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A New Automated Workflow for Well Monitoring Using Permanent Pressure and Rate Measurements

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Abstract

Pressure and rate measurements are essential for the well and reservoir surveillance workflows used in petroleum, geological carbon storage, and geothermal industries. Such well monitoring data are now analyzed in manual, semi-automated and automated modes or in a combination. Automated workflows are widely adopted by the industry nowadays, enabling most efficient knowledge extraction from the data both already accumulated and being received in real-time.

The paper describes a new integrated workflow for automated well monitoring using pressure and rate measurements obtained with permanent gauges and flowmeters. The workflow is based on time-lapse Pressure Transient Analysis (PTA) and integrates the following components: virtual flow-metering, transient identification, feature extraction and pattern recognition in transient pressure responses, and assessment of well performance based on PTA-metrics. The methodology behind the workflow combines different physics-informed and data-driven methods described in the paper. Application of the workflow is illustrated on a field case example from the Norwegian Continental Shelf, where changes in the well, reservoir, and well-reservoir connection performances are automatically monitored during its three-year long injection history. Reliability and accuracy of the automated monitoring results are verified via comparison with the conventional model-based time-lapse PTA.

The automated workflow may be used for a variety of use cases. Being applied to the well history, the workflow enables establishing a historical performance profile and identifying trends and issues in the past. In everyday well monitoring, it may be employed to detect well performance issues early and indicate their possible reasons. Further, it may provide valuable input for in-depth model-based analysis and other reservoir engineering studies. Using the workflow unlocks knowledge hidden in abundant well-monitoring datasets available at operating companies and empowers reservoir engineers to instantly assess well and reservoir performances, understand their interconnectivity, and make prompt, informed decisions.

Introduction

Widespread adoption of wellhead and downhole gauges in combination with flowmeters, particularly in the new wells drilled in the North Sea over the last two decades, has provided big datasets of pressure, temperature and flow rate measurements. This facilitated applications of time-lapse pressure transient analysis (time-lapse PTA, see for example (Horne, 2007)), mostly done by reservoir engineers in manual mode. Many such applications were reported for the fields in the North Sea as presented by (Gringarten, von Schroeter, Rolfsvaag, & Bruner, 2003), (Skrettingland, Giske, Johnsen, & Stavland, 2012), (Shchipanov, Berenblyum, & Kollbotn, 2014) and many others, with a recent application to the Johan Sverdrup field (Walker, Shchipanov, & Selseng, 2021). Automation of PTA and its time-lapse version as a more efficient, alternative method to the manual PTA has been investigated by the academia, R&D and industry for decades (Allain & Horne, 1990), (Olsen & Nordtvedt, 2006), (AlMaraghi & El-Banbi, 2015), (Suzuki, 2018) and (Freites, Corbett, Rongier, & Geiger, 2022). (Suzuki, 2018) summarized recent progress in this area and described a general workflow of automated PTA, which may be divided into the following main stages: data preprocessing (with denoising and outlier removal), transient identification (with pressure and rate synchronization) and interpretation of the identified transients. The interpretation usually focuses on estimating well-reservoir parameters via matching the transient in question with a chosen well-reservoir model, where the model identification may also be automated (AlMaraghi & El-Banbi, 2015).

This paper presents further development of the automated time-lapse PTA workflows based on the developments reviewed above, but has a distinct feature: we try to avoid any use of specific well-reservoir model when designing and developing the new workflow presented. However, the interpretation of transient responses within this workflow is physics-informed, since it's based on analyzing the Bourdet derivative, which widely used in PTA, by applying the PTA-metrics (Shchipanov, Kollbotn, & Namazova, 2023). This approach has some limitations, since it deviates from the mainstream of physics-based models, but at the same time makes the workflow application more (1) flexible due to limited well-reservoir description required and (2) scalable for processing big datasets of different wells in various geological environments. The choice of such physics-informed approach has also some benefits for automation requiring lower level of problem formalization as discussed in (Shchipanov, Namazova, & Muradov, 2023).

The next sections of the paper provide a description of the new workflow developed and its four components as well as references to relevant literature. A field case example follows the workflow description illustrating its application to actual data with discussion of its benefits and limitations in the context of well operations and monitoring. The proposed workflow and its applications described in this paper focus mainly of water injectors, following the limitations of the PTA-metrics applied (Shchipanov, Kollbotn, & Namazova, 2023), where dominating single-phase flow of low-compressible fluids is assumed. At the same time, many components of the workflow presented in this paper may be applied to wells injecting and producing at different conditions (single and two-phase, low- and high-compressible fluids), which is subject to further studies.

A New Workflow for Automated Well Monitoring

The concept of the automated workflow described in this paper has been suggested in (Shchipanov, Kollbotn, & Namazova, 2023), where its potential application domain is also discussed. The workflow consists of four main steps: from the 'well monitoring data' input to outputting the 'performance profile' (as illustrated in Figure 1), and integrates the following four components:

- Virtual flow-metering.
- Pressure transient identification.
- PTA-feature extraction and time-lapse pattern recognition.

- PTA-metrics to get the well performance profile.

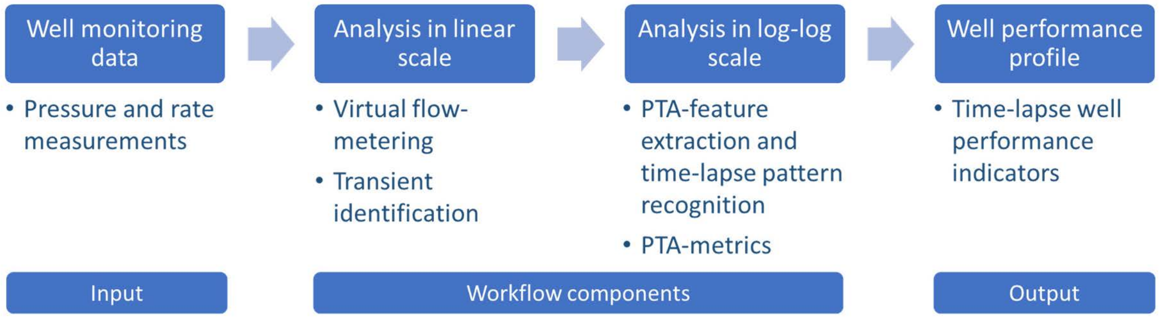

Figure 1—Main steps of the workflow for automated well monitoring.

