8, Figs. 4.10 and 4.11 show the steam injection and oil production rates respectively that were used in the synthetic reservoir in first identification plus control period, 365–1461 days. It can be noted in these figures that there is an initial identification period of 7 months, 365–577 days, in which the rates are first held constant and then 4-month long RBS signals are superimposed, as noted before. The RBS signals have amplitudes of 5 m^3/d and 1 m^3/d for the steam injection rates and oil production rates respectively. Corresponding to the subcool data in Fig. 4.9, we used amplitudes of 10 m^3/d and 1 m^3/d for the steam injection rates and oil production rates respectively. (Note that for the toe oil rate in Fig. 4.11, an initial part of the RBS signal couldn't be

used for operating the well as the secondary well constraint (a minimum BHP of 102 kPa) was violated. Nonetheless, the input-output data for the whole 4 months was used for identifying the heel subcool and toe subcool models. We do the same when we use the MATLAB workflow represented in Fig. 4.7 for our simulation study in the P10 reservoir model case.)
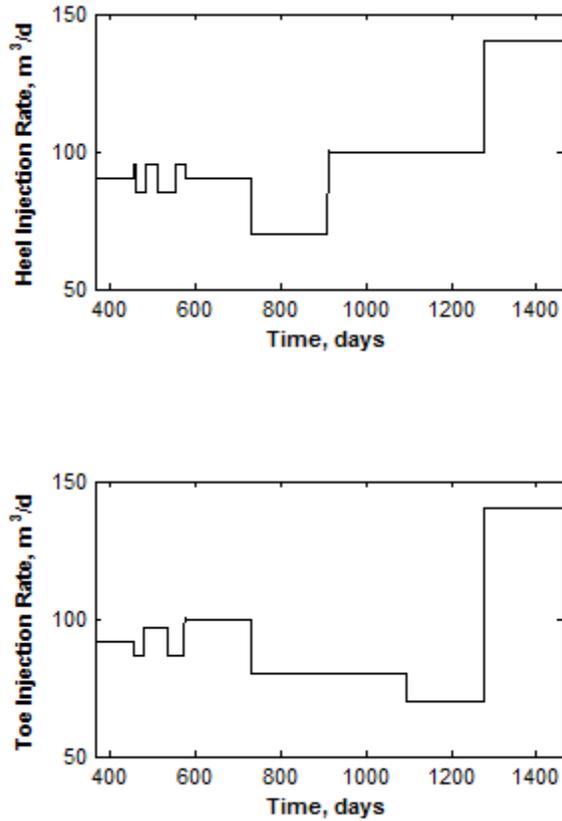
Fig. 4.10: Heel (top) and toe injection rates used for the first identification plus control period in the trial simulation of synthetic reservoir corresponding to Fig. 4.8.

Fig. 4.11: Heel (top) and toe oil rates used for the first identification plus control period in the trial simulation of synthetic reservoir corresponding to Fig. 4.8.

Compared to Fig. 4.8, Fig. 4.12 shows that there is a drastic drop in the simulation performance of identified heel subcool model if the ARX model is used instead of the ARIX model in the first identification plus control period. Similarly, Fig. 4.13 shows the poor simulation performance, compared to Fig. 4.9, of the ARX model for heel subcool in second identification plus control period.
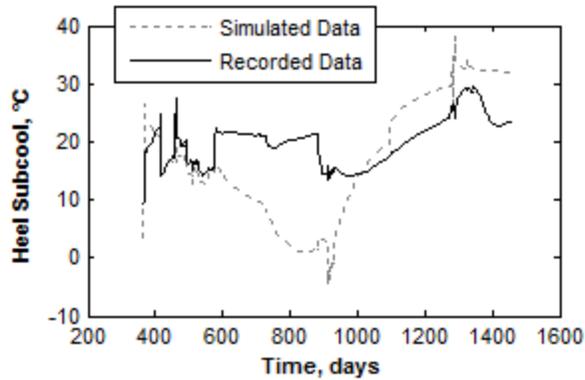
Fig. 4.12: Simulation performance of ARX model for heel subcool, represented by a dashed line, against data recorded from the trial simulation of synthetic reservoir corresponding to Fig. 4.8, for the first identification plus control period.
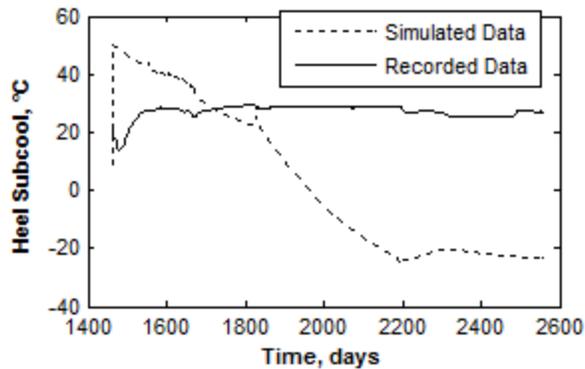
Fig. 4.13: Simulation performance of ARX model for heel subcool, represented by a dashed line, against data recorded from the trial simulation of synthetic reservoir corresponding to Fig. 4.9, for the second identification plus control period.

In Figs. 4.8 and 4.9, to analyze the simulation performance of the identified models we attached importance to whether the simulated subcool moved in the same direction as the recorded subcool, especially at the beginning of the optimization intervals that were outlined in Section 4.3, when step changes in the recorded subcool data can be seen in these figures. This is necessary for MPC to drive the inputs in right direction to control the subcool. (Note that in Figs. 4.8 and 4.9, the identified models match the initial 7 months of the subcool data well

as this is the same data that is used for identification.) The satisfactory performance of the models in this respect gave us the confidence to use them for MPC of subcool along the well pair in synthetic reservoir. E.g., in Fig. 4.8, the identified heel subcool model for first identification plus control period correctly follows the step changes in subcool. However, we also note that the long term subcool trends within the optimization intervals are incorrect; further, the toe subcool model in second identification plus control period in Fig. 4.9 doesn't respond correctly in the last year of the data (2019). Apart from looking at the trends in simulated output, we paid attention to what the input-output relationships were, whether positive or negative, in the identified models. Particularly, we expected from the four small simulations of the P10 reservoir model that we did, in which we used step changes in the primary constraints values, that the heel injection rate-heel subcool relationship is positive and heel oil rate-heel subcool relationship is negative. Table 4.6 shows the gain for each input-output relationship in the identified models in Figs. 4.8 and 4.9. These gains were noted from the GUI of System Identification Toolbox. We had used the same GUI for identifying the models from data from the trial simulations of the synthetic reservoir. A positive gain means a positive relationship between the input and output, and, conversely, a negative value shows a negative relationship. We note in Table 4.6 how the heel injection rate-heel subcool and toe injection rate-toe subcool gains in first identification period are about five times higher than in the second period. This explains why we choose a higher amplitude for the RBS signals for injection rates in the second identification period (15 m^3/d compared to 5 m^3/d in the first identification period) in the MATLAB workflow that we use for our simulation study. We will further comment on the magnitudes of observed gains in Section 6.1.

Table 4.6: Model gains in °C/m³/d for the heel subcool and toe subcool models identified in first and second identification periods from the data recorded from trial simulations of synthetic reservoir.
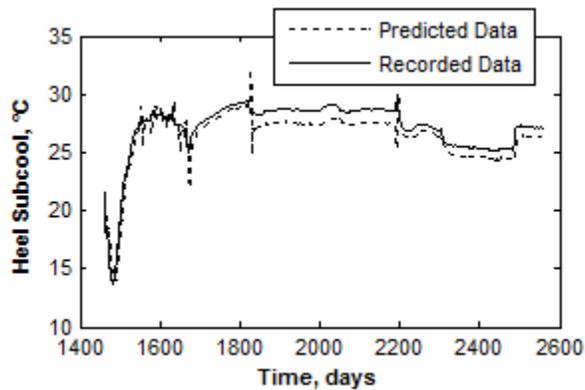
	First Identification Period		Second Identification Period	
	Heel Subcool	Toe Subcool	Heel Subcool	Toe Subcool
Heel Injection Rate	+0.048	+0.111	+0.012	−0.055
Toe Injection Rate	−0.033	−0.025	+0.006	−0.004
Heel Oil Rate	−0.444	+0.264	−0.221	−0.500
Toe Oil Rate	+1.274	−0.464	−0.062	−0.680

Compared to the simulation performances in Figs. 4.8 and 4.9, the 20-step prediction performance (see Section 3.5) for the identified heel subcool models in first and second identification plus control intervals are shown in Figs. 4.14 and 4.15 respectively. Because we chose a sampling interval of 0.25 day for identifying the models, a 20-step prediction horizon means the output is predicted at t is made using past recorded input data, and past recorded output data up to $t -$ 5 days. We note from the prediction performance figures that it is not easy to discern the model quality because the 20-step prediction will simply tend to stay close to the recorded output, even in cases when the identified models have large errors in them. So, we relied on the simulation performances to judge the model quality.
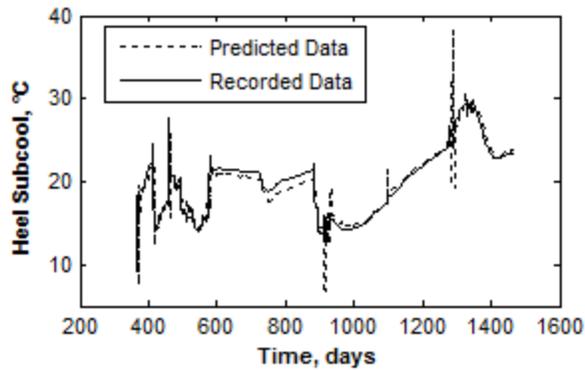
Fig. 4.14: 20-step prediction performance of the model identified for heel subcool, represented by a dashed line, against data recorded from the trial simulation of synthetic reservoir corresponding to Fig. 4.8, for the first identification plus control period.

