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Application of Machine Learning and Advanced Visualizations for Fast and Reliable Deterministic History Matching

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ABSTRACT

Deterministic history matching is the process of calibrating a single geological model to match the historical production and reservoir characterization data. The methods presented in this paper aim to address the history matching problem through progressive integration and reconciliation of all data types. The methodology combines data analytics with intelligent visualizations to swiftly integrate datasets and progressively advance the history matching process. We used a machine learning (ML) algorithm to detect data outliers and exclude anomalies. Applying a fixed window average allowed us to validate the internal heterogeneities of the geological model using core data features. We used a pattern recognition algorithm to create homogeneous groups of wells and create a map of connected reservoir regions (CRR) to assess the spatial permeability distribution adequacy of the geological model. We used a spatial Pythagorean search algorithm to detect the causes of the well productivity problems. Our methodology helped rapidly integrate the pressure dataset, thereby reducing the history matching time and computational requirements. It also helped us rapidly improve the well performance, along with prescriptions of potential causes. In our example, the spatial Pythagorean search recommended a review of the permeability field and input perforation intervals. Furthermore, we determined that the core data consistent with the internal architecture of the geological model resulted in an improved match of historical formation testing and sampling (FTS) pressure data. The presented methodology allowed to rapidly quality check the geological model's spatial connectivity, the result of which was applied to update the permeability field of the static model. Using CRR maps during history matching helped make the same changes across groups of similar wells. Our visualization interface allows both time-based (e.g., water-cut, datum pressure) and depth-based (e.g., FTS, PNL, mobility, PTA) parameters to be displayed, permitting fully integrated decisions regarding the required modifications. We found that integrating all measured reservoir characterization information helped minimize the uncertainty in the proposed history-matched model. The proposed methods improve the history matching process through dataset integration and validation. Leveraging holistic data visualization and ML algorithm, our novel methodology helps establish a reliable reservoir model by integrating geological and engineering datasets and progressively improving the history match. The methods described can be incorporated into an assisted history matching application.

EXTENDED ABSTRACT

Literature review

Reed et al. (1968) proposed one of the earliest documented practices of history matching. Since then, there have been four generations of history matching philosophies: (i) manual deterministic, (ii) automatic deterministic, (iii) automatic stochastic, and (iv) big loop.

Manual deterministic history matching requires trial-and-error approaches to history-match a *single geo-model realization* of the reservoir. Because it requires a trial-and-error approach, it is time-consuming. *Automatic deterministic* history matching is motivated by the intent to remove the trial-and-error process and provide a systematic approach, where a computer can autonomously arrive at a reservoir property description that matches the field performance data. The key contributors to the second wave were Slater et al. (1971), who introduced using gradient descent; Solórzano et al. (1973), who introduced parameterization; and Chen et al. (1974), who introduced the optimal control theory, where permeability was parameterized as a function of distance to control wells. Parameterization establishes a mathematical relationship between known and unknown parameters and indicates that once a few parameters are known the remaining unknowns can be determined. These studies were based on models with 4–50 grid blocks. A limitation of the automatic history matching approach is that, as the

number of model cells and parameters in the objective function increase, the number of simulations runs required to compute the derivative of the cost function n*(M+1) becomes inhibitive.
After slow progress in the development of automatic history matching with deterministic models, during the 1990s, *stochastic modeling* approaches were developed (Guidicelli et al. 1992; Tyler et al. 1993; Calatayud et al. 1994; Jimenez et al. 1997). Here, the main philosophy was to generate several possible geological realizations to detect one or more realizations with property distributions that yield an acceptable match of field performance history. However, a challenge in the stochastic approach (stochastic here refers to multiple geologic realizations) is that a suitable geological realization may require up to several hundred or thousands of samples before detection (Stephen et al. 2012). Furthermore, many of these realizations may have only minor incremental static property differences, resulting in indistinguishable dynamic responses. A more critical problem occurring in the workflow is that this approach fails to recognize that a mismatch between simulated and observed data may not always stem from a geological model problem.

