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NEURAL NETWORKS AND DATA-DRIVEN SURROGATE MODELS FOR SIMULATION OF STEADY-STATE FRACTURE GROWTH

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Abstract. This work is devoted to an assessment of the application of machine learning algorithms in the prediction of a fracture's aspect ratio caused by the hydraulic fracturing. By the aspect ratio in this work is assumed the ratio of the larger half-axis of the fracture to the smaller one. The study shows the prospects of applying data-driven surrogate model methods (deep neural networks learning from data simulated by means of traditional solvers) to particle dynamics modelling of hydraulic fracturing. The solution obtained allows to predict the aspect ratio value quickly, and thus, to evaluate the volume of the hydraulic fracturing fluid injection necessary to achieve the required fracture length.

Keywords: neural networks, surrogate model, hydraulic fracturing, crack

1. Introduction

Nowadays, hydraulic fracturing has become the main method to increase oil production from conventional and unconventional fields. Hydraulic fracturing is a stimulation technique in which a high-permeable fracture is created in a productive layer by a pressurized liquid [1].

Hydraulic fracturing planning, support, and optimization are implemented using the special software (e.g. MFrac, FracPro, FracCADE, Mangrove). These tools use basic analytic solutions in hydraulic fracturing theory [2], and some of the contemporary numerical modelling techniques (Pseudo3D [3], Planar3D [3], and Full3D [4]). Such modelling includes the solution of partial differential equations with corresponding initial and boundary conditions [5]. The amount of the equations can be of high order (10^6–10^9), making such tasks computationally expensive.

The alternatives to resource-intensive numerical modelling are meta-modelling, surrogate modelling [6] or model order reduction approach [7]. These approaches allow to simulate physical systems with lower resource costs while maintaining acceptable accuracy. The modern rapid development of deep learning methods [8] makes it possible to use results obtained by traditional numerical solvers as surrogates [9] to accelerate computationally expensive calculations.

Deep learning technology is a subtype of machine learning most often implemented by artificial neural networks. Deep learning allows to find implicit dependencies and predict the desired values of the target function by processing huge data sets (big data). In particular, this approach becomes a common instrument in problems of the petroleum industry [10,11,12].

To gain high predictive ability, deep learning instruments require large training sample size. Therefore, the amount of data available in natural experiments may not be sufficient. In such cases, the necessary amount of training data can be obtained by modelling: e.g., by

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carrying out a number of numerical experiments. The models constructed on the basis of this approach are called data-driven surrogate models [13,14]. In recent years, this approach has shown great success, for instance, in the tasks of accelerating resource-intensive simulations in computational fluid dynamics [13], electric potential distribution [14], heat transfer [15], etc. In these works, deep neural networks are trained on data simulated with traditional solvers.

In this paper, the analogous approach is used to accelerate the hydraulic fracturing simulation process and to calculate the geometric parameter of the resulted fracture: the aspect ratio value describing the proportional relationship between the larger half-axis of the fracture and the smaller one. The training database is generated using the numerical simulation by means of the particle dynamics method.

2. The steady-state hydraulic fracture modelling

The steady-state hydraulic fracture model is formulated as follows: the fracture is considered to be located in a linearly elastic material; the material consists of three parallel layers lying in the XY plane (Fig. 1); the productive layer is located between the semi-infinite side layers. Parameters of the model are: σ_i is the reservoir stress of the i^{th} layer; K_i is the critical stress intensity factor of the i^{th} layer; E'_i is the elastic modulus of the i^{th} layer multiplied by $\frac{E_i}{1-\nu_i^2}$, where E_i is a Young's modulus and ν_i is a Poisson's ratio of the i^{th} layer; L is the half thickness of the productive layer; V is the volume of the injected hydraulic fracturing fluid.

The challenge is to determine the geometric parameters of the resulting fracture loaded with uniform pressure.

