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A NOVEL SIMILARITY-BASED UPSCALING METHOD FOR HIGHLY HETEROGENEOUS RESERVOIR MODELS

The paper presents a novel method for upscaling geological model grids of hydrocarbon reservoirs, particularly well-suited to highly heterogeneous formations. To determine the optimal number of layers in the upscaled model, the Lorenz coefficient was used. A rapid decline in its value was interpreted as a significant loss of geological information, providing a quantitative criterion for limiting vertical coarsening. Hydraulic Units (HU) were calculated based on the analysis of Reservoir Quality Index (RQI) and Flow Zone Indicator (FZI) parameters. These units served as the basis for transforming the reference model into a rock-type model. Advanced image comparison techniques based on deep artificial neural networks were used to compute the similarity between adjacent layers. This enabled the identification and merging of geologically similar layers while preserving the reliability of the upscaled model. The proposed method outperforms conventional upscaling approaches in terms of both accuracy and computational efficiency. Notably, it eliminates the need for time-consuming optimisation procedures, which are commonly required in standard workflows. Furthermore, the developed algorithm is grounded in robust theoretical principles related to reservoir rock classification and allows continuous improvement of results via retraining or replacement of the image analysis module.

Keywords: Upscaling, heterogeneity; Lorenz coefficient; hydraulic flow unit; image similarity; deep neural network

1. Introduction

For many years, numerical simulations of fluid flow in porous media have been a key tool in supporting decision-making during hydrocarbon reservoir exploitation. To ensure that such decisions are well-founded, they must be subject to the lowest possible level of uncertainty [1], which can be achieved by employing reliable simulation models that accurately represent reservoir

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reality. A key component of such models is the representation of the rock matrix using a grid with appropriate resolution. If the resolution is too low, it leads to a significant loss of petrophysical information and reduces the credibility of the model. On the other hand, if the resolution is too high, the computational cost increases substantially, making it difficult to perform tasks such as sensitivity analysis or scenario simulations. Therefore, it is necessary to find a balance – a "golden mean" – in the level of geological model simplification. This balance is achieved through grid upscaling, a process in which a heterogeneous region of the model (a set of fine-scale blocks) is replaced by a homogeneous representation (single coarse blocks) (Fig. 1). Transitioning from a high-resolution to a low-resolution model always involves averaging of petrophysical parameters, which results in a reduction of geological information. The main goal of upscaling algorithms is to minimise this loss, so that the simulation results obtained from the simplified model remain as close as possible to those obtained from the fine-scale reference model.

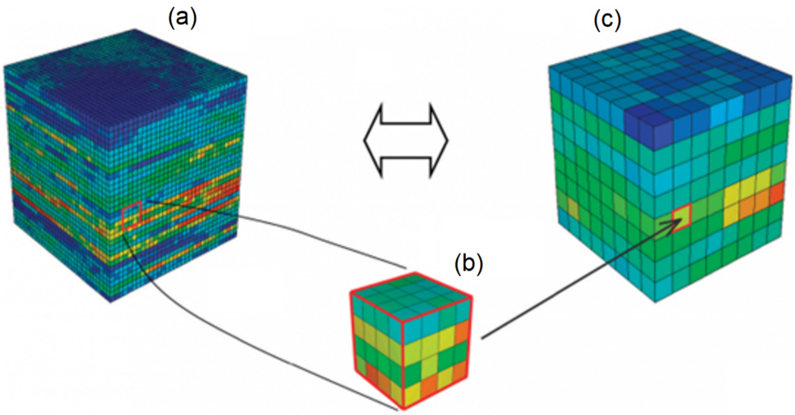

Fig. 1. Upscaling operation scheme: model (c) is a simplification of the reference model (a), achieved by homogenising selected parts (b) of the full model [2]

Among the various upscaling techniques, the Li-Beckner method [3] has been implemented in commercial reservoir simulation software. It allows for the identification of an optimal grouping of model layers while preserving the maximum possible degree of heterogeneity. This is achieved by minimising the difference between the values of a selected petrophysical parameter before and after the grid upscaling operation (Fig. 2).