The workflow uses pressure and rate measurements as the main input, while temperature measurements are currently used as secondary data for improving the results of pressure and rate data interpretation, e.g. for verification of well shut-ins. As a result of the workflow application, the well performance profile distinguishing reservoir and well-reservoir connection contributions is provided. New real-time measurements may be further integrated, and current performance indicators may be calculated based on new transients available. All the workflow components are developed assuming that human interaction should be avoided providing possibility to use the workflow in an automated mode. These four components of the workflow are described below in this section, while the next section illustrates application of this workflow to a well example.

Virtual flow-metering

The well flow rate is often measured more sparsely than its bottomhole or wellhead pressure due to many different reasons like: several wells sharing a single common flowmeter or a test separator with periodic connection to each of the wells; periodic well tests with measuring the rate in the absence of a permanent flowmeter etc. In addition, the rate measurements may be noisy due to well operations or the flow metering quality, or fragmentary due to flow metering failures. On the other hand, the permanent downhole and/or wellhead gauges, when installed in a well, provide high-frequency real time pressure and temperature measurements. This disparity in the pressure and rate measurement sampling rates is a problem for PTA, which requires accurate and synchronized input for flow rates in-line with the pressure time-series. Virtual Flow Metering (VFM) helps to reconstruct

Many well VFM solutions have been published to-date, each one developed for and applicable to a specific well and measurement configuration as required by the given case studies. A typical VFM model provides flowrates estimated from the wellbore pressure difference using some physical wellbore flow model. For instance, (Leskens, Kruif, Belfroid, Smeulers, & Gryzlov, 2008) used an isothermal wellbore flow model, and Kalman filter to update the model's parameters. The authors (Muradov & Davies, 2009) used a non-isothermal wellbore, choke, and reservoir model to zonally VFM an intelligent well using its pressure and temperature measurements, while (Russo, Ursini, Rossi, & Maddeo, 2021) applied and compared both Vertical Lift Performance (VLP)-based and choke- based VFMs for injection wells, with decent results. On top of such case-specific published examples, there are also several commercial, numerical well modelling toolboxes that offer VLP-based VFM options.

The automated well monitoring workflow described in this paper would benefit from integration of a relatively simple, but robust and scalable VFM model having modest input data requirements. The steady-state VLP-based VFM model has been chosen after considering and testing of the wellbore pressure difference based VFM models, using both steady- state and transient wellbore flow models, also trying to integrate wellbore temperature measurements. The model uses only the bottomhole and wellhead pressure difference, which fits well the automated workflow requirements.

Sparing the mathematical details, the VFM algorithm we have developed identifies the suitable pressure and flowrate samples to train the VFM model; estimates, filters, and verifies the evolution of the model coefficients (they tend to change during the well life due to multiple reasons); and finally predicts the missing flowrate values using the pressure measurements where available. This prediction applies only to the time when the well is flowing; as for the shut-in periods (identified as explained later in this paper): the algorithm assigns zero rate values.

Figure 2 and Figure 3 illustrate results of the VFM model testing on a short well monitoring dataset. In this testing, random 10% of true flowrate measurements with subsequent removal of the flowrate measurements were used as the VFM input. The VFM predictor gives 8%-smaller flowrate estimate during this period (Figure 2). Figure 3 illustrates dynamics of one of the coefficients in the VFM model governing the VFM results.

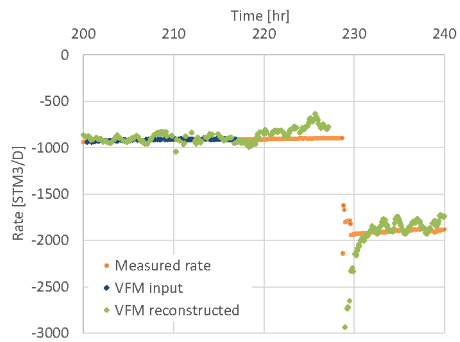

Figure 2—Comparison of the VFM and true flowrate values. Orange: true, high resolution flowrate measurements. Blue: random 10% of the true measurements, excluding all measurements between 220 and 240 hr. Green: the VFM flowrate reconstructed using the 'blue' measurements as input.

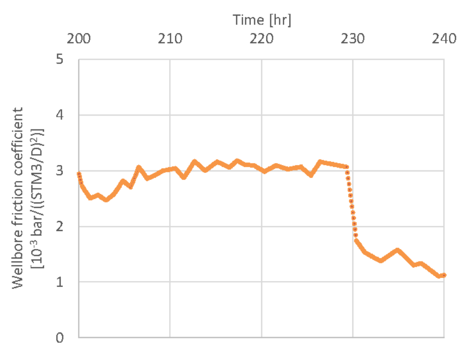

Figure 3—Wellbore friction coefficient from the VFM model for the same period as in Figure 2.

Transient identification

Following the terminology formulated in (Cui, et al., 2023): a pressure transient is a predominantly monotonic change of pressure in response to a sudden change of rate, where transient identification is a process of dividing the pressure time series into sequential transients based on the objectives of the data interpretation. The transient identification therefore focuses on finding break points separating transients. The problem of identifying transients in pressure responses was addressed by many studies reviewed in (Cui, et al., 2023), where a variety of different methods have been suggested, applied and tested. Although decent results of some applications of the methods have been reported, the common limitations of the methods in the context of automated interpretation are the need to select a signal change sensitivity threshold, and the need for denoising of the pressure data. A novel method for transient identification suggested by (Cui, Zhang, Shchipanov, Rong, & Demyanov, 2023) for well shut-ins was extended for identification of flowing periods (Figure 4) and applied in the automated workflow. The extended method is a combination of TPMR (Topographic Prominence Max Rotation) and LMIR (Local Minimum in Rotation) methods focusing on detection of different transients: shut-in and flowing periods respectively as illustrated in Figure 5. The method has two main advantages: (1) extracting maximum information from the raw data by avoiding denoising and (2) minimizing human interaction via avoiding the threshold selection commonly used in other transient identification methods (Cui, et al., 2023).