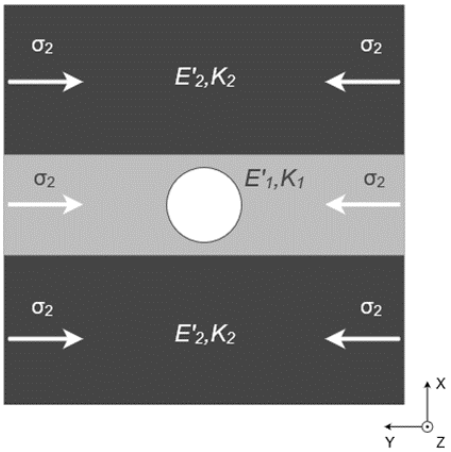

Fig. 1. The structure of the fracture between layers with different stress values

One of the ways to determine the geometric parameters of the resulting fracture in the material is to simulate its growth by the particle dynamics method [16,17].

The particle dynamics method is based on the representation of a material by a set of interacting particles (material points or solid bodies), for which classical dynamic equations are written. The interaction of particles is described by means of the interaction potentials, the main property of which is a short-range repulsion and long-range attraction mechanisms. Before the start of the simulation, the initial distribution of particles in space (i.e. the initial structure of the material) and the initial distribution of particle velocities are specified. This method allows to solve the problem in a three-dimensional formulation and to set various reservoir stresses and physical properties of layers.

One of the benefits of this approach compared to other methods, such as the boundary elements method [18] or the extended finite elements method [19], is that the particle

dynamics method eliminates the necessity of the explicit analytical description of objects' boundaries and geometry [20].

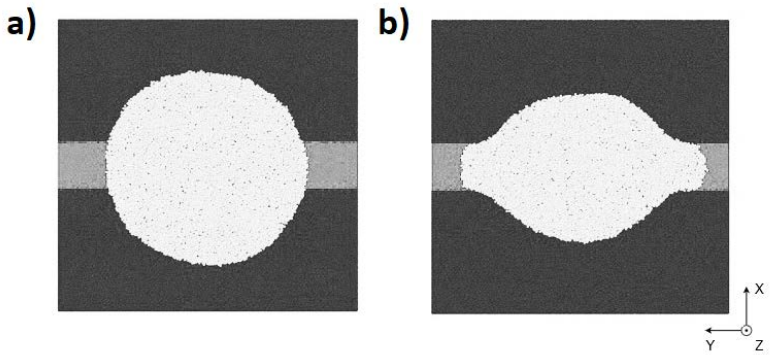

Fig. 2. Examples of the steady-state hydraulic fracture model in the fractured layer obtained by particle dynamics method. Black dots denote side layers. Grey dots denote the productive layer. White dots denote the fracture zone: a) the initial fracture; b) the fracture growing process

The reservoir initial configuration is a rectangular parallelepiped. The initial geometry of the fracture is a cylinder. The particle dynamics simulation continues until the least distance between particles denoting the fracture zone and particles denoting the border zone becomes less than 10% of the model size. The aspect ratio value in the paper is evaluated as the ratio of the greatest distance by the axis Y between particles denoting the fracture zone to the corresponding distance by the axis X (Fig. 2).

The using particle dynamics method implemented with C++ is fully described in [16]. However, such simulation is computationally expensive. To speed-up the calculation process the approximation models are commonly used, which can describe the processes occurring in the medium under consideration. The basic idea of approximation models is to construct the approximation function on the basis of previously performed calculations. As a result of the construction, numerical simulation is reduced to the calculation of this function value.

There are many ways to construct an approximation function. In particular, in modern practice major advances have been achieved in the development of machine learning methods which allow to construct approximation functions of almost any complexity.

3. The machine learning approach

Machine learning is the scientific study of algorithms and statistical models trained on large datasets. It is made instead of specifying their parameters explicitly [21].

The prediction of a hydraulic fracture aspect ratio belongs to the regression problem of the class of so-called «supervised machine learning» tasks. In the regression problem the goal is to predict a certain target variable for a given set of characteristics of the observed object. Thus, each sample in a training dataset (the part of the dataset that is used to train the algorithm) consists of input parameters and a target value.