In the last decade, the term “big loop" history matching was coined and trade-marked by Emerson. It is an efficient iterative modeling loop comprising coupled geo-modeling, optimization, and simulation tools. An example of the big loop workflow is the Intersect-MEPO-Petrel interaction (JPT Staff 2006; Kaleta et al. 2012). Intersect, or any other simulator, performs the numerical simulation, and MEPO performs parameterization, statistical analysis, and optimization. Then, Petrel is triggered to generate new geological realizations based on the parameter settings identified by MEPO to help minimize misfit errors. Big loop is applied to evaluate the impact of both static and dynamic uncertainties (Kaleta et al. 2012).

The challenge with the big loop approach is that the input data may not be adequately characterized to effectively capture the field performance data to be history-matched. Joosten et al. (2011) stated in their paper that “*Features of which we have no indications of their existence could easily dominate the behavior of our entire system (reservoir)*.” This significant uncertainty is one of the main reasons why automatic methods for history matching have had limited success after extensive development. Automatic parameter estimation works only once the correct set of parameters is established. Accordingly, the geological model captures the relevant features of the physical system it is supposed to represent. For example, a producer yields a high water cut because of a high-permeability streak that is a few feet thick between the producer and adjacent injector. If the input logs and core data do not capture this high-permeability streak, an infinite number of geological realizations cannot replicate the expected water breakthrough. Kaleta et al. refer to this as “under-modeling” defined as “necessary but missing characterization in the geological model.” The engineer must manually establish such a-priori characterization in
the geological model and calculate the permeability value of the created feature, considering it as an optimization parameter (Van Doren 2012).

Recent trend in history matching is *post-conditioning* geological models, constructed either using numerical (Ludvigsen et al. 2015, Kayode et al. 2017) or 4D seismic data Stephen et al. (2012). According to Stephen et al. (2012), “*Seismic history matching is the process where we use time-lapse (4D) seismic as conditioning data in addition to more conventional production data as part of history matching. 4D seismic offers spatial information*
that is somewhat missing from production data, and by integrating this data, history matched models will then give a more accurate representation for forecasting.”
A key benefit of seismic-assisted history matching is alleviating non-uniqueness problems by eliminating some of the statistically probable solutions (Kazemi and Stephen 2011). This is because the inter-well information obtained from seismic data helps ensure the quality of the statistically derived inter-well property distribution.

History matching has evolved over the last six decades in terms of computational complexity, size of the geological model, and number and types of historical data used during the calibration process. As revealed in the literature review, history matching is treated as a *post-conditioning* problem, where a geological model is built independently from the core and logs and subsequently calibrated to pressure and production data. Academic research on solving this *post-conditioning* problem has been rapidly expanding in a direction that is impractical for routine deployment in the industry. This is because academia focuses on the continuous improvement of science, whereas the industry considers the cost implications of adopting improved science.

For example, automatic history matching requires several thousands of simulations derived experimentally, making it expensive and prohibitive in terms of computation, storage infrastructure, and simulation runtime (Denney 2003; Doren et al. 2012; Dehghan et al. 2014; Hutahaean et al. 2018). Thus, it is impractical for industrial applications even for large operators with massive computing clusters.

This study aims to present an alternative history matching philosophy involving the construction of *preconditioned* reservoir models, rather than conventional geological models. The assumption behind the novel history matching philosophy is that "*If the geological model approaches a perfect representation of the subsurface, and dynamic, engineering, and production data are without anomalies, and if the numerical description of the physical phenomenon is exact, there would be no need for history matching.*"

In this study, we introduce the term *preconditioned* reservoir models as an alternative to classical static models. Our assumption is that a single preconditioned reservoir model can achieve a history-match faster than numerous plausible realizations derived only from cores and logs.
We build a hypothetical "truth" case model, and then use data from it to derive models that match it using standard geo-statistics and more intelligent methods.

Fig. 1 shows the key characteristics of history-matching practices that have varied over the decades, highlighting the key contributors to each era.

