Well Performance Metrics Suitable for Automated Well Monitoring

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Abstract

Automated well operations is a rapidly growing area with recent progress in automated drilling extending now into automated well monitoring and control during production operations. In reservoir engineering, although the industry continues to guide decision making processes mainly based on physics-based models and simulations, the focus of further developments of the industrial workflows has shifted towards hybrid solutions incorporating machine learning and big data analytics. Development of such solutions requires new approaches to integrate the reservoir physics into the workflows suitable for machine learning and big data analytics.

In this paper, we apply and test new metrics for permanent well monitoring developed based on time-lapse pressure transient analysis, called PTA-metrics. These metrics, inheriting reservoir mechanics gained from PTA, remain comparatively simple and suitable for automated workflows. The metrics have been tested on real well data from sandstone and carbonate fields, including slanted injection and horizontal production and injection wells. The testing has confirmed its capabilities in well monitoring separating reservoir from well-reservoir connection contributions to well performance. Application of the metrics enables on-the-fly well monitoring and alarming on well performance issues highlighting the issue origin: either a reservoir or a well-reservoir connection. At the same time, the testing also revealed that reliable application of the metrics depends on the patterns developed by time-lapse pressure transient responses and their Bourdet derivatives. It was shown that the PTA-metrics give reliable results for stable patterns, while change in the pattern may reduce their reliability. The paper concludes with a discussion of ways for application of the metrics in every-day well and reservoir monitoring practice as well as their integration in automated data interpretation workflows developed in the industry.

Introduction

The oil and gas industry experienced a transition to the next level of well surveillance data availability in the beginning of this century due to massive installation of sensors in wells. Permanent downhole gauge (PDG) is an example of such sensors providing real-time high-precision measurements of pressure and temperature near the sand-face. This transition has stimulated progress and wide applications of Pressure Transient

Analysis (PTA, (Bourdet, 2002)) to monitor changes in well and reservoir performance distinguishing wellbore, near-well, inter-well, and reservoir boundary effects as discussed for example in (Horne, 2007) and (Gringarten, 2008). Many applications of PTA to time-lapse pressure transients were reported for conventional oil and gas reservoirs, including well stimulations and monitoring of well performance under different conditions and over time (Shchipanov, Berenblyum, & Kollbotn, 2014), (Shchipanov, Kollbotn, & Prosvirnov, 2017); monitoring of hydrocarbon recovery and fluid contacts (Suleen, et al., 2017); monitoring of improved / enhanced oil recovery pilots (Skrettingland, Giske, Johnsen, & Stavland, 2012), (Aamodt, et al., 2018) and analysis of well interference and impact of injection (Walker, Shchipanov, & Selseng, 2021), (Namazova, Molina, & Shchipanov, 2021).

The classical PTA (Bourdet, 2002) focuses on pressure (or pseudo pressure for dry gas) transient responses and their Bourdet derivates in the log-log scale. Many analytical models were developed, tested and applied in the industry over decades to describe different well completions and reservoir features (Houze, Viturat, & Fjaere, 2020). A subset of PTA models describing pressure difference and its derivative is applicable for slightly compressible single-phase flow in a reservoir. These models are accurate for the cases of initial oil production before water- or gas-breakthrough or for water injection after an injection pattern has formed. Further, such models may also have limited applicability in the cases of multi-phase flow of oil and water, but the interpretation results are subject to correction to account for multi-phase conditions like the fluid properties and relative permeabilities. In this paper, the slightly compressible single-phase flow case is assumed to be dominating, excluding other cases such as dry gas production mentioned above.

A workflow for time-lapse PTA (Figure 1) suggested in (Shchipanov, Berenblyum, & Kollbotn, 2014) was applied in different studies reported in (Shchipanov, Kollbotn, & Prosvirnov, 2017), (Walker, Shchipanov, & Selseng, 2021) and (Namazova, Molina, & Shchipanov, 2021). Application of the workflow may be illustrated by the example shown in Figure 2 and Figure 3. The example represents a four-year history of water injection with a gradually declining rate (Figure 2). Four periods were selected to represent each year of the injection, and a well-reservoir model (analytical in this case) was chosen to represent the injection in the reservoir segment. First, the model was matched to a selected transient in the log-log scale for each period in focus (Figure 3). Then, the model was tested to match the chosen period of the history in the linear time-scale (highlighted in Figure 2). This step-by-step procedure required adjustment of the model parameters (*kh* and skin) for each next period of the history, that provided reasonable match of the period in focus, but gave a deviation at the full-history scale. In this case, those model parameters that ensured model-matching of the transients during the injection periods, given that they revealed boundary effects not observed in the fall-off responses, further provided reproduction of the data for longer history periods. Note that boundary conditions were fixed in the model in this time-lapse analysis, although in a general case they may also vary.

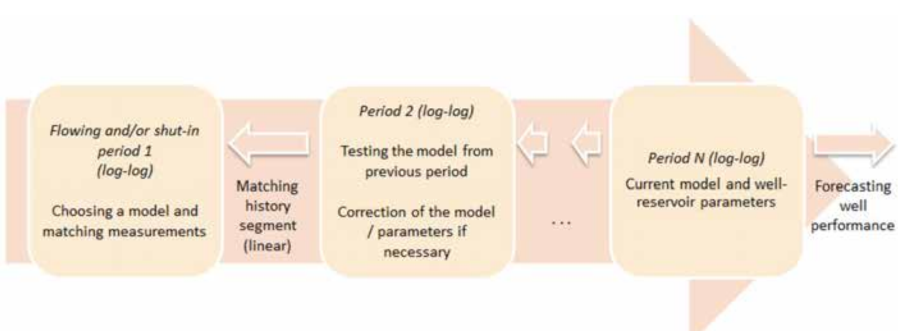

Figure 1—The workflow of the time-lapse pressure transient analysis from (Shchipanov, Berenblyum, & Kollbotn, 2014), a model-based approach.

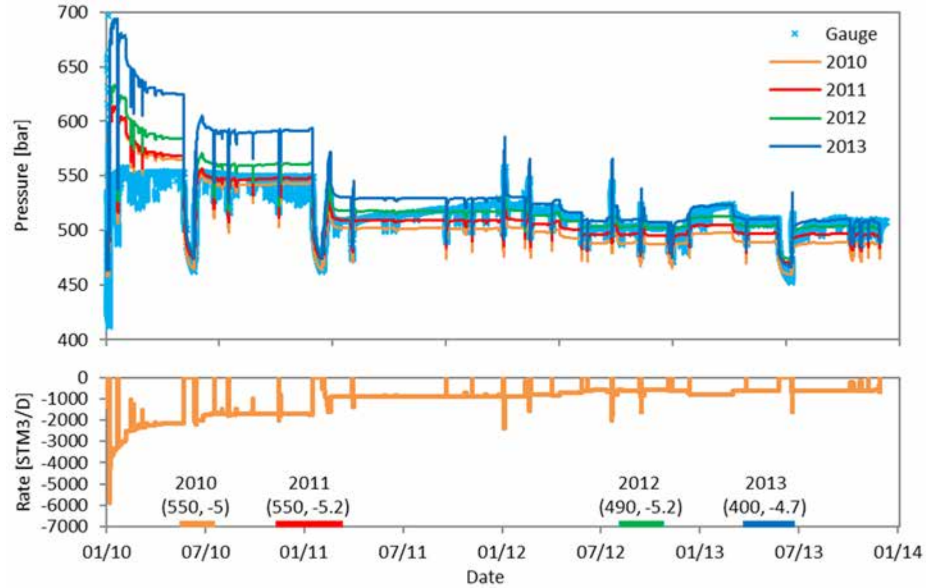

Figure 2—An application of the workflow illustrated in Figure 1 to analyse a four-year history of an injection well. A well- reservoir model was matched to four selected periods (solid lines marked '2010' - '2013'): first, a selected transient in the period in focus was matched in the log-log scale; second, the chosen period of the history was reproduced. *kh* and skin values obtained for each period are given in brackets.

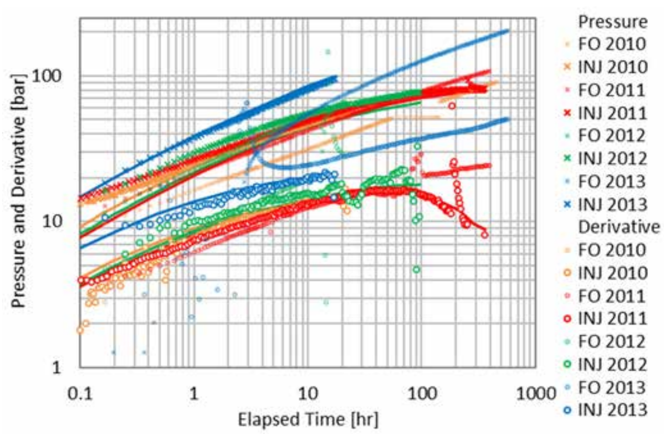

Figure 3—One fall-off (FO) and one injection (INJ) period (markers with no lines) were selected for each of four chosen periods in the well history (Figure 2) and matched with the same well-reservoir model (solid lines, only injection periods), but with varying parameters (*kh* and skin).

