MULTI-OBJECTIVE AHM WORKFLOW INTERGRATING THE 4D SEISMIC DATA

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Hydrocarbon reservoirs are formed during complex geological and tectonic processes. This processes control the reservoir properties and its architecture. Reservoir modelling is frequently used in order to assess and manage the hydrocarbon field. The models are commonly characterized with high level of uncertainty due to limited differently-scaled geological knowledge. The amount of different scale geological uncertainties makes it difficult to manage the field development. High uncertainty tends to high risks in terms of petroleum business. Decreasing the uncertainty level of geological models is an essential pathway in order to make this «tool» work more precisely with sufficiently reliable outcomes in medium- and long-term forecasts of production and field management. Assisted history matching of reservoir simulation models is commonly used to reduce the level of uncertainty so that the quality of predictions based on the model increased.

Assisted History Matching (AHM) is the process of using production history in order to improve the reservoir characterization in a particular hydrocarbon field. The parameters controlling the architecture and behaviour of the reservoir are varied during history matching so that the best match between simulations and the historical production data is obtained. [2]. AHM process involves well production data, however time-lapse seismic (TLS) data also could be used [5]. Time-lapse seismic is a proven technology for reservoir monitoring that has been widely implemented for reservoirs study around the world. TLS or 4D seismic is a common 3D seismic survey repeated in time, so that the results of field production for particular time-period could be tracked spatially. The pressure and saturation differences due to production build the physical basis of TLS usage, as these parameters directly affect the amplitude-frequency response of the field [1].

The implementation of 4D seismic data positively affects the AHM process. This is due to well data defines relatively small representative volume in scale of whole field, which might result in the lack of information about one of the main reservoir management factor – remaining hydrocarbons localization. Combining relatively «local» well production data with «global» TLS interpretation results tends to improve the general understanding of reservoir architecture and dynamic behavior.

There are two commonly used techniques to implement 4D seismic data into AHM process: simulation-to-seismic (Sim2Seis) and seismic-to-simulation (Seis2Sim). The former is used to validate and optimize the reservoir models by estimating a synthetic 4D seismic response, which is based on particular simulation run. This response is then compared with actual TLS data, after which the reservoir model is updated and tuned in order to find a better match. The latter is performed by inverting the seismic data into volumes of pressure and saturation changes so that each outcome of simulation run could be compared with it. Further discussion in aimed on the Seis2Sim technique. AHM process uses objective function (OF), so that the mismatch between production and simulation data is minimized. There are some key issues with defining the OF for TLS data integrated to AHM process. These are concerned with the absence of robust and consistent methods for measuring the mismatch, its sustainability to essential noise in seismic data encountered, as well as rational optimization algorithm choice.

The main purpose of this paper is development of the complex methodology for of time-lapse seismic response implementation into the assisted history matching workflow. Methodology validated on a synthetic Brugge Oil Field model, based on real data from BRENT fields of the North Sea. The dataset is also provided with synthetic 4D seismic data – pressure and saturation difference cubes after 10 years of field production [6].

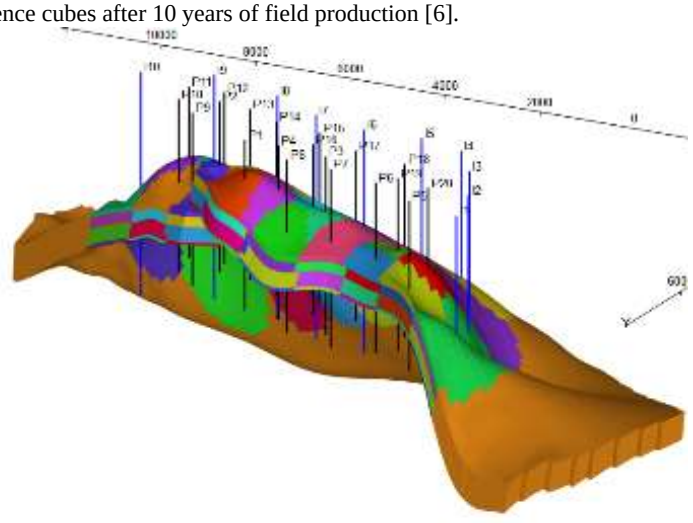

Fig. 1. Subregions for each well and formation used for calculation of 4D seismic objective function