The optimal layer configuration is obtained by minimising an error function defined by Eq. (1):

$$R = \sum_{i=1}^{n_z} \frac{\left(\overline{p}_i^u - \overline{p}_i^o\right)^2}{n_z} + w \sum_{i=1}^{n_z} \frac{\left(\overline{\sigma}_i^u - \overline{\sigma}_i^o\right)^2}{n_z} \tag{1}$$

where:

n_z – the number of layers in the fine-scale model;

$\overline{p}_i^u$ – the average value of the selected property in the upscaled model;

$\overline{p}_i^o$ – the average value of the selected property in the fine-scale model;

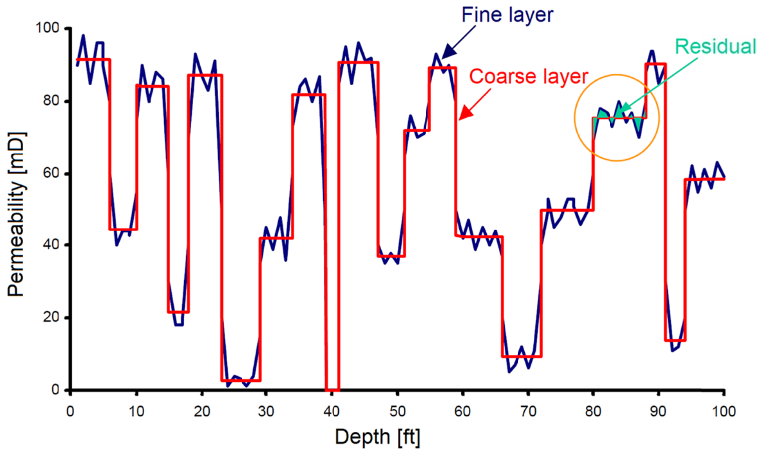

Fig. 2. Layer ordering scheme of a sample geological model preserving permeability heterogeneity as much as possible [3]

w – weighting factor in the range $\langle 0; 1 \rangle$;

$\overline{\sigma}_i^u$ – the standard deviation of the selected property in the upscaled model;

$\overline{\sigma}_i^o$ – the standard deviation of the selected property in the fine-scale model.

The layer-based Li-Beckner method presents two significant limitations that affect the quality of the upscaled model: 1) the optimisation is performed only on the averaged values of petrophysical properties within each layer, rather than on individual grid blocks; 2) the method is applied separately to each property – such as porosity and permeability – without jointly considering their impact on reservoir flow behaviour. Moreover, the method does not provide a clear criterion for determining the optimal number of layers in the upscaled model, even though it is an essential parameter in the design of any upscaling workflow. To address these limitations, a new upscaling method has been developed, particularly applicable in challenging cases of strongly heterogeneous reservoirs.

2. Reference model

To demonstrate the application of the new upscaling algorithm, the SPE-10 model [4] was selected. This model has gained wide recognition within the scientific community and has become a benchmark for evaluating and validating various upscaling methods [5]. The full-scale geological model is described using a grid of 60×220×85 blocks, representing a reservoir volume of 1200×2200×170 ft (amounting to approximately 1.122 million grid blocks). The upper 35 layers (70 ft) correspond to the epicontinental Tarbert formation, while the lower 50 layers (100 ft) represent the fluvial Upper Ness formation. Both formations exhibit significant heterogeneity in permeability – spanning 8 to 12 orders of magnitude. The SPE-10 model is a subset of a larger geological framework describing the Middle Jurassic Brent sequence in the northern North Sea, developed as part of the international PUNQ project (Production Forecasting with Uncertainty

Quantification). Structurally, the model is relatively simple; however, it is characterised by extremely high heterogeneity in petrophysical parameters. Its very high resolution (over one million blocks) makes it unsuitable for direct application of trivial upscaling techniques. A subset of the blocks (approximately 2.5%) has zero porosity and is therefore considered inactive. The modelled reservoir section includes five vertical wells – four production wells located at the model corners and one injection well located at the centre (Fig. 3). Both production and injection wells exploit the full reservoir thickness. The oil production process is simulated over a 20-year period, assuming a constant bottom-hole pressure of 27.58 MPa at the production wells and a fixed water injection rate of 795 m^3/day.

