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Algorithm for estimating the flow rate of an oil producing well based on dynamometer data

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Abstract. The paper proposes an algorithm for determining the flow rate of an oil producing well based on dynamometer data. The dynamogram is presented as a two-dimensional image processed using a convolutional neural network that solves the problem of nonlinear regression between the dynamogram image and the flow rate value. The structure of the dynamometer data collection and processing system is presented, the main steps of the data analysis algorithm are described. The resulting model makes it possible to estimate the production rate with an error in the range of 15-20%.

1. Introduction

The main characteristic of an oil producing well is the flow rate, i.e. the volume of products extracted from an oil well during the day. One of the most common methods of oil production from marginal wells is the use of sucker rod pumping units. To improve production efficiency, it is necessary to control the well operation mode by establishing and maintaining the pumping equipment productivity corresponding to the rate of fluid flow to the bottom of the well. Therefore, it is necessary to be able to determine the current production rate of the well in real time.

To determine the flow rate of a well, flow meters are most often used. There are methods that make it possible to estimate the flow rate of a well without a flow meter, using the data of the dependence of the force at the suspension point of the rod string on the stroke of the polished rod (dynamogram). An alternative option is to calculate the flow rate according to the dependence of the power consumption of the electric drive of the pumping unit on the movement of the suspension point of the rod string (wattmetrogram) [1]. This article discusses the possibilities of practical application of flow rate estimation algorithms based on the approximation of the dependence of the flow meter readings on the shape of the dynamometer chart, which will make it possible to abandon constant measurements using a flow sensor.

2. Diagnostics and control based on dynamometer and wattmeter data

In [2], the issues of automatic control of fluid height and bottom hole pressure in wells are considered. The combined model of the rod string and the well allows to determine the dynamic operating conditions of the well and increases the cumulative oil production by maintaining the optimal height of the liquid level.

In [3], the use of dynamometer data in the system of intelligent diagnostics of the state of sucker rod pumps of oil wells is considered. The use of a neural network classifier for diagnosing the state of the sucker rod pumping unit based on the extracted features has been tested on real field data.

In [4], an approach to solving the problem of predicting the technical state of sucker rod pumps using neural network technologies is considered. The neural network model makes it possible to predict the load values on the polished rod based on the accumulated historical data.

The work [5] proposes a method for diagnostics of sucker rod pump systems by analyzing the segments between the points of valve opening and closing, determined on the maps of downhole dynamometers.

In articles [6-8], the issues of bench modeling of loads on the drive of sucker rod installations are considered. A method of mechanical modeling of loads on the balancer head is proposed. An approach has been developed for diagnosing the state of sucker rod pump units based on dynamometer data.

The primary information from the sensors comes in real time due to the creation of a permanent communication channel between the dynamograph, the equipment for fixing the currents consumed by the electric drive installed on the sucker rod pumping unit, and an intelligent control system created on the basis of a control computer (figure 1) [1, 9-11].

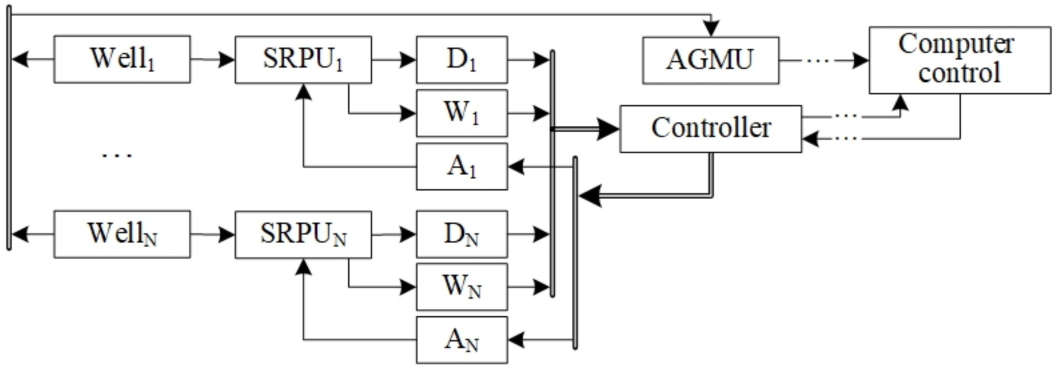

Figure 1. Intelligent diagnostic and control system.

