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Development of Fracture Models for Korolev Field: Characterization to Simulation

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Abstract

Korolev field is a large Devonian-Carboniferous carbonate buildup with a flow system dominated by natural fractures. Currently TCO is looking into potential IOR opportunities at Korolev field, which might help to unlock additional resources beyond the scope of current development plans. Therefore, characterization and modeling of the fracture system is of fundamental importance for a new flow- simulation model to assess and predict IOR performance.

The fracture modeling workflow closely integrates matrix and fracture modeling, which facilitates identification of important parameters for fracture distribution early in the modeling process. Fracture prediction is based on correlations with various geological parameters, such as stratigraphy, depositional facies, mechanical properties and geomorphological features, which provides a soft probability trend for distribution of fracture parameters.

Fracture network characterization based on analysis of well log and core data only is very limited in scale. Pressure Transient Tests (PTT) and Pulse Tests provide important insights into characteristics of fracture network at the larger scale than the conventional wireline data allows. Therefore, it is important to incorporate dynamic dataset as a fracture characterization constraint during modelling of fracture distribution. Most of the wells at Korolev field have good quality pressure buildup and pulse test data. TCO developed a workflow to incorporate dynamic data into the fracture modeling process for the full- field dual porosity, dual permeability (DPDK) model. The first step in the workflow is to calibrate fracture density distribution to match well productivity indices (PI) observed in the field. The next step involves dynamic simulation of pressure buildup tests and their comparison to the actual measured data. The last step is to validate the geologic model with available pulse test data.

Dynamic data integration required multiple iterations and loopbacks to fracture characterization and property distribution. Close collaboration between fracture experts, earth scientists and reservoir engineers along the whole process was essential for successful implementation of dynamic data into fracture characterization and modeling. Calibration with the available dynamic data led to better understanding of spatial distribution of fracture properties and provided important additional constraint for the fracture model

construction. Improved fracture model at Korolev is the key factor for more reliable production forecasts and evaluation of future development opportunities.

Introduction

Korolev is an oil field located at the Western Part of Kazakhstan near super-giant Tengiz oil field. Based on current understanding, Korolev is a highly fractured reservoir where fluid flow is dominated by the fracture network, which requires implementation of dual porosity dual permeability black oil model. More details about the field and description of the previously used simulation model SIM06K is given in the paper by (Abdrakhmanova et al. 2014). SIM06K model focused on primary depletion for Korolev and did not capture the range of uncertainties that have significant influences at IOR recovery. Latest simulation model SIM15K discussed in this paper leverages better geological characterization based on the latest 3D seismic data and integration of extensive set of dynamic data.

Conventional fracture characterization

TCO acquired new 3D seismic data at Korolev in 2010. The new data significantly improved seismic imaging within the reservoir interval and enabled seismic facies regions to be mapped. The seismic facies were calibrated to the available core data and further complemented with FMI-based facies interpretation (Bachtel et. al 2014), which allowed to obtain improved understanding of depositional model of the Korolev field (Fig. 1). At Korolev, the slope deposits encroach almost over the entire platform at the base of Unit 1 or Visean B and there is a significant volume of prograding slope sequences from the Visean B to Serpukhovian. The rocks within the prograding slope sequences are fracture-prone early in its depositional history, which explains why the entire Korolev field seems to be fractured. The updated depositional model explains why many of lost circulation events and bit drops at Korolev occurred within what is the 'structural' platform. Almost all those events can be traced to this newly recognized progradational slope sequences that extend far into the platform. These observations were the main control on the spatial prediction of fracture distribution.

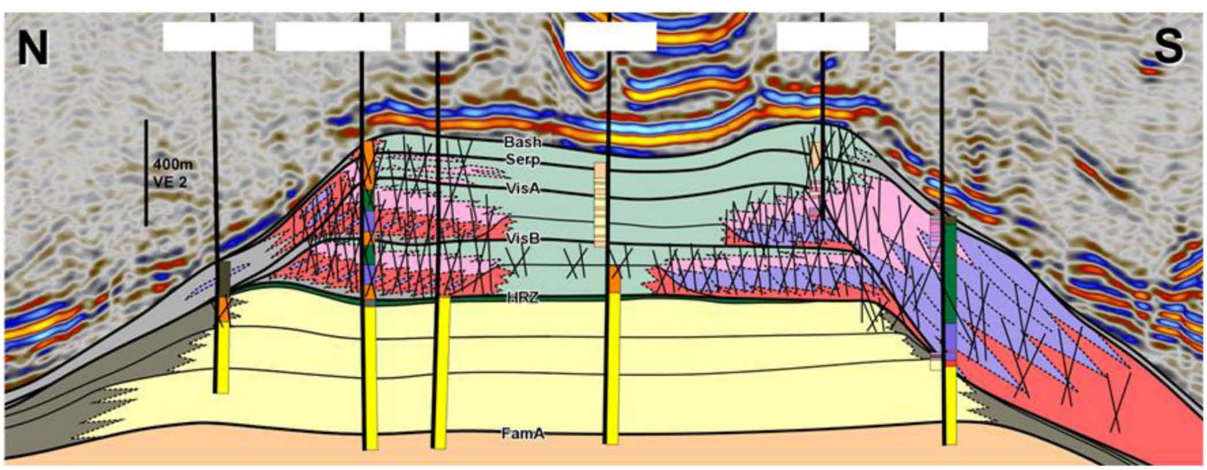


Figure 1—Improved understanding of reservoir architecture of the Korolev field

The initial phase of fracture characterization includes identifying and quantifying the following fracture properties: density, porosity, orientation, aperture, and geometry (length and height). For estimation of fracture density were used Formation Microimager (FMI) logs, PEF and caliper logs, information about drill bit drops and loss circulation zones, Stoneley-wave data, temperature and production logs. Fracture porosity, aperture and orientation was estimated from image logs, while fracture porosity was also calibrated with conventional logs and PTT interpretations. Only those fractures that are potentially effective or contributing to flow are used to define fracture density and porosity curves. As information about fracture geometry can not be measured with any downhole tools, analogs and outcrops were used to identify geologically reasonable ranges. All those estimated fracture properties from the wells were spatially distributed with multiple regression algorithm based on the relationship between the predictor parameters with fracture density and porosity (Fig. 2).