Fig. 4.15: 20-step prediction performance of the model identified for heel subcool, represented by a dashed line, against data recorded from the trial simulation of synthetic reservoir corresponding to Fig. 4.9, for the second identification plus control period.

We noted in Section 3.6 that for using an identified model in a model-based controller, the rule of thumb is to use a sampling interval, T_s, that is 0.1–0.2 times the time constant of the process and a bandwidth of $[0\ pT_s\ /\ \pi\tau]$, expressed as a fraction of Nyquist frequency. For the identified models in Figs. 4.8 and 4.9, we roughly estimated the time constants and noted the approximate settling times from the GUI of System Identification Toolbox. To do so, we looked at the step

response plot, which plots the identified model response to a step input. Table 4.7 lists the time constants and settling times observed for the heel subcool and toe subcool models identified in the first and second identification. For the heel subcool models in the two identification periods, time constant noted is a rough estimate for all the four inputs. On the other hand, for the toe subcool models, the time constants varied for the four input-output relationships (corresponding to the four inputs); so a range of values is noted in the table. The settling times for the identified models are the approximate values for the four inputs.

Table 4.7: Time constants and settling times for the heel subcool and toe subcool models identified in the trial simulations of synthetic reservoir.

	First Identification Period		Second Identification Period	
	Time Constant (days)	Settling Time (days)	Time Constant (days)	Settling Time (days)
Heel Subcool	0.5	2	1	4
Toe Subcool	1–10	20	3–4	15

As a reasonable value for sampling interval, we use 0.25 day in our simulation study. A very large value, e.g. 1 day, will be too small for the smallest time constant observed; a very small value will also be similarly problematic. Note that the identified models in Figs. 4.8 and 4.9 were in fact identified from input-output data (obtained from the trial simulations of synthetic reservoir) that has a sampling interval of 0.25. Further, the RBS signals that were used in the synthetic reservoir for identifying the heel subcool and toe subcool models in Fig. 4.8 for first identification period have a bandwidth of 0–0.011, expressed as a fraction of Nyquist frequency. If we consider the smallest time constant observed Table 4.7, the recommended bandwidth comes out to be 0–0.318, corresponding to $p = 2$, $Ts = 0.25$ day and $\tau = 0.5$ days. This value is nearly 30 times larger than that used for the models in Fig. 4.8. However, using bandwidths much lower than the

recommended bandwidth was a very significant conclusion that emerged from the trial simulations of synthetic reservoir. E.g., Fig. 4.16 shows the simulation performance for heel subcool and toe subcool models identified in first identification period when a bandwidth of 0–0.064 is used, which is still nearly five times lower than the recommended bandwidth; other things, including the sampling interval, remain the same as the models in Fig. 4.8. The simulation performance vastly degrades compared to Fig. 4.8. Hence, for identifying the heel subcool and toe subcool models in our simulation study, we use a very low bandwidth of 0–0.011.
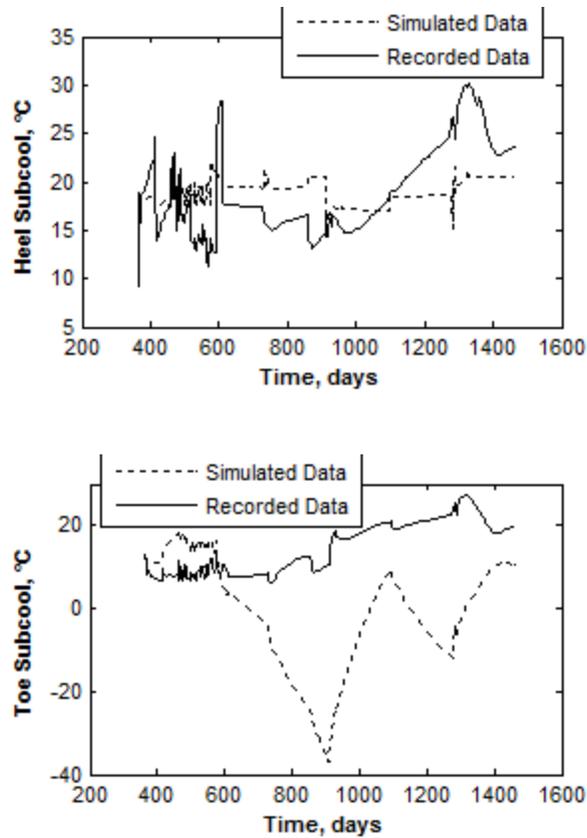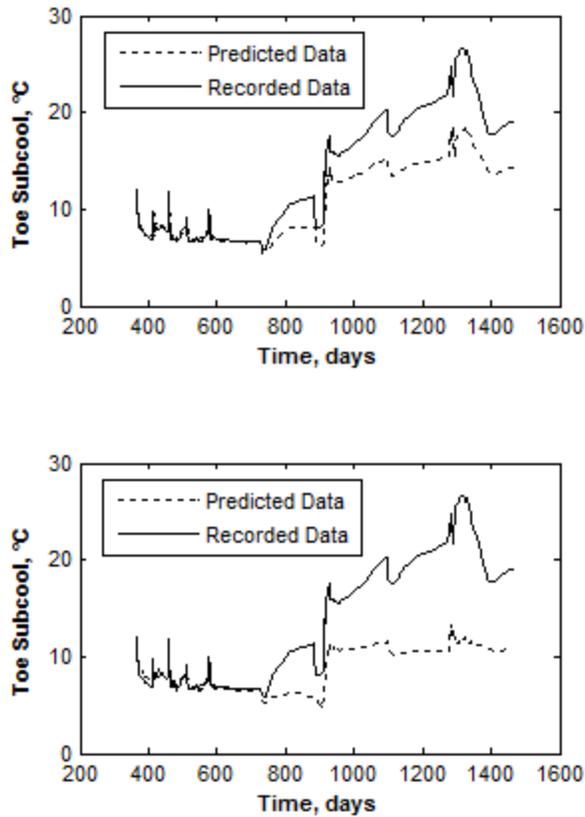
Fig. 4.16: Simulation performance of models identified for heel subcool (top) and toe subcool, represented by a dashed line, against data recorded from the trial simulation of synthetic reservoir corresponding to Fig. 4.8, for the first identification plus control period. To identify the models, RBS signals were used in the synthetic reservoir that had a bandwidth that was one-fifth the recommended amount. Other things, including the sampling interval, remain the same as the models in Fig. 4.8.

In our simulation study, the low bandwidth for RBS signals leads to a need for a much longer estimation period for the identified models compared to the rule of thumb, which is to keep it at least five times the time constant of the process. As noted before, we identify the models based on 4 months of input-output data. All the identified models plotted above were identified using 4 months of data as well. E.g., in Figs. 4.10 and 4.11, we can see in the initial part of the plots that the low-bandwidth RBS signals only have a few (3–5) step changes. Hence, say, if we

use only 2 months, which would be half the length of the RBS signals in these figures, the signal will excite very low frequencies in the process leading to a poor identified model. As we will see in Chap. 5, this is indeed the case.

For MPC of subcool along the well pair in reservoir, because of the lesser than expected performance of identified models (which we will discuss in Section 6.1), we choose a relatively short prediction horizon of 5 days compared to the settling times in Table 4.7; prediction over a longer horizon will anyways not be very accurate as demonstrated in Fig. 4.17. The figure shows the prediction performance of the identified toe subcool model shown in Fig. 4.8 for the first identification plus control period. We can see that using 60-step (15-day) prediction horizon, instead of a 20-step (5-day) horizon, deteriorates the prediction performance to nearly the same as the simulation performance in Fig. 4.8. Further, for MPC in our simulation study, input and output weights for heel and toe injection rates, oil rates and subcool (i.e., a total of four inputs and two outputs) are 0.1, 0.1, 0.5, 0.5, 0.7 and 0.7 respectively. The input weights are roughly chosen based on the observed gains of identified models from trial simulations for different input-output relationships, as shown in Table 4.6. Roughly speaking, let's say, we consider a MISO process, the input changes calculated by the MPC Controller will be proportional to the gains for the different inputs if all the input weights are equal. Accordingly, in our case, because we can see for the first identification period that the gains for oil rate on an average much higher than for the injection rates, we keep oil rate weights five times higher than the injection rate weights to keep the changes in oil rates as calculated by the MPC controller smaller compared to changes in injection rates. At the weights given above for the inputs, we try using higher weights, 1.0, for the outputs, which leads to an unstable controller. We show a case of unstable controller in Chap. 5. The failure of higher weights, again, arises from the weak performance of the identified models.