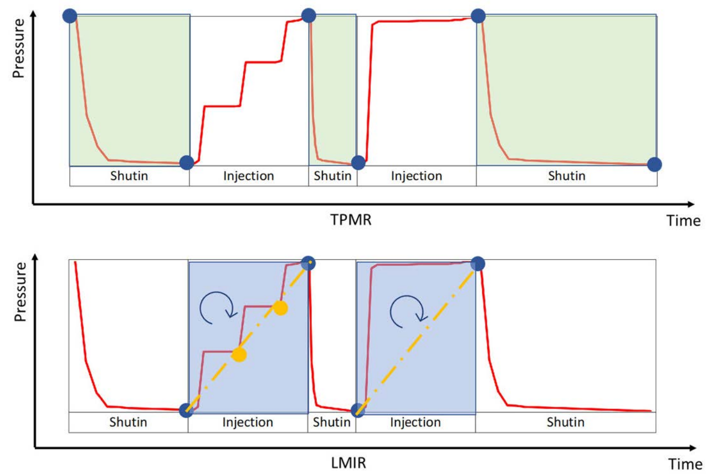

Figure 4—Illustration of transient identification in TPMR (top) and LMIR (bottom) methods.

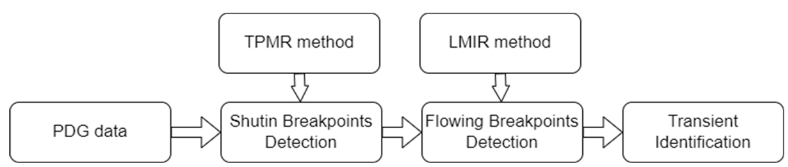

Figure 5—Workflow of combining TPMR and LMIR methods for transient identification including shut-in and flowing periods.

Proper transient identification is crucial for PTA, since accurate identification of the starting break point of a transient and sequential synchronization with corresponding rate govern reliability of the PTA interpretation results. This is important not only for the transient in question, but also for the well history preceding the transient, which has an impact via the superposition effects (Bourdet, 2002). In the latter case, proper transient identification may help in reliable rate time-allocation throughout the well history for common cases of uncertain rates.

The workflow of the extended method consists of two main stages. First, the breakpoints indicating start and end of shut-in transients are detected using the TPMR method (Figure 5, Figure 6, a). This automatically provides detection of flowing transients (called further 'long flowing transients') between the shut-ins identified. Second, the breakpoints of multi-rate periods (assuming step-wise rate changes) are detected within the long flowing transients using the LMIR method (Figure 5, Figure 6, b). As a result, the well pressure history is divided into sequential flowing and shut-in transients, also differentiating flowing transients governed by step-wise rate changes. Both TPMR and LMIR methods do not require denoising, so raw data from permanent gauges may be used without any pre-processing. No threshold selection is needed during the whole process, while some requirements for minimum duration of a transient may be used to tune outcome of the transient identification for a dataset in focus. All these advantages make the extended method a robust component for the automated workflow developed.

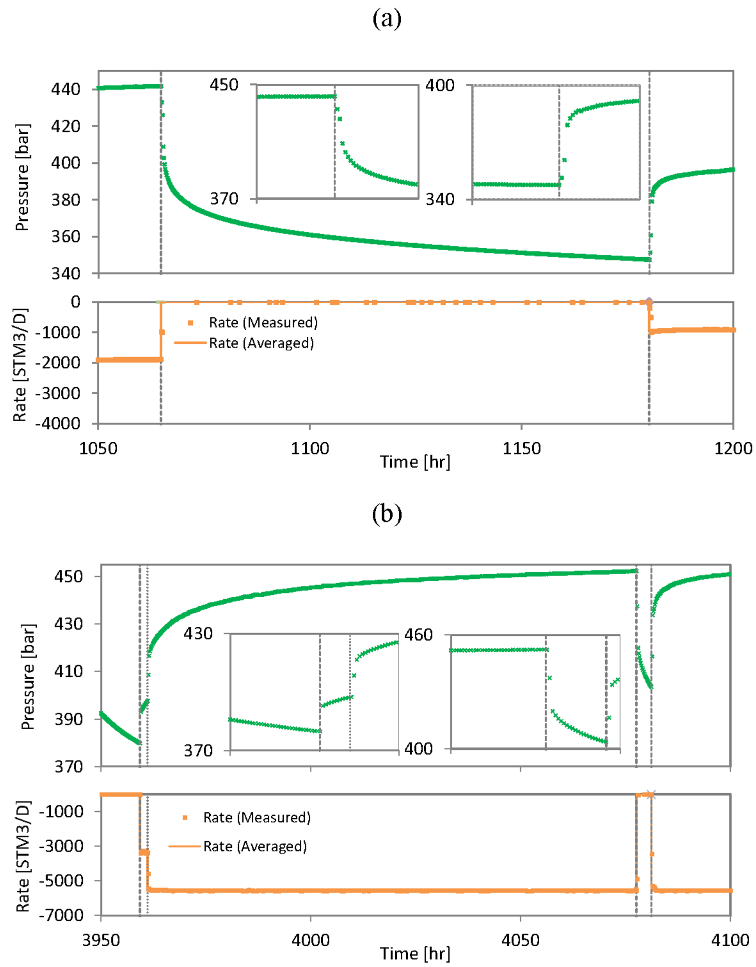

Figure 6—Results of automated transient identification for shut-in (a) and flowing (b) periods.