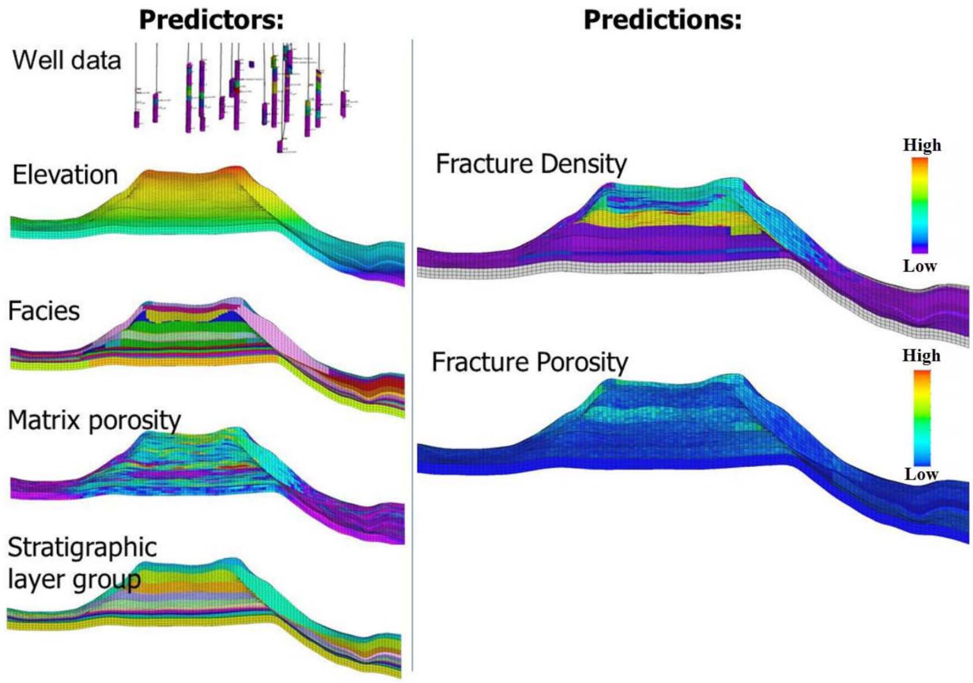


Figure 2—Fracture Predictor Parameters and Initial Fracture Spatial Distributions

Fracture permeability tensors are derived based on fracture density transform (Fig. 3), which was correlated to fracture density distributions generated with discrete fracture modeling software.

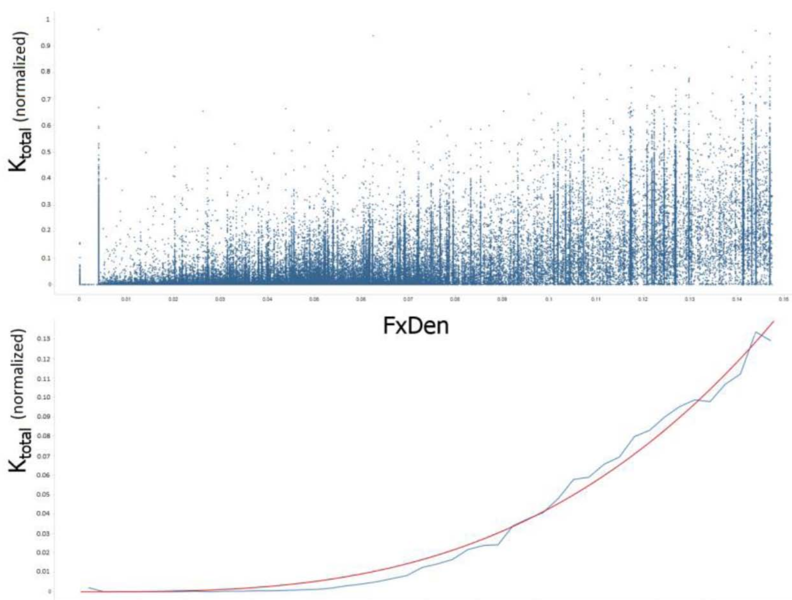


Figure 3—Fracture Permeability vs Density Transform

Overview of Dynamic Data Integration

The dynamic data integration (DDI) workflow was developed as the next phase in characterizing the fracture network. The objective of DDI is to validate how well fracture trends predict actual dynamic behavior that is observed in the wells. After the "best guess" fracture distribution is generated, its dynamic response is simulated and the results compared to the actual Productivity Indices (PI), PTTs and Pulse Tests at the Korolev wells. During the first step the model is validated using well PI data.

Then, possible trends and areas which need improvement are identified and fracture model is modified accordingly. The process is repeated until with results are satisfactory. The output from the PI calibration is the input for calibration to PTT data where the transient responses of the wells are matched. Next stage is to calibrate the model to pulse test data to verify that the appropriate level of connectivity is captured with the fracture model. Note that the dynamic data integration workflow is applied on the fracture trend which is a smooth spatial prediction that was developed from multiple variable analyses. The last step in the fracture modeling is to introduce fracture heterogeneity prior to conducting a conventional history match. The dynamic data integration process does constrains the fracture model itself, whereas static well pressures are history matched by conventional process which is largely dependent on total STOOIP, rock compressibility and aquifer strength rather than on fracture properties. A diagram of the fracture characterization and modeling workflow is shown in Fig. 4.