Fig. 4.17: 20-step (top) and 60-step prediction performance of the model identified for toe subcool, represented by a dashed line, against data recorded from the trial simulation of synthetic reservoir corresponding to Fig. 4.8, for the first identification plus control period.

Finally, we consider a few other identification details for the last part of this discussion. All ARX/ARIX models in our simulation study have two poles and one zero. Although not mentioned before, the identified models in the figures above also have the same number of poles and zeros. The vital conclusions for our simulation study that came out of the trial simulations of synthetic reservoir were to use low-bandwidth RBS signals for the inputs in identification periods and keep the identification periods long, with RBS signals superimposed on constant rates. These conclusions improve the performance of identified models just enough to be able to use them in the MPC controller in the simulation study.

Apart from these major conclusions, givdiscreteen the less-than-expected performance of the identified models, when the model orders were varied for identification of models from the input-output data from the trial simulations of synthetic reservoir, no significant and consistent conclusions could be noted. So, for the simulation study, we try to keep the model orders small without worrying much as to its effect would be on performance and use the orders noted above. Similarly, identifying the models by minimizing the one-step prediction error or the simulation error (see Section 3.5) also didn't seem significant. We choose the latter for our simulation study. The identified models in the figures above also minimized simulation error for estimation. Further, since the input-output data for identification is in fact simulated data, from the synthetic reservoir, there is no delay in it (i.e., outputs depend on the inputs instantaneously), as opposed to a delay of one sampling interval that we had considered for the models in Chap. 3. This arises from the way a simulator outputs information; the values output by the simulator at any time represent the average amounts over the previous time step in the simulation because the simulator equations are solved in discrete time. However, the Model Predictive Control Toolbox, which we use in the MATLAB workflow used in our simulation study, doesn't accept models without a time delay. Hence, in the MATLAB workflow a delay of one sampling interval is artificially introduced in the input-output data prior to identifying linear models by shifting the output data up a sampling interval. The models are then identified with a delay of one sampling interval, which can subsequently be used in the Model Predictive Control Toolbox. Also, the data for identification is not detrended as the trends in recorded input-output data during the identification period in the trial simulations are very different from the overall trends in the identification plus control period.

We note that in the field, the engineer only has reservoir models at his disposal to find suitable identification and control parameters. However, in our work, to be able to understand and work around the several issues we had identifying

reasonable linear models, we took the liberty to use both the synthetic reservoir and the P10 reservoir model to try different parameter values.

For the identification and control parameters that we use, the run time for the MATLAB workflow used in our simulation study is of the order of a day with an Intel® Core™ i7-2600 3.40 GHz processor and 12 GB RAM. Most of this time is taken for the simulation of synthetic reservoir.

5. Results

Using the P10 reservoir model to optimize injection and production rates and find the subcool set points, MPC of subcool along the well pair in reservoir leads to an 18.23% improvement in NPV compared to a direct application of the optimized rates. The contribution of the first identification plus control period (the first three years of the SAGD production phase subject to RTO using MPC, 2014–2016 or 365–1461 days) to the net improvement is 8.60% and that of the second identification plus control period (2017–2019 or 1461–2556 days) is 26.17%. Table 5.1 lists the NPV, cumulative oil production and cSOR amounts with MPC and without MPC for the whole 6 years, first identification plus control period and second identification plus control period and shows the corresponding percentage improvements with MPC as opposed to without MPC. Fig. 5.1 shows the heel and toe injection rates with MPC and without MPC. Fig. 5.2 shows the heel and toe oil rates with MPC and without MPC. Fig. 5.3 shows the MPC controller's tracking performance for the heel subcool and toe subcool. Note that without MPC, the optimum injection and production rates are directly used for SAGD. Hence, in Figs. 5.1 and 5.2, the plots without MPC, which are colored red, are simply the optimum values obtained from the P10 reservoir model. In Fig. 5.3, which shows the heel and toe subcool with MPC and without MPC, the black dashed plots show subcool recorded from the P10 reservoir model when the optimized rates found by CMOST are directly used. These form the set points for the MPC controller. The red plots show the heel subcool and toe subcool recorded from the synthetic reservoir when MPC is not used. The red plot deviates from the black dashed plot because of the differences between the reservoir model and the synthetic reservoir. The green plots are for heel subcool and toe subcool when MPC is used for real-time production optimization of SAGD in the reservoir. It can be seen that the toe subcool tracks better than the heel subcool.

Table 5.1: NPV, cumulative oil production and cSOR statistics for the total identification and control period, first identification plus control period and second identification plus control period in the P10 reservoir model case.

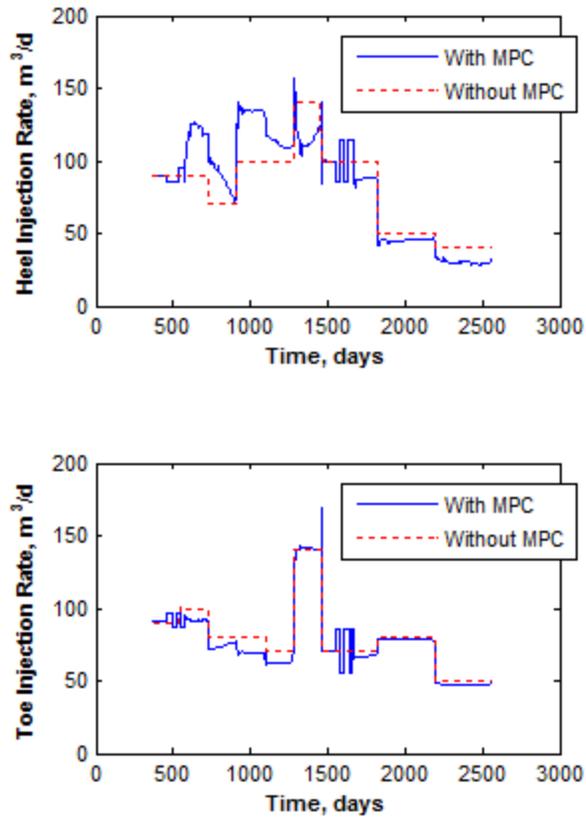|	Period	Without MPC	With MPC	Improvement (%)
NPV (million $)	Total	7.12	8.42	18.23
	First Period	3.21	3.49	8.60
	Second Period	3.90	4.92	26.17
Cumulative Oil Production ($x10^5 m^3$)	Total	3.45	3.69	7.00
	First Period	1.80	1.89	5.19
	Second Period	1.65	1.80	8.97
cSOR	Total	4.08	3.80	6.86
	First Period	4.67	4.58	1.93
	Second Period	3.45	2.98	13.62

Fig. 5.1: Comparison of heel (top) and toe injection rates with MPC and without MPC in the P10 reservoir model case.
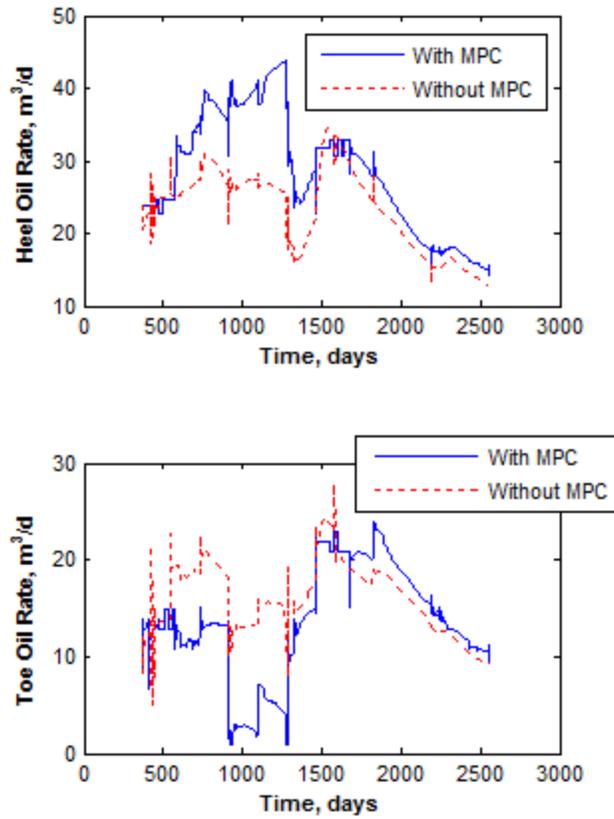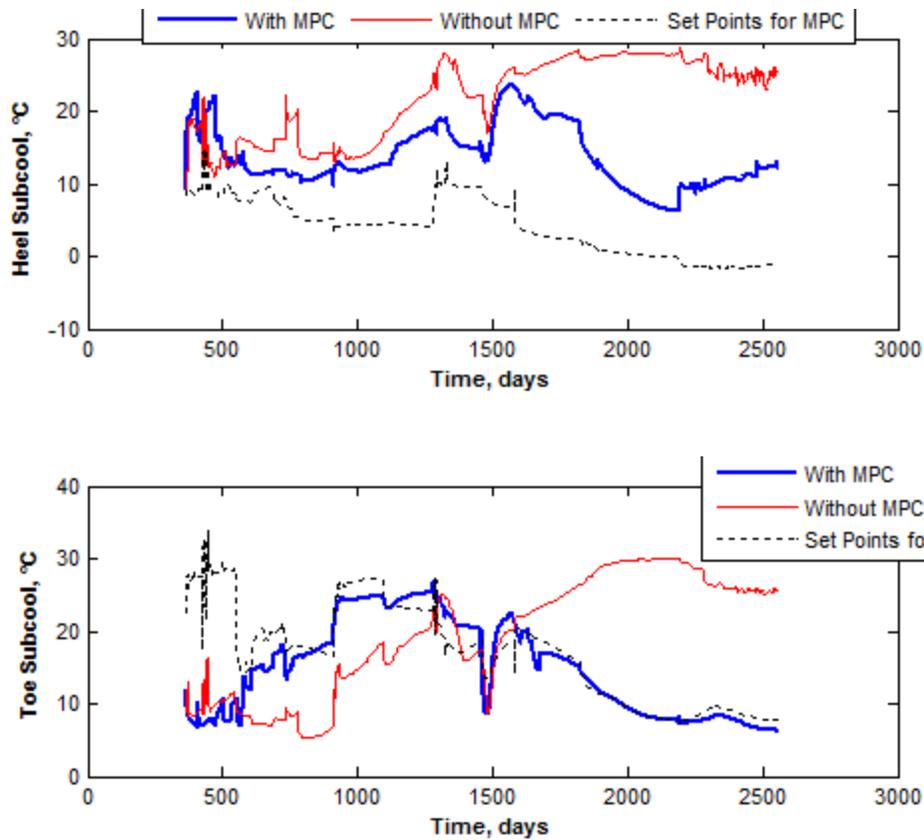
Fig. 5.2: Comparison of heel (top) and toe oil rates with MPC and without MPC in the P10 reservoir model case.