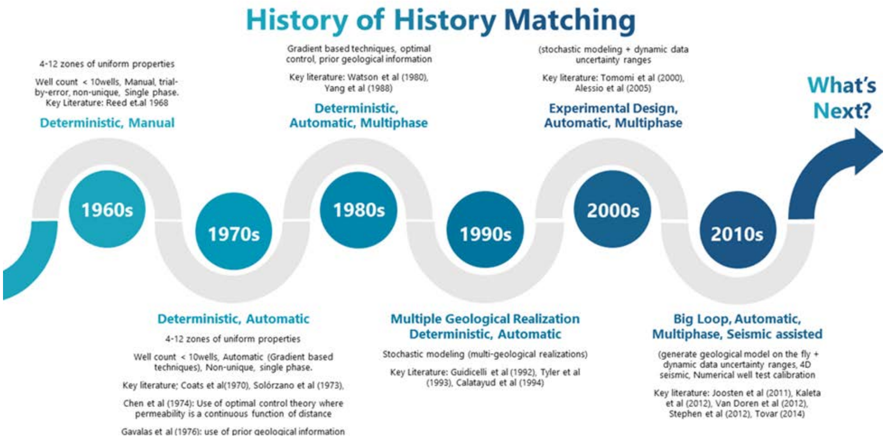

Figure 1:Summary of key history-matching characteristics and key related studies over historical timeline

Methodology description
While stochastic-based history matching relies on statistics and probability to generate a band of history-matched models, deterministic history matching relies on the experience of an engineer aided by data analytics and visualization. The proposed methods utilize data analytics to provide engineering insights into the model, production, and engineering data issues. The history matching improves when these issues are fixed.
Rather than presenting a software or field example, this study describes useful artificial intelligence (AI) functionalities using hypothetical model examples.
A hypothetical reservoir was created having three heterogeneity regions shown in **Fig. 2a.** Using sequential Gaussian simulation, and the parameters in Table 1, porosity and permeability were populated as shown in Fig. 2b and Fig. 2c.

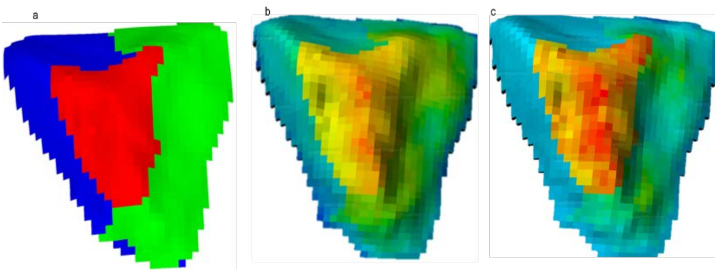

Figure 2: (a) Conceptual depositional facies map for the hypothetical reservoir. Region-1, Region-2, and Region-3 are colored red, green, and blue, respectively. (b) porosity and (c) permeability models

	Region-1	Region-2	Region-3
Min Porosity/Permeability	0.05/0.1	0/0.1	0/0.1
Max Porosity/Permeability	0.2/2500	0.15/1000	0.1/300
Mean Porosity/Permeability	0.15/1000	0.1/100	0.05/50
SD Porosity/Permeability	0.02/875	0.02/50	0.02/2

Table 1—Input parameters used to distribute porosity and permeability in the hypothetical model.
Five petrophysical rock types (PRT) were assumed based on the hypothetical Winland equation expressed in Eq.1. The PRT bands are reported in **Table 2**, and 3D distribution of PRT is shown in **Fig. 4**.

$$R_{35} = 10^{(0.935+0.245*log10(permeability)+0.314*log10(porosity*100))} \qquad (1)$$

PRT1	PRT2	PRT3	PRT4	PRT5
$20 < R_{35} < 40$	$40 < R_{35} < 60$	$60 < R_{35} < 90$	$90 < R_{35} < 120$	$R_{35} > 120$

Table 2: R35 bands for hypothetical PRT models

Water saturation was distributed into the hypothetical model using Eq. 2.

$s_w = 10^{(0.3-(0.7*log10(J)))}$ (2). The J function is defined as $J = \frac{P_c * \sqrt{\frac{K}{\phi}}}{\sigma cos\theta}$ (3).
where Pc is the capillary pressure defined as $P_c = 0.433\Delta\gamma h$ (4)
where $\Delta\gamma$ is the difference in specific gravity between oil and water and h is the positive height above the free-water level (FWL). In this study, the FWL was assumed to be 10800 fts and $\Delta\gamma$ was assumed to be 0.3. $\sigma cos\theta$ indicates the wettability preference and is assumed to be 13. **Fig. 5** plots water saturation versus height above the FWL colored with respect to the PRT and 3D water saturation map.