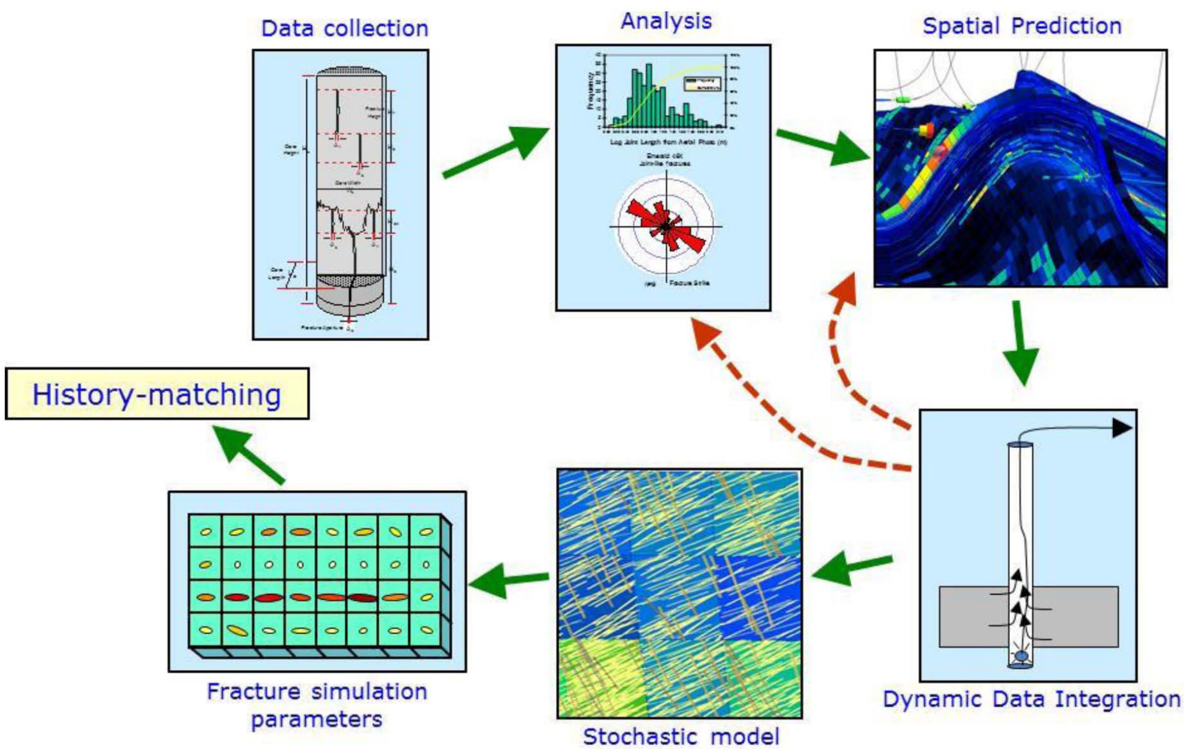
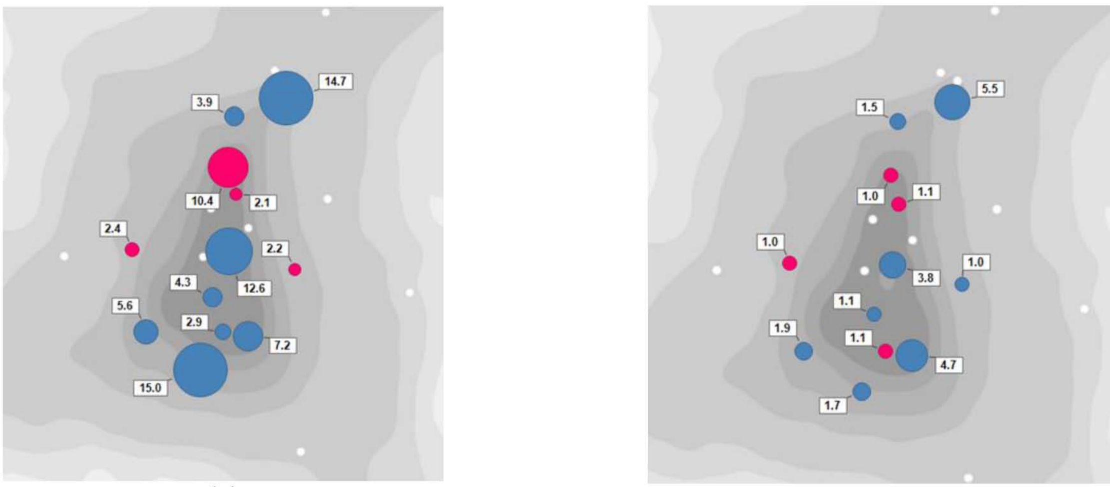


Figure 4—Fracture Characterization and Modeling Workflow

Calibration with Productivity Indices

Well PIs depend on well permeability-thickness (kh), which is a reservoir property and skin factor, which is a wellbore effect. Well PIs can be used as proxies for fracture density/connectivity and as a validation of initial fracture trends. Productivity index data are available for all producing Korolev wells and have a high level of reliability making them the best tool to identify the first order trends in fracture distribution. Well PI combined with PLT data can be used to define trends corresponding to different stratigraphic intervals and understand potential pressure barriers and baffles.

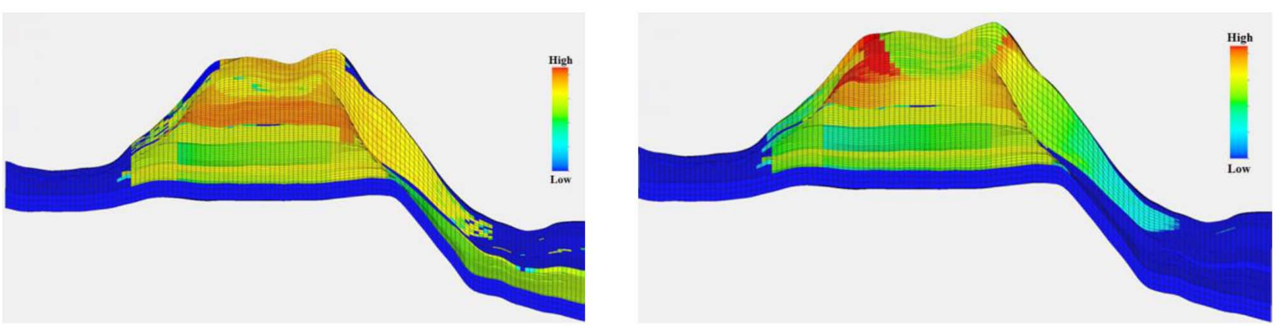
The mismatches in productivity indices from the reservoir simulation model run with the initial trend of fracture properties from the multivariant analysis is shown in (Fig. 5a). The size of the bubbles corresponds to mismatch ratio and the color shows whether the model is over- or under-predicting. It is apparent from this figure that the initial model did not accurately capture the actual well performance. Applying the trends which are described in the next section significantly improved the fracture model and reduced the mismatches to acceptable levels (Fig. 5b).