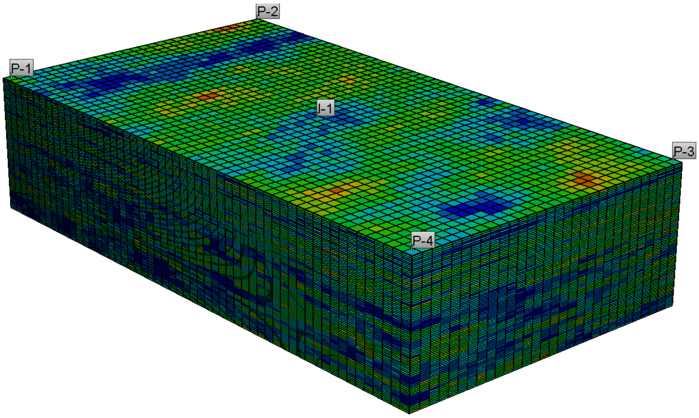

Fig. 3. Well placement in the SPE-10 model: P-1, P-2, P-3, P-4 – production wells, I-1 – injection well

To accelerate the simulation process, a reduced version of the SPE-10 model developed by Coats Engineering Inc. was used. This version consists of 141,000 active blocks, defined by a coarser grid of 30×55×85, which fully preserves the vertical heterogeneity of the petrophysical parameters – crucial for investigating the proposed upscaling method – while reducing resolution in the horizontal directions. All simulations related to oil production in the SPE-10 case study were performed using the CMG IMEX black-oil simulator.

3. Proposed upscaling method

The first step in the proposed upscaling method was to determine the optimal number of layers in the upscaled model – that is, the minimum number of layers that allows the model to retain an acceptable level of heterogeneity relative to the reference case, while reducing the total number of grid blocks. To achieve this, a classical measure of heterogeneity was used: the Lorenz coefficient, which is widely applied to describe the variability of vertical permeability distributions in reservoir rocks [6]. The Lorenz coefficient ranges from 0 (perfectly homogeneous system) to 1 (perfectly heterogeneous system). In practice, such extremes are not observed; real reservoir systems typically yield Lorenz coefficient values between 0.2 and 0.6 [7]. In this study, Lorenz coefficients were calculated for multiple levels of vertical averaging in the reference model, corresponding to different layer counts in the upscaled model. Layer aggregation was performed using both arithmetic and harmonic averaging. As the vertical resolution of the computational grid decreased, a consistent decline in the Lorenz coefficient was observed. Analysis of this trend enabled the identification of a threshold value, beyond which further simplification would cause a sharp loss of geological information and primary similarity in the reliability of the upscaled model [8] (Fig. 4). For the SPE-10 reference model, this threshold corresponded to an 18-layer configuration in the upscaled model.

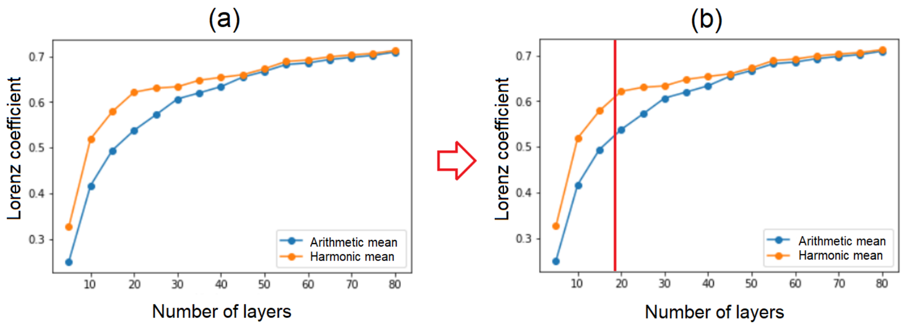

Fig. 4. Lorenz coefficient values for layers averaged using arithmetic and harmonic means (a), and threshold (red line) defining maximum simplification level of the reference model (b)

Knowing the target number of layers in the upscaled model is not sufficient to perform an optimal upscaling operation. A critical task is to determine which layers can be merged, and subsequently, how this merging should be performed. To guide this process, the similarity criterion for adjacent layers was based on hydraulic units (HU), which describe zones of the reservoir rock that exhibit similar flow properties [9].