PTA-features and pattern recognition

Identifying flow regimes in pressure transient responses via interpretation of their reflections in the Bourdet derivative was in the focus of many studies starting from (Allain & Horne, 1990). This was done mainly in the context of well-reservoir model identification. Recently, many automated PTA approaches have been developed. Most of the research focused on implementing supervised (AlMaraghi & El-Banbi, 2015) and unsupervised (Freites, Corbett, Rongier, & Geiger, 2022) machine learning (ML) methods to automatically identify and classify a reservoir model by analyzing the entire sequence of flow regimes in a pressure transient. Although these approaches were found to be quite accurate, there are questions about their robustness, as most of the models were trained on synthetic data. Another approach (Suzuki, 2018) focused on the similarity-based flow regime detection within a single pressure transient. The studies reviewed methods for identification of flow regimes. However, these approaches are still not fully automated, as human interventions are required for preprocessing, and for setting distance thresholds and other hyperparameters.

The transient identification methods described above provide families of pressure transients which may be plotted in log-log scale in combination with pressure derivatives as commonly done in PTA. Analyzing the Bourdet (or semilog) derivative of a pressure transient response in the log-log scale is the standard approach to distinguish between different flow regimes occurring during production or injection well operations (Bourdet, 2002). Each flow regime has a characteristic derivative slope or signature. Figure 7 illustrates a sequence of flow regimes identified in a synthetic well response using the method described further.

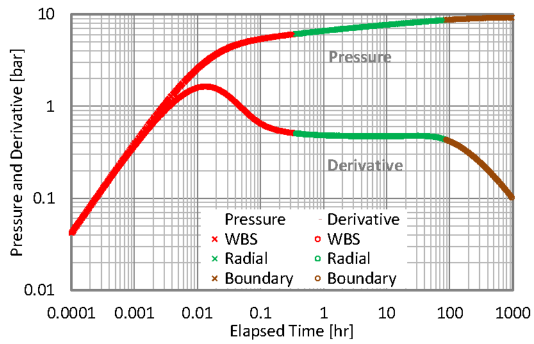

Figure 7—Sequence of flow regimes identified in a pressure derivative of a synthetic well response.

A sequence and durations of flow regimes may vary from transient to transient throughout a well's lifetime, so analyzing time-lapse pressure transients / derivatives together can reveal 'stable' (i.e. consistent or recurring) and changing (i.e. inconsistent) sequences of flow regimes (called further as 'patterns') formed by the pressure and derivative families. Figure 8 illustrates changing and stable patterns found in the family of pressure derivatives for transient responses of a synthetic well. The patterns contain crucial information about the well performance changes, which may be further extracted with specific metrics like the ones from (Shchipanov, Kollbotn, & Namazova, 2023) which are used in this study. Recognition of the patterns may therefore help with extracting this information. A set of PTA-features associated with different flow regimes may be introduced, where each feature may represent a set of different flow regimes having similar signature in the Bourdet derivative.

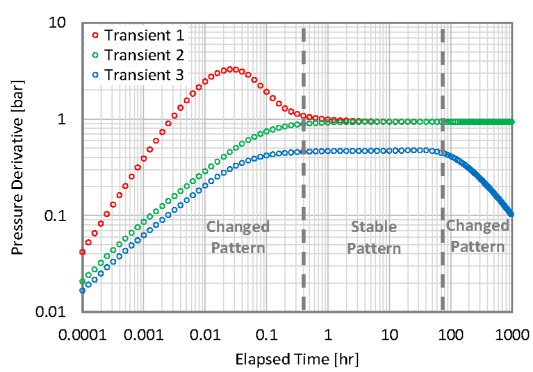

Figure 8—Sequences of flow regimes in pressure derivatives of time-lapse responses of a synthetic well with stable and changed patterns highlighted.

Figure 9 illustrates the set of PTA-features used in the workflow described. The features are separated based on the slope of the derivative in the log-log scale. Some features may be associated with a single flow regime (e.g. radial), while others – with multiple flow regimes reflected with similar slope derivative (e.g. the 'linear-up' feature may be associated with linear or composite reservoir flow regimes). Some features may overlap, such as the first feature associated with WBS (wellbore storage) and boundary effects. An automated deterministic method was developed to tackle the feature extraction or classification problem. Similar classification problem, but in the context of model identification or finding a well-reservoir model most suitable for observed pressure response, was addressed in many studies, see for example (Guyaguler, Horne, & Tauzin, 2003) and (AlMaraghi & El-Banbi, 2015). The proposed method is a bespoke, unsupervised, non- parametric machine learning classification model. It involves an unsupervised learning process to classify PTA-features within a single pressure transient. A convolution-like sliding window is combined with similarity-based identification, using normalized Euclidean distance to achieve this.

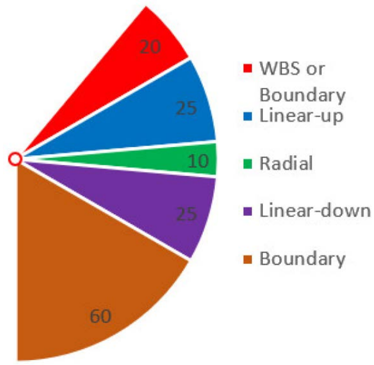

Figure 9—A diagram illustrating set of PTA-features associated with different flow regimes. The numbers are the sector sizes in degrees.

A set of hyperparameters that can be tuned by an embedded optimization function is used to provide manual (user-defined) and optimized options. Each PTA-feature is treated as a separate class with a specific range of values for the derivative's slope (Figure 9). The unsupervised learning element is based on the assumed pressure transient data structure, consisting of a sequence of flow regimes occurring successively in early, middle, and late-time regions. Therefore, the model learns to allocate PTA-features over time to minimize the normalized Euclidean distance metric. As a result, the pressure derivative in question is divided into a sequence of PTA- features. As an example, Figure 10 illustrates results of PTA-feature extraction for one transient and comparison with the feature extraction obtained by an expert (human-involved) interpretation. The expert interpretation may also involve identification of transitions between flow regimes, which is not covered here.