Application of such model-based workflow provides estimates of a set of model parameters, which may include well and reservoir properties (like the well skin and the reservoir flow capacity, *kh*) and boundary conditions (e.g. the presence and distance to faults and other wells). Variation of these parameters with time is explored by matching the sequential transients and the production / injection history periods. Such time-lapse analysis is model-dependent, i.e. the chosen model determines the set of well-reservoir parameters monitored. It also implies that the fluid PVT and other necessary data (like the pore volume compressibility) should be specified in the model. In addition, a PTA analyst performing such analysis should have specific competence to provide reliable results. All these aspects narrow the applicability of such model-based workflows down to a mere analysis of particular periods of histories of particular wells, usually when significant well performance issues are clearly identified. Such identification is usually carried out in a manual mode and sometimes with a delay. This leaves a vast amount of well monitoring data out of scope, compromising early detection and complicating analysis of well performance. It also limits understanding of the well performance variations over time and in the context of operations of other wells.

Consequently, automation of the model-based PTA has been in the research focus for many decades, starting from automation of well test interpretation (Allain & Horne, 1990) and continued with analysis of pressure measurements with permanent downhole gauges, see for example (Olsen & Nordtvedt, 2006) and (Suzuki, 2018). (Suzuki, 2018) has summarized the research progress in the automation of model-based PTA and suggested improvements to address real field data. Following (Olsen & Nordtvedt, 2006), an automated PTA workflow usually consists of several steps including data pre-processing (outlier removal, denoising and transient detection) and the automated interpretation itself aiming at estimating parameters of a well-reservoir model (like the well skin, reservoir flow capacity etc.). The model may also be identified in an automated mode. (Suzuki, 2018) focused on further development of such workflows via solving challenges appeared in applications to real well data including separation of signal from noise and presence of non-reservoir responses. All these studies have formed a basis for developing of automated model-based PTA workflows in the industry.

The model-based approach has however some limitations in the context of on-the-fly analysis and, especially, of automated well control. Among such limitations are: (1) the need for specifying input parameters for models, e.g. well completion details, fluid properties etc.; (2) sensitivity of the interpretation to noise and non-reservoir responses, calling for outlier removal and denoising; and (3) in some cases, a need for human interaction for setting up data pre-processing parameters (like thresholds) and quality control of interpretation results. A hybrid data-driven approach, inheriting reservoir physics, but focusing only on available well measurements (like pressure and rate) may be a useful component in the model-based PTA workflows described above, e.g. for fast first-order analysis of large data-sets. At the same time, such data-driven approach may also be of value alone, in particular for on-the-fly interpretation and automated well control.

Recent developments in automation of drilling operations have provided automated workflows which are already in use in the industry (Heredia, et al., 2021), while the next level of automation - autonomous drilling, is now in focus of the research and development (Cayeux, Mihai, Carlsen, & Stokka, 2020) and (Mihai, et al., 2022). Although production operations are quite different in physics and time-scales from drilling operations, the approaches to automation of monitoring and, especially, control problems have certain similarities. These may include on-the-fly data interpretation and operational control, use of hybrid model- and data-driven approaches, and combination of automated and manual modes to ensure safe and efficient operations (Cayeux, et al., 2021).

The general application area of such automated interpretation employing hybrid data-driven approaches in the context of industry workflows for analysis of well surveillance data may include:

- Pre-processing and QA/QC of well surveillance data to provide input for model-based interpretation (like time-lapse PTA) and/or performance prediction (like reservoir simulation).
- Monitoring and historical analysis of well-reservoir performance to identify performance issues and highlight wells and data segments for in-depth analysis.
- On-the-fly interpretation and early detection of well-reservoir performance issues and their origins.
- Automated well control to prevent unwanted events, e.g. well performance decline or conformance issues in well operations.
- Accumulating and classifying knowledge gained from big well-surveillance datasets, previously overlooked due to limited capacity and performance of conventional model-based interpretation workflows used in the industry.

The paper focuses on testing and analyzing of such hybrid data-driven approach for time-lapse PTA with two distinguishing features:

- Only well pressure and rate measurements are used as input data.

- Only general understanding from physics-based (PTA) models is utilized without the need to choose and tune a specific model for a particular data set.

Such hybrid approach may become a component of an automated PTA-based workflow for analysis of data from permanent gauges in combination with automated data pre-processing and transient identification, discussed in the literature, see for example (Suzuki, 2018). The automated pre-processing and identification can provide time-lapse transient families, while the automated hybrid approach - interpretation of these families.

PTA-metrics

The simplest and widely used well performance indicator is the productivity index (PI). In theory, PI is considered as a product of all the parameters (well, reservoir and fluid) governing well productivity excluding pressure drop between the well and the reservoir (Houze, Viturat, & Fjaere, 2020). The average pressure in the well drainage area may be here considered as the reservoir pressure. If the parameters are constant, PI should also remain unchanged. PI therefore includes contributions by both the reservoir (e.g. permeability-thickness product) and the well-reservoir connection (e.g. the completion skin) performances. This may be considered as a limitation of the PI as a performance indicator, since contributions to the well performance of the reservoir and well-reservoir connection are not distinguished.

A steady-state PI may be calculated in practice as the ratio of the stabilized rate to the difference between the average reservoir pressure (within the drainage area of the well) and the stabilized wellbore flowing pressure. A transient PI is also often calculated as the ratio of the flow rate (during flowing period or before shut-in in focus) and pressure difference between current transient flowing (or shut-in) pressure and a reference pressure, e.g. the maximum (minimum) pressure at the end of previous shut-in (flowing) period. Although such PI estimation is approximate, it may be useful for operating monitoring of well performance. Here, PI may vary with time even when the well-reservoir parameters mentioned above remain unchanged, since it's a function of the well pressure that may be not stabilized. In the case of transient PI: (1) the same time-window should be used to compare PIs of the same well, but (2) even in this case, validity of comparison of PI estimates depends on the consistency of flow regimes within the time-window chosen since a change of the regimes may bias the estimation. Such PI estimation procedure is further considered in the paper.

The PI concept is widely used in well performance monitoring in the oil and gas industry including semi- and fully-automated well surveillance workflows due to simplicity of implementation and interpretation of the results. It also serves the well management purpose to monitor the state and dynamics of the well productivity, in order to alarm when the well needs attention in terms of inspection, production logging, workover, etc.

Time-lapse Pressure Transient Analysis (PTA) discussed above is usually applied as a next step in well monitoring workflows focusing on specific periods and pressure transients in the well history highlighted by the PI monitoring or operational events (such as well stimulations, treatments etc.). While requiring more input data (like the well, reservoir and fluid descriptions) and resources, the time-lapse PTA gives a more detailed analysis of the well and reservoir performances, reservoir features (like fractures and faults) and boundary conditions in the well drainage area (like well interference effects), all potentially variable with time.

Upgrading the PI concept with the features available in PTA while keeping the simplicity of PI-application in terms of required input data and calculation procedure may help to improve the well monitoring workflows, especially in the context of the popularity of semi- and fully-automated workflows preferring simple and robust solutions. PTA-metrics described in the appendix equations (1)-(3) were suggested in our attempts to achieve this. The metrics include three Performance Indicators: the one describing the well (WPI), the reservoir (RPI), and the well-reservoir connection (CPI) performances. The

WPI is analogue to the PI, while the RPI and the CPI serve to further distinguish contributions of the reservoir and the well connection performances to the WPI. In practical applications of the metrics, relative indictors (WPI, RPI and CPI) will be further analyzed as ratios to reference values of WPI, RPI and CPI obtained for a reference transient in the transient family.

Figure 4 illustrates application of the PTA-metrics to a simple synthetic example of a vertical well with wellbore storage (WBS) and skin. In this example, the reference response (Transient 1) of the well to a certain production rate is compared with the response of the same well to the same rate, but with a doubled flow capacity, *kh*, and a doubled pressure drop due to a higher skin (Transient 2). The PTA-metrics assume that the compared transients / Bourdet derivatives form a stable pattern in the log-log plot. The stable pattern means that transients / derivatives may move vertically up and down in the log-log plot (also with some horizontal movements), but the derivative form / signature remains the same for all compared transients. The blue square (Figure 4) contains the observed stable pattern in the log-log scale (the time- window of 0-100 hr), while the derivative decline for the second transient shows where the pattern is no longer stable i.e. is changing (in the full time-window of 0-1000 hr). Figure 4-b shows variation of the relative performance indicators, calculated according to (1)-(3), with time. 'True values' of the performance indicators within the model-based approach and the stable pattern (0-100 hr) may be calculated using equations (4)-(6) in the appendix, providing the ratios of WPI as 1.0 (the same pressure drop), RPI = 2.0 (double *kh*), and CPI = 0.5 (skin of 8 gives double pressure drop if compared to the response with zero skin). The PTA-metrics (Figure 4-b) give 0.97, 1.92 and 0.50 for relative WPI, RPI and CPI in the 'stable pattern' time-window for the same case in Figure 4-a. Minor deviations of the RPI and WPI from the 'true value' are governed by the WBS effect, which works as noise in the RPI/WPI calculations, while the integral manner of the calculations smooths the noise out.