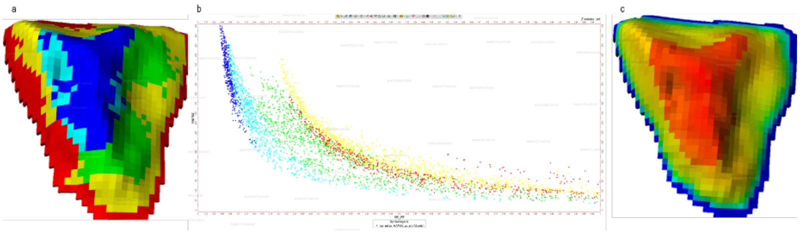

Figure 3: (a) 3D distribution of PRTs, (b) Water saturation versus HAFWL for all cells and (c) 3D water saturation map in the hypothetical model

Then, some wells were defined in the hypothetical 3D model (**Fig. 4a**) to obtain the core porosity, permeability and rock-type. Note that the hypothetical model has only 10 layers, and each well is cored in only few of these layers. Therefore, the amount of core data is limited. Fig. 4b shows the porosity vs. permeability plot of cored data colored with respect to the PRT. Finally, Fig. 4c shows the full set of wells (producers and injectors) defined in the hypothetical model.

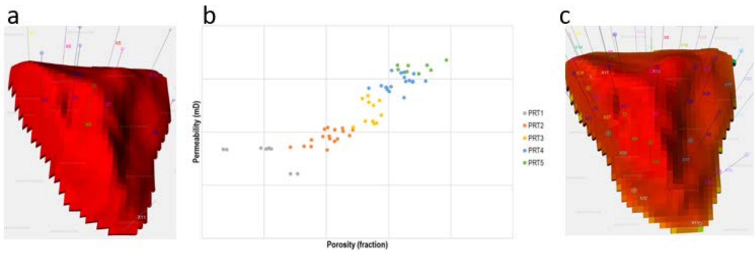

Figure 4: (a) Location of cored wells, (b) Core porosity versus permeability colored by PRT; and (c) Full set of wells containing the producers and injectors

Production and injection were conducted for six years, **Fig. 5** shows the periodic datum pressures of the wells.

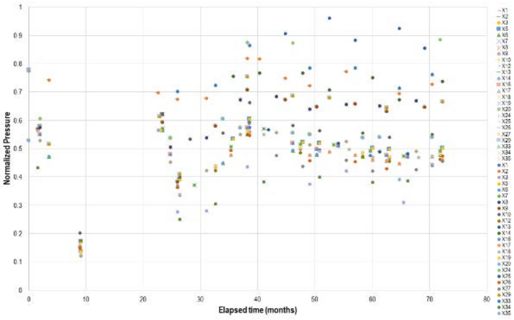

Figure 5: Periodic shut-in pressures for all producing wells in the hypothetical model

Typically, a simulation study begins from the geological modeling phase, using core and log data obtained from wells to create a 3D permeability field. In some applications, facies or seismic data are used as trends, or a purely statistics-driven approach, called sequential Gaussian simulation (SGS), is adopted when such data are not available. Then, the engineer receives the static model and calibrates it with respect to the pressure and production data through a process termed history-matching.

Using the cored data obtained from the wells shown in Fig. 4a, a geological model scenario using SGS was created. The permeability and porosity fields are shown in **Fig. 6**.

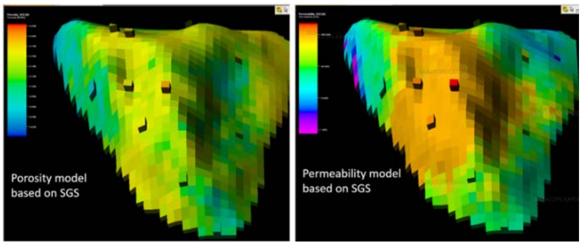

Figure 6: (a) Porosity and (b) permeability model derived from core data using SGS

Because the R35 equation (Eq. 1) and bands (Table 2) are assumed to be derived from special core analysis (SCAL) conducted on cored data; they should remain the same for any geo-model realization that is built from the same set of core data. Consequently, the R35 and band were used to calculate the PRT and water saturation (s_w) for the SGS model. Fig. 7 depicts a comparison between the PRT for the topmost layer in the SGS and original hypothetical models. It is observed that the PRT at the cored well location is the same for all wells; however, the spatial occurrence of the PRTs is different in the SGS compared with that adopted in the original model.