To identify hydraulic units, petrophysical parameters indicative of fluid flow capacity in porous media were computed: the Reservoir Quality Index (RQI) and the Flow Zone Indicator (FZI) [10]. Both parameters were calculated for each individual grid block in the reference model. Next, the derivative of the cumulative distribution function (CDF) of FZI values was computed. Discontinuities or sharp gradients in the derivative were interpreted as boundaries between hydraulic units. Based on this analysis, six distinct HU zones were identified, with each unit defined by a specific range of FZI values. These intervals were centred around the median FZI values within their respective ranges. The resulting flow unit partitions, representing zones of similar flow characteristics, are shown in Fig. 5.

The identification of hydraulic units enabled the transformation of the numerical model such that each grid block is represented by its corresponding HU. This approach resulted in a rock-type model. Figs. 6 and 7 illustrate two adjacent layers characterised respectively by similar and distinct flow properties. Given the apparent difference in visual similarity between neighbouring layers, an intelligent image recognition algorithm was employed to determine the optimal scheme for upscaling the reference model's grid.

To quantify the similarity between adjacent layers, a Siamese Network based on the ResNet50 convolutional neural network was utilised. Both Siamese and convolutional neural networks are widely used architectures in artificial intelligence, gaining increasing popularity in various

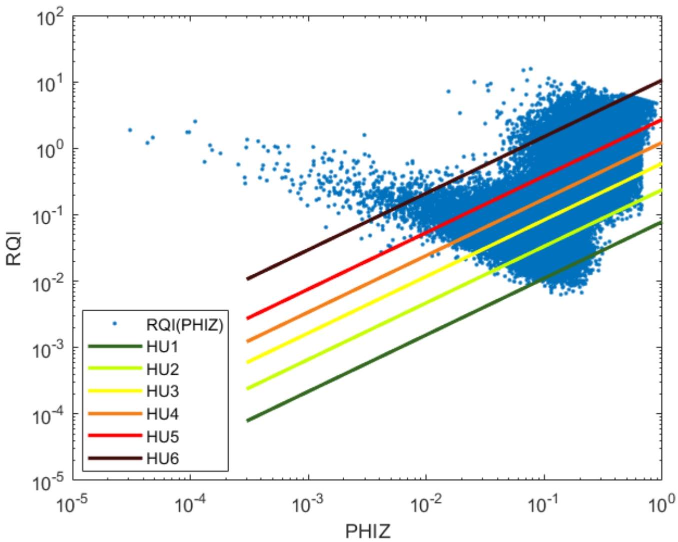

Fig. 5. Identified hydraulic units (HU) on the plot of $RQI(\varphi_z)$

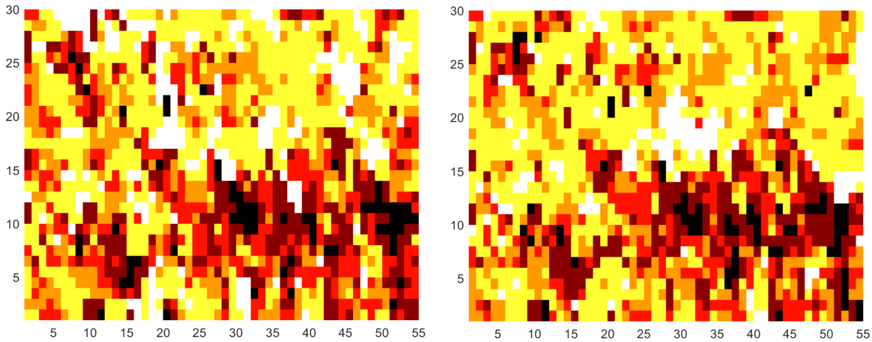

Fig. 6. Example of adjacent layers with similar flow properties (layers no. 66 and 67)