Here: SRPU – sucker rod pumping units, D – dynamograph, W – fixing consumed electric currents, A – actuator, AGMU – automated group measuring unit.

Based on the results of diagnostics and monitoring of the state of the equipment, the operating modes of the installation are controlled through the actuators.

The well flow rate is the amount of fluid in the cavity of the downhole sucker rod pump during the double stroke. GOST R 8.615-2005 defines the requirements for the error when measuring the amount of crude oil, the methods for calculating the flow rate from the dynamometer chart cannot be used for commercial purposes due to the tangible error in the result, but they allow to accurately estimate the current flow rate of the well to control the productivity of the installation [12, 13].

In [1], a comparison was made of various algorithms for assessing the flow rate: according to the dynamometer chart and according to the wattmetrogram.

To estimate the well flow rate, the formula proposed by Sh. F. Takhautdinov is widely used [12]:

$$Q = F_{ar} \cdot S_r \cdot n \cdot \alpha, \tag{1}$$

Where Q – the well fluid flow rate (bbl/day); F_{ar} – cross-sectional area of the plunger of the submersible pump (sq.inch); S_r – effective stroke length of the polished rod (inch); n – swing frequency of the pumping unit (min^{-1}); α – pump flow rate.

According to [14], the performance of the sucker rod pumping unit Q is proportional to the work performed by the drive on the wellhead rod. The work is determined by the active power consumed by the pump unit drive and the pressure developed by the pump at the wellhead.

In [15], it was proposed to take into account not the absolute values of pressure and power, but their relative increments. To identify interdependencies, active power diagrams are recorded at various wellhead pressures and the corresponding wellhead dynamometer charts.

3. Approximation of the dependence of the well flow rate on dynamometer data

The initial data for assessing the flow rate of the well are represented by a set of dynamometer charts and measurements of automated group measuring units (AGMU). Measurements were used for four wells equipped with sucker rod pumps. The series of experiments includes 2629 examples of dynamometer charts and corresponding measurements of the AGMU.

The block diagram of the processing and analysis of the collected data when constructing a neural network regression model that makes it possible to estimate the flow rate based on the current dynamometer data of each well is shown in figure 2.

The module for collecting parameters $F(t)$, $S(t)$ and measurements from AGMU for each well allows to create and update a historical database (BD_1). The data $F(t)$, $S(t)$ then needs to be normalized and oversampled (2) to bring it to a fixed length. Next, a visual image of each dynamometer chart is constructed with the possibility of saving in BD_2 in tandem with the normalized flow rate value obtained from the AGMU. Data from DB_2 are used to build a training, test and validation sample and create a neural network model (5) of the regression dependence of the flow rate on dynamometer data. Models for each well are saved to the model bank (DB3) for subsequent use and operational assessment of the flow rate D^* based on the incoming data from the dynamometer (6).

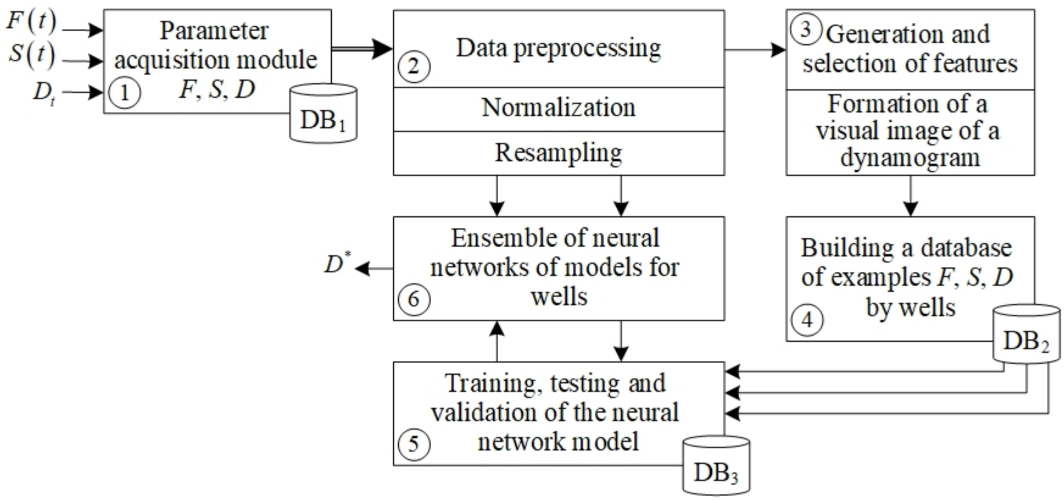

Figure 2. Block diagram of the processing and analysis of the collected data when building a neural network regression model.