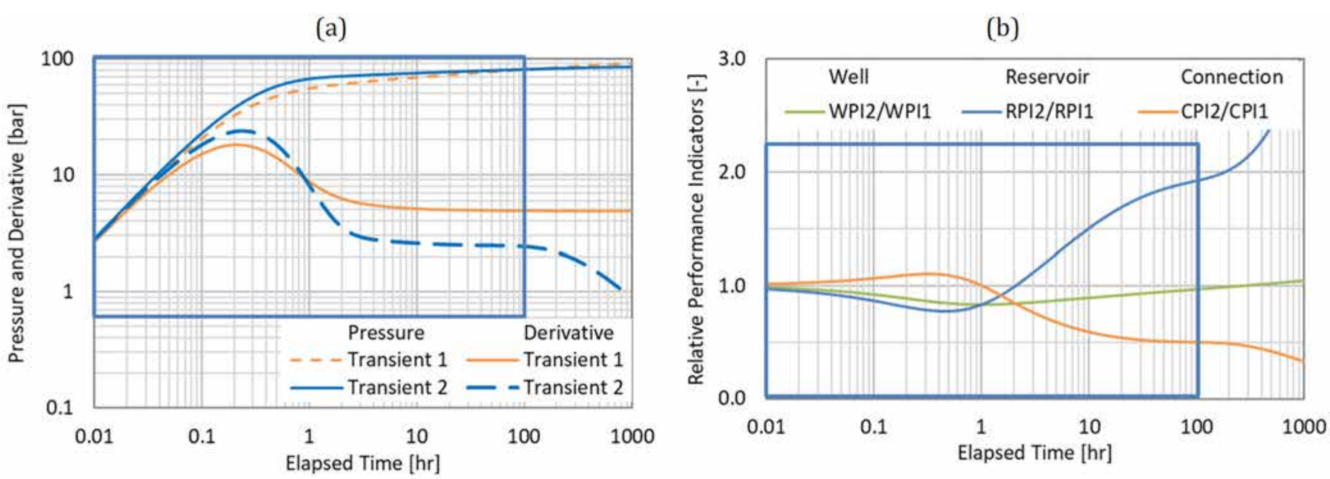

Figure 4—Performance analysis for two vertical wells with a WBS effect: the second well has a double *kh* value and increased skin (8, changed from 0 for the first well). This combination of parameters however provides the same pressure drop at the end of the 'stable pattern' time window in blue. The resulting WPI, RPI and CPI at the end of the 'stable pattern' time-window are 0.97, 1.92 and 0.50.

The integrals in the WPI and RPI calculations (in the appendix) are used to:

- denoise the pressure and derivative: large noise level is usually observed for early time, while WBS, fluctuating rate or after-flow may also be considered as noise in the well response;
- track information on the curvature of the pressure and derivative curves (e.g. a more convex pressure drop curve gives a lower resulting WPI).

Many new wells drilled in the oil and gas industry are horizontal. The main flow regime in PTA of vertical (or slanted) wells is radial flow, which is used in the PTA-metrics (similarly to the classical PTA) as the reference flow regime. In practice, production or injection in horizontal wells usually generates a sequence of flow regimes (Bourdet, 2002): the radial flow (in the cross-section) around the horizontal wellbore (or the linear flow to induced fractures, if the well was fractured), followed by the linear flow to the well, and finally the flow governed by the reservoir boundary(s) or well interference. The late radial flow regime (in the plane) is rarely observed in practice due to well locations being relatively close to each other and to the boundaries. Figure 5 illustrates pressure responses with the commonly observed flow regimes in horizontal wells. The PTA-metrics we have introduced may be also applied to horizontal well responses, but the complexity and interplay of the horizontal well flow regimes may reduce the metrics reliability.

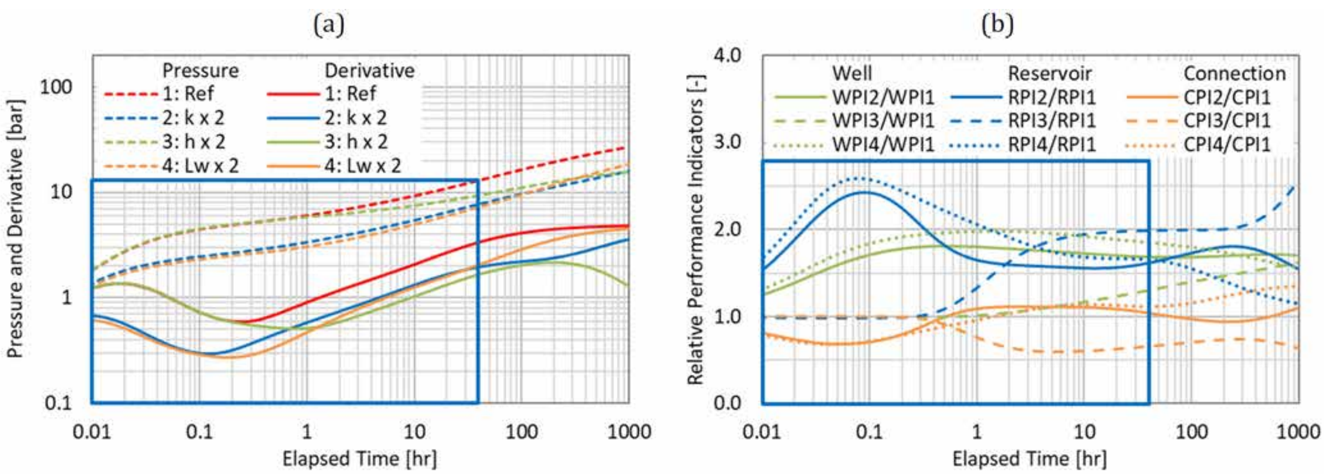

Figure 5—Pressure transients and their Bourdet derivatives obtained on a synthetic model of a horizontal well with WBS (Ref) and the transients / derivatives obtained on the same model, but with changed parameters: doubled permeability (k × 2), pay thickness (h × 2) and effective well length (Lw × 2). Boundary conditions: infinite reservoir model in the cases 1 and 4, no-flow fault in case 2 and constant pressure fault in case 3 (a). Relative WPI, RPI and CPI for three cases above as ratios to the reference case (Ref) indicators (b).

Synthetic transient responses presented in Figure 5-a represent deviations from the reference horizontal well response due to different reasons: the doubled permeability value (k), pay thickness (h) or effective well length (Lw). Different boundary conditions were also imposed to represent variety of potential scenarios. A stable pattern in this case may be recognized for the time-window of first 40 hr, where all the responses behave similarly with the only difference of the pressure / derivatives of the 'doubled parameter' cases moving down in the log-log plot. Here, the doubling of the thickness generates a proportional move of the derivative (like in the case of a vertical well), while the pressure drop moves gradually down according to the 'partial penetration skin' (Bourdet, 2002). The cases with doubled permeability and well length move down with a coefficient of ~1.6, while the pressure drop is around twice lower (like in the case of a vertical well). This transient behavior is represented by the PTA-metrics (Figure 5-b), while the changes of the well and reservoir parameters (doubling the parameter values in this case) may not be reflected by the proportionate response change unlike in the case of a vertical well (where the doubled permeability case's response ends up with a twice lower pressure derivative).

Summarizing the horizontal well analysis above: the PTA-metrics, initially suggested for a vertical well case, do reveal the changes in the well-reservoir performance, but the complexity and interplay of flow regimes may result in inaccurate estimating of the relative performance indicators for horizontal well cases. Nevertheless, the PTA-metrics may be further tested on real horizontal well cases to verify its capabilities and limitations.

Applications of the PTA-metrics to monitor wells on the Norwegian Continental Shelf

The synthetic examples, presented above, showed the main capabilities, advantages and limitations of the PTA-metrics in comparison with the classical PTA and the PI monitoring. This section demonstrates testing of the metrics on real field examples, previously analyzed using the model-based approach for time-lapse PTA (using Saphir interpretation and simulation tool). Hereafter, the changes of the well- reservoir parameters obtained in the model-based results are compared with the results of the PTA-metrics to verify the ability of the metrics to reproduce the model-based results. Potential reasons for the observed deviations in transient pressure responses are also shortly discussed, while detailed analysis of the reasons is a subject for specific case studies. Two aspects should be noted in the context of such comparison: (1) the PTA-metrics provide relative changes of performance indicators from reference values and (2) accuracy of the metrics is discussed as the deviation of the metrics (1)-(3) in the appendix from the indicators (4)-(6) calculated from the model parameters providing 'reasonable-match' of the measurements by the model. The model response may also deviate from the measurements (in contrast to the synthetic cases discussed above) making the accuracy discussion comparative.