At the first step, the structure of the training sample is formed thusly: preprocessed data contains feature vectors x of input parameters used in the particle dynamics method to obtain the model of the fracture (item 2). These parameters (features) are transformed to dimensionless in the following way [22]:

$$x = \left[\frac{E\prime_2}{E\prime_1}\ \frac{K_2}{K_1}\ \frac{K_1}{\Delta\sigma\sqrt{L}}\ \frac{E\prime_1 V}{\Delta\sigma L^3}\right]. \quad (1)$$

Each element from x is mapped to the certain aspect ratio value from the corresponding vector y: $y = [AR]$, where $[AR]$ means the vector of aspect ratio values, $\Delta\sigma$ is the stress

difference between the productive and the side layers and the other values are defined in item 2, E'_1 and K_1 are related to the productive layer, whereas E'_2 and K_2 are related to the side layers, *AR* is the aspect ratio value of the fracture.

The objective is to find such function $f(x)$ that would approximate the dataset with as high accuracy as possible: $f(x) = y$.

The chosen machine learning method to approximate this function is a deep fully connected neural network. So, in this case, the neural network represents the function $f(x)$, and the final objective is to find the right architecture. It is implemented using Python's framework Keras [23]: a high-level open source API capable of running on top of TensorFlow library.

The process of a neural network training is an iterative reduction of the loss (error) function value by adjusting the weights of the neural network using the gradient descent method. Each iteration is called "the epoch". One epoch consists of one complete training cycle on the training dataset which includes several training iterations on smaller sub-datasets (batches). The loss function on each epoch produces one value describing the difference between the predicted values for each feature vector x and the corresponding values of y. The ability of the neural network to predict correctly new examples that differ from those used for training is also evaluated on each epoch. It is evaluated the same way by using the test dataset instead of the training dataset.

The dataset used is generated by varying the feature values of x in ranges shown in Table 1. Values of features are varied under the assumption of the fact that the fracture volume increases for every configuration of listed parameters because of the permanent fluid injection. Thus, the calculation of the aspect ratio value is performed by the particle dynamics method for each feature set (it. 2). The process of the fracture growing is modeled several times (for instance, four times) for the same feature values, because the initial distribution of particles is set stochastically. Therefore, there are four different aspect ratio values for each input feature vector.

Table 1. The range of feature values variation

Feature	$\frac{E'_2}{E'_1}$	$\frac{K_2}{K_1}$	$\frac{K_1}{\Delta\sigma\sqrt{L}}$	$\frac{E'_1 V}{\Delta\sigma L^3}$
Minimum value	0.2	0.2	0.01	0
Maximum value	5	5	1	20

Hence, the input (training set) is the matrix of the dimension $N \times M$, where N is the number of elements in training dataset and M is the dimension of the feature vector x. The used dataset is split into 630000 samples for the training set and 157000 for the test set (approximately 80% to 20% of the whole dataset).

The values of the resulting input (training matrix) are linearly scaled from 0 to 1 for a fair comparison between them. Also, it is a well-known fact that feature scaling can improve the convergence speed of the gradient descent algorithm used while adjusting the weights of the neural network [24]. The most widely used measure of forecast accuracy is "Mean Absolute Percentage Error" (MAPE) [25]. It is used in the paper as the loss function.

4. Architecture setting

Any neural network in addition to the weights adjusted during the training process is also characterized by a set of hyperparameters defining the neural network architecture. The quality of results produced by an artificial neural network depends significantly on the proper hyperparameters configuration. The selection of the model hyperparameters in this work is

implemented using the random search algorithm: different neural network architectures are generated by selecting the hyperparameters' values randomly.

The number of hidden layers of the neural network is varied and some hyperparameters are varied within each hidden layer: the number of neurons (32, 64, 128, and 256); the neurons' activation function ("relu", "tanh", "linear", "sigmoid"); the dropout value (0, 0.1, 0.2, 0.3); the size of batch sub-datasets: 8, 16, 32.

