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The Application of Neural Networks to Forecast Radial Jet Drilling Effectiveness

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Abstract: This paper aims to study the applicability of machine-learning algorithms, specifically neural networks, for forecasting the effectiveness of Improved recovery methods. Radial jet drilling is the case operation in this study. Understanding changes in reservoir flow properties and their effect on liquid flow rate is essential to evaluate the radial jet drilling effectiveness. Therefore, liquid flow rate after radial jet drilling is the target variable, while geological and process parameters have been taken as features. The effect of various network parameters on learning quality has been assessed. As a result, conclusions on the applicability of neural networks to evaluate the radial jet drilling potential of wells in various geological conditions of carbonate reservoirs have been made.

Keywords: radial jet drilling; reservoir flow simulation; technology effectiveness; machine learning; neural network; carbonate reservoirs

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1. Introduction

The global oilfield development trends show a considerable increase in the number of improved recovery methods (IOR) due to the ever-growing share of unconventional resources. IOR is conducted to improve well productivity and oil recovery, increase injection well performance, isolate water inflows, etc. The study target herein is carbonate reservoirs of Perm Krai (Russia). To enhance well productivity, a range of IOR technologies are extensively performed at these reservoirs: acid fracturing, bottomhole acidizing, casing perforation and radial water jet drilling (RJD).

Addressed in this study, radial jet drilling is the most promising technology based on the ratio of the operation cost to the resulting incremental oil flow rate.

Radial jet drilling technology was first proposed by Rad Tech International Inc. in the late 1970s. The technology involves creating highly permeable flow channels in producing reservoir intervals, thereby increasing displacement coverage, and jetting directional flow channels to tap bypassed oil [1].

The radial jet drilling technique creates two to four channels in the producing reservoir interval, usually with a 90° angle between the channels. The channels are 3 to 8 cm in diameter and up to 100 m long. To clean the channel and increase its permeability, the jetting using a high-pressure nozzle is followed by the acid treatment in carbonate reservoirs [2].

The technology is extensively and successfully deployed in oil production worldwide. For example, the RJD practice at some overseas oil fields is presented in [3]. A significant oil production increase by 200% has been observed at the Tarim oil fields (China). In Ref. [4], described is the RJD application for oil recovery from a reservoir with low permeability and ultra-maturity near wellbore using enhanced stimulation to force the withdrawal. Successful operations have been noted in a thick oil-saturated reservoir, where radial channels extend beyond the depleted area, engaging untapped interbeds, and in case of good reservoir energy properties. In Ref. [5], the flow-rate growth factor as a result of RJD under various reservoir conditions was estimated; it can be noted that the highest incremental flow rates are typical of reservoirs with low permeability and four radial channels. When comparing incremental flow rates depending on the number and length of channels and reservoir permeability, the greatest effects were attained for low permeability reservoirs with four 300 ft (91 m) long channels.

In Refs. [6,7] it is noted that RJD is most effective under high-viscosity oil conditions involving the formation of no-flow areas in reservoir's low-permeability areas.

In Ref. [8], the effectiveness of radial jet drilling technology at the Vakhitovskoye oil field (Russia) at production target D1 is analyzed. The success rate of radial drilling is estimated at 75%. Recorded has been oil production increase of 1.5 to 5 times following the technology deployment.

The article discusses the problem of the methodology for predicting the effectiveness of IOR technologies on the example of RJD technology using neural networks.

The oil industry has been extensively implementing machine learning for routine processes automation, well log data interpretation and seismic data processing. Such tasks involve a huge bulk of data.

There are a lot of machine learning algorithms that solve three tasks—regression, classification and clustering. Main types of algorithms employ supervised, unsupervised learning—a type of machine learning algorithm used to draw inferences from a dataset consisting of input data without labeled responses, semi-supervised learning and reinforcement learning [9].

Supervised learning algorithms will be described in more detail, as they will be considered in this study. Supervised learning is facilitated by an algorithm for learning a function that maps an input to an output based on example input-output pairs. It infers a function from labeled training data consisting of a set of training examples. Advantages and disadvantages of some algorithms will be described next. The principle of linear regression is to find a linear relationship in the data. As advantages of linear regression can be defined the simplicity and the speed, while the main disadvantages are the inability to capture nonlinear relations without first transforming the inputs [10]. Naive Bayes a collection of classification algorithms based on the Bayes theorem. This algorithm facilitates easy understanding, configuration, and interpretation of results, but it fails to predict rare events and it is prone to overfitting [11]. Regression trees learn in a hierarchically fashion by repeatedly splitting your dataset into separate branches that maximize the information gain of each split. Ensemble methods, such as Random Forests and Gradient Boosted Trees, combine predictions from many individual trees. Decision trees can learn non-linear relationships and are robust to outliers. However, unconstrained, individual trees are prone to overfitting [12]. Support Vector Machine is a binary classification method which creates a model that can generalize well with an optimum global solution. It works very well with a separated margin and a non-linear function; the main disadvantages of this algorithm are a long training time and poor performance when working with noisy data. Deep learning refers to multi-layer neural networks that can learn extremely complex patterns. Their architectures can be adapted to many types of problems. In addition, they are computationally intensive to train, and they require much more expertise to tune [8–12].

Application of machine learning for the oil and gas industry tasks seems practical for the following reasons: 1. A rich experience in different studies of wells (well logs, well tests and others), different operations on wells (for example IOR technologies) and a lot of information about reservoirs from laboratory studies (fluid studies and core studies), allowing to create large databases, analyze them and create predictive models; 2. Algorithmic developments: improved activation functions, optimized weights initialization algorithms, more advanced optimizers, such as RMSProp and Adam, improved gradient propagation methods, etc.; 3. Hardware upgrades (GPUs, TPUs).

The application of Generative Adversarial Networks to solve the problem of incomplete seismic data is described in Ref. [13]. The study shows a coefficient of determination between 0.8 and 0.99, which is accurate enough to reproduce seismic data that could not be recorded during the survey. The results of seismic data recovery are also provided in References [14–16] and others.