A slanted injection well in a fractured carbonate reservoir

A slanted injector is considered as the first example, which represents a case with presence of radial (followed by hemi- radial, not observed in the presented data) flow regime, suitable for the metrics application as discussed above. The well penetrates a segment of a naturally fractured reservoir surrounded by few production wells (Figure 6). The well was stimulated to create a hydraulic fracture. A step-rate test (SRT) consisting of 14 steps was carried out after the stimulation and a short period of water injection (Figure 7-a). The test started after a short shut-in, where pressure was not fully equilibrated and large noise in the rate measurements is observed for the first two steps.

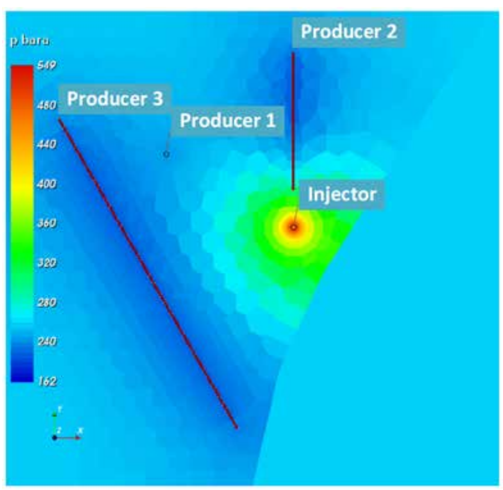

Figure 6—A slanted injector and nearby producers in a segment of a fractured carbonate field. Pressure (bar) field from a reservoir simulation.

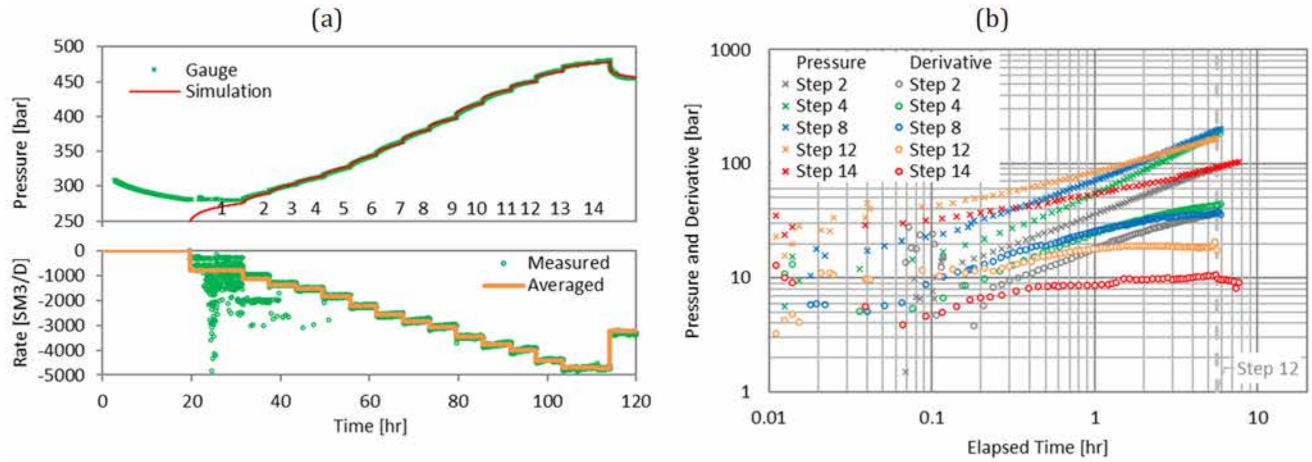

Figure 7—Step-rate test of a slanted fractured well (a) and selected pressure transients for steps 2, 4, 8, 12 and 14 in the log-log scale (b). Figure 7-a shows the pressure measurements and the results of simulations with estimated well-reservoir parameters from (Shchipanov, Kollbotn, & Prosvirnov, 2017).

The SRT data (Figure 7) have been interpreted using the model-based approach in (Shchipanov, Kollbotn, & Prosvirnov, 2017), where estimated well-reservoir parameters provided reasonable match of the observations (Figure 7-a).

The interpretation provided estimates for PI, reservoir flow capacity, *kh*, and well skin for each step, where relative values (Figure 8-b) were then calculated following the relationships (4)-(6) in the appendix.

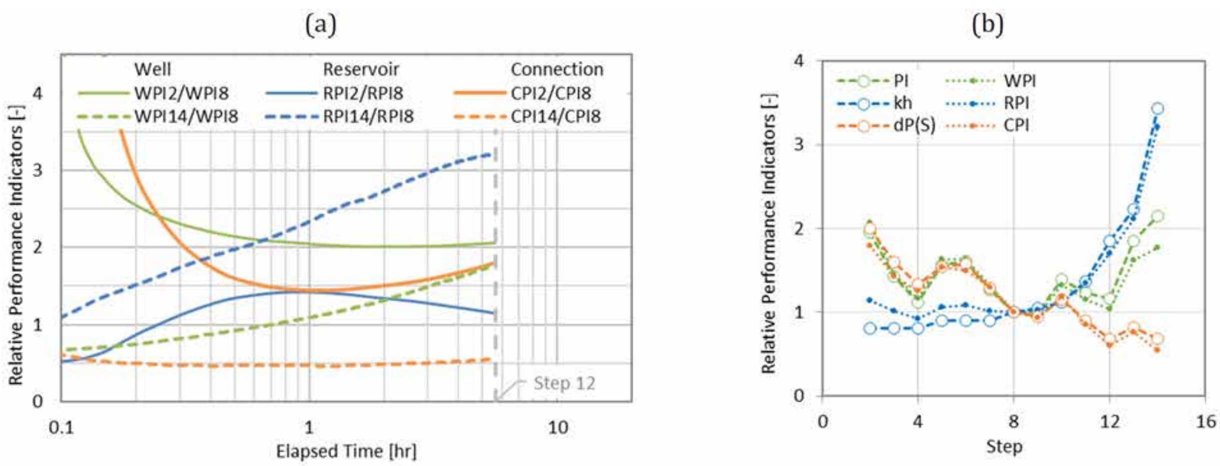

Figure 8—Relative performance indicators for well (WPI), reservoir (RPI) and connection (CPI) as pressure functions for steps 2 and 14, calculated as the ratios to the indicators at the step 8 (a) and the relative indictors for the model-based PTA interpretation results (PI, kh and dP (S) according to the metrics (4)-(6)) and for the PTA-metrics at the end of time-window limited by duration of step 12 (WPI, RPI and CPI, (1)-(3) in the appendix) (b). Average deviations of the PTA-metrics results from the model-based approach for WPI, RPI and CPI are 6, 12 and 6 %.

The transient responses for all the steps were further interpreted applying the PTA-metrics (1)-(3) in the appendix. The first steps of the well test seem to experience effect from the previous injection and non- equilibrated pressure before the test (Figure 7-a). The shortest step 12 limited the time-window for comparison of the indicators. Analyzing the pattern formed by the transients and their derivatives (Figure 7-b), radial flow regime may be interpreted for the steps starting from step 8. Previous steps 2-7 seem to be affected by pressure equilibration in the near-well area, as may be argued in particular by the increasing pressure drop at each step from 2 to 7. Following this observation, step 8 was chosen as the reference for the relative performance indicators. Figure 8-a illustrates the indicators as time functions. Stabilization of the indicators with time is a function of stability of the transient pattern. In this context, the transients 2-8 form more stable pattern than 8-14. Despite some pattern instability, the PTA-metrics provided the relative indicators in line with those obtained with the model-based interpretation (Figure 8-b). It seems that the deviation of the performance indicators from the reference values at the step 8 is related to (1) the pressure equilibration for steps 2-7 and (2) the reservoir effects such as increasing flow capacity due to pressurization of fractured reservoir for steps 8-14. Comparison of the indicators in Figure 8-b gives the average deviations of 6 % for WPI, 12 % for RPI and 6 % for CPI from the model-estimated parameters, confirming the relative accuracy of the PTA-metrics for the cases of vertical / slanted wells with radial flow regime observed.

A horizontal production well in a sandstone reservoir

The time-lapse PTA study reported in (Molina, 2020) and (Namazova, Molina, & Shchipanov, 2021) was chosen to test the PTA-metrics for the case of single-phase oil production. Oil production from the Southern part of a sandstone fault-block reservoir with three producers and one injector is considered in this field study (Figure 9). Production from the reservoir segment was under pressure depletion for one year (Wells A, B and C) followed by pressure support using water injection (from Well D). Water breakthrough was not observed during the analyzed period of history. History of the horizontal well C with four time- lapse shut-in surveys was chosen as an example for testing of the PTA-metrics in this paper (Figure 10-a). The well was producing with the pressure falling slightly below the bubble point pressure, which however did not lead to gas separation in the reservoir (Molina, 2020).