Neural networks generated with different hyperparameters values (different architectures) are then evaluated via the cross-validation method [26], and the best architecture is chosen. Cross validation is used to eliminate the effect of the dataset splitting into the training and test set when evaluating the quality of the choice of the neural network hyperparameters.

For each set of hyperparameters the new configuration of the neural network is constructed, trained and cross-validated on the equal number of epochs. The final configuration of the neural network that demonstrated the most optimal result is shown in Fig. 3.

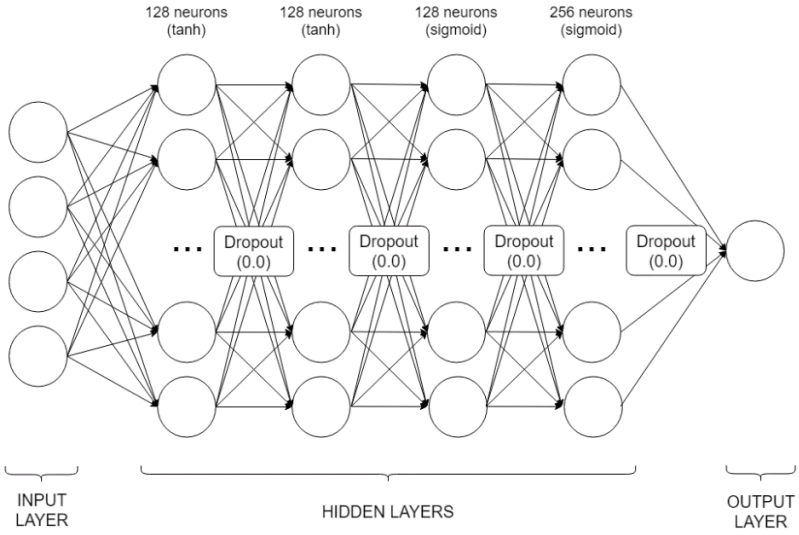

Fig. 3. The configuration of the neural network

5. Results

As anticipated, the loss values of the neural network used decline with the epoch number increasing for both the train and test sets. The training process is stopped after the 300th epoch: the chosen loss value (MAPE) on the number of epochs for test dataset fluctuates around a constant value. Figure 4 demonstrates that the MAPE value does not exceed 5% on a significant part of the test set (more than 80% of 157000 test samples). Figure 5 shows the example of the comparison between the fracture's aspect ratio values calculated by means of the particle dynamics method and neural network results. These results are obtained by assuming that parameters $\frac{E_2^{'}}{E_1^{'}}, \frac{K_2}{K_1}, \frac{K_1}{\Delta\sigma\sqrt{L}}$ are constant. For this reason, we can see how the dimensionless parameter $\frac{E_1^{'}V}{\Delta\sigma L^3}$ affects the changes in fracture growth.

A scatter of aspect ratio values is caused by the fact that the initial distribution of the fracture particles was set stochastically. Therefore, fracture distribution process is modelled four times for the same feature vector.

These examples show that the fracture's aspect ratio values calculated with the neural network accurately approximate fracture's aspect ratio values calculated with particle dynamics method.