Fig. 5.3: Comparison of heel (top) and toe subcool with MPC and without MPC in the P10 reservoir model case. MPC tracks the set points.

In the P80 reservoir model case, using MPC to control the subcool along the well pair in reservoir improves NPV by 8.81%, including the first 6 months of 2014 when no identification or control is done. The contribution of the first identification plus control period (2014–2016 or 365–1461 days) to this improvement is −0.59%, and that of the second identification plus control period (2017–2019 or 1461–2556 days) is 21.02%. Table 5.2 lists the NPV, cumulative oil production and cSOR amounts with MPC and without MPC for the total period, first identification plus control period, and second identification plus control period, and shows the corresponding percentage improvements with MPC as opposed to without MPC. Fig. 5.4 shows the heel and toe injection rates with MPC and without MPC. Fig. 5.5 shows the heel and toe oil rates with MPC and

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without MPC. Fig. 5.6 shows the MPC controller's tracking performance for the heel subcool and toe subcool. Toe subcool is seen to track better here as well.

Table 5.2: NPV, cumulative oil production and cSOR statistics for the total identification and control period, first identification plus control period and second identification plus control period in the P80 reservoir model case.

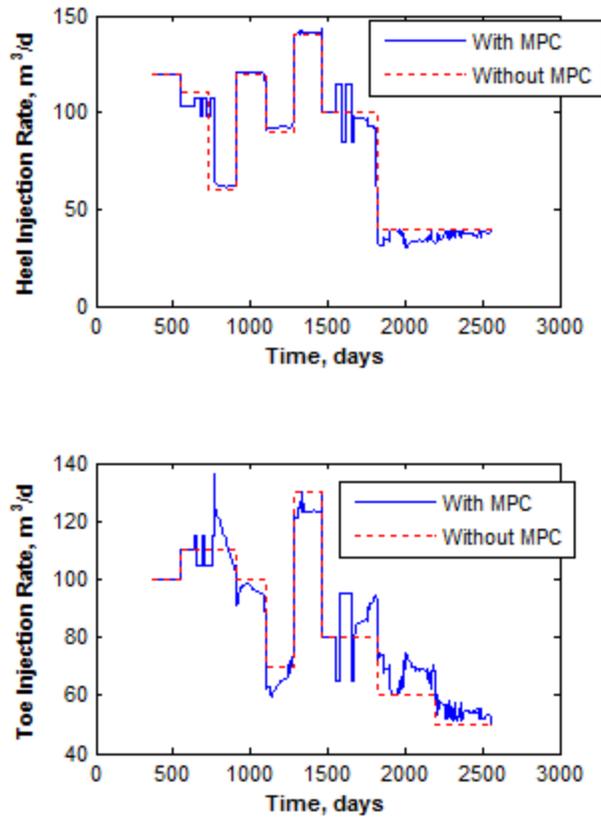|	Period	Without MPC	With MPC	Improvement (%)
NPV (million $)	Total	8.91	9.70	8.81
	First Period	5.04	5.00	−0.59
	Second Period	3.88	4.69	21.02
Cumulative Oil Production $(x10^5 \, m^3)$	Total	3.80	3.97	4.36
	First Period	2.21	2.20	−0.50
	Second Period	1.59	1.77	11.11
cSOR	Total	3.84	3.69	3.91
	First Period	4.16	4.16	0.00
	Second Period	3.39	3.11	8.26

Fig. 5.4: Comparison of heel (top) and toe injection rates with MPC and without MPC in the P80 reservoir model case.
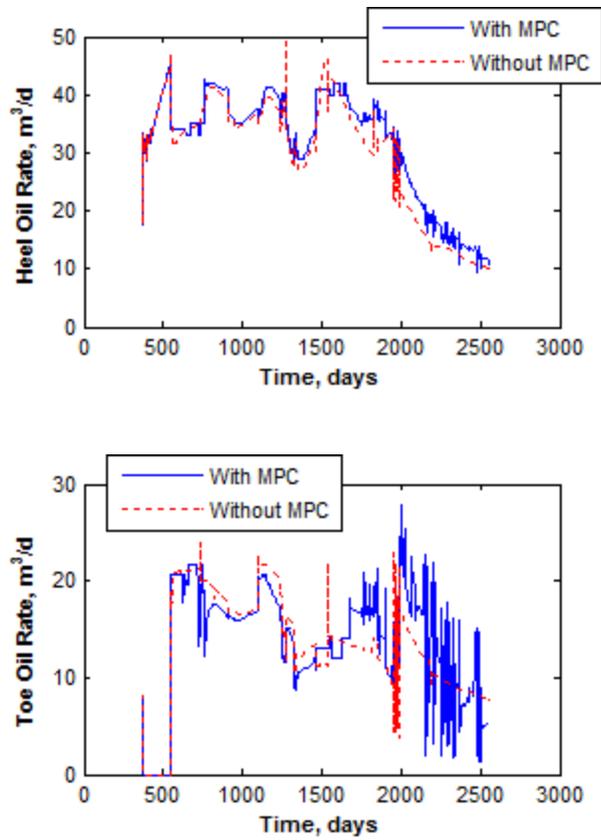
Fig. 5.5: Comparison of heel (top) and toe oil rates with MPC and without MPC in the P80 reservoir model case.
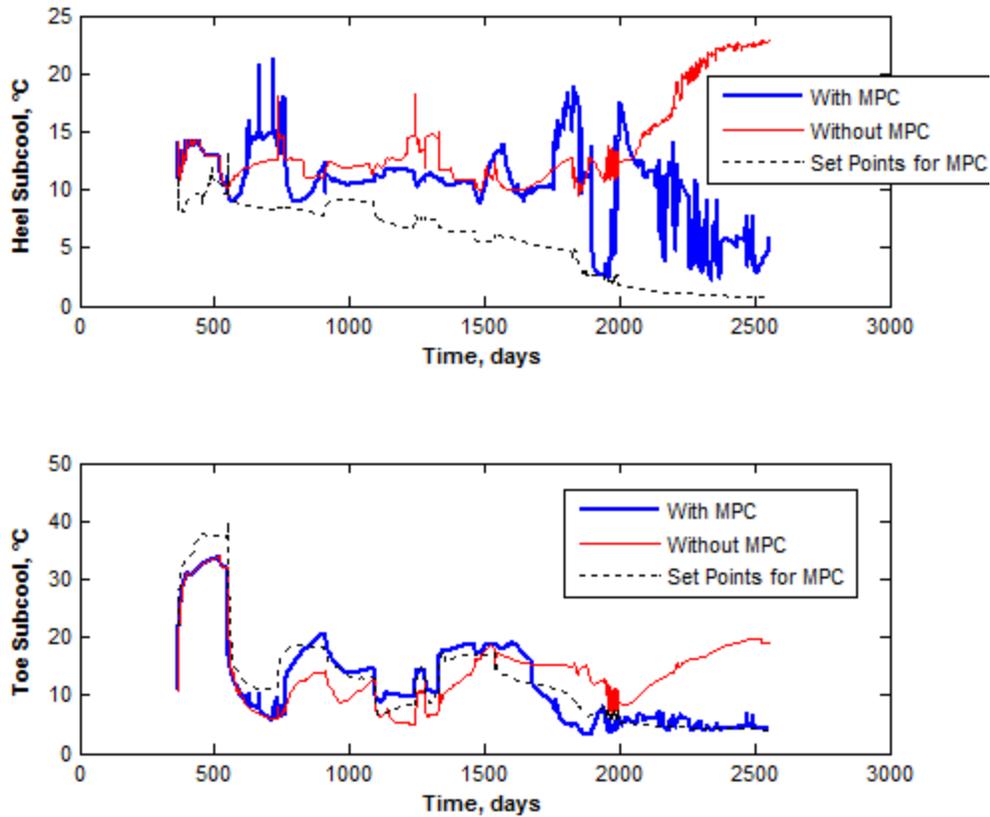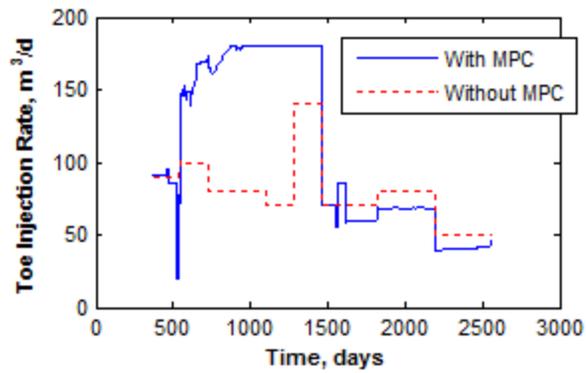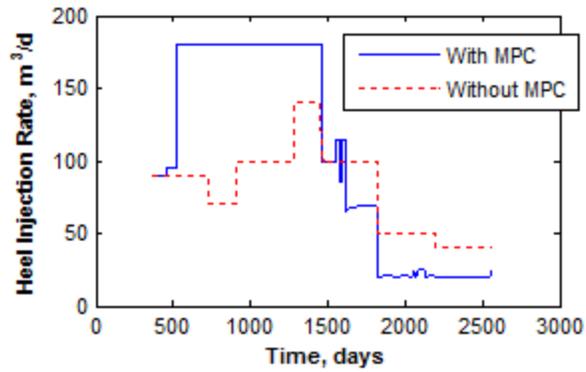
Fig. 5.6: Comparison of heel (top) and toe subcool with MPC and without MPC in the P80 reservoir model case. MPC tracks the set points.