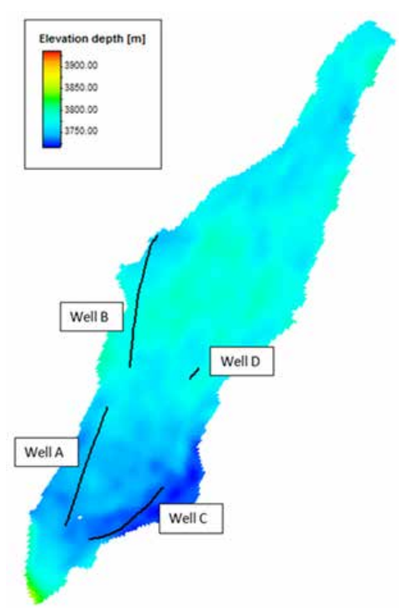

Figure 9—A sandstone fault-block reservoir with three producers (Wells A, B and C) and one injector (Well D) - a top reservoir depth map.

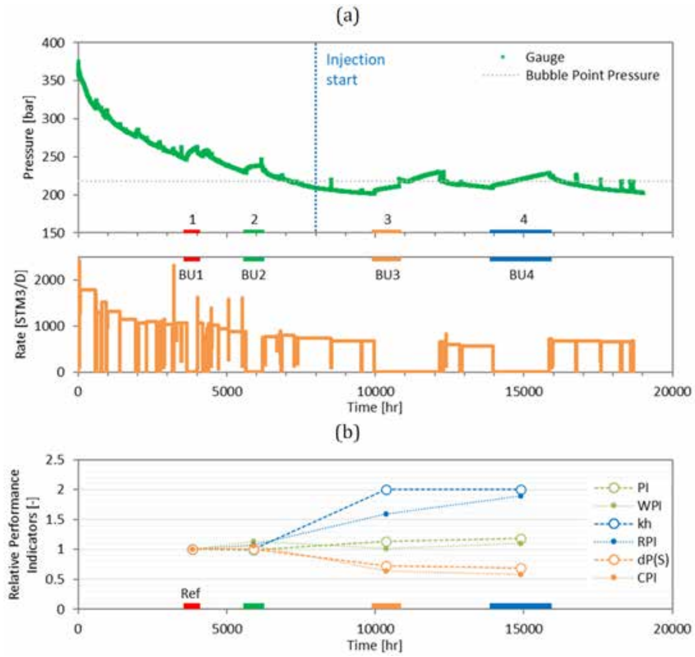

Figure 10—History for a horizontal oil producer with time-lapse transients highlighted: two shut-ins before start of the injection (BU1 and BU2) and two – after the injection start (BU3 and 4), (a) and comparison of the time-lapse interpretation results using the model-based approach (PI, kh and dP(S)) and the PTA-metrics (WPI, RPI and CPI), (b). Average deviation of the PTA- metrics results from the model-based approach for WPI, RPI and CPI is 11 % (for all the indicators).

The well shut-in surveys (Figure 10-a) were designed to monitor production well interference during the depletion phase (build- ups (BU) 1 and 2) followed by the well shut-ins focused on the injection impact (BU3 and 4). The analysis of the time-lapse shut- in responses (the commonly used approach) in the log-log scale has revealed both the interference effects and injection impact (Figure 11-a). Thus, the deviation of BU1 (derivative), where all producers were shut-in, from BU2, where only the well in focus was shut-in, clearly demonstrated communication of the production wells via comparison of the late-time responses (the boundary effects in the BU2 derivative observed). Comparison of the BU responses before (BU1 and 2) and after (BU3 and 4) injection start has revealed downward move of the derivatives for the after-injection responses, which was associated with connection of the bottom layer under injection to the well C drainage area and increase of the pay thickness of the reservoir (Namazova, Molina, & Shchipanov, 2021).

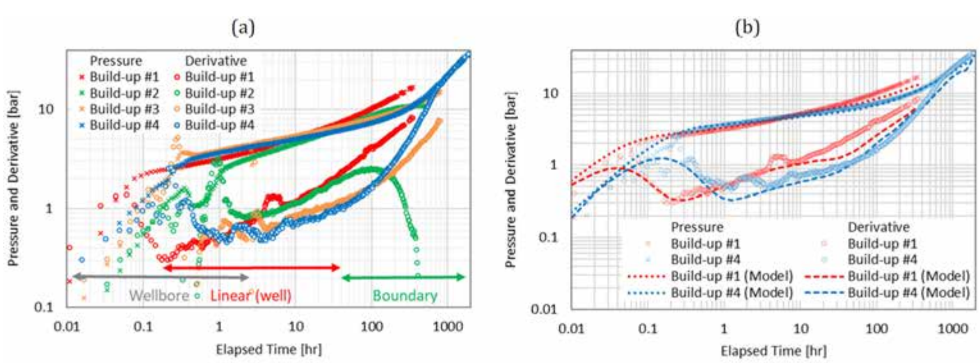

Figure 11—Pressure transients and their Bourdet derivatives for four time-lapse well shut-in periods illustrated in Figure 10 (a) and results of matching of 1st and 4th transients with the 'box-model' (Namazova, Molina, & Shchipanov, 2021), where pay thickness was doubled to match the 4th transient (b).

The studies (Molina, 2020) and (Namazova, Molina, & Shchipanov, 2021) used a set of reservoir models to match the time-lapse responses and well histories employing the workflow presented in (Shchipanov, Berenblyum, & Kollbotn, 2014) and summarized above. Figure 11-b illustrates such a match for the first and fourth shut-ins with a simplified ‘box-model’, where doubling of the pay-thickness reflecting connection to the bottom reservoir layer in combination with skin adjustment was used to reproduce the observed change of the transient responses.

The time-lapse responses in Figure 11-a were used to test the PTA-metrics. Since the metrics were introduced for stable time-lapse patterns, a time-window for such pattern (with the length of 40 hr) was first chosen based on the Bourdet derivative pattern for the transients in focus (Figure 11-a). The choice of the time-window was governed by capturing the end of the linear flow (to the horizontal well) regime, before the start of the boundary effects featured in the derivatives.

The first shut-in response was used as the reference, and deviation of the performance indicators from the reference values was then analyzed. Figure 12 shows an example of such analysis, where the compared transients (Figure 12-a) were first used to calculate the performance indicators, while a plot of the relative indicators (Figure 12-b) was further generated to estimate WPI, RPI and CPI changes at the end of the time-window.

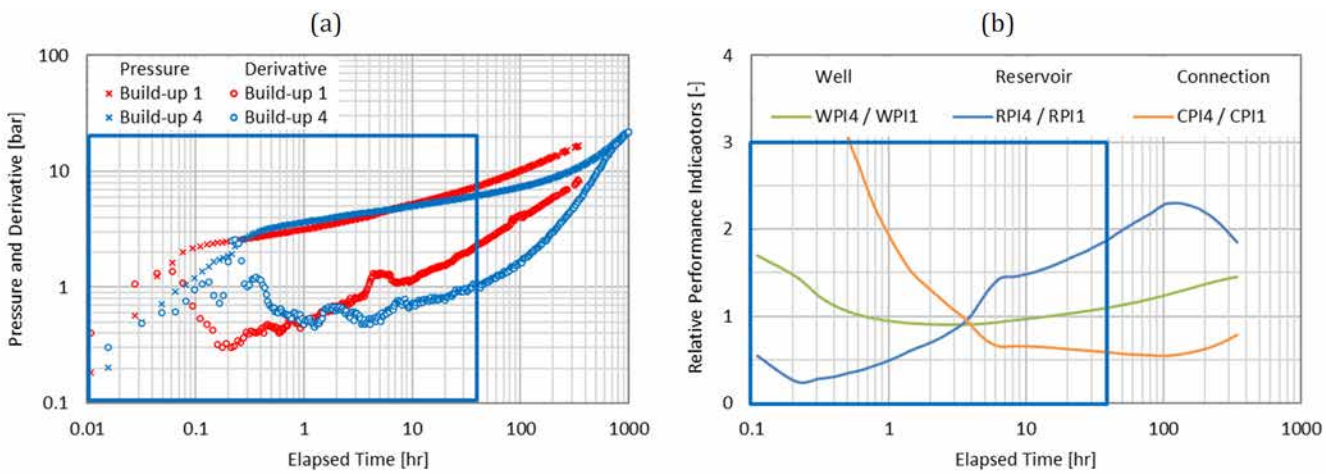

Figure 12—The pressure transients and their Bourdet derivatives for 1st and 4th build-ups shown in Figure 11-a (a) and the relative performance indicators for these transients calculated using the PTA-metrics (b). The blue square shows the selected time- window with stable pattern. Resulting relative WPI, RPI and CPI at the end of the time-window are 1.10, 1.89 and 0.58.

Figure 10-b summarizes the results of the time-lapse PTA application with the model-based approach in comparison with the PTA-metrics results. The comparison shows that the PTA-metrics followed the changes in the well, reservoir and well-reservoir connection performances. The average deviation (11%) looks reasonable for such proxy-approach as the PTA-metrics. The results of the testing of the PTA- metrics on this example have confirmed applicability of the metrics to interpret a time-lapse shut-in survey of a horizontal production well for a single-phase production period. The performance changes revealed by the model-based interpretation are similarly reflected by the PTA-metrics.