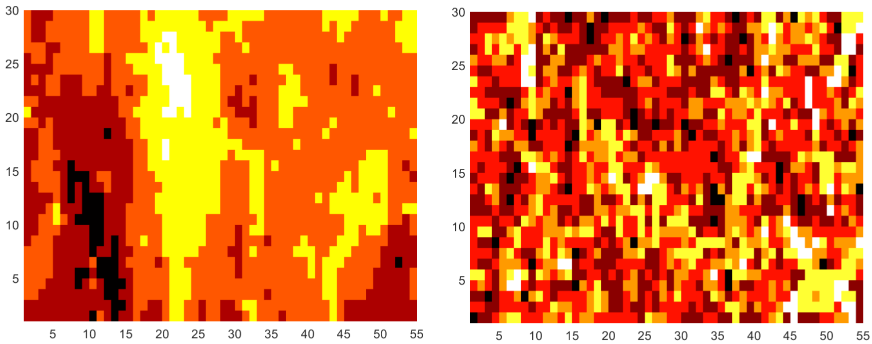

Fig. 7. Example of adjacent layers with different flow properties (layers no. 35 and 36)

image processing tasks [11-14]. The input to the network consisted of pairs of images representing layers, and the output was a percentage similarity score – the higher the score, the greater the similarity between the input images. A score of 100% would indicate identical images. Fig. 8 depicts the similarity scores between layers in the reference model, where each layer is compared to the one immediately beneath it.

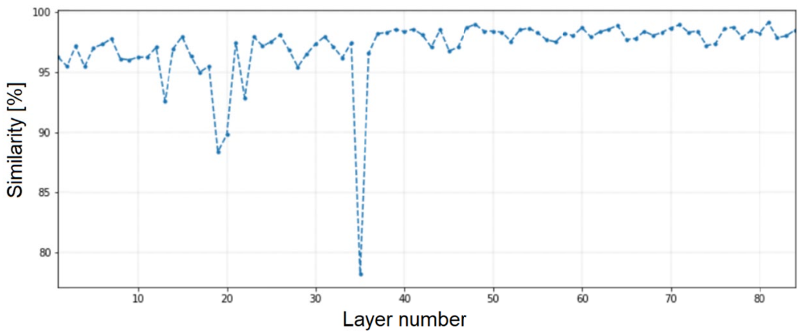

Fig. 8. Similarity between adjacent layers determined using Siamese network based on ResNet50

To determine the optimal upscaling scheme, it was decided to merge first those layers with the highest similarity. The proposed grouping scheme is shown in Fig. 9, while Fig. 10 contrasts the new method with a classical upscaling approach using the example of three adjacent layers.

The workflow of the novel HU-NN upscaling method is presented in Fig. 11.

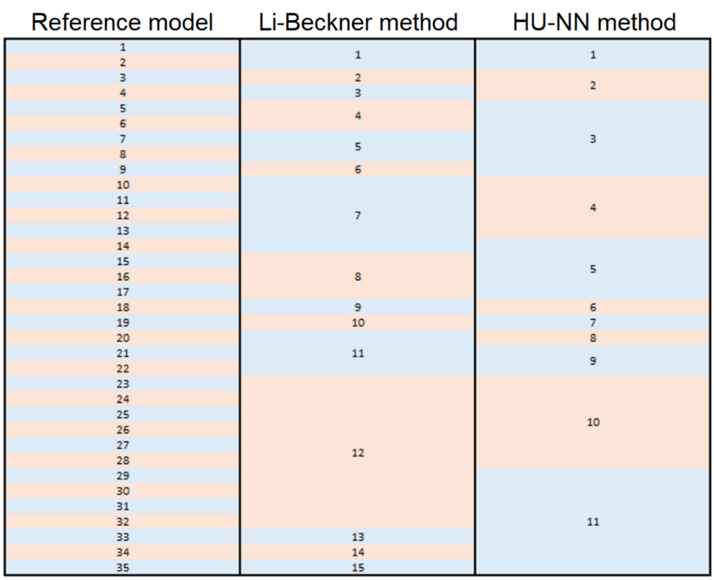

Fig. 9. Comparison of layer grouping schemes: classical Li-Beckner method versus new HU-NN upscaling method for upper 35 layers