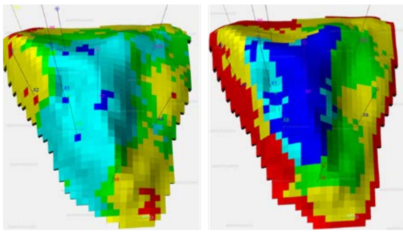

Figure 7: Comparison between PRT of the (a) SGS model and (b) original hypothetical model. This comparison indicates that PRTs remain the same at cored well locations while spatial distribution differs

In other implementations thoroughly documented in the literature (e.g., Amaefule et al. 2013; Johnson 1994), porosity and permeability can be predicted at some of the non-cored wells if these wells have the requisite log measurements, such as density, sonic, and neutron, which introduces additional cost of drilling but could provide more control data for geological modeling. The production-injection constraints, relative permeability and PVT tables from the base case hypothetical model were incorporated, and the SGS model was simulated. **Fig. 8** plots the pressure matches among the producers.

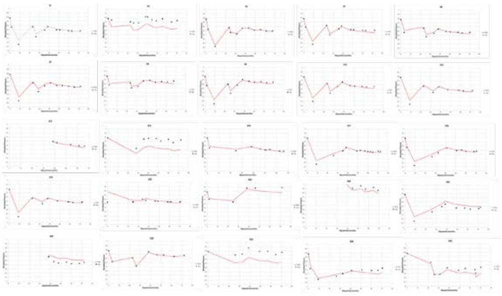

Figure 8: Well-by-well pressure match plot for the SGS model

It is observed that some wells, especially in locations where the permeability field was different from the hypothetical model, exhibited a poorer fit between the simulated and historical pressures. Several SGS models were created by varying the variogram range hoping that a scenario that reasonably fits the historical pressures of all wells could be obtained. For multi-scenario evaluation, a pressure misfit co-efficient was defined as the percentage of the total pressure data that is matched within an absolute difference of 20 psi. Fig. 9 shows a few SGS realizations and corresponding misfit coefficients.

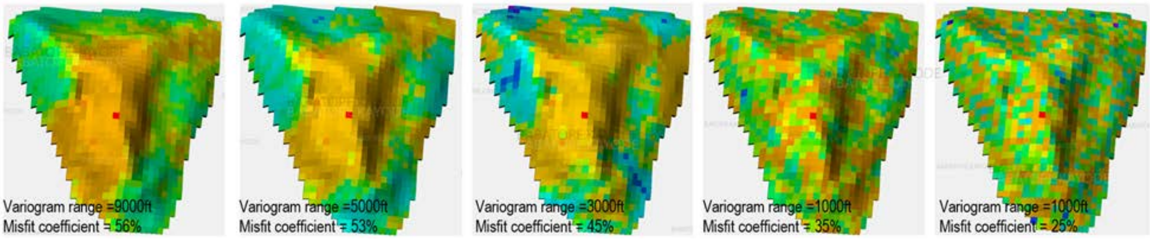

Figure 9: Multi-realizations of SGS models and their corresponding misfit coefficients

Using the *preconditioned* modeling approach proposed in this study, we begin with the available pressure data and derive insights that can be incorporated into the static modeling phase. The theoretical foundation for this was laid down by Kayode and Stephen (2023). This new generation of history-matching philosophy termed *preconditioned modeling*, proposes the following 5 steps:

<u>Time-slice multivariate Gaussian distribution for pressure anomaly detection</u>. There are various potential causes of anomalies in the historical pressure database. (i) The pressure data are not stabilized values. (ii) Stabilized pressure data not converted into reservoir datum equivalent. (iii) Bottom-hole flowing pressure recorded as static pressure, etc. When the pressure of an individual well is plotted, it may be difficult to spot these anomalies; however, when the collective dataset is plotted, an AI anomaly detection algorithm can be employed to flag possible data anomalies Kayode et al. (2023). **Fig. 10a** shows the static pressure dataset collected using our hypothetical model (shown earlier in Fig. 5), showing the red-colored data points flagged as anomalies. Note, however, that the flagged data points are not necessarily erroneous; the flag signals the engineer to further assess the data points because they look suspicious in relation to the other data points. The goal of this first step is to help the engineer avoid the trap of later trying to history-match the possibly erroneous pressure data. In the present discussion, because these data points were obtained from the hypothetical model simulation, we know that they are not erroneous; therefore, we left them in our dataset.