A horizontal injection well in a fractured carbonate reservoir

A case of water injection in an oil-bearing fractured carbonate reservoir was considered as the final field example in this paper. The case was previously studied with application of the model-based time-lapse PTA interpretation in (Shchipanov, Berenblyum, & Kollbotn, 2014). The case is the most complicated from the cases studied in the paper since cold water is injected in a high pressure - high temperature reservoir containing natural fractures and faults, let alone the field is developed with horizontal wells, stimulated to create multiple fractures. The assumptions of isothermal single-phase flow for analysis of water injection in such environment looks oversimplified, since multi-phase and reservoir cooling effects may play significant role, especially at initial injection stage. However, an analysis with such assumptions may be carried if the effects above are accounted for in interpreting the results.

The horizontal injection well in focus (Injector 1) is surrounded by injection and production wells forming an injection pattern (Figure 13). The injector is equipped with a PDG and a flowmeter, having pressure and rate measurements over a two-year history of water injection containing a series of injection and shut- in periods (Figure 14-a). The well was stimulated with a multi-stage fracture job. The stimulation was carried out between the first and second well shut-ins highlighted in Figure 14-a. Time-lapse pressure transients for the selected three fall-off and three injection periods are shown in the log-log plot in Figure 15-a. In this time-lapse analysis the injection periods were analyzed in line with shut-ins, where integration of the injection periods helped to reveal communication with nearby producers as discussed further.

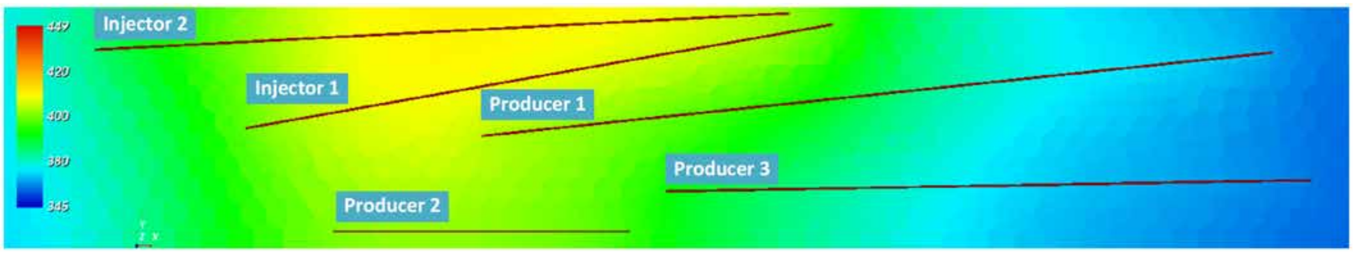

Figure 13—A reservoir segment containing the horizontal injection well in focus (Injector 1) and nearby injection (Injector 2) and production (Producer 1-3) wells. Pressure (bar) field from a reservoir simulation.

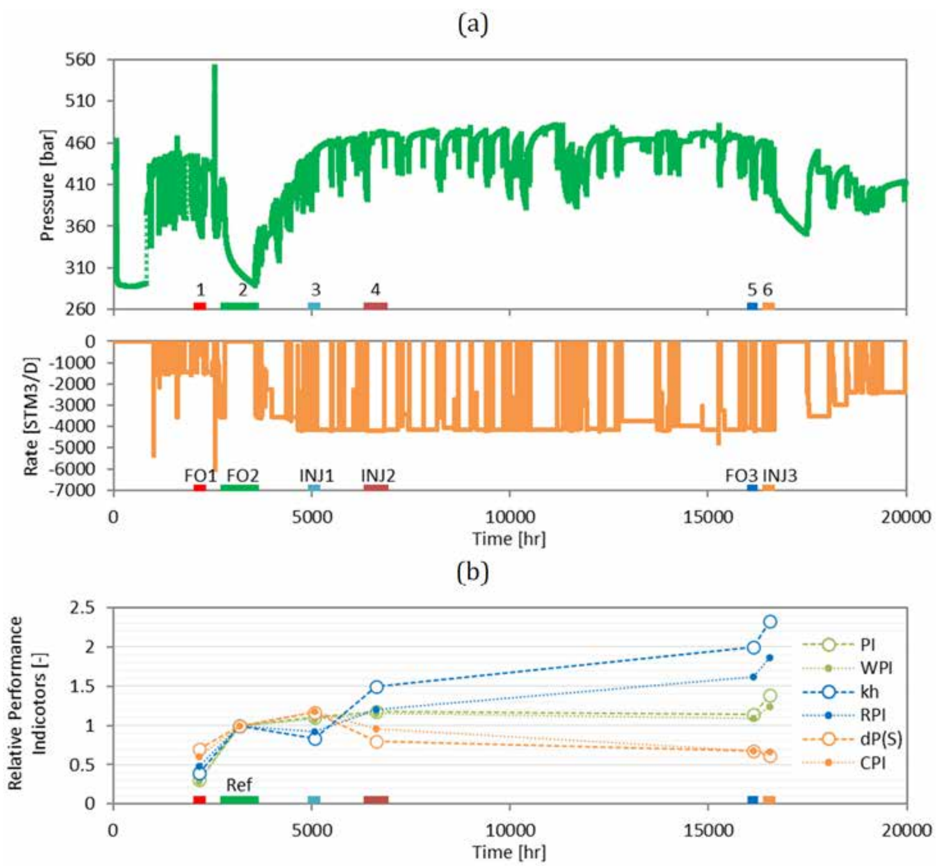

Figure 14—History for a horizontal water injector with time-lapse transients highlighted: three well shut-in with pressure fall-off (FO) and three injection (INJ) periods, (a), and comparison of the time-lapse interpretation results using the model-based approach (PI, kh and dP(S)) and the PTA-metrics (WPI, RPI and CPI), (b). Average deviations of the PTA-metrics results from the model-based approach for WPI, RPI and CPI are 4, 17 and 9 %.

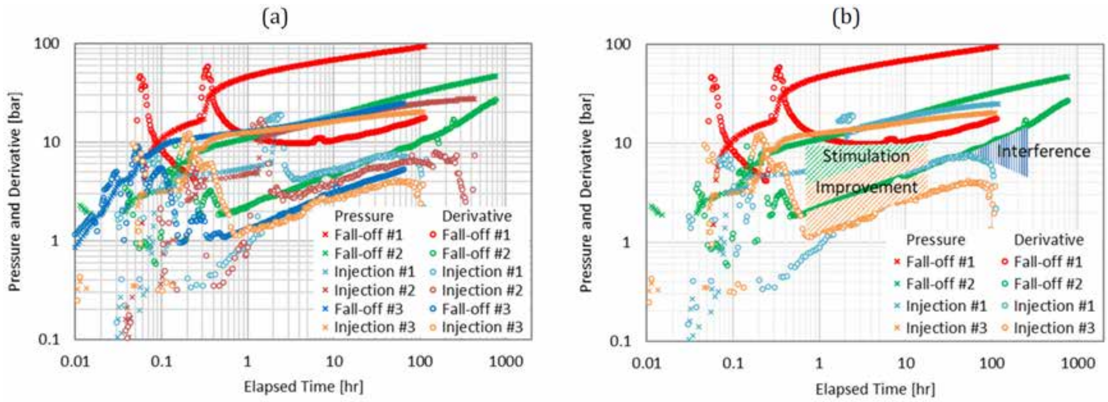

Figure 15—Pressure transients and their Bourdet derivatives for time-lapse fall-off and injection periods shown in Figure 14-a, (a), and four selected time-lapse transients illustrating effects of well stimulation, improved reservoir performance and well interference (b).

Comparison of these transient responses (Figure 15-b) reveals effects from:

- the stimulation: change of the derivative slope at early time before 10 hr (fall-off 1 and 2);
- improvement of the reservoir performance: shifting of the derivates down between 1 and 40 hr (fall- off 1 and fall-off 2 / injection 3) and
- interference with nearby wells: a change from the positive (fall-off 2) to the negative (injections 1, 3) slope of the Bourdet derivative after 40 hr.

Testing of the PTA-metrics in application to this field case was further carried out via comparison of the time-lapse PTA metrics with the model-based interpretation results previously presented in (Shchipanov, Berenblyum, & Kollbotn, 2014). The model-based interpretation provided matching of the selected transients with the same well-reservoir model, but with time-varying model parameters, including *kh* and skin. This variation reflected changes in the well and reservoir performances and boundary conditions, representing interference with nearby wells. The simple model of a horizontal well with a negative skin reflecting the stimulation effect was used in this paper to calculate reference model-based performance indicators ((4)-(6) in the appendix). This model provided a reasonable match of the transients (Figure 16), although a better match of the early-time response (see, for example, fall-off 2) may be found with application of a detailed multi-fracture model in (Shchipanov, Berenblyum, & Kollbotn, 2014).