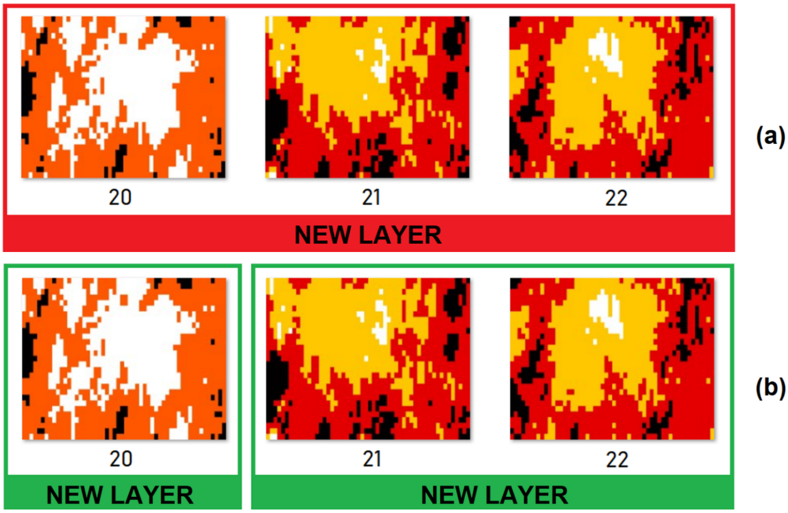

Fig. 10. Comparison of layer grouping by Li-Beckner (a) and HU-NN (b) methods for layers no. 20, 21, and 22; HU-NN does not merge layers with differing flow properties (layers 20 and 21)

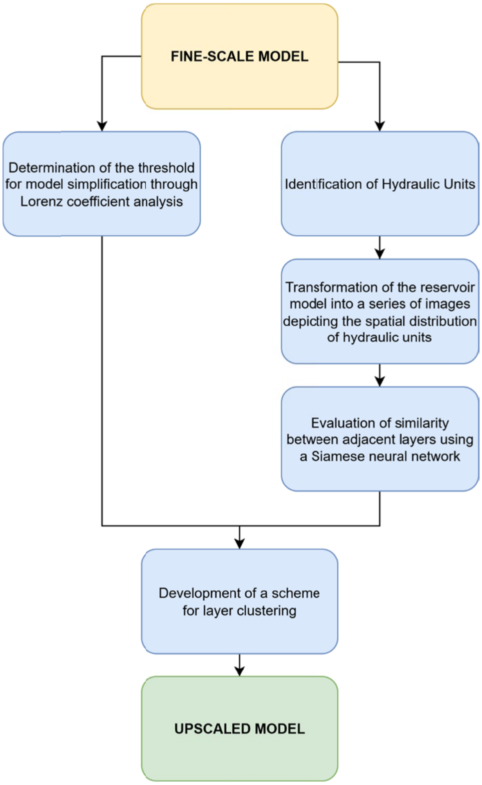

Fig. 11. Scheme of the new HU-NN upscaling method

4. Results

Comparative results of reservoir simulation for oil production using models upscaled by the classical Li-Beckner method and the proposed HU-NN approach are presented in Figs. 12-14. As can be observed, the simulation outcomes obtained with the HU-NN upscaled model closely

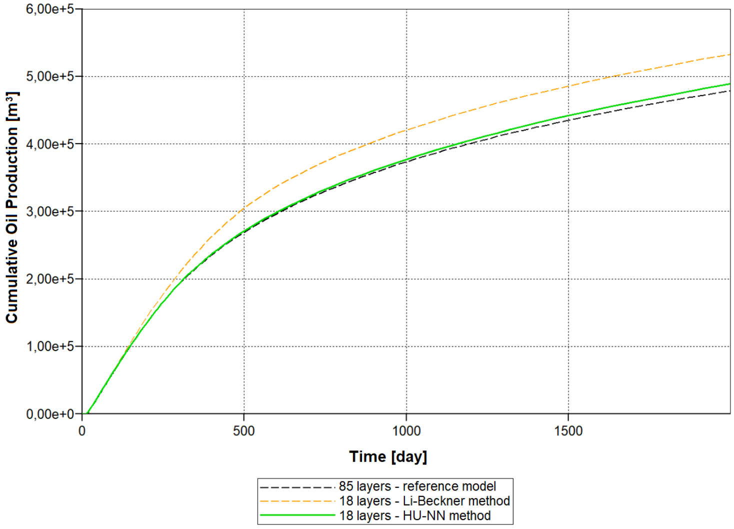

Fig. 12. Comparison of cumulative oil production predictions using models upscaled by Li-Beckner and HU-NN methods