We now explain a unique problem that the P80 reservoir model case posed, which needed changes in the synthetic reservoir before the results presented above for the P80 case could be obtained. As noted in Section 4.5, the optimum toe oil rate obtained from the reservoir model for the first 6 months of 2014 is zero. Hence, these first six months are excluded from any identification or control. Further, it was seen that during the first and second identification plus control periods, when we tried to use the optimum toe oil rate for simulating the synthetic reservoir, the long tubing string was operating either at a fraction of that oil rate or was shut in a lot of the simulation time, because of the violation of the secondary well constraint (minimum BHP of 102 kPa) used for the long tubing string. In retrospect, this is expected because the reservoir model is a P80 realization

whereas the synthetic reservoir is a P60 realization (see Section 4.1). Combined with the high relative weights for oil rates used in the objective function for the MPC controller in the MATLAB workflow that we use in in this work, this issue with well constraints made MPC of subcool along the well pair in reservoir unfeasible. Because the controller weights for oil rates are relatively high (0.1 for heel and toe oil rates compared to 0.7 for the heel subcool and toe subcool), the oil rates calculated by the controller to achieve the subcool set points remained close to their optimum values; but when the toe oil rate calculated by the controller for a sampling interval was used in the synthetic reservoir using the MATLAB workflow, the long tubing string couldn't be operated using that rate because of the constraint issue. Ideally, we would have liked to lower the relative weight for the oil rates to avoid the constraint issue, e.g., by using higher weights for the outputs; however, as noted in Section 4.5, high outputs lead to controller instability in our work due to the marginal performance of the identified linear models in our work (also see below for an example of unstable controller action in our work). To circumvent the issue with well constraints in the P80 reservoir model case, we modify the producer well dimensions in the synthetic reservoir so that the long tubing string can be operated at a higher oil rate than originally possible. Liner ID/OD are reduced from their original values noted in Table 4.2, 0.219 m/0.241 m, to 0.139 m/0.161 m, and tubing ID/OD are reduced from 0.076 m/0.079 m to 0.036 m/0.049. (Note that this should change the NPV results both without and with MPC.) However, despite this modification some of the issue with the toe tubing string constraints remains as indicated by the rapidly fluctuating toe oil rate in the second control period in Fig. 5.5—the toe oil rate drops from the controller-calculated value when the secondary constraint gets violated. Consequently, the heel subcool also shows large fluctuations with MPC in the second control period, as seen in Fig. 5.6. This also results in minor fluctuations in values calculated by the MPC controller for the injection rates and the heel oil rate. (This happens because of the fact that the heel subcool and toe subcool recorded from the synthetic reservoir at sampling instants feed back into

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the controller based on which the states of the model that it uses are updated; however, the controller is unable to "see" that the toe oil rate calculated by it in the previous sampling interval is different from the rate at which the tubing string actually operates in the presence of a constraint issue.)

For the P10 reservoir model case, Figs. 5.7 through 5.9 represent a scenario in which the MPC controller is unstable. For these results, the linear models are identified using only 2 months of input-output data as opposed to 4 months for the results in Figs. 5.1 through 5.3. Hence, the total identification period length is 5 months, including the initial 3 months of constant rates prior to the RBS signals. Combined with the low-bandwidth RBS signals used for identification (see Section 4.5), this results in poor identified models, which consequently leads to the controller instability.

Fig. 5.7: Comparison of heel (top) and toe injection rates with MPC and without MPC in the P10 reservoir model case when linear models are identified using only 2 months of input-output data.
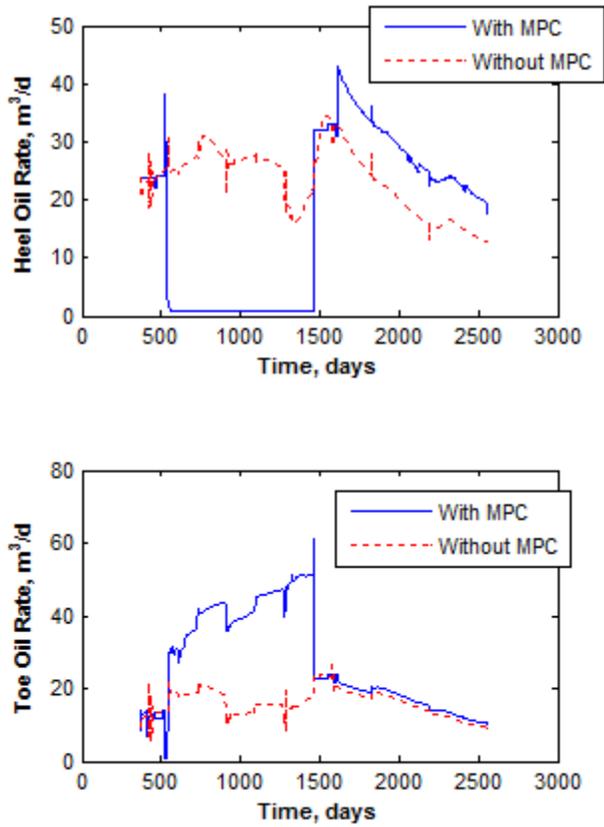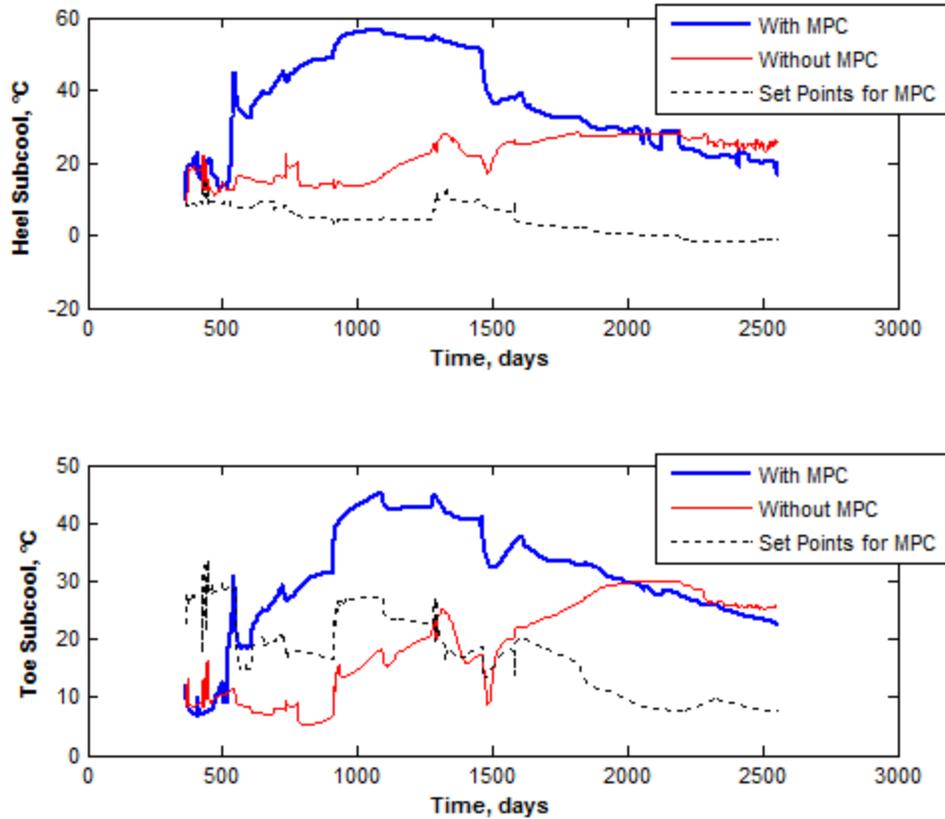
Fig. 5.8: Comparison of heel (top) and toe oil rates with MPC and without MPC in the P10 reservoir model case when linear models are identified using only 2 months of input-output data.