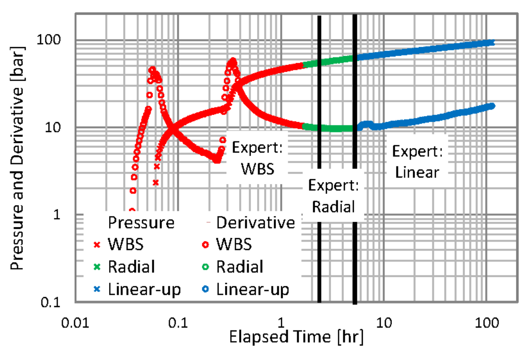

Figure 10—Comparison of the automated feature extraction (color) with manual interpretation ('expert' lines).

The pattern recognition may then be carried out as a sequential feature extraction for each transient of a time-lapse family in focus and comparison of the features extracted for this family of transients. As a result, the pattern recognition identifies periods of stable and changing patterns, as shown in Figure 11. Identifying stable patterns provides basis for reliable application of the PTA- metrics suggested in (Shchipanov, Kollbotn, & Namazova, 2023). The next section describes these metrics, finishing overview of the workflow components.

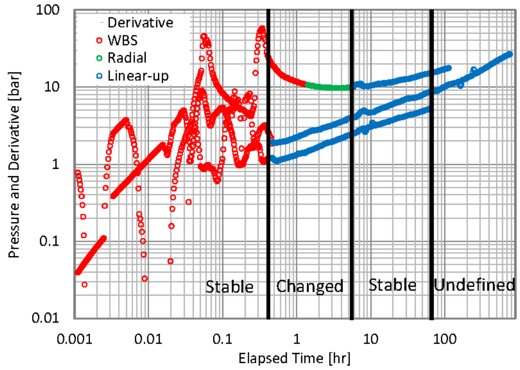

Figure 11—Reflection of flow regimes in pressure derivatives of time-lapse responses of a real well via PTA-features identified. The response duration is divided into 'stable', 'changed' and 'undefined' patterns.

PTA-metrics and well performance profile

The PTA-metrics suggested in (Shchipanov, Kollbotn, & Namazova, 2023) enable evaluation of well performance with differentiating contributions from reservoir and well-reservoir connection. The metrics are based on the Bourdet derivative and aim to track three performance indicators for: reservoir (RPI), well-reservoir connection (CPI), and overall well performance (WPI) as the product of the first two indicators (Figure 12, Appendix).

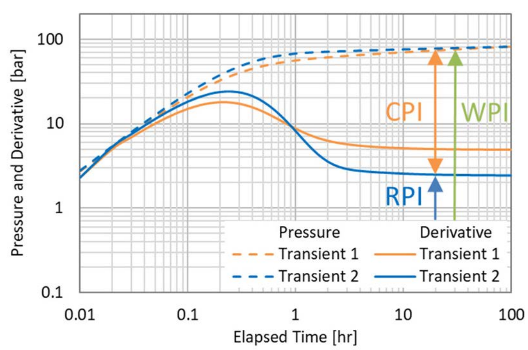

Figure 12—An illustration of well performance indicators according to the PTA-metrics (Shchipanov, Namazova, & Muradov, 2023).

Dynamics of these performance indicators enables identifying issues with the well completion (like increasing skin) or reservoir (like decreasing flow capacity). This is essential for efficient well management and forms the key objective of the workflow applications. These performance indicators should be calculated from the pressure transients and their derivatives within the stable pattern time-window to ensure reliable evaluations as it was shown in (Shchipanov, Namazova, & Muradov, 2023). Therefore, stable patterns recognized at the previous step are used within this workflow for conditioning the calculations of the performance indicators.

Figure 13 illustrates application of the metrics to analysis of time- lapse pressure transient responses in combination with the relative reservoir performance indicator calculated based on two different time-windows. In the first case (dash-line), the window was manually chosen as discussed in (Shchipanov, Namazova, & Muradov, 2023). In the second case (solid-line), the window with stable derivative pattern was automatically chosen based on the pattern recognition approach described in the previous section. Limiting the indicator calculation by the stable pattern window results in stabilization of the performance indicator estimates, while the manual window selection gave a variable indicator. At the same time, the final estimates for the indicator calculated at the end of the windows are close to each other for the transients in focus

(Figure 13) illustrating the value of using integrals for the metrics calculations (Shchipanov, Kollbotn, & Namazova, 2023).

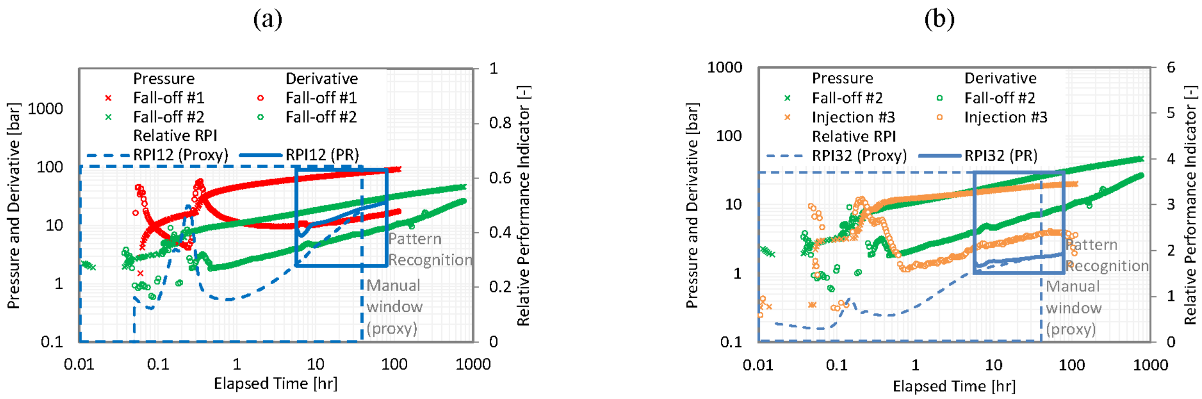

Figure 13—Two fall-off pressure transient responses and results of PTA-metrics application using proxy stable pattern from (Shchipanov, Namazova, & Muradov, 2023) marked as 'proxy' and stable pattern automatically recognized marked as 'PR' (a) and similar plot with the same reference fall-off comparted to an injection response (b).