The potential for use of machine-learning algorithms for well log data interpretation has been amply described. In Ref. [17], the use of a Bayesian neural network for forecasting missing intervals of geophysical survey results is proposed. Correlation coefficients for test sets ranged between 0.94 and 0.97. The application of various algorithms for the interpretation of logging curves is described in References [18–20].

A few works address the prediction of section lithology while drilling [21–24].

Predictive analytics problems are also solved while optimizing oil and gas field development processes. In Ref. [25], key applications of neural networks in hydrocarbon development and production are overviewed. Neural networks for the prediction of well operation processes are presented in References [26–28]. As noted, the predicted value error is less than 5% against the actual values when using the Long Short-Term Memory algorithm. Surrogate modeling to replace reservoir simulators is described in References [29,30].

The problems of virtual flow logging based on machine-learning models are addressed in References [31,32].

Many numbers of works cover intelligent history matching of dynamic reservoir models [33–35] and others.

The problems of forecasting the effectiveness of oil recovery enhancement technologies, production stimulation and well stimulation are considered in References [36–44], where the following algorithms are mainly used: Shallow and Deep Artificial Neural Networks (ANN), Naïve Bayes (NB), Decision Tree (DT), Random Forest (RF) and Dimension Reduction using Principal Component Analysis (PCA); the model's correlation coefficients vary significantly between 0.6 and 0.9.

It should be noted that while artificial intelligence technologies are extensively used in the oil and gas industry, their efficiency is variable for different tasks. High accuracy of models is observed in the problems with large arrays of data (well logging and seismic surveys), while for the IOR technology effectiveness forecasting the prediction accuracy is lower due to a much smaller amount of data, as well as many factors influencing the technology effectiveness, such as geological, process, technical and human factors.

This study analyzes the efficiency of radial jet drilling technology in the Perm Krai, proposes a method for predicting the effectiveness of the technology RJD and analyzes the applicability of neural networks with different architectures and optimization algorithms.

During the study, it was found that it is more expedient to build a model for each stratigraphic interval; as a result, it was possible to obtain models with correlation coefficients from 0.59 to 0.81 and an absolute error from 3.6 to 1.98 m^3/day, which made it possible to significantly improve the results standard statistical methodology for predicting the effectiveness of radial jet drilling.

In future works, it is necessary to expand the selection with other wells stimulation technologies for carbonate reservoirs in the Perm region—acid treatments, hydraulic fracturing, etc. There are also plans to develop a methodology of predicting efficiency of IOR technologies in various geological conditions and software that allows integrating the forecast of input fluid rates after stimulation of wells with long-term forecasts in reservoir simulation models

2. Case Study

This study discusses the RJD operations carried out in the wells accessing the carbonate reservoirs of various ages and structures of Perm Krai oilfields. These reservoirs belong to the Famennian, Tournaisian, and Bashkirian ages.

The reservoirs of different geological ages are characterized by different properties and field dynamics. The rocks of Famennian deposits represent accumulations of porous and vuggy reservoirs of the Solikamsk depression. The reservoir properties of the Famennian deposits are strongly affected by rock fracturing. The reservoirs of Tournaisian deposits feature high heterogeneity of geological section and small thicknesses, which results in low productivity of the wells [45]. The Bashkirian reservoirs are of porous type, with porosity represented by intra-form and inter-form voids. The best reservoir properties are seen in biomorphic limestones with foraminiferal structure, while in some interlayers they are dense due to secondary calcitization [46].

Various IOR technologies are used for carbonate reservoirs of Perm Krai, including RJD.

The RJD technology is one of the core techniques (Figure 1) used in the Chernushinskaya (21%), Osinskaya (29%), and Nozhovskaya (30%) oilfield groups. In the Severnaya oilfield group, the key technologies include acid treatment (36%) and acid fracturing (29%). The most frequently deployed technology in the Osinskaya and Kungurskaya oilfield groups is re-perforation with acid treatment (29%). Drilling perforation, sidetracking, additional perforation and re-perforation are applied much less frequently than other techniques (2–12%) in all the groups of oil fields.

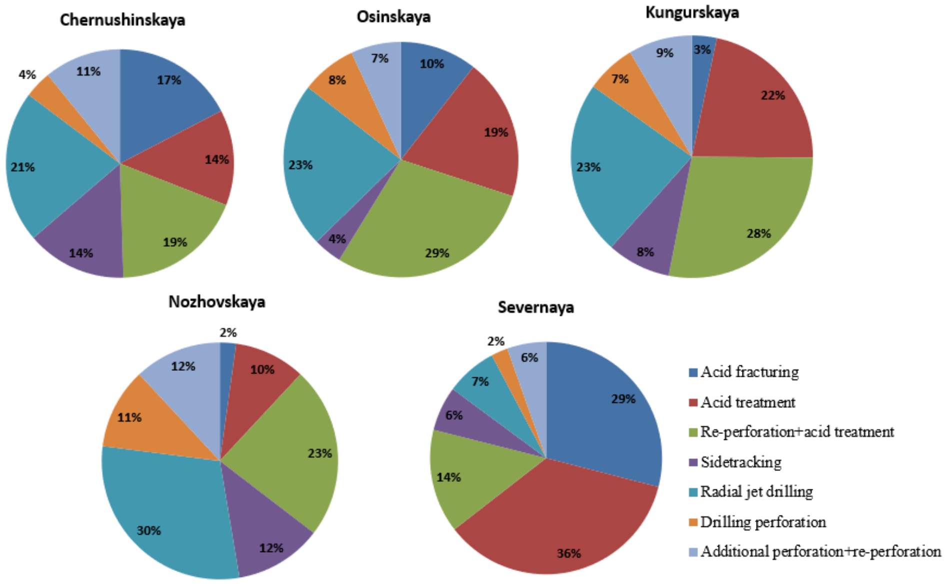


Figure 1. Distribution of IOR technologies by oilfield groups in Perm Krai.

A total of 590 radial drilling operations have been carried out in carbonate reservoirs in different strata: Bashkirian (Bsh), Vereian (V3V4), Kashirian-Vereian (KV) and Tournaisian-Famenian (T-Fm). Figure 2 shows the distribution of wells from different reservoirs by cumulative incremental oil production due to the RJD operations.