For each example, the dependences of the force $F(t)$ and the stroke $S(t)$, which form the dynamogram, were brought into the range [0, 1] using minimax normalization:

$$X' = \frac{X - X_{\min}}{X_{\max} - X_{\min}}. \quad (2)$$

To unify the length of each row $F(t)$ and $S(t)$ for various examples, resampling is applied based on the cubic spline interpolation algorithm and the subsequent reduction of the length of each row to n = 256 samples.

For each example sample, a normalized dynamogram is constructed as a dependence of $F(S(t))$ in the form of an image in grayscale of 72 by 72 pixels (figure 3).

Figure 3. Visualization of a sample of dynamograms from a series of experiments.

The value of measurement with AGMU is similarly reduced to the range [0, 1] using minimax normalization.

All data are divided into training (70% of the total number of records) and test (30%). Of the training set, 10% of the examples are used as a control set to prevent overfitting of the neural network regression model. Thus, the training set contains 1656 examples.

To solve the problem of multivariate neural network regression, a convolutional neural network of the following architecture is used (tables 1, 2).

Table 1. Convolutional neural network architecture for predicting flow rate based on dynamogram shape.

Neuron layer type	Layer configuration	Number of parameters
Conv2D	(72, 72, 32)	320
MaxPooling	(36, 36, 32)	0
Conv2D	(36, 36, 64)	18469
Conv2D	(36, 36, 32)	18464
MaxPooling	(18, 18, 32)	0
Flatten	(10368)	0
Dense	(128)	1327232
Dense	(1)	129

Table 2. Training parameters of the neural network model.

Parameter	Value
Package size	512
Mean squared error control on a validation set to prevent overfitting	5 iterations
Optimizing the learning rate factor	
Optimization algorithm	NAdam [16]
Number of training iterations	100

The graph of the dependence of MSE on the training and control samples on the number of iterations of training the model is shown in figure 4 (resulting MSE = 0.3774 for the control sample).

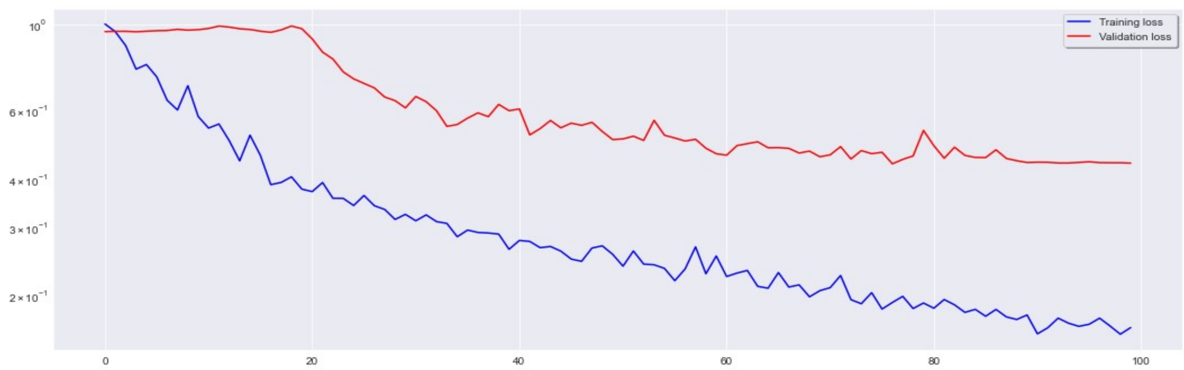

Figure 4. Dependence of MSE on training and control samples on the number of training epochs.

4. Results and discussion
The production rate forecast for the model for 75 random examples of the test sample is shown in figure 5.