(a) (b)

Figure 5—Korolev wells PI Mismatch plots for initial fracture properties distribution (a) and after calibration with geologically consistent trends (b)

A comparison of the initial and the final fracture permeability distributions resulting from the changes to match well productivity indices are shown in Fig. 6a and Fig. 6b respectively.



(a) (b)

Figure 6—Korolev fracture permeability distribution: initial (a) and after calibration with Well PI (b)

Trends used for calibration of Dynamics Data

A series of conceptual trends for fracture distribution were developed based on the updated depositional model and were used to calibrate dynamic data in a geologically-consistent way. One of examples of such trends is a depth trend in the slope where the fracture density decreases from a proximal to a distal position (Fig. 7).

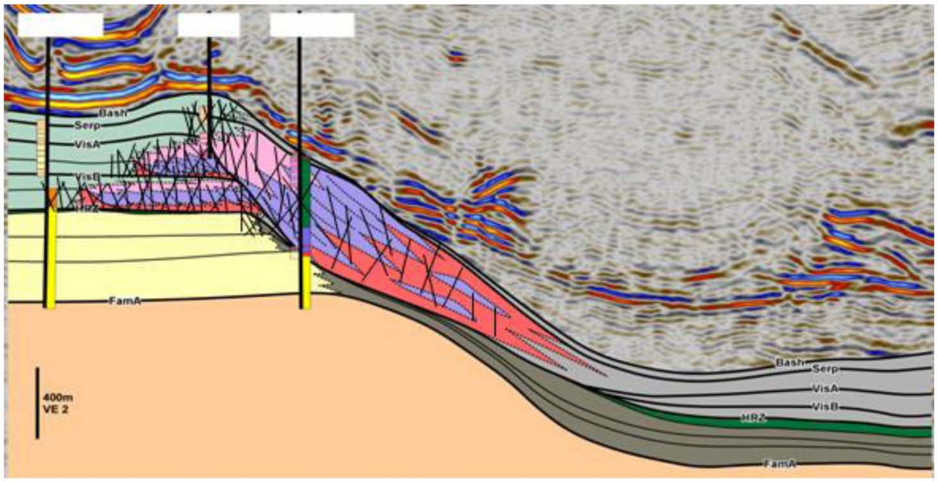


Figure 7—Slope to Basin geological trend

This concept is based on the change in lithology along the slope profile from the fracture-prone in- situ boundstone and breccia to the more grain-dominated material. This trend is supported by well data where the highest fracture density is in the outer platform - upper slope position and gradually decreases basinward. Quantitatively this trend was implemented by using variable multiplier (Fig. 8b) on top of initial spatial fracture distribution, which is based on multiple regression analysis (Fig. 8a).

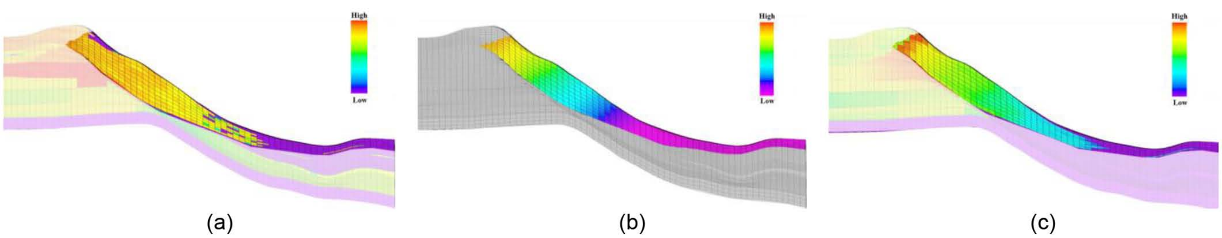


Figure 8—Example of geologically consistent trend applied for honoring Dynamic Data with initial realization for fracture permeability (a); multiplier gradually decreasing basinward (b); and corrected fracture permeability distribution with using varial multiplier (c)

Another example of the used trends is an increase fracture density towards the platform margins (Fig. 9). This trend reflects the latest depositional model which points to the presence of a fracture-prone prograding slope and a less-fractured karst-modified platform-top. The position of platform to slope transition varies by stratigraphic interval and was mapped seismically. Central platform wells are associated with lower fracture density and a matrix-dominated PLT profile, while margin wells have much higher fracture density and a distinct fracture-dominated inflow profile.