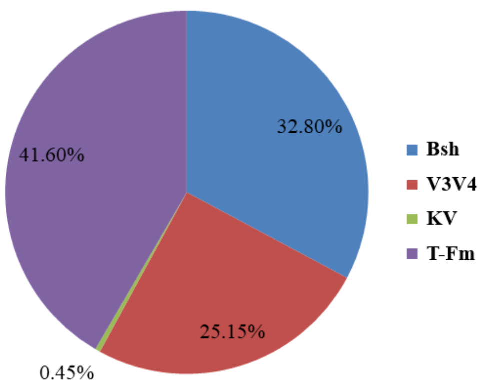
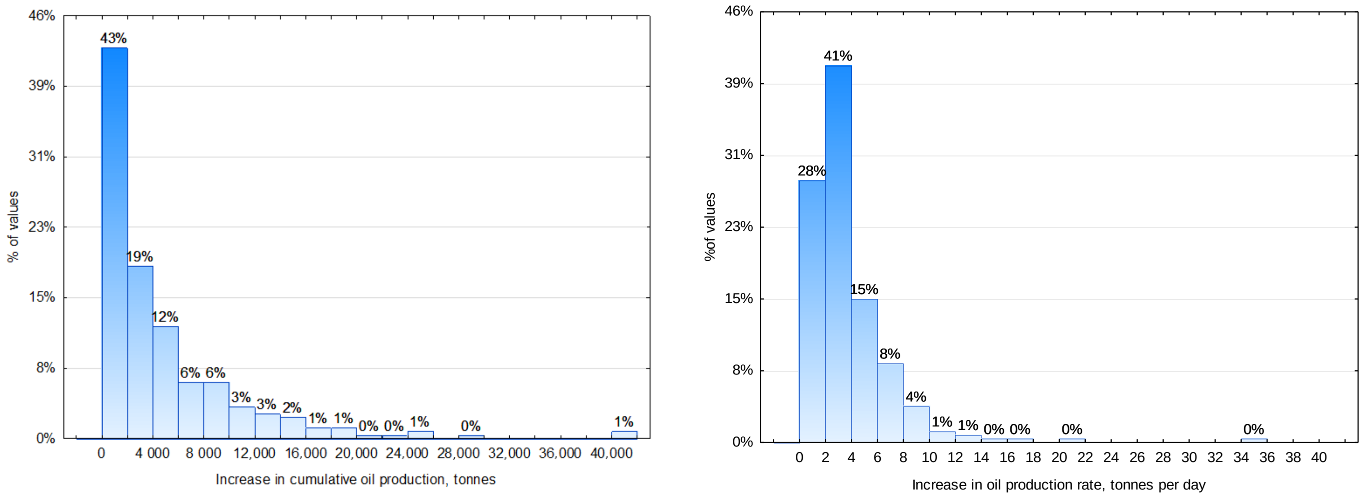


Figure 2. Distribution of reservoirs by cumulative incremental oil production due to RJD.

For the Perm Krai's carbonate reservoirs over the past 10 years, the RJD technology has become a core technique for declining wells with end-of-life low flow rates.

Figure 3 shows the distribution of cumulative incremental oil production and incremental oil flow rates.



(**a**) (**b**)

Figure 3. Value distribution bar chart: (**a**) cumulative incremental oil production due to RJD and (**b**) incremental oil flow rates due to RJD.

Figure 3 shows a dramatic spread of values for incremental oil production (0.5–139,798 tons, with a standard deviation of 10,395 tons) and incremental oil flow rates after the RJD technology deployment (0.2–35.5 tons/day, with a standard deviation of 3.4 tons/day). Since the technology effectiveness varies greatly subject to geological and process conditions, an all-inclusive approach to the selection of candidate wells is essential to enhance the process efficiency of the technology application. The relevance of this work is premised on high uncertainty of the outcome.

Efficient radial jet drilling relies on the comprehensive approach to candidate wells and the selection of priority wells subject to geological and process conditions. For this purpose, the effect from IOR operations shall be forecasted and the incremental oil flow rates shall be understood at the stage of candidate well selection, which will allow a cost–benefit estimate of the planned IOR.

3. Materials, Methods and Background

Presently, the following techniques are mainly used to forecast the IOR effects: forecast based on geological and field analysis, statistical analysis, machine-learning methods and reservoir simulation [47–49].

When using geological and field analysis, the results are limited to a specific productivity factor estimate, with disregard for a set of geological and process parameters. A detailed 'manual' analysis of wells based on geological and field production analysis using analytical and statistical methods is time-consuming and relatively subjective [50].

The basic model for forecasting the RJD effectiveness, used by a regional oil company, involves statistical forecasting of incremental liquid and oil flow rates through the well-productivity factor [51,52]. That is, the effect of RJD is estimated for similar wells or neighboring wells and recalculated for a RJD candidate well using the well-productivity factor. Only liquid flow rate, reservoir pressure and bottomhole pressure parameters are involved in the calculation. In our opinion, these parameters are insufficient to reliably predict the potential of wells for RJD. The results of the comparison of predicted and actual values according to the basic technique are given in Figure 4. The *R-squared* of this model is very low and equals to 0.16.