Fig. 5.9: Comparison of heel (top) and toe subcool with MPC and without MPC in the P10 reservoir model case when linear models are identified using only 2 months of input-output data. MPC tracks the set points.

In the MALAB workflow that we use for our simulation study, we use upper and lower bounds on the inputs and input rates (i.e. the change in an input from one sampling interval to another) for the objective function of the MPC controller (see Eqs. 2.2). The upper bounds used for the injection rates, rate of change of injection rates, oil rates and rate of change of oil rates are 180 m^3/d, 10 m^3/d per sampling interval, 100 m^3/d and 2 m^3/d per sampling interval respectively. The corresponding lower bounds are 20 m^3/d, −10 m^3/d per sampling interval, 1 m^3/d and −2 m^3/d per sampling interval. In Figs. 5.7 and 5.8, the unstable controller performance is highlighted by the fact that the injection rates are at their upper bounds (180 m^3/d) and the toe oil rate is at its lower bounds (1 m^3/d) for all or

most of the first control period. Correspondingly, this results in a very high heel subcool and toe subcool in the first control period (577–1461 days), as shown in Fig. 5.9. However, in the second control period (1673–2556 days) the controller seems to be stable despite identification of linear models from only 2 months of input-output data. Still, the controller is almost completely ineffective in tracking heel subcool and toe subcool unlike what's seen in Fig. 5.3; some of this can be attributed to the fact that the controller is given worse conditions to begin with as it has to act to bring down the high heel subcool and toe subcool at the end of the first control period.

The net result of using only 2 months of input-output data for identification is that NPV deteriorates by 47.46% when MPC is used to control the subcool along the well pair in reservoir as opposed to without MPC. Out of this net decrease in NPV, the first identification plus control period sees a decrease in NPV by 197.42%. In the second identification plus control period, NPV improves by 76.19%; however this is because of the fact that very little oil is produced in the first period due to an unstable controller, rather than that the controller performs very well.

6. Discussion, Conclusions and Recommendation for Future Work

6.1. Discussion

In SAGD, unless steam bypasses the bitumen in place by directly travelling from the injector to the producer, conduction is the main heat transfer mechanism around the production liner. Because of the resulting sharp temperature gradients, interwell subcool is a strong function of liquid level above the produce. In one of his 2D simulations, Edmunds (2000) found that increasing drawdown from injector to producer by 5 kPa increased subcool by around 30°C. Hence, a linear model, having a high gain, should be easily identifiable between injection/production rates, and interwell subcool at different points along the well pair, based on historic production data, as long as the data contains sufficient variation in the rates.

However, the models that we could identify in this work were quite the opposite of this expectation. The gain values in general for the different input-output relationships are of the order of 0.1 °C/m^3/d, as noted in Table 4.6. We noted that the models that could be identified from input-output data from the trial simulations of synthetic reservoir have a marginally reasonable performance at best when simulated to match the data. This is reflected in our simulation study as a little higher than the chosen weights for heel subcool and toe subcool, relative to the input weights, for the MPC controller leads to controller instability. Also, identification is not as easy as expected. The rates need to be held constant for 3 months in identification periods before the use of RBS signals for identifying the linear models, to be able to achieve a reasonably good model performance.

After an analysis of the results obtained in this work, with hindsight we conclude that the lower than expected linear model performance is because of steam breakthrough in the highly heterogeneous reservoir used.

In SAGD, with a dual tubing string well configuration, which is typically used in practice, steam preferentially goes into some intervals due to heterogeneity and the production temperature varies along the producer. Under these circumstances, the optimum operating conditions for SAGD in a highly heterogeneous reservoir involves a small amount of steam production along the producer; some steam production also helps heat up the colder intervals (Edmunds and Gittins 1993). Some steam production is acceptable as long as there is sufficient surface steam treatment capacity available. This situation can be avoided by using intelligent wells, which contain ICVs for a more uniform steam distribution in the injector and differential steam trap control in different intervals in the producer.
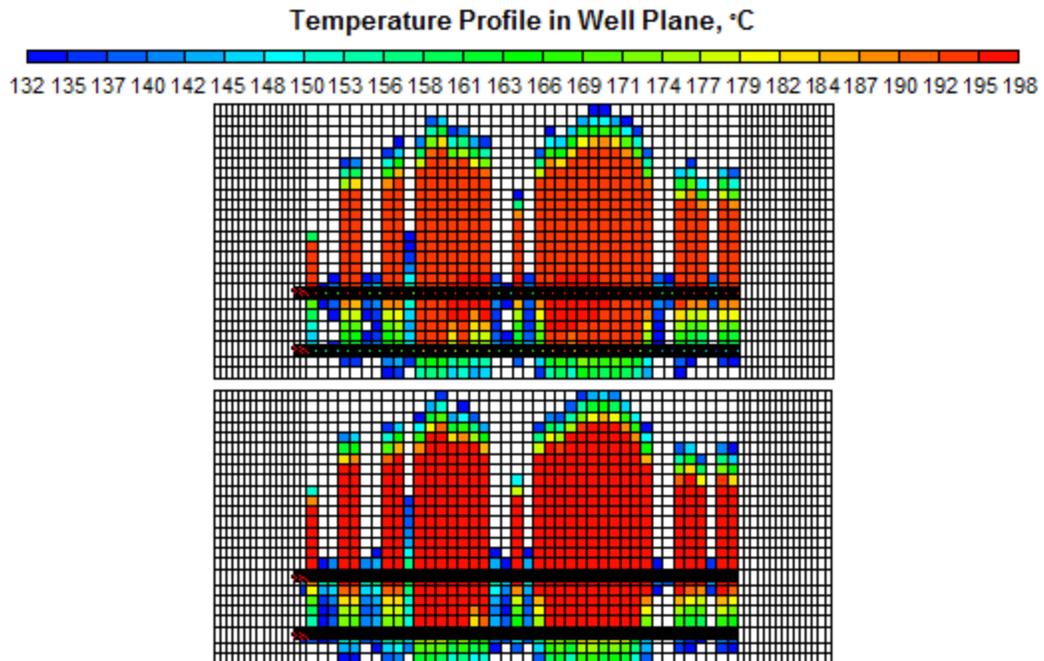
So, soon after the start of production in SAGD using dual tubing string wells, steam channels get established from injector to producer. It difficult to reverse the steam breakthrough once it happens because of the high mobility ratio of steam, and the steam channels are maintained throughout the life of the field (Stone et al. 2010). Even in 2D when heterogeneity is no longer a consideration, as analysis of Edmunds (2000) showed, steam tends to stay in the producer after it breaks through even after pressure differential between injector and producer is somewhat reduced. This is a nonlinear effect in the SAGD process. (Such nonlinearity is also observed when production is so low in an interval that the injector gets submerged in the liquid pool. Once the liquid level rises above the injector, the production temperature gets effectively decoupled from the liquid pool level due to convective effects pointed out by Edmunds (2000).)