<u>Clustering of historical datum pressure using a pattern recognition algorithm</u>. An AI pattern recognition algorithm identifies groups of wells with similar trends and magnitudes of historical pressures. A description of the algorithm was discussed in a previous study conducted by Kayode et al. (2023). Fig. 10b reveals six clusters. This clustering does not necessarily imply a lack of communication between clusters. It simply implies that, within each cluster, wells are in a near-instantaneous communication; there may be additional inter-cluster communication as well.

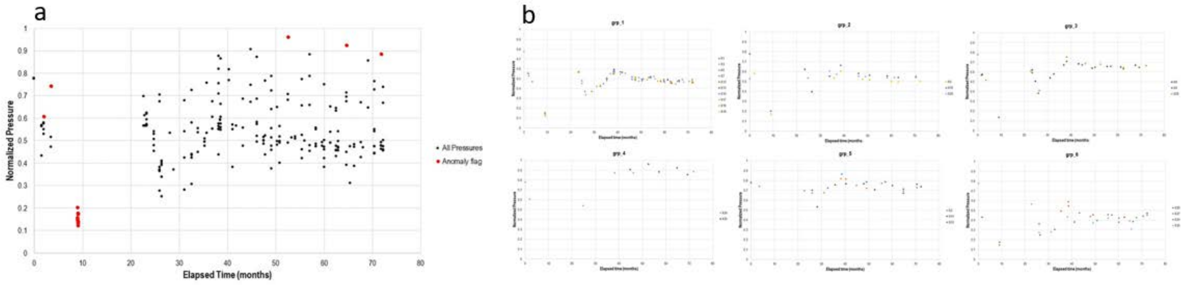

Figure 10: (a) Red-colored datapoints flagged as anomaly, (b) Groups of wells exhibiting similar trends and magnitudes of historical pressures

<u>The AI module outputs a field map depicting all well locations color-coded according to the group they belong</u>. It creates closed polygons around each group of wells, termed as connected reservoir regions (CRR), **Fig. 11b**.

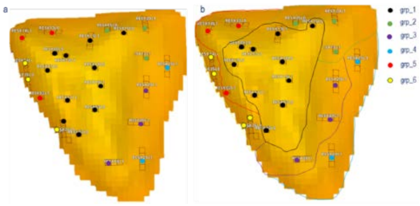

Figure 11: (a) Well locations colored by pressure group and (b) closed polygons around each well group

<u>Analysis of core data to determine intra-reservoir architecture</u>. This is achieved by plotting the core permeability versus core depth, from which an AI module delineates zones of the reservoir that have significant permeability contrast. This is accomplished by creating a plot of average permeability within a constant reservoir thickness and applying a user-defined *minimum* contrast ratio to delineate intra-reservoir zones. The red curve in **Fig. 12** shows the results of 100ft interval averages, and the vertical lines are the boundaries where the trend of the red curve shows significant changes.

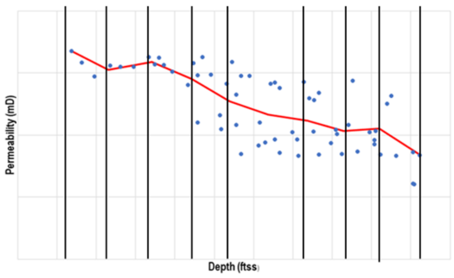

Figure 12: Intra-reservoir architecture derived from core permeability data

<u>During geo-modeling, the zones defined in step-4 and CRR polygons established in step-3 are incorporated</u>. CRR are used as spatial containers, whereas zones are used as vertical containers. Each zone can be further subdivided into layers as required. Only core data obtained from a well situated within a given CRR are used to distribute the 3D permeability within that CRR. Within each CRR, only cored data within a given zone are used in the permeability distribution within that zone, aiming to replicate the zonal core data statistics within each model zone. The geo-model is reviewed and refined until the constant interval average signature in the 3D model adequately matches that of the core data. **Fig. 13a-c** is a comparison of the hypothetical reservoir, its SGS based model, and its *preconditioned* model. It is observed that the *preconditioned* model has a better visual semblance with the hypothetical reservoir than the SGS model. Furthermore, Fig. 13d shows a better match of the intra-reservoir architecture of core data (red) by the preconditioned model (black) than the SGS model (green).