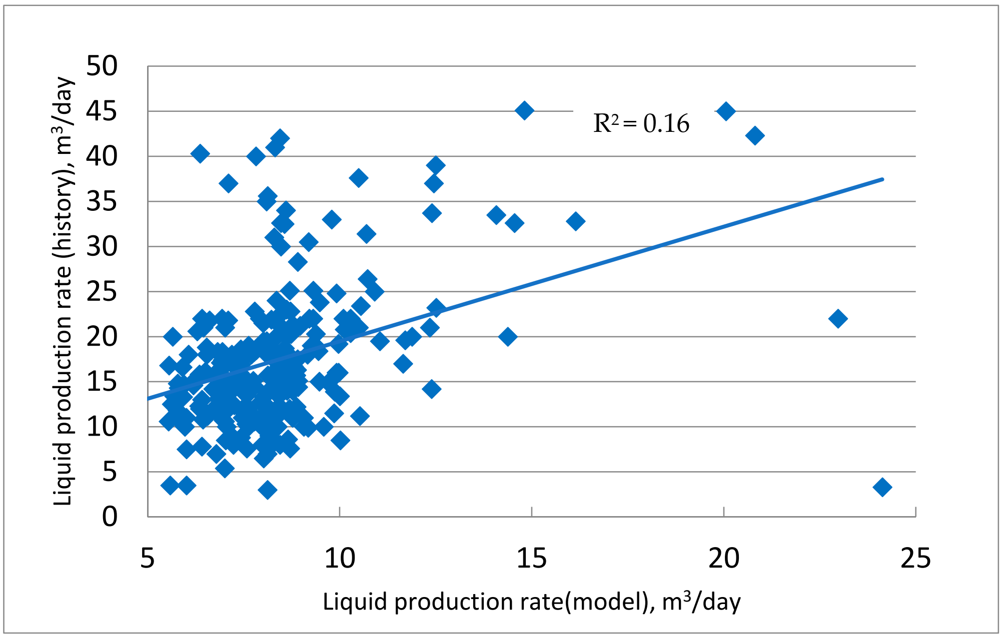


Figure 4. Forecast results of liquid flow rate after RJD using the basic technique.

When using geologic and dynamic simulation, the subjectivity of modeling and history-matching shall be factored in, which markedly affects the model's forecasting performance. High time consumption and cost of work in geologic and hydrodynamic simulation dictate the need for its application mainly for designing high cost well (sidetracks and horizontal wellbores).

Clearly, no methodology provides an accurate forecast of incremental oil production, but only evaluates the operation potential at a specific well.

This study evaluates the applicability of machine-learning techniques, specifically neural networks, for the RJD effectiveness forecasting tasks. Supervised learning requires a sample of independent feature parameters and a target variable. A multi-layer perceptron with different network setting parameters was used in this work. The perceptron model is shown in Figure 5.

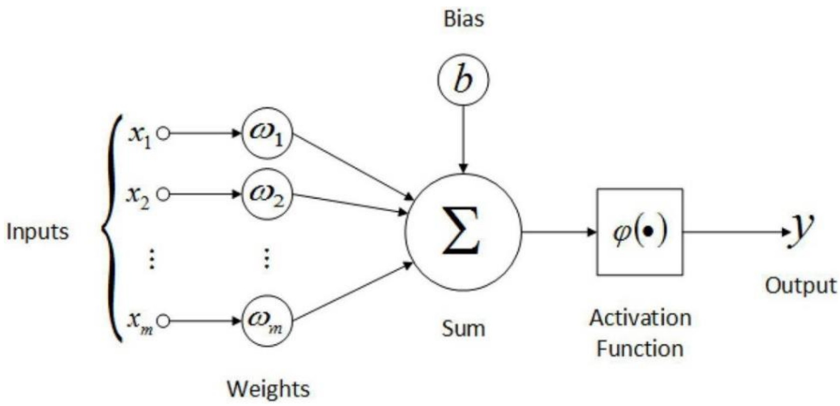


Figure 5. Perceptron model.

Inputs are the features that are fed into the input of the neural network; weights are values that are calculated during the training of the model. With every error, i.e., training error, the values of the weights are updated. The purpose of the bias is to shift each point in a specific direction for a specified distance. Bias allows for the higher quality and training of the model is faster; the MLP consists of three or more layers (an input and an output layer with one or more hidden layers) of nonlinearly-activating nodes; activation or step functions are used to generate non-linear neural network. Weighted summation: the multiplication of every feature or input value associated with related values of weights gives us a sum of values that is known as weighted summation [53,54].

The calculation process is described by Formula (1):

$$a = \varphi\left(\sum_{i=1}^{n} \omega_i x_i\right) \tag{1}$$

Post-IOR flow rate is the target variable here. When evaluating the RJD technology effectiveness, changes in the liquid flow rate are assessed, since the RJD alters flow properties of the near-wellbore and far-field formation areas. The liquid flow rate change parameter is used in the simulation of well productivity enhancement activities on reservoir simulation models in standard simulators.

To forecast the effectiveness of the technology, a database of geological and process parameters has been created. For neural networks training, the parameters that influence the RJD technology effectiveness the most have been selected, as described in the articles [47,48]:

- average thickness hnn, m;
- porosity Kpor, %;
- average oil viscosity in the formations μ, mPa·s;
- piezoconductivity χ, cm^2·s;
- reservoir pressure Pres, MPa;
- bottomhole pressure Pbhp, MPa;
- well skin factor S;
- liquid production rate before the RJD, qliq, m^3/day;
- water cut, W, unit fraction;
- compartmentalization for oil layers, Kcomp (oil), units.

A total of 590 radial drilling operations have been carried out at 43 oil fields in Perm Krai. Geophysical survey results and performance data are available for all the wells, while well test results have been obtained for 259 wells only. Therefore, training and testing were conducted for these wells only. It should be noted that all operations were carried out in the carbonate reservoir, but for formations of different stratigraphic intervals: Bashkirian (104 RJD jobs), Tournaisian (131 RJD jobs) and Famennian (24 RJD jobs).

The study was conducted in several steps:

1. Training and testing over the whole set (259 wells). Sweeping through various network hyper-parameters. The training and testing sets were divided randomly in an 85/15 ratio, respectively;
2. Training and testing separately for the Bashkirian and Tournaisian strata. The jobs performed on the Famennian reservoirs are insufficient to be reviewed individually. The training and testing sets were divided randomly in an 85/15 ratio and 70/30 ratio, respectively [55];
3. Training on the wells accessing the Bashkirian reservoir and testing on the wells exploiting the Tournaisian reservoir.

Mean absolute error (*MAE*) (Formula (2)) and coefficient of determination (R^2) (Formula (3)) between the rated and actual values were used as metrics to assess the quality of the models obtained:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{2}$$

$$R^2 = 1 - \frac{\sum (y_i - \hat{y})^2}{\sum (y_i - \overline{y})^2} \tag{3}$$

Data before calculation were standardized using Formula (4):

$$x_{st} = \frac{x_0 - \overline{x}}{\sqrt{\sigma^2}} \quad (4)$$

The mean square deviation is the error function.