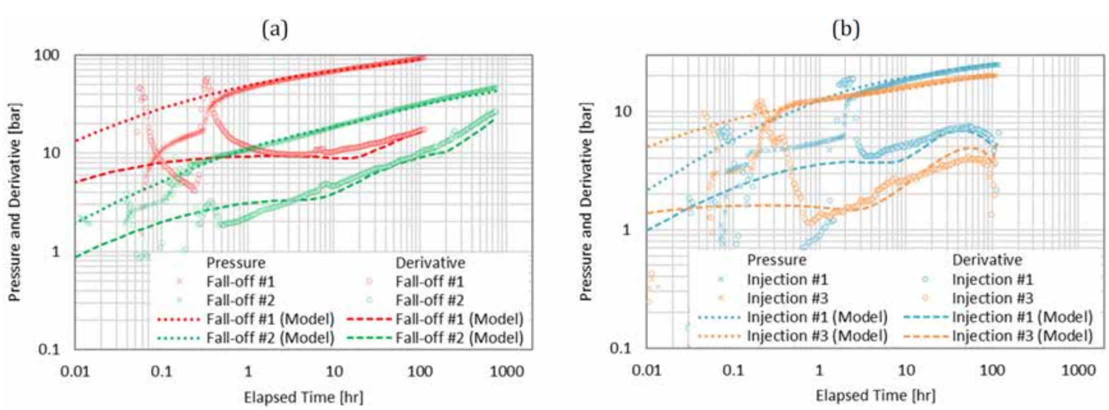

Figure 16—Matching results of the model of horizontal well with skin to the time-lapse fall-off (a) and injection (b) responses from Figure 15.

It should be noted that there are many potential reasons for shifting down of the transients and their derivatives in the log-log plot (Figure 15) including increase in the fluid mobility (kh/μ, where μ – fluid viscosity) or effective well length. Here, increasing the mobility, k/μ, and net-pay thickness, h, have different reflection in the log-log plot as it was shown before. Increasing permeability, k, at constant thickness and viscosity (h and μ), was used in this study to match the time-lapse transients above, although the other reasons mentioned above may play role in the observed derivative pattern. Studying the reasons for the observed changes is however out of the paper scope.

A performance analysis using the PTA-metrics was further applied to the same time-lapse transients. Taking applicability of the metrics to stable transient patterns, a time-window of 40 hours was chosen based on the linear flow regime observed in all the compared transients, ending for the injection periods at 40 hr due to transition to the boundary effect in the derivative (Figure 15). The fall-off 2 obtained during the well shut-in after the stimulation was chosen as the reference transient and all the fall-off and injection transients were compared to this transient using the PTA-metrics. Figure 17 and Figure 18 illustrate application of the metrics to fall-off 1 and 2 and fall-off 2 and injection 3. The figures show that the performance indicators are fluctuating at early time (before 1 hr) due to transient fluctuations, but the trends are stabilized at later time (after 10 hr).

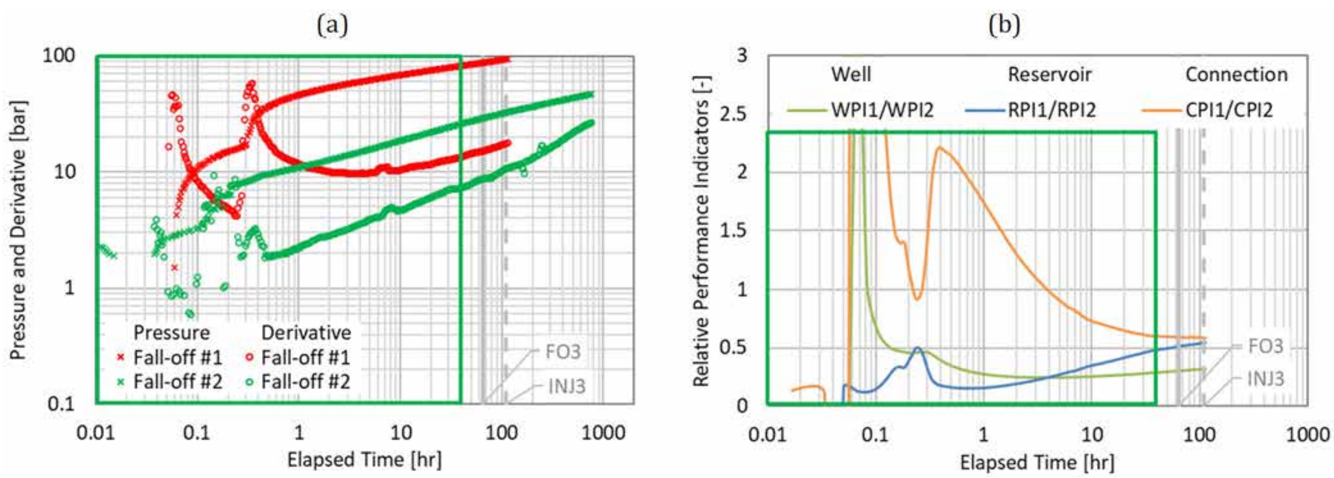

Figure 17—Application of the PTA-metrics to analyze changes of well-reservoir performance for fall-off 1 and 2 (reference), (a). Resulting relative WPI, RPI and CPI (b) give the following values at the end of time-window selected (40 hr): 0.29, 0.48 and 0.60.

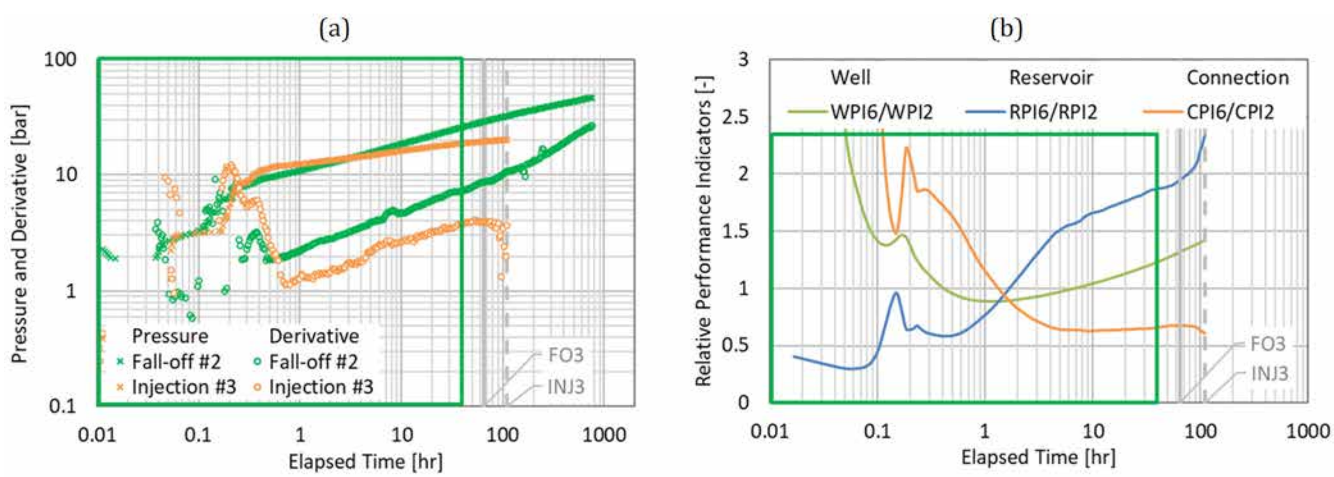

Figure 18—Application of the PTA-metrics to analyze changes of well-reservoir performance for fall-off 2 (reference) and injection 3 (a). Resulting relative WPI, RPI and CPI (b) give the following values at the end of time-window selected (40 hr): 1.24, 1.87 and 0.66.

The results of the time-lapse PTA using the model-based approach and PTA-metrics are shown in Figure 14-b. The WPI dynamics may be compared with the Productivity Index (PI) calculated, RPI – with the reservoir flow capacity, *kh*, while the CPI with the change in the pressure drop due to skin. The comparison has shown that the PTA-metrics reproduced the model-based monitoring results with reasonable accuracy. Here, the well (WPI) and well-reservoir connection (CPI) indicators are reproduced with the average deviation less than 10%. The reservoir performance (RPI) has larger deviation due to the reasons discussed for the synthetic horizontal well case above. Taking the simplicity and model- independence of the PTA-metrics application, the results provided by the metrics look quite promising.

Discussion

The applications of PTA-metrics to the field cases described above were conditioned by selection of a time-window (the relative indicators were calculated at the end of this window), where a stable (i.e. consistent between time-lapse transients) pressure-derivative pattern is observed. This procedure has grounds in the theoretical basis for the PTA-metrics (see appendix) employing the Bourdet derivative as a measure for reservoir performance. The stable patterns are often observed in actual well responses, at least in a limited time-window. A changing pattern is however a more general case, especially for long transients, due to such history-dependent effects as well stimulations, impact of nearby wells, and many other effects which may vary with time and may be independent from the well in focus.