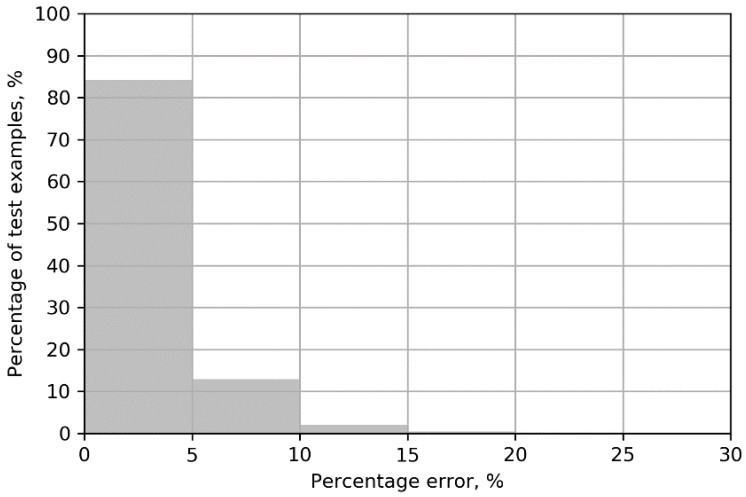

Fig. 4. The neural network's MAPE distribution on the test data

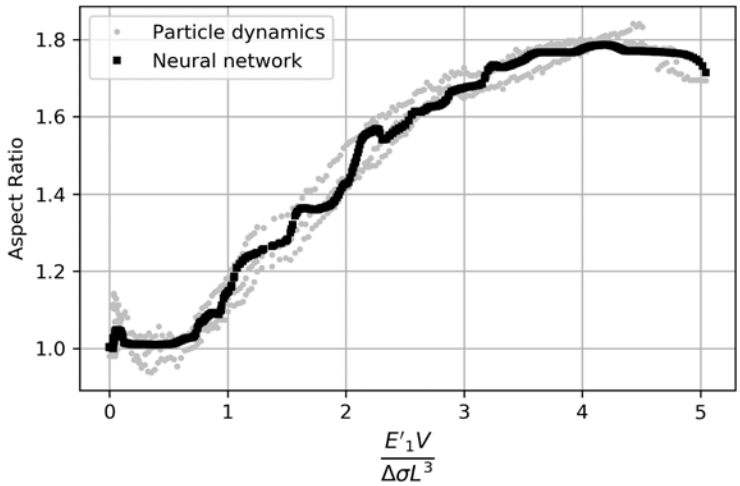

Fig. 5. The example of the results comparison for:
$\frac{E_2^{'}}{E_1^{'}}$=2.8; $\frac{K_2}{K_1} = 0.2$; $\frac{K_1}{\Delta\sigma\sqrt{L}} = 1.2875$

6. Conclusion

As a result of this work, the practical scientific and technical significance of the proposed approach is proved. The data-driven surrogate modeling approach is successfully applied to the task of evaluating the steady-state hydraulic fracture shape. The most optimal architecture and the hyperparameters of the deep neural network are found by means of the random search algorithm. The artificial neural network is trained and validated using the dataset generated by the particle dynamics. During the surrogate modeling process, the neural network's hyperparameters are varied for each hidden layer and the most optimal ones are used.

Thus, the calculation time is decreased from 1.5 hrs. to 0.05 sec. At the same time, the accuracy is maintained on a high level since the MAPE value does not exceed 5%. The number of examples with larger error values decreases significantly with the percentage error increasing. The result obtained demonstrates the promising perspectives of machine learning application in the area of such problems as physical quantities prediction on the basis of numerically obtained data. Unlike the existing numerical simulation methods to solve the task, the application of machine learning algorithms does not involve significant time and computational costs and can be considered as the most optimal.

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References

[1] Gandossi L, Von Estorff U. *An overview of hydraulic fracturing and other reservoir stimulation technologies for shale gas production – Update 2015*. Available from: https://ec.europa.eu/jrc/en/publication/eur-scientific-and-technical-research-reports/overview-hydraulic-fracturing-and-other-formation-stimulation-technologies-shale-gas-0 [Accessed 15th august 2019].

[2] Linkov AM. The particle velocity, speed equation and universal asymptotics for the efficient modelling of hydraulic fractures. *J. Appl. Math. Mech.* 2015;79(1): 54-63.

[3] Meyer B. Design formulae for 2-d and 3-d vertical hydraulic fractures: Model comparison and parametric studies. In: *Proc. Unconventional Gas Technology Symposium.* Society of Petroleum Engineers; 1986. p.391-408.

[4] Khasanov M, Paderin G, Shel E, Yakovlev A, Pustovskikh A. Approaches to modeling hydraulic fracturing and their development. *Oil Industry Journal*. 2017;2017(12): 37-41. (In Russian)

[5] Gladkov IO, Linkov AM. Solution of a Plane Hydrofracture Problem with Stress Contrast. *Journal of Applied Mechanics and Technical Physics*. 2018;59(2): 341-351.