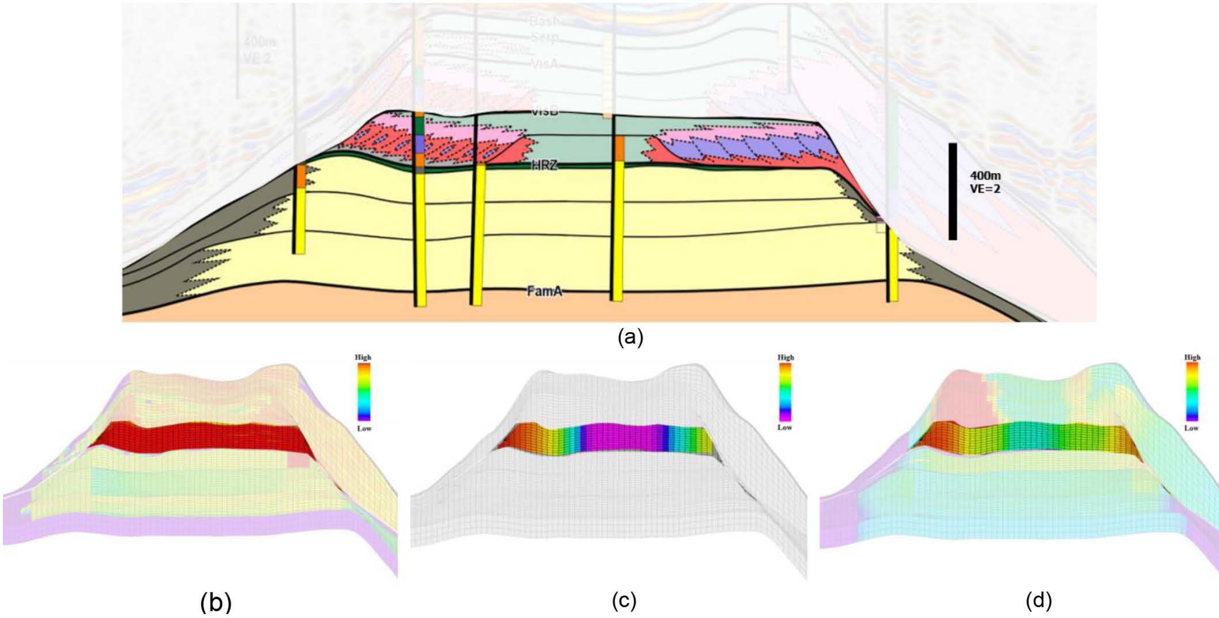


Figure 9—Platform to Margin geological trend with latest conceptual depositional model (a); initial realization for fracture permeability (b); multiplier applied for platform to margin trend (c); and corrected fracture permeability distribution with using variable multiplier (d)

Several other trends based on conceptual depositional model (Fig. 1) were applied in similar way to calibrate fracture model with available dynamic data.

Calibration with Pressure Transient Tests

The pressure transient tests allow independent assessment of well kh (permeability-thickness), and they incorporate a large radius of investigation. So, the next step of dynamic data integration workflow was to qualitatively match pressure transient behavior in the wells by applying conceptual trends to the fracture model calibrated with well PI (Fig. 6b).

The pressure buildup data for all 12 Korolev wells were simulated with results plotted against the actual data and the fracture model adjusted to achieve a qualitative match. At the Fig. 10 is shown an example of the actual pressure buildup data (in green); response from the previous model SIM06K (in pink), where fracture model was not calibrated with dynamic data and output results from the model calibrated with PTT (in orange) by applying geologically consistent multipliers at the fracture model calibrated with well PI. As it can be seen improvement in fracture characterization with PTT data is significant.

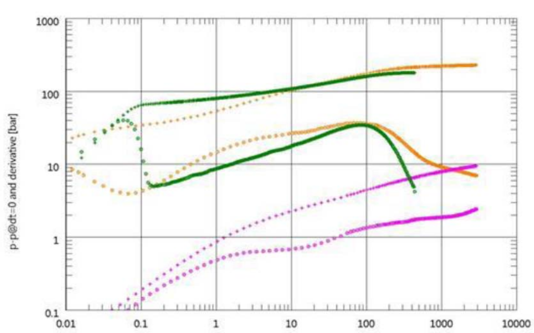
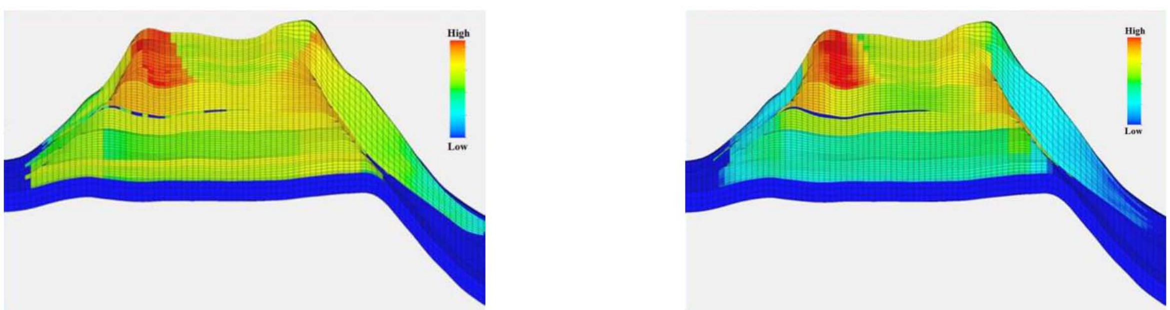


Figure 10—Comparison of actual PTT response (green) with calibrated model (orange) and previously used SIM06K model (pink)

Prior to modifying the fracture model, extensive set of sensitivity cases was run to determine what parameters impact pressure transient response at the simulation model. Results from these sensitivities are following:

- *It is necessary to include local grid refinement around each well in the model to capture early time response at the well, however no significant effect was observed by adding a wider range of grid refinement except a few grid cells around the well*
- *The simulator can be run with all wells producing at the same time to collect data for PTT comparisons; there was no significant difference observed by using the actual time interval from the PTT tests in the model*
- *There is no effect observed from additional production history, therefore in the model was used only rate at which the well was producing right before the well was shut-in*
- *DPDK simulation model have its limitations on mimicking actual transition behavior between fracture dominated flow to matrix and fracture flow. Thus, typical feature of dual porosity behavior, so called "troug"h could not be matched with variation of any relevant data such as KSIGMA parameter. So, main parameter that was matched during PTT calibration phase was kh line*

The modifications to the underlying fracture model required to achieve a reasonable match to the field data include similar approach with using to geological trends as was done in Well PI calibration phase with emphasizing some of the trends or making them more smooth in some specific regions. A comparison of the model before and after the changes made to match the pressure transient tests is shown in Figure 11.