4. Results

In the first step, calculations were carried out for the whole set of wells.

A neural network with three layers was used, while the activation function of rectified linear unit (ReLU) was applied for non-linear activation between the layers (Goodfellow et al., 2016). The Adam algorithm [56] was used as an optimizer. The number of neurons in each layer was compared (Table 1).

Table 1. Comparison of networks with a different number of neurons in each layer.

Number of Neurons per Layer	Epochs	Activation Function	MAE (Train)	R^2 (Train)	MAE (Test)	R^2 (Test)
16–8–1	300	ReLU	4.1	0.57	4.3	0.5
128–64–1	168	ReLU	3.3	0.68	5.1	0.4

Next, various optimizers were compared (Table 2).

Table 2. Comparison of network optimizers.

Number of Neurons per Layer	Optimizer	Epochs	Activation Function	MAE (Train)	R^2 (Train)	MAE (Test)	R^2 (Test)
16–8–1	Adam	300	ReLU	4.1	0.57	4.3	0.5
16–8–1	RMSprop	300	ReLU	4.3	0.54	4.5	0.4
16–8–1	Adamax	300	ReLU	5.4	0.4	6.3	0.34
16–8–1	Nadam	300	ReLU	2.9	0.73	5.1	0.38

A sweep of various activation functions was also run (Table 3).

Table 3. Comparison of activation functions.

Number of Neurons per Layer	Optimizer	Epochs	Activation Function	MAE (Train)	R^2 (Train)	MAE (Test)	R^2 (Test)
16–8–1	Adam	300	ReLU	4.1	0.57	4.3	0.5
16–8–1	Adam	300	sigmoid	15	0.4	16	0.3
16–8–1	Adam	300	linear	4.2	0.52	4.7	0.48
16–8–1	Adam	300	LeakyReLU	3.2	0.7	3.7	0.57
16–8–1	Adam	300	PReLU	3.8	0.65	5.8	0.44
16–8–1	Adam	300	ELU	3.9	0.63	4.9	0.47

The number of network layers was then compared (Table 4).

Table 4. Comparison of networks with a different number of layers.

Number of Neurons per Layer	Optimizer	Epochs	Activation Function	MAE (Train)	R^2 (Train)	MAE (Test)	R^2 (Test)
16–8–1	Adam	300	LeakyReLU	3.2	0.7	3.7	0.57
128–64–1	Adam	300	LeakyReLU	2.9	0.73	3.7	0.57
64–32–28–1	Adam	300	LeakyReLU	3.4	0.65	3.7	0.52
64–32–28–12–1	Adam	300	LeakyReLU	3.2	0.7	5.4	0.32

The values of model quality metrics in the result of calculations are not high. However, it should be noted that a wide range of factors have an impact on the effect of the technology deployment in the well: geological, process, technical and human factors. Therefore, the mean absolute error of flow rate after RJD of 2.9–3.7 m^3/day is in general a satisfactory result, which allows evaluating well potential in different geological conditions. Moreover, the reservoirs belong to different stratigraphic intervals, as pointed out in the case study section. Thus, the Famennian reservoirs defined by fracturing, differ greatly in their flow properties. Initial liquid flow rates with them can be relatively high (up to 50 m^3/day), yet the effect dwindles very quickly, probably due to reservoir pressure decline and typical fracture closing.

It is suggested to enter the obtained well potential values in terms of liquid flow rate into the hydrodynamic simulator (Tempest, T-Navigator and Eclipse) and forecast the further dynamics of indicators for a long-term period.

The analysis of Tables 1–4 shows that the most successful option is a multilayer perceptron with three layers, with a few neurons per layer of 128–64–1, Adam optimizer, LeakyReLU activation function [57]. Combinations of different activation functions in different layers were also tested in the course of the study, yet no improvement in the results was observed.

For the Bashkirian (Bsh) reservoirs, an improvement in the model performance was observed, R^2 (Train)—0.81, R^2 (Test)—0.68 (Table 5), but in this case, activation function Relu was better than LeakyReLU. The dataset of wells for the reservoir is of the same stratigraphic interval, with similar properties and dynamics of the efficiency of RJD.

Table 5. The training results for the Bsh reservoirs.

Number of Neurons per Layer	Optimizer	Epochs	Activation Function	MAE (Train)	R^2 (Train)	MAE (Test)	R^2 (Test)
128–64–1	Adam	300	LeakyReLU	3.3	0.72	3.9	0.58
128–64–1	Adam	265	ReLU	2.6	0.81	3.6	0.68

The training results are shown in Figure 6.

The training quality for wells at the Tournaisian (T) reservoirs is lower (Table 6).

Table 6. The training results for the T reservoirs.

Number of Neurons per Layer	Optimizer	Epochs	Activation Function	MAE (Train)	R^2 (Train)	MAE (Test)	R^2 (Test)
128–64–1	Adam	265	ReLU	1.98	0.68	2.6	0.59

The training results are shown in Figure 7.

While for the T reservoirs, there is a number of fields with higher-viscosity oil (48–87 mPa·s), the liquid flow rate is comparable with the rest of the wells, which may explain the lower coefficients of determination against the Bsh reservoirs. However, these results are improving the quality of predictions from basic statistic model (described in the materials, methods and background) and the mean absolute error here is lower and equals 1.9–2.6 m^3/day, which allows quite a reliable forecasting of the wells flow rates. It is also expected that an increase the numbers of wells in the dataset will lead to an increase in the quality of the forecast, which is why the model is useful to predict the effectiveness RJD for T reservoirs wells.