In the last field case considered above, such a changing pattern is first observed when comparing the first and second fall-off responses. The changing pattern is governed by the well stimulation and localized in time (0-10 hr), having limited impact on the PTA-metrics results. The chosen time-window containing the stable pattern (40 hr long) is only a part of the longer, overall changing pattern if we consider all the data available (762 hr for the longest transient – 3rd fall-off, Figure 15). Here, the interference with nearby wells seems to be the main governing factor explaining the variance of the pressure derivatives at late times (after 40 hr). Impact of the changing pattern on the PTA-metrics application reliability may be studied by extending the time-window in the metrics application. Thus, durations of 3rd fall-off (65 hr) and 3rd injection (111 hr) periods may be used as limitation for the time-window.

Figure 19 illustrates the impact of the extended PTA-metrics integration windows, containing changing patterns, on the PTA-metrics results. The extension of the window to 65 hr (the pattern based on the 3rd fall-off duration) leads to some deviation of the PTA-metrics results, but the combined (the average over the indicators WPI, RPI and CPI) average deviation (from the model-based values) for the 'FO3' case (11%) remains almost the same as for the stable pattern (10 %). Further extension of the time-window to 111 hr (the pattern based on the 3rd injection duration) caused increase of the combined average deviation to 17 %. The increasing deviation for the last pattern analyzed is explained by the impact of changing boundary conditions causing change in the pattern. That is, the reference indicator was probing the reservoir at eventually different conditions and regimes than the subsequent one, based on a longer transient period. In all the cases, the RPI demonstrated the largest deviations, followed by the CPI and, finally, the WPI being the most accurate indicator. This sensitivity study confirmed that PTA-metrics reliability is, as expected, governed by the stability (consistency) of the pressure-derivative pattern within the selected time window. On the other hand, interestingly, the PTA-metrics still captured time-trends of the indicators for the changing patterns studied, although with larger deviations for the model-based results.

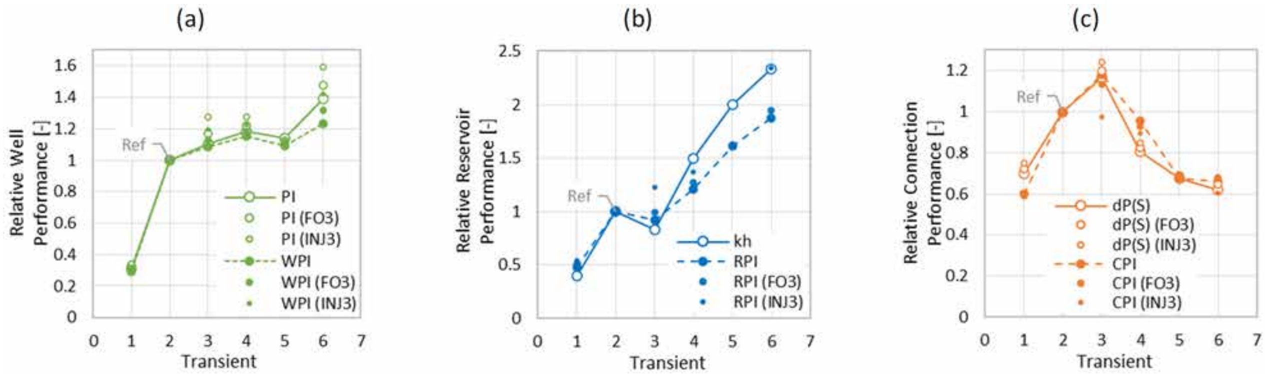

Figure 19—Impact of the patterns governing calculations on the relative well (a), reservoir (b) and connection (c) performance indicators. Here, the relative PI, kh, dP(S) and WPI, RPI, CPI are the estimates from Figure 14-b; surrounded by the cases with 'FO3' and 'INJ3' in the legends referencing to the relative indicators calculated within modified time-windows chosen based on durations of the transients: FO2 or INJ3. Average deviations for relative WPI, RPI and CPI for the stable pattern are 4, 17 and 9 %, for 'FO3 pattern' - 4, 21 and 9 % and for 'INJ3 pattern' – 5, 31 and 16 %.

Results and conclusions

New metrics based on interpretation of pressure transients and their Bourdet derivatives commonly employed in Pressure Transient Analysis (PTA) have been tested in this study on different well data sets for production and injection wells on the Norwegian Continental Shelf. The PTA-metrics are theoretically derived using the analytical solution for single-phase slightly-compressible flow with dominating radial flow regime (Bourdet, 2002). The metrics may also be relatively well applied to wells with the dominating linear flow regime, as it was demonstrated by the synthetic examples presented. However, accuracy of the results may be reduced by the complexity and interplay of flow regimes in this case.

The PTA-metrics have been tested on data from real slanted and horizontal wells, including producers and injectors in sandstone and carbonate fields. The metrics were compared with results of the conventional time-lapse model-based interpretation and the following conclusions may be drawn:

- The metrics reproduced results of the conventional interpretation with high accuracy (the average deviation from the model-based estimates is less than 12%) for the case of slanted (fractured) well with dominating radial flow regime.
- The metrics also reproduce the model-based interpretation results for the real cases of horizontal wells with dominating linear flow regime but may provide larger average deviations (11-17% in the cases studies). The larger deviations are due to the change from reference for the metrics (radial) to linear flow regime as it was also demonstrated on the synthetic well examples. Still, such deviations are well acceptable for the objectives of well operation monitoring and alarming on performance issues of horizontal wells.
- Successful application of the metrics depends, in general case, on the time-lapse pressure-derivative patterns developed in the log-log scale. Thus, if the main flow regime (radial or linear) is followed by another regime(s), e.g. boundary dominated, selection of a time-window limiting the main flow regime is necessary for accurate application of the metrics.

The metrics, having quite simple mathematical formulation given in the appendix, can be used as an extended formulation of the productivity index (PI), widely employed in the every-day well monitoring practice. In comparison to the PI, the PTA-metrics, inheriting features from PTA, are able to distinguish between the reservoir and the well-reservoir connection contributions to well performance. This helps to highlight well performance issues and to guide operating decisions in a short time-frame. Simplicity of the metrics formulation and model-independence further make it suitable for automated workflows, which are now extensively developed in the industry. The PTA-metrics may be a component of such workflows, which may also include automated data pre-processing methods, like the ones listed in (Suzuki, 2018). Such workflows can unlock information hidden in big data sets already accumulated in the industry as well as can be used for on-the-fly well monitoring and early alarming on performance issues.

Acknowledgments

Lars Kollbotn has significantly contributed to development of the model-based time-lapse PTA workflow, discussed as the starting point in this paper, and to formulating and review of the ideas forming basis for the PTA-metrics. His contributions at different stages of the metrics development are gratefully acknowledged. The authors acknowledge the AutoWell project funded by the Research Council of Norway and the industry partners including ConocoPhillips Skandinavia, Lundin Energy Norway, Sumitomo Corporation Europe Norway Branch, Wintershall Dea Norge and Aker BP (grant no. 326580) for support of the study and preparation and publishing of this manuscript. ConocoPhillips Skandinavia and Wintershall Dea Norge are acknowledged for providing access to the field cases first analyzed in (Shchipanov, Berenblyum, & Kollbotn, 2014), (Shchipanov, Kollbotn, & Prosvirnov, 2017) and (Molina, 2020), (Namazova, Molina, & Shchipanov, 2021) and used in this study as examples. Kappa Eng. is acknowledged for access to academic license of Kappa Workstation. The interpretations and conclusions presented in this paper are those of the authors and not necessarily those of the industry partners of the AutoWell project.

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Appendix

The PTA-metrics includes three performance indicators calculated as:

$$I_1 = \left(\frac{Q_{base}}{Q} \frac{1}{t_{ref}} \int_0^{t_{ref}} \Delta p dt \right)^{-1}, \tag{1}$$

$$I_2 = \left(\frac{Q_{base}}{Q} \frac{1}{t_{ref}} \int_0^{t_{ref}} \Delta p' dt \right)^{-1}, \tag{2}$$

$$I_3 = I_1 / I_2, \tag{3}$$

the performance indicators resulted from the model-based approach are:

$$I_1^m = \frac{Q}{\Delta p}, \tag{4}$$

$$I_2^m = kh, \tag{5}$$

$$I_3^m = \frac{\Delta p - \Delta p_S}{\Delta p}, \tag{6}$$

where I_1 - well performance indicator (WPI), bar^{-1}; I_2 - reservoir performance indicator (RPI), bar^{-1}; I_3 - well-reservoir connection performance indicator (CPI); I_1^m - well productivity or injectivity index (denoted 'PI'); I_2^m - reservoir performance governed by flow capacity (denoted 'kh'); I_3^m - pressure drop change due to skin (denoted 'dP(S)'); kh - reservoir flow capacity or permeability-thickness product, mD·m; Δp - pressure drop, bar; $\Delta p'$ - the Bourdet derivative of the pressure drop, bar/hr; Δp_s - pressure drop due to skin, bar; Q - rate, m^3/day; Q_{base} – rate for the reference transient, m^3/day; t - time, hr; t_{ref} - current time, hr. The relative performance indictors may be calculated for all six performance indictors above as ratios to reference values, calculated for a chosen reference transient.