The pattern recognition technique described above may be applied for a series of time-lapse pressure responses and their derivatives, where one transient may be selected as the reference ('Fall-off #2' is the reference in Figure 13-a and Figure 13-b) and the rest are compared with the reference transient. The pattern recognition method provides the time-window with a stable pattern for the transients to compare, and is used further for estimating three relative well performance indicators based on the PTA-metrics (Figure 12, Appendix). As a result, the well performance profile is obtained for the well history in focus.

Integrating the workflow components

The components described above are combined in the integrated workflow according to the sketch in Figure 1. Although these components may be used separately to solve particular tasks (e.g. virtual flow metering or transient identification), their combination should improve quality and reliability of well monitoring focusing on performance profile due to the following reasons:

- VFM improves the flow rate data set by filling gaps in the data and reducing noise and outliers of the existing flow rate measurements.
- Transient identification provides synchronized and consistent pressure-rate dataset for subsequent time-lapse PTA.
- The two components above enable reliable PTA-feature extraction and time-lapse pattern recognition, while the latter ensures accuracy of the PTA-metrics application.

As one can see, each of these components plays a unique and important role and all are crucial for successful and reliable application of the workflow.

Application of the workflow to pressure and rate measurements provided by permanent downhole gauges and flowmeters is illustrated in the next section in combination with verification of the final workflow results via comparison with the conventional model-based time-lapse PTA interpretation routinely carried out in the industry (Houze, Viturat, & Fjaere, 2020).

Case study

The well case of a horizontal multi-fractured water injector (Figure 14) first studied with the model-based time-lapse PTA approach in (Shchipanov, Berenblyum, & Kollbotn, 2014) and then used in verifying of the PTA-metrics by (Shchipanov, Namazova, & Muradov, 2023) is further used in this paper to illustrate application of the workflow. The comparison of the model-based interpretation with the PTA-metrics results was carried out in (Shchipanov, Namazova, & Muradov, 2023), where time-lapse transients and proxy-stable patterns were obtained manually (an expert judgement). This study provides results of similar interpretation, however all the steps above preceding the PTA-metrics application were made automatically following the workflow described in the previous sections. We further illustrate the workflow application step-by-step and compare the well performance profiles obtained with the model-based approach (Shchipanov, Berenblyum, & Kollbotn, 2014) and the manual PTA-metrics application (Shchipanov, Namazova, & Muradov, 2023) with the profile obtained with the automated workflow in this paper.

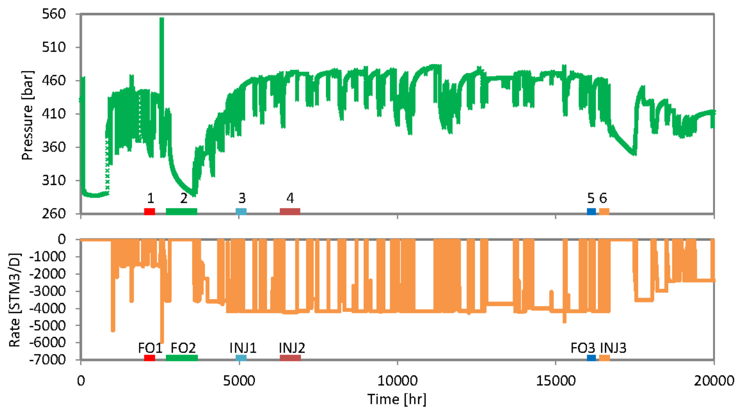

Figure 14—Injection well history from (Shchipanov, Berenblyum, & Kollbotn, 2014) with selected time-lapse shut-in and flowing responses highlighted.

Virtual flow metering may be the first step in the automated workflow application, which is a necessary step in the case when rate history contains gaps in measurements. In this study, we moved a part of the available rate data into a validation set to test the method performance: here artificial removal of rate measurements for periods of time was used to create a dataset containing gaps to illustrate performance of the virtual flow-metering (VFM) component of the workflow. Figure 15 in combination with Figure 2 illustrate how missing rates may be restored with the VFM model implemented in the workflow.

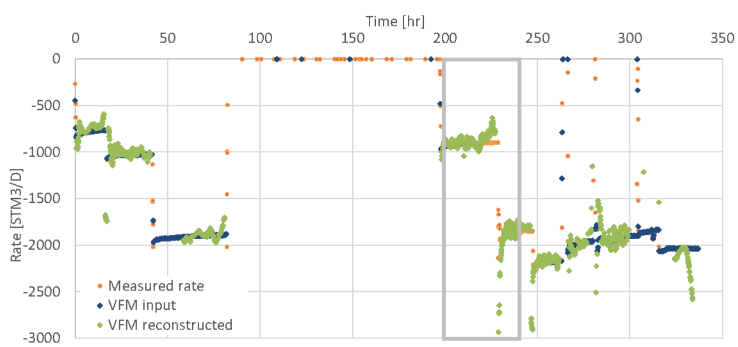

Figure 15—Virtual flow-metering results for a two-week segment of the well history (Figure 14). The period 200-240 hr is zoomed in Figure 2 with description of the testing procedure.

The second step in the workflow is transient identification, which resulted in identifying time-lapse pressure transient responses. Following (Shchipanov, Berenblyum, & Kollbotn, 2014), six time-lapse responses highlighted in Figure 14 were automatically identified and used further for PTA-feature extraction and pattern recognition. The results of automated transient identification coincide with the manual identification results obtained previously, as it may be seen based on the results zoomed in Figure 6 and comparison of the families of time-lapse pressure responses in Figure 16-a and -b containing similar transients. Resampling of raw data was also used in the automated workflow (Figure 16-b) to speed-up calculations, which did not change the pressure and derivative trends in the time-lapse family.