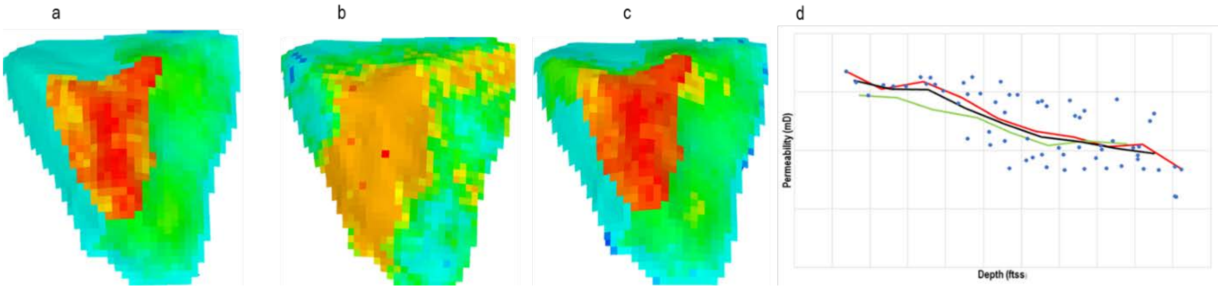

Figure 13: Permeability model of (a) hypothetical reservoir, (b) SGS model and (c) preconditioned model of the reservoir, (d) 100ft window average of core data (red), SGS model (green) and preconditioned model (black)

Fig. 14 shows the comparison of simulated pressure from the preconditioned model with observed pressure, it depicts a better fit than the equivalent plot for the SGS model earlier shown as Fig. 8.

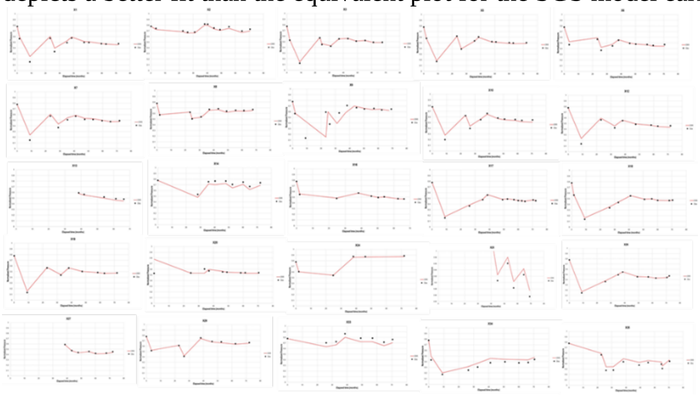
Figure 14: Well-by-well pressure match of wells in the preconditioned model

NB: space limitation imposed by AAPG extended abstract did not permit the inclusion of advanced visualization for history matching in this discussion. The author can be contacted at babkay2000@yahoo.co.uk for the full manuscript.

Discussion of results

The current practice of geological modeling requires the use of core (and sometimes log) data to create a model of a reservoir's geological understanding. The model performance was then compared to field performance data to evaluate the misfit. The geological model was iteratively corrected in a *post-conditioning* process to reduce performance misfit.

The proposed modeling approach advocates a departure from geological modeling to *preconditioned modeling*, with the goal of creating a *reservoir model* (not a geological model) that will honor field performance data. Geological modeling creates a model of the reservoir's geology, whereas *preconditioned modeling* creates a model of the reservoir's performance.

The 80's and 90's experienced the rapid development and adoption of reservoir geo-statistics as an approach to distribute well data in 3D space using purely probabilistic approaches. The 00's and 10's brought stochastic inversion methods and cloud computing. In this work we capitalize on the recent advent of data mining, AI, and ML frameworks to develop algorithms that extract insights from reservoir data for better reservoir modeling. The incorporation of the AI-derived intra-reservoir architecture makes the reservoir model phenomenological, in addition to being statistically representative, and could help improve the match of historical RFT discontinuities.