[6] Ahmed M, Qin N. Surrogate-based aerodynamic design optimization: Use of surrogates in aerodynamic design optimization. In: *Proc. of 13th International Conference on Aerospace Sciences & Aviation Technology*; 2009. p.ASAT-13-AE-14.

[7] Schilders Wil, Van der Vorst H, Rommes J. *Model Order Reduction: Theory, Research Aspects and Applications.* Berlin: Springer; 2008.

[8] Bengio Y. Learning deep architectures for AI, Foundations and trends in Machine Learning. *Journal Foundations and Trends in Machine Learning*. 2009;2(1): 1-127.

[9] Kononenko O, Kononenko I. *Machine Learning and Finite Element Method for Physical Systems Modeling.* Arxiv [Preprint] 2018. Available from: https://arxiv.org/abs/1801.07337 [Accessed: 15 July 2018].

[10] Andrianova A, Simonov M, Perets D, Margarit A, Serebryakova D, Bogdanov Y, Budennyy S, Volkov N, Tsanda A, Bukharev A. *Application of Machine Learning for Oilfield Data Quality Improvement.* Society of Petroleum Engineers; 2018.

[11] Simonov MV, Perets DS, Kotezhekov VS. Adaptive Tool for Solving Applied Problems of Oil Engineering. In: *Proc. of 20th conference on oil and gas geological exploration and development*; 2018.

[12] Chebyshev IS, Baryshnikov ES, Legkokonets VA. Application of machine learning to predict the acoustic properties of rock samples. *Proneft.* 2018;4(10): 67-70.

[13] Parish EJ, Duraisamy K. A paradigm for data-driven predictive modeling using field inversion and machine learning. *J. Comput. Phys.* 2016;305: 758-774.

[14] Shan T, Tang W, Dang X, Li M, Yang F, Xu Shu, Wu J. Study on a Poisson's Equation Solver Based On Deep Learning Technique. Arxiv [Preprint] 2017. Available from: https://arxiv.org/abs/1712.05559.

[15] Sharma RI, Farimani AB, Gomes J, Eastman P, Pande V. Weakly-Supervised Deep Learning of Heat Transport via Physics Informed Loss. Arxiv [Preprint] 2018. Available from: https://arxiv.org/abs/1807.11374.

[16] Tsaplin VA, Kuzkin VA. On using quasi-random lattices for simulation of isotropic materials. *Materials Physics and Mechanics*. 2017;32(3): 321-327.
[17] Krivtsov AM. Molecular Dynamics Simulation of Plastic Effects upon Spalling. *Physics of the Solid State*. 2004;46(6): 1055-1060.
[18] Linkov A. *Boundary Integral Equations in Elasticity Theory*. Kluwer: Dordrecht; 2002.
[19] Liu F, Gordon PA, Valiveti DM. Modeling competing hydraulic fracture propagation with the extended finite element method. *Acta Geotechnica*. 2017;13(2): 243-265.
[20] Li Z, Bian X, Tang YH, Karniadakis GE. A dissipative particle dynamics method for arbitrarily complex geometries. *Journal of Computational Physics*. 2016;355: 534-547.
[21] Bishop CM. *Pattern Recognition and Machine Learnin*g. Springer; 2006.
[22] Shel EV, Paderin GV. Analytical solution of the pseudo-3D model for hydraulic fracturing in a storage-dominated regime. *Int. J. Rock. Mech. Min. Sci.* 2019;114: 92-100.
[23] Gulli A, Pal S. *Deep Learning with Keras.* Packt Publishing Ltd; 2017.
[24] Grus J. *Data Science from Scratch.* Sebastopol, CA: O'Reilly; 2015.
[25] Tofallis C. Better Measure of Relative Prediction Accuracy for Model Selection and Model Estimation. *Journal of the Operational Research Society*. 2014;66(8): 1352-1362.
[26] Grossman R, Seni G, Elder J, Agarwal N, Liu H. *Ensemble Methods in Data Mining: Improving Accuracy Through Combining Predictions.* Morgan & Claypool; 2010.