Steam breakthrough also occurs in the reservoir models used in this work, which have a pair of dual tubing string wells. The temperature maps in Figs. 6.1a through 6.1d show the steam chamber evolution with MPC and without MPC in

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the *J-K* plane containing the wells in synthetic reservoir in the P10 reservoir model case; steam is seen to break through even before the start of first identification period, 01-01-2014 (365 days). We also note from Fig. 5.3 that the optimum heel subcool obtained from optimization of well settings in the P10 reservoir model using CMOST is negative towards the end of simulation period. The overall effect of the steam breakthrough is to impair the ability to control the production stream subcool. This makes identification of a good linear model to represent the process dynamics unfeasible due to the inherent nonlinearity arising from the direct steam flow from the injector to the producer, and poses challenges in the identification process. Stone et al. (2014), who used wells with a dual tubing string configuration and PID controllers on the short and long injection tubing strings to control interwell subcool, also find that the toe subcool failed to reach its control target once steam broke through in the heel half of the producer.
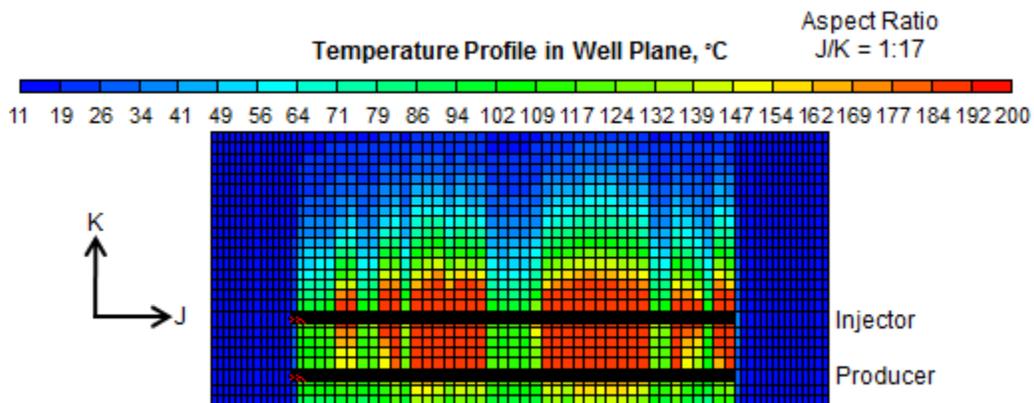
Fig. 6.1a: Reservoir steam chamber shape on 01-01-2014 (365 days), before the start of first identification period, when with MPC and without MPC cases are the same.

Temperature Profile in Well Plane, °C

132 135 137 140 142 145 148 150 153 156 158 161 163 166 169 171 174 177 179 182 184 187 190 192 195 198

Fig. 6.1b: Reservoir steam chamber shape without MPC (top) and with MPC on 01-01-2016 (1095 days) in the P10 reservoir model case. The temperatures of white cells lie below the range of the temperature scale.

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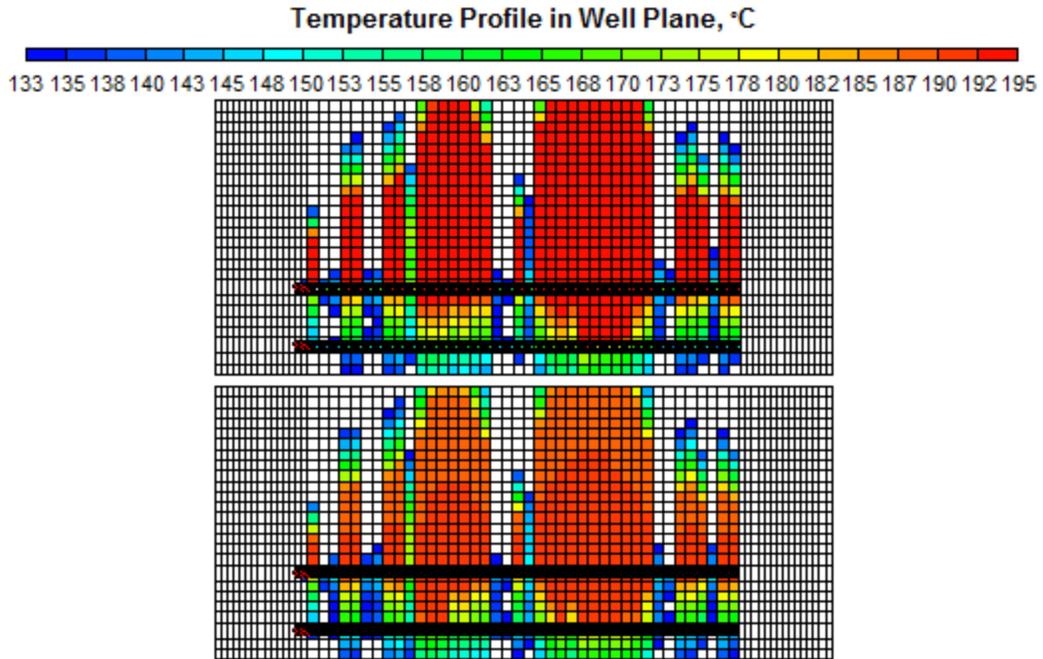
Fig. 6.1c: Reservoir steam chamber shape without MPC (top) and with MPC on 01-01-2018 (1826 days) in the P10 reservoir model case. The temperatures of white cells lie below the range of the temperature scale.
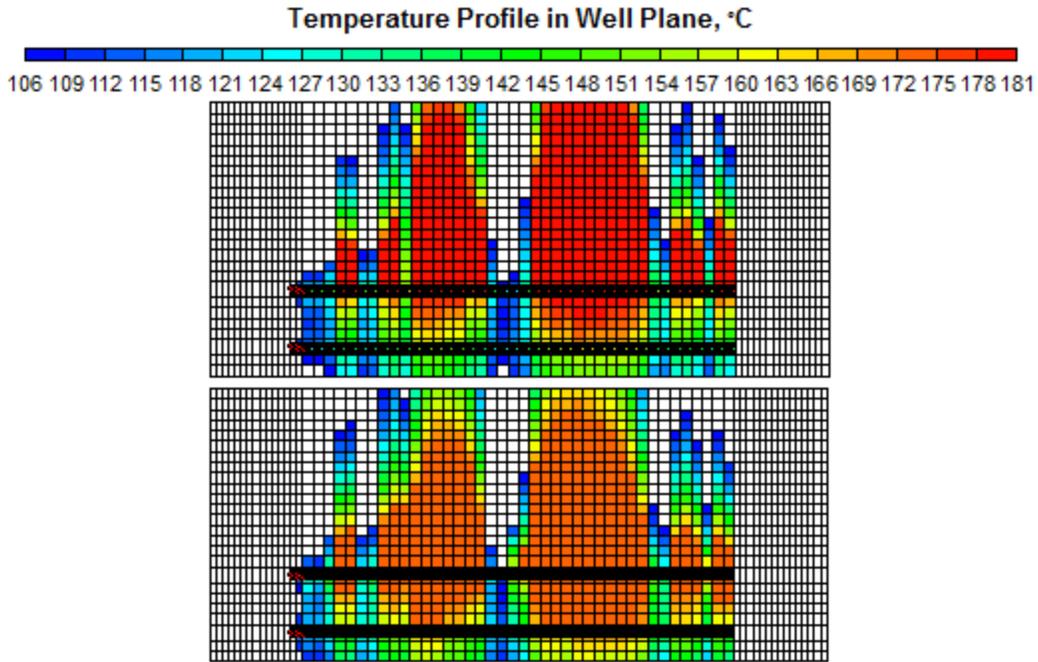
Fig. 6.1d: Reservoir steam chamber shape without MPC (top) and with MPC on 01-01-2020 (2556 days) in the P10 reservoir model case. The temperatures of white cells lie below the range of the temperature scale.

However, despite the issue with steam breakthrough, it is noted from Figs. 6.1a through 6.1d that MPC is able to control the steam chamber growth and increase the recovery within the limits of the process. In these figures, which have been obtained from Results 3D®, version 2013.10 (Results 3D 2013), the scale along the well direction is smaller by a factor of 17 compared to the perpendicular direction to show the entire grid dimension in the well direction. Near the middle of the plane each grid block is 17.5 m in the well direction. Results 3D allows up to a maximum of 25 intervals in the temperature scale. Accordingly, in each of these figures a range for the temperature scale is selected so that the difference in temperatures profiles between the wells with MPC and without MPC gets highlighted. The white colored grid blocks couldn't be accommodated within the temperature scale and have temperatures below the range covered by the scale. Fig. 6.1b shows that on 01-01-2016 (1095 days), with MPC the proportion of heat

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being transferred to the reservoir in the heel half compared to the toe half is more (this is evident from the fact that the coldest interwell regions in the heel half warm up while not so much in the toe half) and the steam chamber is slightly more uniform. At the same time, the total heat delivery is higher with MPC (which agrees with Figs. 5.1 and 5.2, which show that with MPC, heel rates increase and toe rates decrease in the first control period). On 01-01-2018 (1826 days), as shown in Fig. 6.1c, with MPC the near-producer temperatures are more uniform (which would mean higher oil production rates and lower SOR), and the total heat delivery is lower (which agrees with the lower heel and toe injection rates in the second control period with MPC as seen in Figs. 5.1 and 5.2). On the last date of simulation in our study, 01-01-2020 (2556 days), as shown in Fig. 6.1d, with MPC the steam chamber is more uniform and the total heat delivery is lower. The net effect of these differences is an 18.23% improvement in NPV.

Corresponding to Figs. 6.1b through 6.1d, Figs. 6.2a through 6.2c show the temperature profile in the blocks in the well plane in the layer $k = 5$, which lies in between the wells, from $j = 16$ to $j = 55$ (i.e., the range of blocks that runs along the whole length of the well after the packer). The distance on the x-axis in these figures is measured from the center of the $j = 16$ block, and temperature is plotted up to the center of $j = 55$ block. Within a block, the temperature remains constant.

Fig. 6.2a: Temperature profile, with MPC and without MPC, in the synthetic reservoir in the P10 case on 01-01-2016 (1095 days) in the range of blocks in well plane in the layer _k_ = 5, which lies in between the wells, from _j_ = 16 to _j_ = 55.