Using CRR polygons to control the regional permeability distribution ensures that the connectivity pattern of the reservoir model reflects observations from historical datum pressures. Conventionally, inter-well model connectivity is one of the reservoir characterization items that we address using history matching (Yuhong et al. 2008). According to Yuhong et al. (2008), "*It is quite obvious that once the facies model (reservoir connectivity pattern) is wrong, it is very difficult to correct the model merely by tweaking variograms of porosity and permeability*." An earlier study by Gomes et al. (2004) presented the same conclusions. They said "*The reservoir framework (facies) is in fact one of the most important steps to begin building the geological model. One can use very complex techniques to populate the reservoir model properties, but if the framework is not* *correct, the model will not be reliable, history matching may not be achieved and field performance forecasts could be wrong*."

During geo-model construction, a depositional facies model (where available) is used to guide the permeability and porosity distribution in a way that captures the predominant reservoir connectivity trends. Some observations regarding the depositional facies are included.

i. Depositional facies description involves visual inspection and description of cores, and the results may be influenced by the experience and interpretation of the geologist involved.

ii. The depositional facies description was conducted on the cored wells. In some cases, cored wells are a fraction of the total set of development wells.

iii. Similar depositional facies at neighboring well locations do not necessarily indicate reservoir continuity between these wells. This is because depositional facies could be comprised of several Petro-physical facies, ranging from excellent permeability to excellent baffle.

iv. In some cases, depositional facies are distributed in 3D using geo-statistical algorithms such as sequential indicator simulation (SIS). The resulting connectivity patterns may need to be reviewed during history matching.

The use of CRR polygons derived from pressure clusters has the following benefits.

i. Time-lapse static pressure data are a measurement, not an interpretation. Therefore, it is not subjective. A pressure gauge was lowered into a shut-in well, and the stabilized shut-in pressure was measured and corrected to the reservoir datum.

ii. In many countries, statutory government regulation states that each well should have at least one shut-in pressure survey per year. This was used for reservoir management. This means that unlike the sometimes-limited depositional facies data, historical datum pressure data are available for almost all development wells.

iii. If pressures measured on neighboring wells year-to-year follow a similar trend, then this is evidence (unless otherwise proven) that there is instantaneous connectivity between these wells. If the measured pressures exhibit different trends, then a barrier or baffle limits the connectivity between the wells. That is, the time-lapse pressure measurement results from neighboring wells are indicators of the inter-well connectivity status.

iv. Seismic information is subsurface information that has the largest spatial resolution (Stephen et al. 2006). Kayode et al. (2019) demonstrated that CRR maps derived from pressure clusters were similar to seismic acoustic impedance maps.

This study focused on the pre-conditioning of datum pressure and intra-reservoir architecture into geological modeling, while other reservoir behaviors that could be used for model preconditioning include well-test pressure transient, water-cut, etc.

Finally, on the one hand is the search has been on for an automatic history matching application that would be fed with inputs to automatically output a band of history-matched model. Several researchers agree that a functional and generalized application that does this is not feasible in the near term (Gupta et al. 2008; Cancelliere et al. 2011). On the other hand, is manual history matching, in which the engineer receives a single deterministic model, tends to do whatever is necessary for the model to match historical data. As discussed by Little et al. (2006), "*such model could result in unquantified uncertainty that could affect forecast results.*"

The proposed use of the *preconditioned model*, AI-driven productivity review, pattern recognition, *SPS*, and *Geoprobe* algorithms, together with the integrated visualization window, constitutes an advisory system for building better models and for the detection of potential causes of model-history performance misfits.

Conclusions

(i) In this application example, a *preconditioned* model predicts 90% of the wells' datum pressures prior to history matching. The match quality of several realizations of the SGS ranged between 30 and 60%.

(ii) AI algorithms helped quickly identify wells that had productivity problems and the reason behind the misfit data. (missing in this extended abstract)

(iii) After achieving satisfactory pressure matching using the AI Geoprobe algorithm, a well-by-well pressure match is no longer necessary, resulting in significant time savings. (missing in this extended abstract)

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NB: space limitation imposed by AAPG extended abstract did not permit the inclusion of advanced visualization for history matching. The author can be contacted at babkay2000@yahoo.co.uk for the full manuscript.