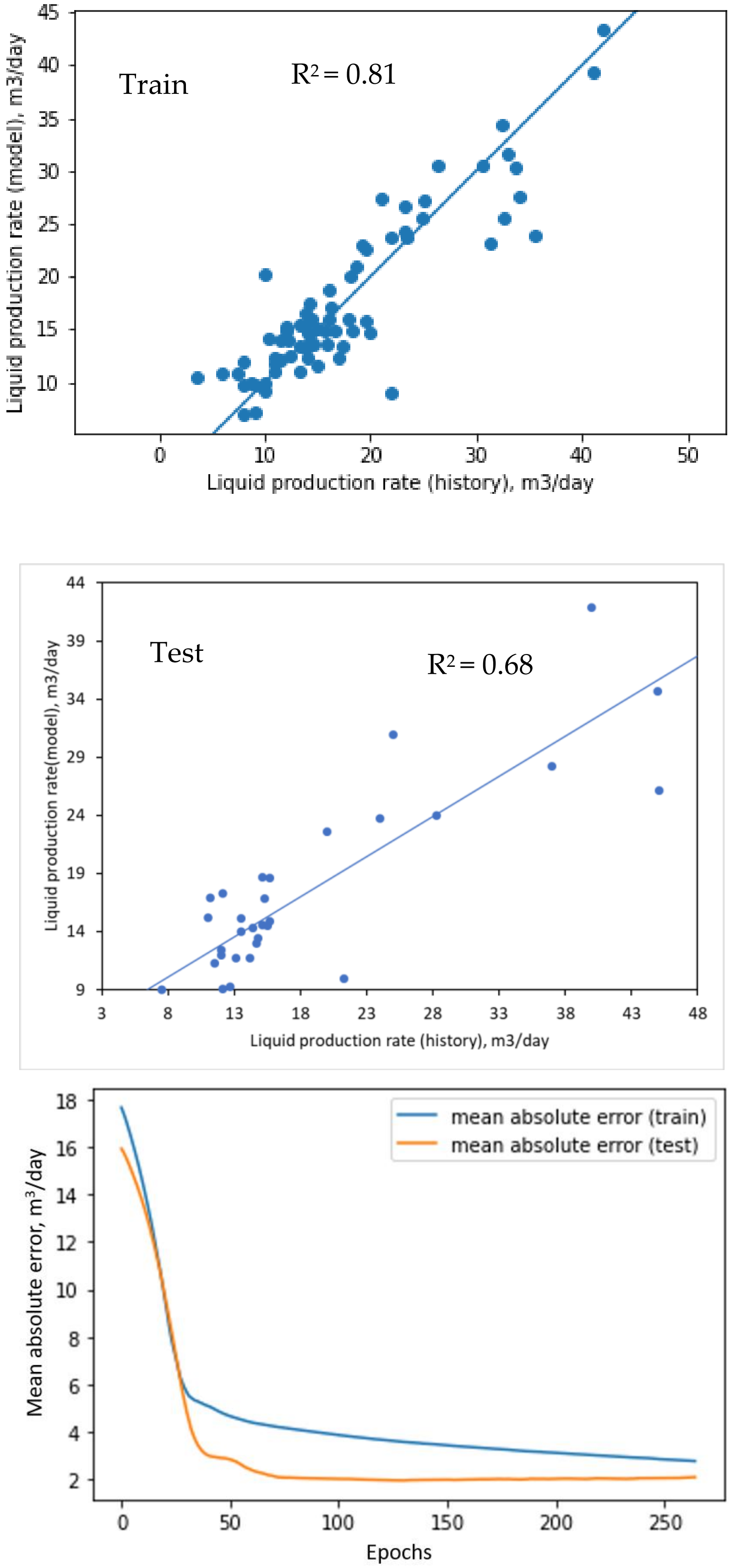


Figure 6. Training results for Bsh reservoir sets.

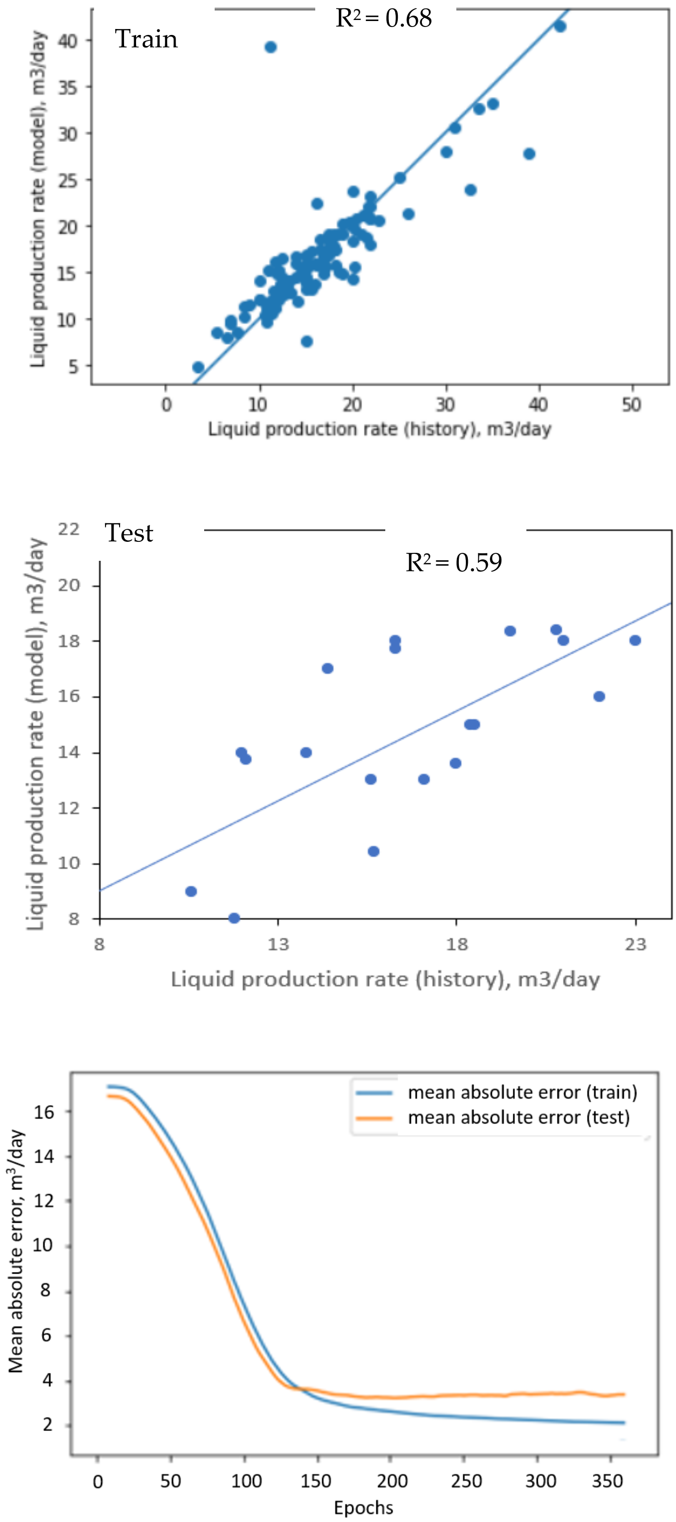


Figure 7. Training results for T reservoirs set.