(a) (b)

Figure 11—Korolev fracture permeability distribution before (a) and after PTT calibration (b)

Calibration with Pulse Tests

The last stage of the dynamic data involves integration of Pulse Tests to calibrate the fracture model at the larger distances. Pressure response amplitude of the Pulse Tests relates to fast path interwell permeability and porosity, while magnitude of the pressure derivative is strongly dependent on the permeability-thickness (kh) between the pulsing and the listening wells.

There are a total of 23 interference tests conducted in Korolev in various directions across the field to provide an estimate of diffusivity. Only the highest quality tests were selected to be used for the last stage of DDI. Wells location from these tests are shown in Figure 12, which are covering most part of the field.

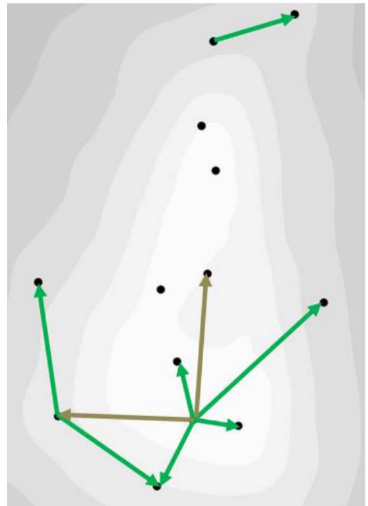
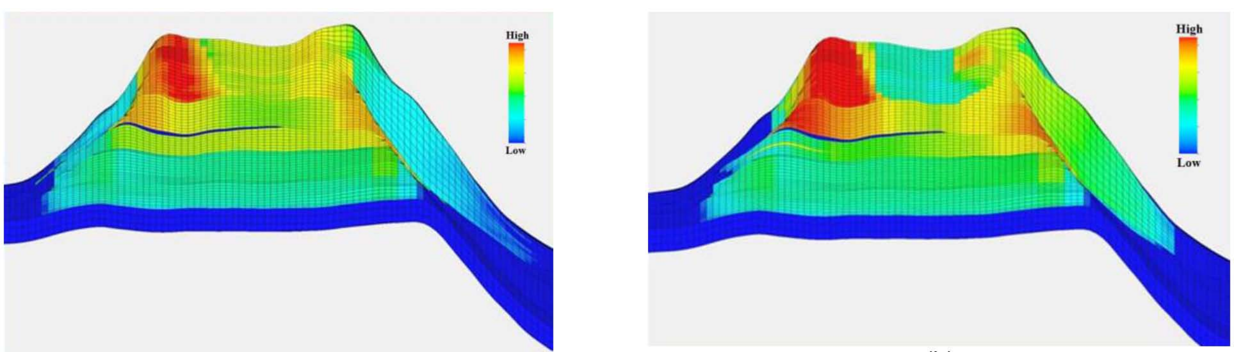


Figure 12—Pulse Tests Used for the last stage of DDI for calibration fracture model

The changes to the model that were required to obtain an acceptable match included implementation of high perm streak at one of the area, reducing fracture permeability at multiple regions and creating additional transition trend.

A cross section showing the kh distribution before and after the pulse test calibration are shown in Fig. 13. Example of pulse test response with comparison of calibrated simulation model SIM15K with previous model SIM06K show significant improvement in fracture characterization. After selecting model calibrated with Pulse Tests, additional set of pressure transient tests were simulated to ensure that the changes model to match the pulse tests did not affect the quality of the PTT matches.



(a) (b)

Figure 13—Korolev fracture permeability distribution before (a) and after Pulse Test calibration (b)

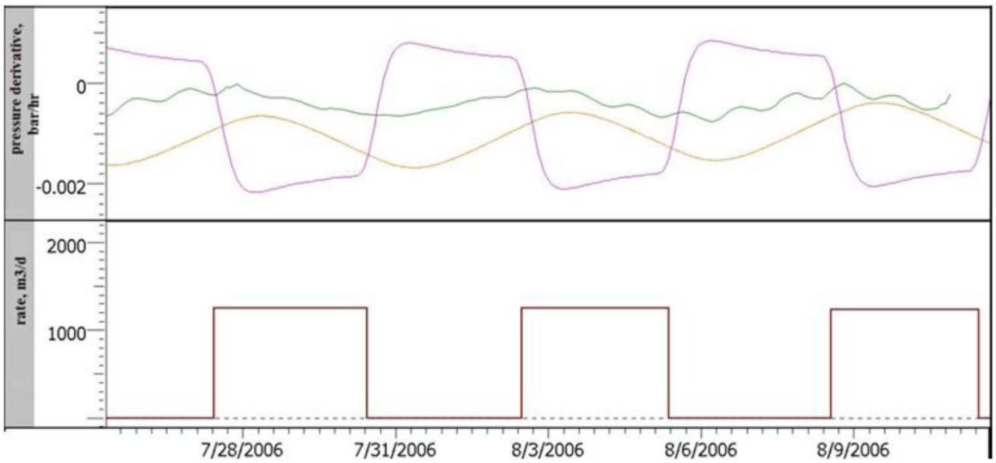


Figure 14—Example of one of the Pulse Test at Korolev with comparison of Actual pressure response (green), calibrated SIM15K (orange) and not calibrated SIM06K (pink)

FRACTURE MODEL EXTENT

The uncertainty in fracture extent is dependent on well control. The Low-case fracture model has fractures that are a 1 km step out from wells that have evidence of significant fracture presence. The Mid-case fracture model is delineated with wells with no or very little fracture presence. And the fractures in the High-case model are 1 km out from the Mid-case fracture model extent. Areal and cross sectional views of the Low-, Mid-, High-case fracture models selected after the pressure transient test calibration are shown in Fig. 15.