Fig. 6.2b: Temperature profile, with MPC and without MPC, in the synthetic reservoir in the P10 case on 01-01-2018 (1826 days) in the range of blocks in well plane in the layer _k_ = 5, which lies in between the wells, from _j_ = 16 to _j_ = 55.
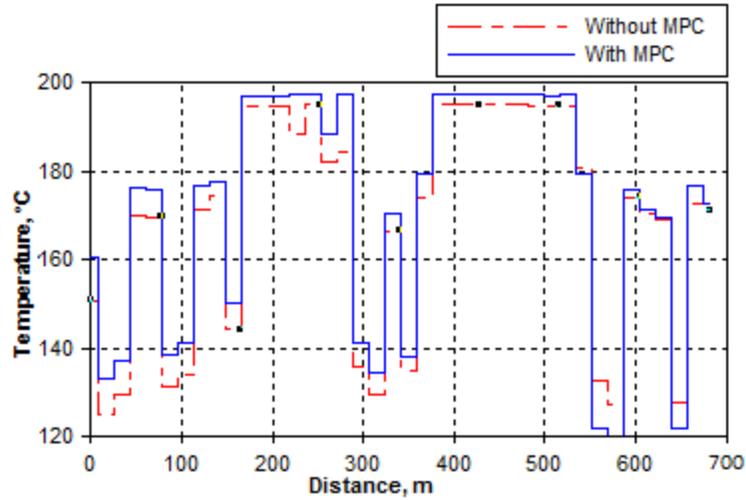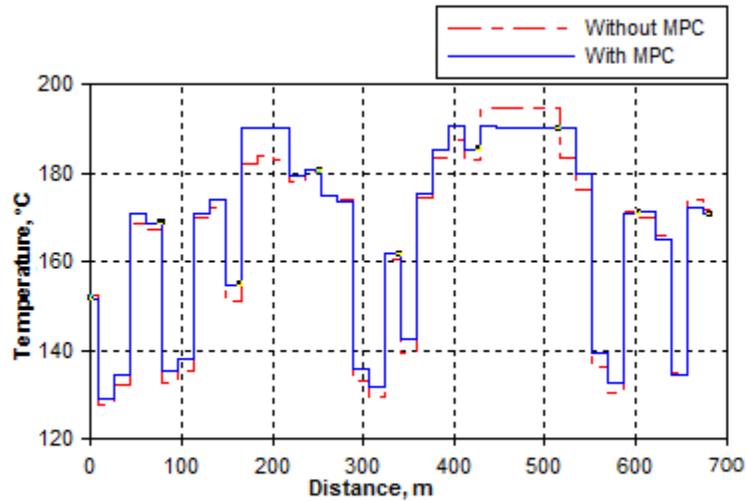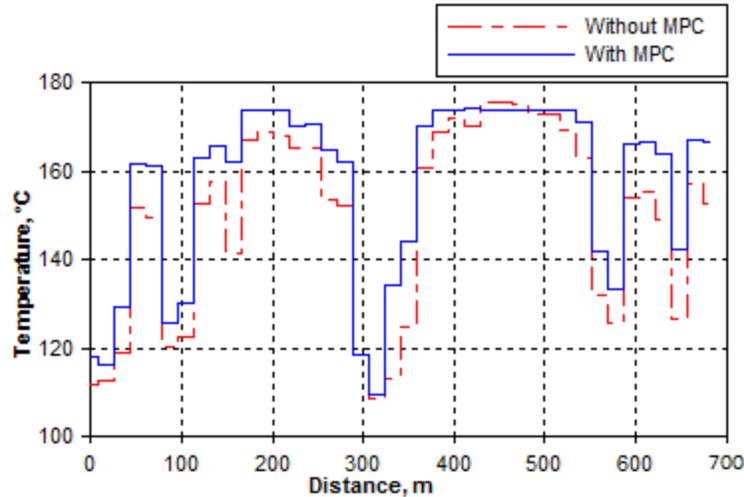
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Fig. 6.2c: Temperature profile, with MPC and without MPC, in the synthetic reservoir in the P10 case on 01-01-2020 (2556 days) in the range of blocks in well plane in the layer *k* = 5, which lies in between the wells, from *j* = 16 to *j* = 55.

In the P80 case, the first 3 years of SAGD production considered for control and identification see a slight decrease in NPV (there is almost no changes in total oil production and cSOR) with MPC as opposed to without MPC, but the net NPV at the end of second control period is still higher from a more uniform steam chamber. We believe that some of these results, in contrast to the P10 reservoir model case where there is a more uniform improvement seen in the first and second control periods, can be attributed to the fact that the producer well dimensions in synthetic reservoir were modified to circumvent the long-tubing string constraint issue, as noted in Chap 5.

We expect from these results that the MPC of subcool along SAGD well pairs will work very well in the case the injector and producer use an intelligent completion, which has ICVs along with downhole pressure and temperature measurement devices. ICVs isolate the completion into different intervals and provide the ability to shape the steam chamber as well as control steam breakthrough in the producer. With this configuration, identification of good

linear models will be much easier as opposed to the difficulties we face in our simulation study, and real-time production optimization by means of the MPC strategy will optimize the SAGD process. Gotawala and Gates (2012) have already demonstrated the potential of ICVs to control steam flow with an analytical 2D liquid pool model. They used a PID controller on the injection rates to control the steam breakthrough and successfully revert to steam trap conditions, and then maintain the subcool at a particular target. In the 3D model used by Gotawala and Gates (2009), using PID control for the six ICVs along the injector, a significant improvement in steam conformance was registered. The results observed in these works highlight that a further extension of the MPC strategy used in our work for RTO of the SAGD process to wells with ICVs is necessary to obtain the desired results.

6.2. Conclusions

The following conclusions are drawn from our simulation study, with respect to the hypothesis stated in the introduction to this thesis:

1. Despite the limitations of a dual tubing string well configuration in controlling steam breakthrough in SAGD and the associated issue with identification of a good linear model for MPC, the improvement in NPV with the application of MPC to control the subcool along the well pair in reservoir in both the cases considered in our numerical study helps us to conclude that MPC can be used for real-time production optimization of SAGD. MPC considers all the variables of the process while controlling it to improve the efficiency and increase the oil recovery. At the same time, a unique capability of the MPC strategy is that it allows handling of constraints on process variables. Hence, MPC offers a more advanced control strategy compared to PID control, as used in few other works for real-time optimization of SAGD.

2. In case of SAGD, it is possible to identify linear data driven models of the process from the high frequency data from intelligent wells, which have downhole pressure and temperature sensors, along with the use of surface measurements. In our work, models were identified that related injection and oil production rates to subcool along the SAGD well pair. To identify accurate models, the inputs had to be held constant for a few months and then long RBS signals with a very small bandwidth had to be used that lasted a further few months. In practice, this won't be feasible as the rates will move a lot. However, this issue will be eliminated if intelligent wells with ICVs are used to divide the production interval into isolated segments, in which steam breakthrough can be individually controlled. In this case, because of a strong relationship between the liquid pool level above the producer and the interwell subcool, a process model could be identified simply based on the past production data alone (which will normally have enough excitation in it for good identification).

3. Additionally, a high accuracy of the identified linear models is not needed for MPC. In the multilevel oilfield control framework that we consider in this work, as discussed in the introduction to this thesis, the linear models used for MPC only supplement the reservoir models, which are used to optimize the injection/production plans. As such, they don't need to capture the dynamics accurately. In our work, because of the nonlinearity in the SAGD process due to steam breakthrough very early into the production phase, it was not possible to accurately represent the dynamics using linear models built from the input-output data from the process using system identification. The best models that could be identified based on the recorded input-output data from the trial simulations of synthetic reservoir only have correct short-term subcool trends when simulated to match the long-term data, as noted in Section 4.5. Despite this, MPC is seen to track the subcool set points in both our cases. However, to get the results, the output weights for MPC calculations had to be kept low in order to avoid controller instability.

6.3. Recommendation for Future Work

Extending naturally from the discussion of results before, we recommend for future a simulation study similar to the one done in this work, but with both the injector and the producer having ICVs. E.g., the completion length used in this work can be divided into four or five sections to control the steam chamber independently in these sections. This will make identification of good linear models for MPC easy and from a practical point of view, will be a much better demonstration of the MPC strategy for real-time optimization of the steam chamber growth and production.

Further, owing to the issues in system identification, our efforts in this work were confined to obtaining workable linear models that we could use in the MPC controller for controlling the subcool along the well pair in reservoir. We could do so with ARX/ARIX models having two poles and one zero. Using wells with ICVs, we could further investigate higher model orders to see if they improve the validation performance significantly. Also, we used the ARX/ARIX models because there were no disturbances in our synthetic reservoir. However, if actual field data is used to estimate and validate linear models, different structures will need to be tried to identify which noise assumption works the best. E.g., the BJ model is suitable when the disturbance enters mostly at the output as measurement noise. On a related matter, an active area of research in digital oil fields is real-time cleansing of sensor data. Based on a statistical analysis, data that is judged to be bad can be rejected and replaced. For further thoughts on how real-time data from oil fields can be put to use, we refer to Rassenfoss (2013) and Horne (2013).

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