In general, it should be noted that training and prediction for individual targets of different stratigraphic units provides a significant improvement in model quality metrics. The obtained models can be used with sufficient reliability for the prediction of wells' potential for RJD.

Despite reservoirs being from different strata, though located in the same territory and the same oilfields and being composed of carbonate rocks, we carried out training for the Bsh reservoirs set and testing for the T reservoirs set with a 44/56 ratio and opposite training on T and testing on Bsh (Table 7, Figure 8).

Table 7. The training results for the wells at Bsh and T reservoirs.

Train/Test	Number of Neurons per Layer	Optimiser	Epochs	Activation function	MAE (Train)	R^2 (Train)	MAE (Test)	R^2 (Test)
Bsh/T	128–64–1	Adam	365	ReLU	1.74	0.81	7.8	0.12
T/Bsh	128–64–1	Adam	365	ReLU	2.8	0.64	5.7	0.43

Training for reservoir wells of the Bashkirian age shows reliable results but does not allow predicting the RJD effect for the Tournaisian reservoir wells, which show the overfitting of the model. In another case, the model fits on T reservoirs better, but it is also not suitable for forecasting. To solve problems of overfitting, the dropout method was used. Dropout is a regular technique that reduces the odds of overfitting by dropping out neurons at random, during every epoch [58,59]. It did not work well.

The low quality of the Bsh/T and T/Bsh models does not allow them to be used for forecasts. It was noting the difference in the geological structure of these reservoirs and oil properties. The efficiency of radial jet drilling at these strata's is different and has different dynamics. The ranges of some parameters also differ significantly (Table 8), and therefore, it is not possible to train the model on one type of reservoir and obtain predictions for another.

Table 8. Descriptions statistics for Bsh and T reservoirs parameters.

	Bashkirian Reservoir			
	qliq, m3/day	μ, mPa·s	χ, cm2·s	Kcomp, units
mean	5.33	15.59	176.96	6.67
std	4.97	11.28	314.74	3.36
min	0.10	1.02	2.00	1.00
max	27.20	34.71	1840.00	17.00
		Tornesian reservoir		
mean	4.94	34.04	145.00	8.87
std	3.46	29.51	651.57	4.18
min	0.11	1.51	2.00	1.00
max	23.00	87.1	7409.40	28.00