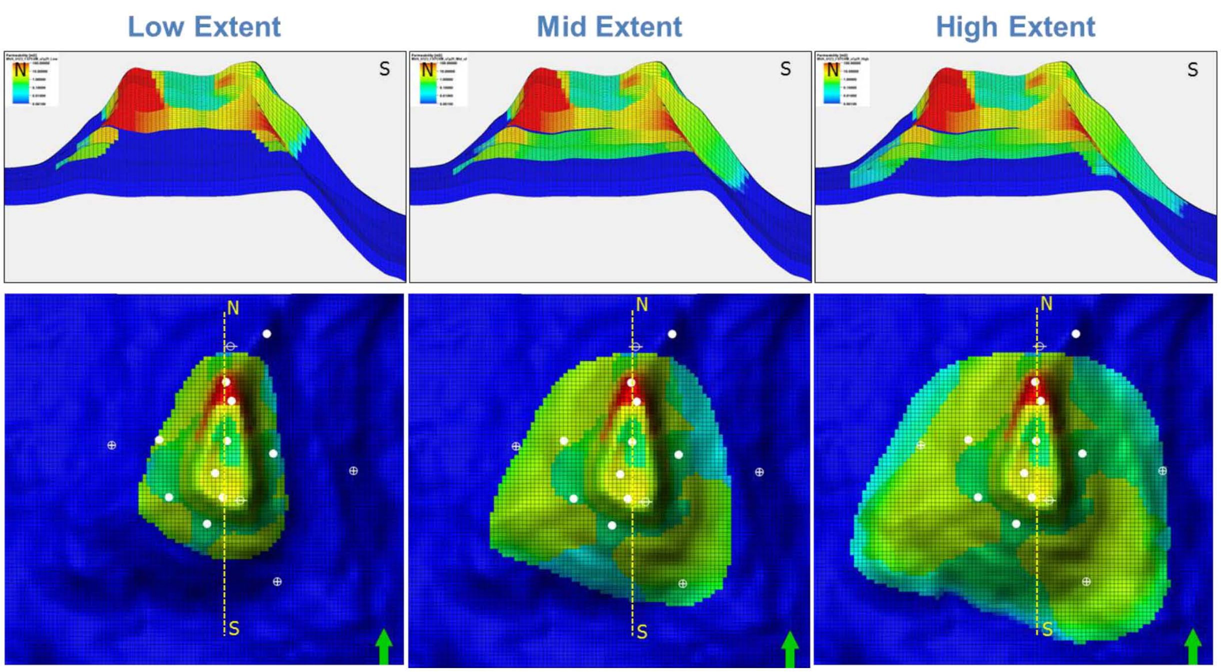


Figure 15—Areal view and cross sectional view of PTT calibrated Low-, Mid- and High-Case fracture models

FRACTURE HETEROGENEITY MODELING

Given that fracture heterogeneity is a key reservoir uncertainty, Low-, Mid- and High-fracture heterogeneity models were generated to be used in the brownfield experimental design. Fracture heterogeneity was imposed at the calibrated models from the dynamic data integration to capture a range of fracture permeability parameters and generate multiple realizations. The impact of heterogeneity on cumulative recovery from primary depletion and a full field waterflood was primary criteria used to select the Low, Mid and High realizations that are used in the brownfield experimental design.

The three variables that control the spatial distribution of fracture permeability include the ratio of cells with low to high fracture permeability, variogram length to capture spatial distribution of fracture permeability and the ratio of low to high permeability. The combination of the fracture heterogeneity modeling parameter variables and the calibrated Low, Mid and High fracture models from the dynamic data integration resulted in generating 144 fracture heterogeneity models.

Cloud transforms are used to create a range of fracture permeability distributions for the calibrated fracture models that mimics the effects of the percolation threshold and permeability ratios on the forecasted production profiles. The workflow enables conditioning to the wells, allows for uncertainty in the kh distribution away from the well control and does not require a kh correction for the entire model to maintain the dynamic data matches.

The 'percolation threshold' is associated with the bimodal distribution of fracture permeability as shown in Fig. 16. This distribution was populated using in house workflow of Discrete Fractures generation ensuring the bimodal nature of the heterogeneity modeling parameters is captured. The lower fracture densities can be associated with high fracture permeabilities if the fractures (although small in number) cut across cell boundaries or they can have no fracture permeability if the fractures are contained within the cell.

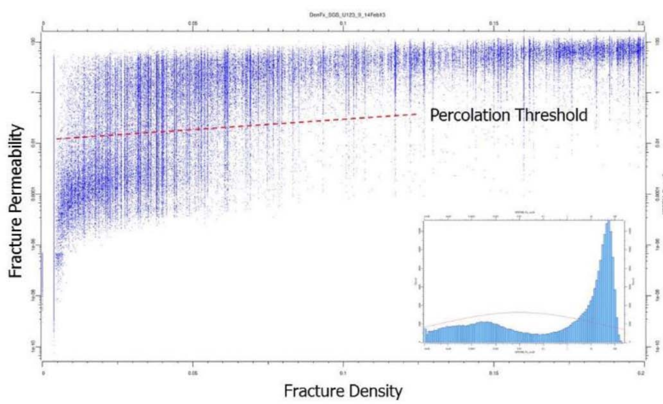


Figure 16—Fracture Density vs. Fracture Permeaiblity from simulation of Discrete Fractures

Cloud transforms were created by combining fracture density vs. proportion of low/high fracture permeability and fracture permeability vs. permeability ratio. The workflow to generate the transforms is diagrammed in Fig. 17. At the Fig. 18 is shown the cloud transform and the distribution of the fracture density bin (highlighted in darker grey) for the 50% low/high fracture permeability proportion and high fracture permeability ratio. The bimodal nature of the relationship between fracture density and fracture permeability is evident in this example and holds true for all transforms. There are 48 cloud transforms that result from the combinations of the heterogeneity modeling parameters. These transforms were applied to the calibrated low, mid and high fracture models to yield the 144 fracture heterogeneity models. Assignment of fracture permeability is influenced by the fracture permeability from cells lying within variogram length of the distribution.