At first, each of the four geological formations were analyzed, so that the structural, geological and uncertainties were stated and encountered into the workflow for geological modelling. These included analysis of depositional conditions, assessment of porosity-permeability relationship per facies, various saturation models. Prior geological knowledge about

channel thickness/width relationship used for reducing the uncertainty of geobody geometry in Schelde fluvial formation [7]. In total, 27 variables are used in workflow to define the geological setting for each case. Additional 18 parameters used to manage the OWC and petrophysical uncertainties (poro-perm, J-function, relative permeabilities). Secondly, the unique approach for measuring the mismatch proposed. Instead of using cell-by-cell technique, specific regions were defined for each formation within each producer and injector.

After that, the objective function for TLS data is defined:

$$4D_{OF} = min \sum_{s} w_s \left(\sum_{\Delta P, \Delta S} w_{\Delta P, \Delta S} X \right)$$

where s – subregions, w_s – weight of each subregion, ΔP & ΔS – pressure and oil saturation parameters estimated within each subregion, $w_{\Delta P, \Delta S}$ – weights of these parameters, X – difference of pressure or oil saturation between TLS and simulation data.

Due to significant difference between the physical meaning and actual values of TLS and well data, objective functions for them calculated separately. This resulted in further optimisation with two different objective functions, which is multi-objective optimisation. Multi-objective methods improve performance of the optimisation and history matching phases by increasing the diversity of possible solutions for the same computational cost of Single Objective methods. Obtaining a more diverse set of solution is important to ensure robustness of the predictions and decisions made [8]. Thus, the well production data OF is defined as:

$$well_{OF} = min \sum_{q_o, q_w, BHP} \frac{w_{q_o, q_w, BHP}}{\sum_{q_o, q_w, BHP} w_{q_o, q_w, BHP}} \left(\sum_{well} \frac{w_{well}}{\sum_{well} w_{well}} \left(\frac{\sum_{n=k}^{N} l_n S}{\sum_{n=k}^{N} l_n} \right)^{0.5} \right)$$

where $w_{q_o, q_w, BHP}$ – weights of parameters in objective function, w_{well} – weights for wells, S – error between calculated and historical values of each parameter, n – number of timestep, l_n – length of timestep between k-step and N (last) step.

Finally, after sensitivity analysis and parameterisation validation through stochastic Latin Hyperube sampling, multi-objective optimization performed by Particle Swarm Optimization algorithm. Particle Swarm Optimisation is a multi-agent based global optimisation algorithm. Swarms (populations) are initially placed in random positions of the search space, moving in random directions. The direction itself represents the experienced success of each particle and its neighborhood in searching of the better location (solution). This algorithm is simple, fast and effective in searching for the global optima [3].

This experiment included 600 iterations for multi-objective optimization, after which the best-fit models were obtained by Pareto-front analysis of defined OFs. The Pareto front is defined as the set of non-dominated solutions, where each objective is considered as equally good [4]. Best-matched results are presented for some wells on the figure bellow:

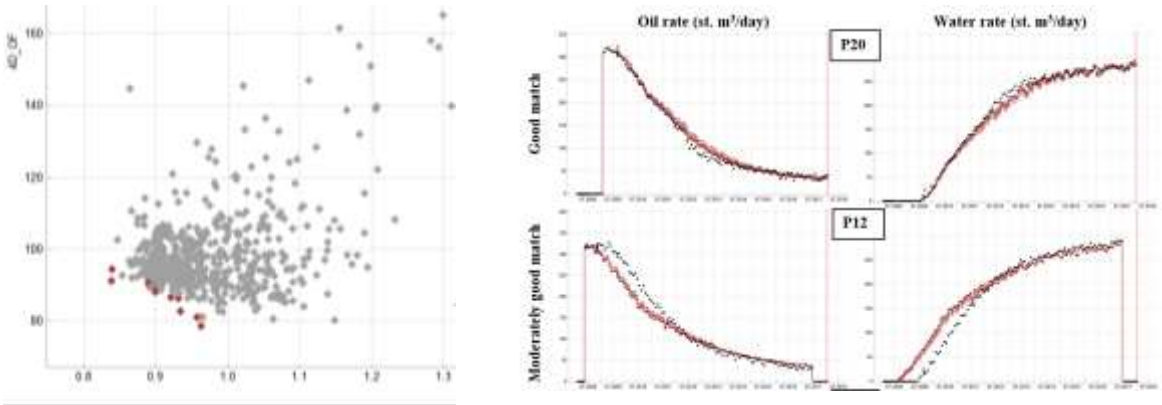

Fig. 2. Pareto-front with multiobjective solutions (left) and oil/water rates of some producers in best-fit(red) cases

The following conclusion is made as a result of this study:

- Proposed methodology is simple and ready-to-use in petroleum industry, it has satisfactory testing results;
- The scope for further research in this area is developed. It is concerned with weighting of regions used in TLS objective function, choice of the proper optimisation algorithm and its. Finally, the reliable amount of algorithm iterations is the point to look at. There must be a tradeoff found between the amount of time spent on the AHM and the reliability of it outcomes.

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MACHINE-LEARNING PREDICTIONS CO_2 SOLUBILITY AND RESIDUAL TRAPPING INDEXES

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Ongoing human activities that emit carbon dioxide (CO_2) into the atmosphere cause severe air pollution that leads to complex changes in the climate, which poses threats to human life and ecosystems. Geological CO_2 storage (GCS) is seen as a promising solution to address this environmental issue by removing some of the CO_2 emissions. To ensure the success of GCS projects, it is crucial to understand the efficiency of CO_2 solubility and residual trapping in saline aquifers. There are different strategies to reduce CO_2 emissions, including carbon capture and storage (CCS) and carbon capture utilization and storage (CCUS). The distinction between CCS and CCUS is based on the final destination of the captured CO_2. In CCUS, the captured CO_2 is used to enhance oil production and provide long-term carbon storage. On the other hand, underground CCS only focuses on storage efficiency in target formations [1,2]. To predict the solubility trapping index (STI) and residual trapping index (RTI) of CO_2 in saline aquifers, this study employs four robust machine learning (ML) and deep learning (DL) algorithms.

Data collection and description.

To construct reliable ML or DL models for predicting CO_2 trapping indexes in potential storage reservoir formations, a large and trustworthy database is required. In this study, 6811 simulation records pertaining to CO_2 residual and solubility trapping indexes were compiled from published sources [1].

Methodology.

To predict STI and RTI accurately, four different machine learning and deep learning models - Extreme Learning Machine (ELM), Least Square Support Vector Machine (LSSVM), General Regression Neural Network (GRNN), and Convolutional Neural Network (CNN) were used on a dataset of 6811 simulation records from published studies. To evaluate the performance of the models, statistical error metrics such as Root Mean Squared Error (RMSE), Coefficient of Determination (R^2), and Average Absolute Relative Error (AARE) were used along with score and robustness analyses. The dataset was divided into training and testing subsets, and each model was evaluated based on its ability to predict CO_2 STI and RTI. A sensitivity analysis was conducted, and it was found that the most consistent results were obtained when the data records were split into 80 % training and 20 % testing subsets. The workflow for developing the models and predicting STI and RTI based on eight input variables is described in Figure.

Fig. Schematic diagram of the implemented workflow for developing, evaluating, and comparing the ML and DL models for STI and RTI prediction. Reproduced with permission from [1]

Table presents the R2, RMSE, and AARE values for each model's predictions of STI and RTI with respect to the testing and training subsets and for the trained model applied to the complete dataset. The best performing LSSVM model, considering results for the complete dataset, yielded the most dependable STI and RTI predictions. It delivered AARE, RMSE, and R2 values of 1.1583 %, 0.0043, and 0.9985, respectively, for STI, and 1.3886 %, 0.0105, and 0.9965, respectively, for RTI.