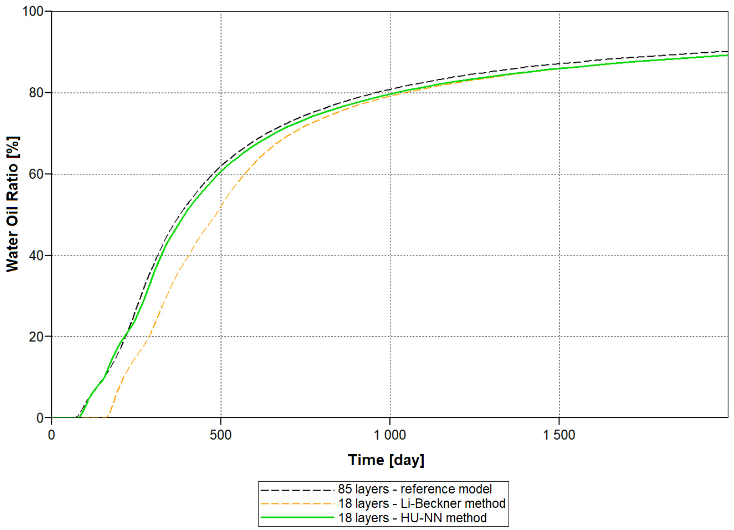

Fig. 13. Comparison of water oil ratio predictions obtained from models upscaled by Li-Beckner and HU-NN methods

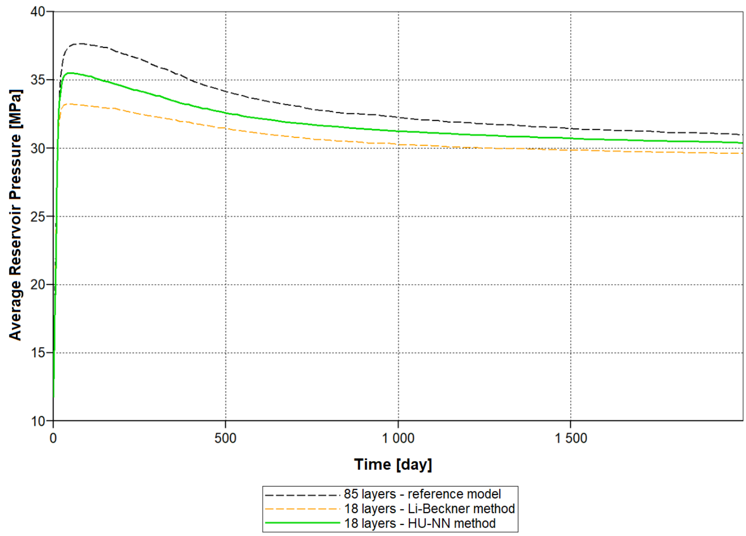

Fig. 14. Comparison of average reservoir pressure predictions from models upscaled by Li-Beckner and HU-NN methods

match those from the reference (cumulative oil production, water oil ratio) or show a remarkable improvement over the results obtained with the classical upscaling method (pressure values). Moreover, due to the nature of neural networks, the new layer grouping method exhibits very low computational complexity: the computational effort is constant with respect to the horizontal dimensions of the reference model and linear concerning its vertical dimension. This leads to exceptionally fast computation times, virtually independent of input size (i.e., the number of blocks or layers). While for the SPE-10 reference model, the computational times of both upscaling methods – new and classical – are comparable and measured in seconds, for larger models, the HU-NN method maintains this performance level. In contrast, the Li-Beckner method's runtime increases substantially to the scale of minutes.

5. Conclusions

This study introduced a novel upscaling algorithm based on deep neural networks, which assesses the similarity of petrophysical images of adjacent layers within a reservoir numerical model. This pioneering approach not only delivers superior accuracy compared to classical methods but also features low computational complexity.

The proposed methodology for determining the optimal number of layers in the upscaled model proved highly effective for constructing significantly simplified models. It enables the identification of a generalisation threshold beyond which the loss of petrophysical information would render the model unreliable. The fidelity of the simplified model relative to the reference is further enhanced by grounding the approach in robust theoretical principles for delineating reservoir zones with similar flow properties.

A major advantage of the proposed solution is its potential for full automation, making it highly attractive for integration into widely used reservoir simulators. This opens opportunities for continuous improvement of upscaling quality through refinement or retraining of the intelligent image analysis algorithm.

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