(a) (b)

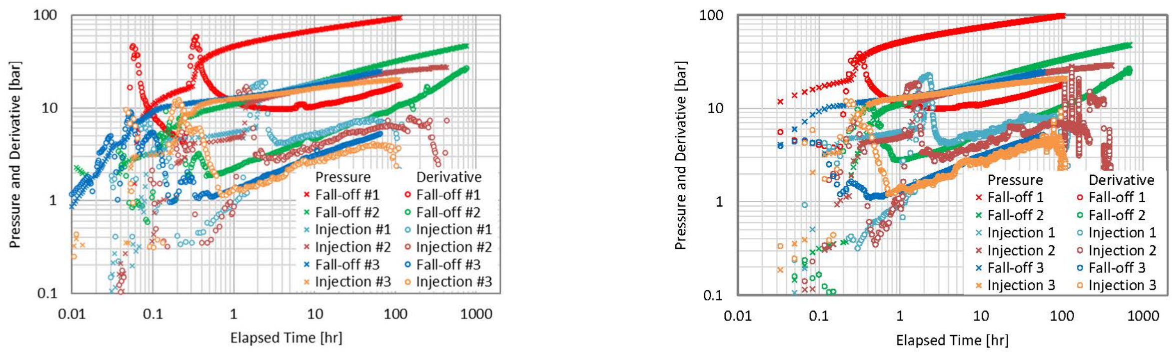

Figure 16—Family of time-lapse pressure transient responses and their derivatives from Figure 14, obtained in manual interpretation as presented in (Shchipanov, Namazova, & Muradov, 2023) with smoothing factor 0.2 (a) and with the automated workflow with default smoothing factor 0.1 and resampling (b).

The time-lapse pressure transients and their derivatives in the log-log scale (Figure 16) reflect changes in the well and reservoir performance over time (Shchipanov, Namazova, & Muradov, 2023). In particular, the observation of the radial flow regime in fall-off 1 and the dominating linear flow regime in fall-off 2 reflects the well stimulation effect, while moving down of the derivates (in all the responses that follow) indicates improved reservoir performance over time. In addition, comparison of the flowing and shut-in periods indicates well interference effects (Shchipanov, Namazova, & Muradov, 2023).

The resulted time-lapse family of the transients in the log-log scale (Figure 16-b) is further automatically interpreted to extract PTA-features and recognize patterns after some smoothing (Figure 17). The results of the pattern recognition contain time- window of the stable pattern, which may be used to condition the PTA-metrics application. Staying within the stable-pattern window is the main condition for reliable PTA-metrics application as it was indicated in (Shchipanov, Kollbotn, & Namazova, 2023) and further confirmed for the case in focus in (Shchipanov, Namazova, & Muradov, 2023).

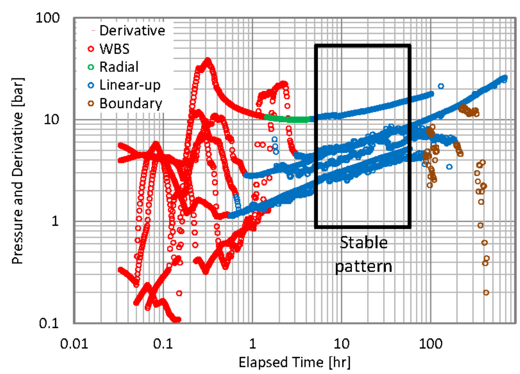

Figure 17—PTA-features and stable pattern recognized in time-lapse pressure derivatives from Figure 16-b.

The PTA-features and patterns recognized in the time-lapse responses (Figure 17) govern application of the PTA-metrics, where relative well (WPI), reservoir (RPI) and well-reservoir connection (CPI) performance indicators are calculated at the end of the time window of the stable pattern. The approximate stable pattern window was manually chosen in (Shchipanov, Namazova, & Muradov, 2023) providing the performance profiles marked as ‘Proxy’ in Figure 18. Automated identification of the time- window based on the stable pattern recognized (Figure 17) ensures more consistent estimates of performance indicators as shown in Figure 13, improving reliability of the performance profile. Figure 18 plots the relative performance indicators for all transients in focus obtained within the stable-pattern time-windows identified in Figure 17 (marked as ‘PR’).

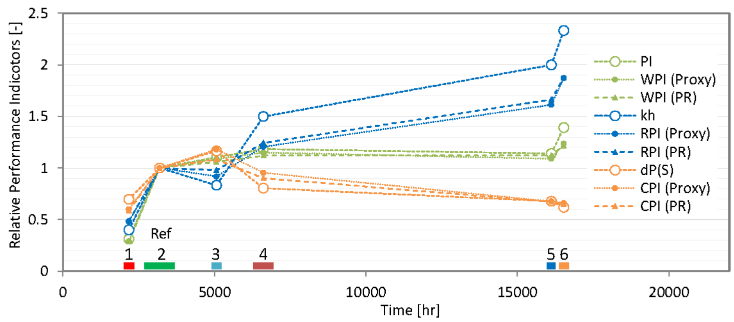

Figure 18—The results of conventional model-based time-lapse PTA (PI, kh and dP(S)) and the performance profile (WPI (Proxy), RPI (Proxy) and CPI (Proxy)) obtained in the manual interpretation in (Shchipanov, Namazova, & Muradov, 2023) in comparison with the same profile obtained with the automated workflow (WPI (PR), RPI (PR) and CPI (PR)).