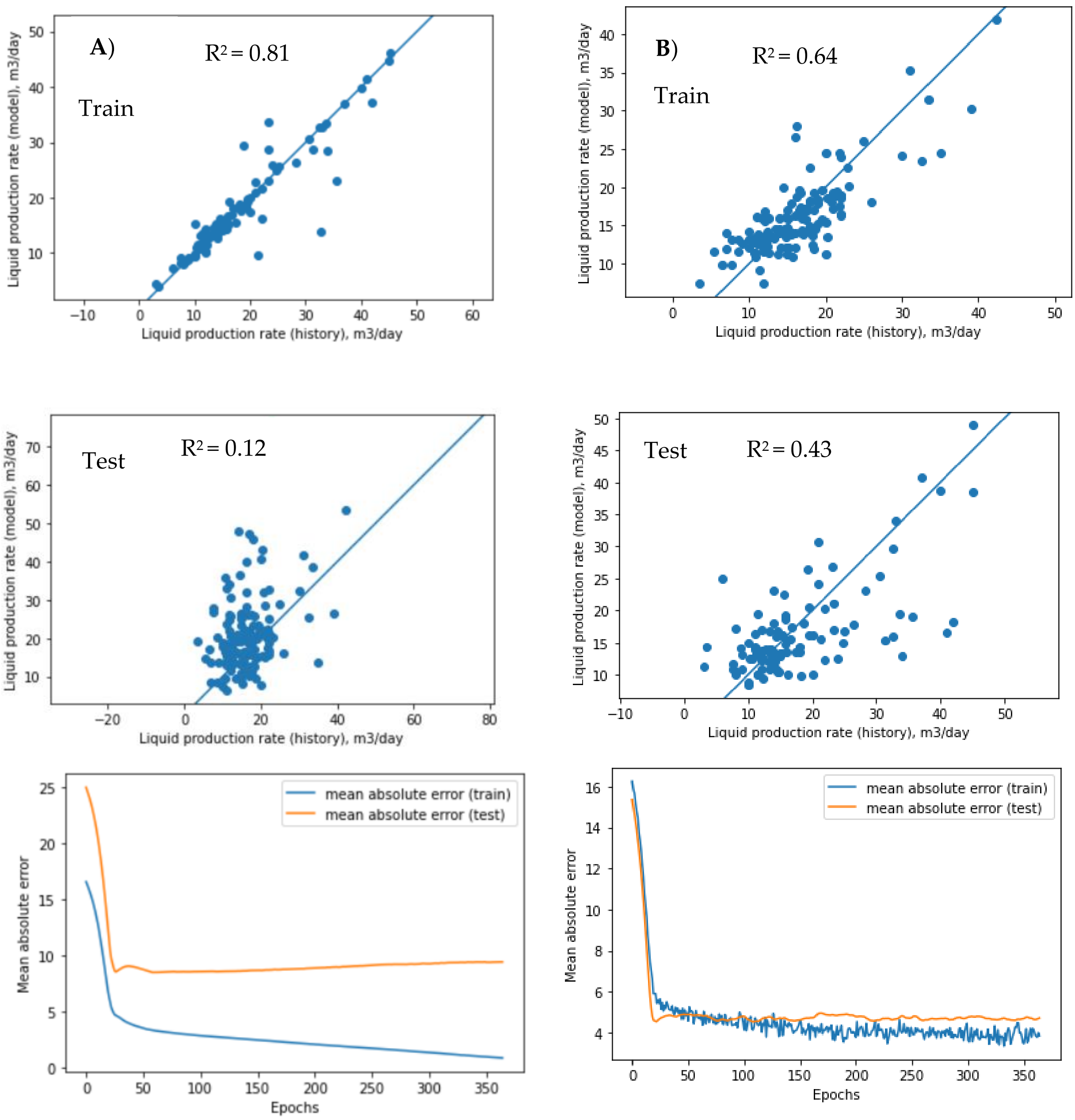


Figure 8. Results of training for the wells at Bsh and T reservoirs: (**A**) Train/test—Bsh/T; (**B**) Train/test—T/Bsh.

5. Discussion

It is possible to forecast liquid flow rates following RJD by single model for all carbonate reservoirs of Perm Krai (mean absolute error is 3.3 m^3/day), yet it would be more accurate to say that this is a forecast of well potential for RJD in different geological conditions. The best training/testing result was obtained on a multilayer perceptron with 3 layers, 128–64–1 neurons per layer, using the Adam optimizer and the LeakyReLU activation function. The training results: mean absolute error of flow rate after RJD is 2.9/3.7 m^3/day and R-squared is 0.73/0.57 for training and prediction, respectively. Overall, these results improved the prediction quality for the existing statistical approach that consists of forecasting liquid flow rates through the specific-productivity coefficient for the analogue wells (Figure 5), where *R-squared* is 0.16. Models fitted on dataset with all wells of different strata reservoir do not have high accuracy. Wells from each strata have different dynamics of flow rates, reservoir pressure and productivity. Additionally, the Tournaisian reservoir features high heterogeneity and fissures, and some oil fields have high-viscosity oil, while Bashkirian reservoirs are of a porous type and wells have more stable liquid flow rates.

For improving the quality of the model's datasets, all reservoirs were divided to sets with the same strata. This might help, because reservoir properties and flow rates have become more homogeneous. However, the results are ambiguous

When building multilayer perceptron models individually for wells of different reservoirs, note the increase in model quality for the Bashkirian reservoirs wells, slight decrease for the Tournaisian reservoirs by the *R-squared* metric and improvement by the *MAE* metric. For the Bashkirian reservoir wells, *MAE* is 2.6/3.6 m^3/day and *R-squared* is 0.81/0.68; for the Tournaisian reservoir wells, *MAE* is 1.98/2.6 m^3/day; *R-squared* is 0.68/0.59. Building a separate model for the Famennian reservoir wells failed due to the low amount of sampling values (24 wells). The lower quality for the T model is also explained by the complexity of the reservoir, the heterogeneity of its properties and fluid properties.

There are a lot of problems when the dataset is sparser, and it is difficult to adequately model the problem, overfitting, data preparation and others. In order to solve these problems, preparation and filtering of the data were carried out, and various parameters of the multilayer perceptron were selected to solve the problems of retraining. Moreover, the data for the training/test were divided in various proportions from 70/30% to 85/15%, using the dropout method.

It is important to note that the accuracy of these models has become significantly higher in comparison with the standard statistical forecasting method. Models are proposed to be tested in future radial jet drilling operations.

Using the models trained on reservoirs of the same age to forecast the effect for wells of a different age is not realistic. When the train/test data are Bsh/T (*MAE* is 7.8 m^3/day; R-squared is 0.12), overfitting is observed; in order to solve problems of overfitting, the dropout method was used. This helped to model T/Bsh (*MAE* is 5.7 m^3/day; R-squared is 0.43), and of course, this model remained unusable. This case shows how important it is to use geological data very carefully to build machine learning models. To build models, it is important to understand the processes of formation of rocks, their properties and their influence on the processes of oil production.

Perhaps the most accurate models would be those built individually for the formations of different stratigraphic intervals as well as separately for oil fields; however, there is a lack of actual RJD experience, as of now.

The main strengths of this approach are as follows:

- Targeted approach to predicting the efficiency of radial jet drilling in various geological conditions;
- Improvement of forecast quality in comparison with the standard approach;
- Automatization of efficiency calculations;
- The possibility of combining the obtained models with reservoir simulation models for long-term forecasts.

The limitations of this approach are as follows:

- In the context of machine learning, no high values of metrics for assessing the quality of the models;
- It is necessary to increase the dataset values for additional training of the models;
- The study was limited only to neural networks (multilayer perceptron), and it is necessary to use other algorithms of machine learning.

6. Conclusions

The study has assessed the applicability of neural networks to forecast the radial jet drilling technology effectiveness. In the course of the study, models were built to predict the efficiency of the RJD for all carbonate reservoirs in Perm Krai (Russia) and individually for reservoirs of various ages. Individual reservoir models made it possible to improve the quality of the forecast in comparison with the existing standard methodology; it is proposed to use them for the selection of wells for the RJD.

The use of multilayer perceptron models has improved the quality of forecasting compared to the basic method used by the regional oil company. The application of neural networks allows to deploy a set of geological and process parameters, which enables a comprehensive selection of candidate wells. The use of forecasting models is viable in combination with reservoir simulation models, which will allow using dynamic parameters required for the neural network model (reservoir pressure, bottomhole pressure and current liquid flow rate) from the simulation model at any time, even for long-term forecasts, which the authors have in sight for their future research. Other relevant future research problems are the following: 1. Improvement of the model's quality, which can be attained through a more detailed analysis of the dataset, its correction and increase of sampling values; 2. Application of other neural network models and recurrent models; 3. Application of machine-learning methods, such as support vector machine, random forest and Naïve Bayes; 4. Methodology development of predicting efficiency of IOR technologies in various geological conditions.

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