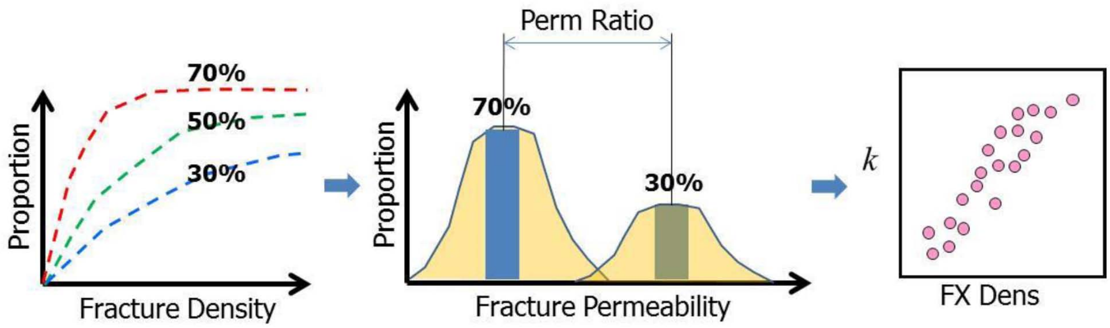


Figure 17—Workflow to Generate Cloud Transforms for Modeling Fracture Heterogeneity

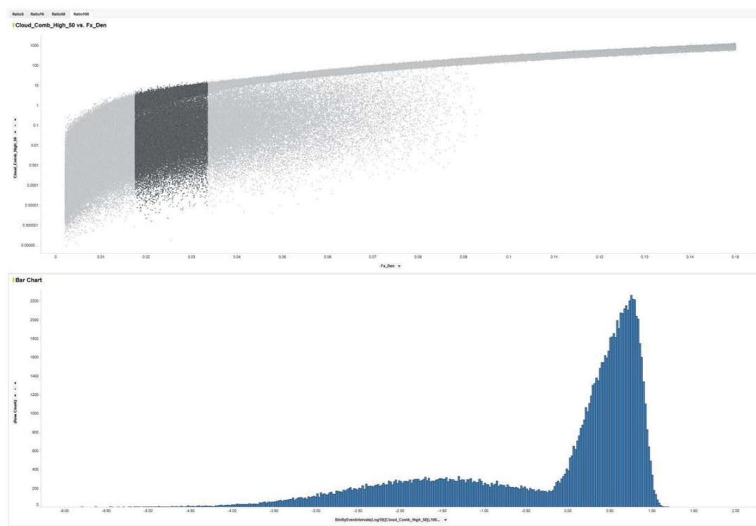


Figure 18—Example Cloud Transform for Modeling Fracture Heterogeneity

Examples fracture heterogeneity models are shown in Fig. 19.

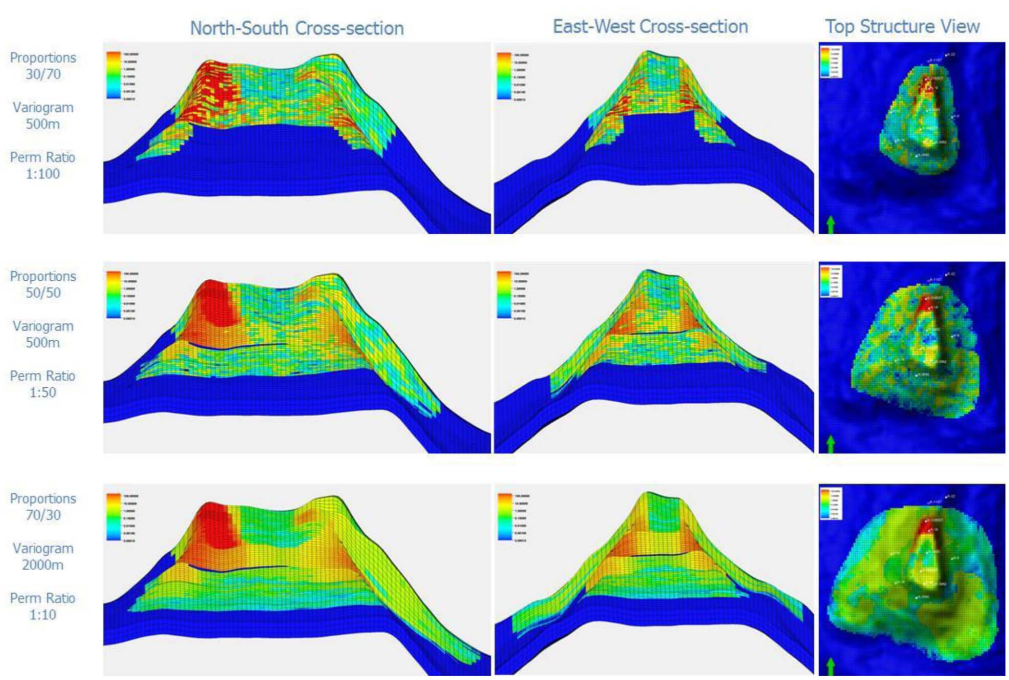


Figure 19—Example Fracture Heterogeneity Models

Finally, Lorenz coefficients were calculated for each of the fracture heterogeneity models to validate a sufficient range of heterogeneity exists to select a low, mid and high fracture model. The Lorenz coefficients were calculated using Chevron's flow diagnostics tool with two designs of well pattern layouts: regular five-spot pattern and 8 peripheral injectors with the existing well. The resulting range of coefficients was 0.55 to 0.80 which was deemed sufficient and appropriate for the evaluation based on validation with CDF curves.

Conclusion

A robust innovative methodology for calibrating full-field fracture model was utilized, which involves integration of dynamic data into geological model. Calibration of the fracture model with available data of well PI, PTT and Pulse Tests was conducted with implementation of geologically consistent smooth trends, which lead to better understanding of fractures spatial distribution and reduction in range of uncertainties for fracture properties during Experimental Design phase. Simulation model with improved fracture characterization is the key to reliable production forecast for potential future IOR application at Korolev.

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