As a result of the automated workflow application to the well history (Figure 14), well performance profile is obtained (Figure 18). Here, as discussed above, the multi-fracture well stimulation resulted in significant improvement of the well performance (transients 1 and 2), while further improvement was observed, which may be associated with a growing effective well length and flow capacity of the reservoir caused by injection and pressure build-up (Shchipanov, Berenblyum, & Kollbotn, 2014). Following the results from (Shchipanov, Namazova, & Muradov, 2023), comparison of the well performance profile, obtained with the standard model-based interpretation (productivity index (*PI*), reservoir flow capacity (*kh*) and skin-related pressure drop (*dP(S)*), following the relationships (5)-(8) in the appendix) with the profiles obtained with manual (WPI (Proxy), RPI (Proxy) and CPI (Proxy)) and automated (WPI (PR), RPI (PR), CPI (PR)) applications of the PTA-metrics (both profiles following the relationships (1)-(4) in the appendix) demonstrates that the last two profiles are quite similar and both follow the model-based profile. This provides verification of the profiles based on PTA-metrics, confirmed that both manual and automated workflows provided reliable results. However, the automated workflow does not require human interaction and enables fast interpretation of big pressure and rate datasets widely available in field operating companies. The well performance profile and observed changes in the relative performances of the well-reservoir connection and the reservoir itself provide crucial information for well operations. Thus, changes of the performance indicators may be used in evaluating well stimulation jobs, treatments or near well effects (like formation damage) guiding closer look at the well data and flagging potential measures to be taken.

Discussion

The workflow is based on a model-independent (though still physics-informed), data-driven approach that does not require human interaction and uses only pressure and rate time-series. The obvious application domain for such an approach is analysis of big datasets, where the automated workflow can give ‘simple answers’ within a reasonable timeframe and computational costs. Real-time data interpretation may be considered as an extreme scenario of such application. The particular use-cases of the current workflow include nearly real-time well and reservoir performance monitoring. Here, the well performance deterioration and unwanted events may be detected and alarmed promptly, preventing or limiting any further performance impairment as well as financial losses. Another scenario for using the workflow is analysis of large historical datasets, where automated interpretation enables extraction of detailed time-lapse information on well performance changes correlating these with each other and with trends of the measured quantities (like pressures and rates).

Although the workflow assumes model-independency, most of its components may also be integrated into conventional model- driven workflows. Thus, virtual flow metering and transient identification may be used for data preprocessing, providing families of time-lapse pressure transients in log-log plots available for further matching with a well-reservoir model and estimating the model parameters. The PTA-feature extraction may facilitate automated model-identification widely discussed in the literature (Guyaguler, Horne, & Tauzin, 2003), (AlMaraghi & El-Banbi, 2015). The well performance profiles resulted from pattern recognition and PTA-metrics application may be converted into time-lapse multipliers for model parameters such as permeability-thickness product (*kh*) and well skin factor. This demonstrates added value of the workflow for the conventional model-based approach commonly used in the industry, not mentioning that the well performance profiles may be obviously used for preliminary analysis of big datasets to highlight specific periods of interest for in-depth analysis using fit-for-purpose models.

Results and conclusions

The automated workflow presented in this paper integrates different physics-informed data-driven methods aimed at fast and efficient analysis of big sets of well monitoring data combining pressure and rate measurements.

The following conclusions on the workflow components may be drawn:

- Virtual flow metering is an efficient way to address fragmented rate datasets, where rate reconstruction based on combination of wellhead and downhole pressure measurements can help to fill in the gaps in the fragmented datasets, ensuring reliable all-around analysis of pressure transient data.
- Transient identification methods enable automated division of the well history into sequential transients for both flowing and shut-in periods with following representation of time-lapse pressure transients and their Bourdet derivatives in the log-log scale. A consistent averaged rate history may also be associated with the transient sequences, simplifying and speeding-up the superposition calculations.
- PTA-feature extraction and pattern recognition provide a sustainable basis for applying the PTA-metrics in automated mode with reliable results governed by stable patterns recognized.

The proposed workflow has been verified on the real field data set previously analyzed by the standard PTA approach. Although comparison of the results of this model-based approach with those from the physics-informed data-driven workflow is conditional due to the reasons described in (Shchipanov, Namazova, & Muradov, 2023), it provided reasonable basis for verification of the automated workflow results. The study clearly demonstrated that integration and sequential use of the workflow components enables:

- Drastic reduction of time and resources needed for data preprocessing: QA/QC, synchronization and labeling (selecting of transients) of the raw data made automatically within a ‘few-minute’ time-frame.
- Automated extraction of the PTA-features in the preprocessed data with following pattern recognition improves stability and reliability of following application of well performance metrics. The PTA-metrics introduced by (Shchipanov, Kollbotn, & Namazova, 2023) were used in this study, although other metrics may be applied to the patterns revealed as well.
- The well performance profile obtained with the PTA-metrics follows the profile obtained with the standard model-based approach used in the industry. Applying the metrics within the stable-pattern time-windows obtained with the pattern recognition reduced the deviation observed in the manual metrics applications reported earlier.

Applying this workflow empowers reservoir engineers to instantly assess the well and reservoir performances, understand their interconnectivity facilitating prompt and informed decisions.

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Abbreviations

CPI- connection (well-reservoir) performance indicator
LMIR- local minimum in rotation (method)
PR- pattern recognition
PTA- pressure transient analysis
QA/QC- quality assurance / quality control
RPI- reservoir performance indicator
TPMR- topographic prominence max rotation (method)
VFM- virtual flow metering
VLP- vertical lift performance
WBS- wellbore storage
WPI- well performance indicator

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Appendix

The well performance metrics introduced in (Shchipanov, Kollbotn, & Namazova, 2023) include the following performance indicators calculated as:

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

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

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

$$I_{i,D} = I_i / I_{i,base}, \ i = 1, \ \ldots, 3, \tag{4}$$

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

$$I_1^m = \frac{Q}{\Delta p}, \tag{5}$$

$$I_2^m = kh, \tag{6}$$

$$I_3^m = \frac{\Delta p - \Delta p_S}{\Delta p}, \tag{7}$$

$$I_{i,D}^m = I_i^m / I_{i,base}^m, \ i = 1, \ \ldots, 3, \tag{8}$$

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)'); $I_{i,D}$ and $I_{i,D}^m$ – relative performance indicators for the PTA-metrics and the model-based approach, kh - reservoir flow capacity or permeability- thickness product, mD·m; Δp - pressure drop, bar; $\Delta p'$ - the Bourdet derivative of the pressure drop, bar; 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.