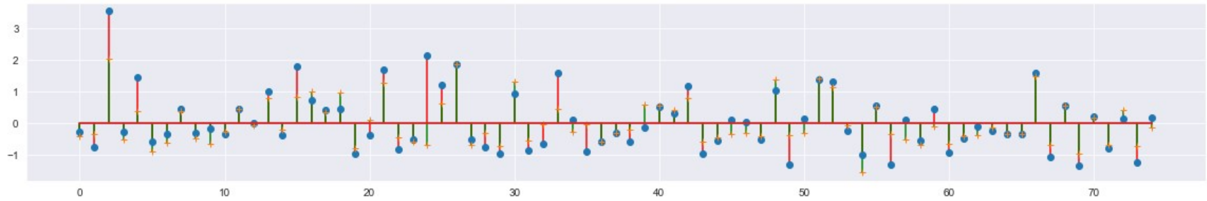

Figure 5. Forecast ("cross" marker) and true value ("circle" marker) production rate for 75 random examples.

The 50 most successful predictions for the initial data of the test sample are shown in figure 6.

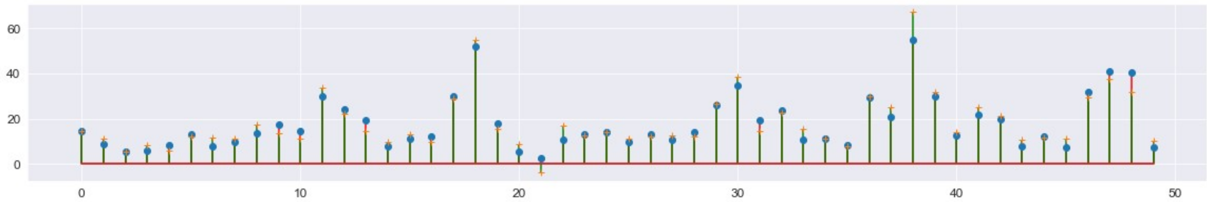

Figure 6. Forecast ("cross" marker) and true value ("circle" marker) production rate for 50 random examples from the test sample.

The 50 least successful predictions on the test sample and visualization of dynamometer charts, flow rate according to AGMU and predicted values are shown in figure 7.

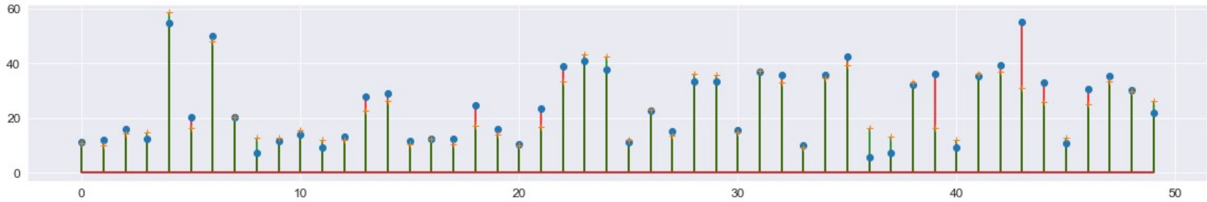

Figure 7. Forecast ("cross" marker) and true value ("circle" marker) flow rate value for the 50 least successful forecasts from the test sample.

In the course of testing the calculation algorithms, an estimate of the relative error in determining the flow rate using the dynamometer chart was obtained at the level of 15-20%.

5. Conclusion
Clarification of the experimental conditions, improvement of the procedure for identifying unknown parameters of the model and telemetry parameters will increase the accuracy of the assessment.

Evaluation of the relationship between the calculated and measured values of the flow rate shows the consistency of the approach to determining the flow rate from a two-dimensional image of a dynamometer chart, which allows one to estimate the flow rate of a well without a flow meter. Thus, operational control of the operation modes of each well is provided by expanding the functionality of the control station of the sucker rod pumping unit based on the use of diagnostic information additionally for control purposes.

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References

[1] Tagirova K F and Ramazanov A R 2019 Automatic Control of the Oil Production Equipment Perfor-mance Based on Diagnostic Data. *International Russian Automation Conference, Springer, Cham* 158-169
[2] Hansen B et al. 2019 Model predictive automatic control of sucker rod pump system with simulation case study. *Computers & Chemical Engineering* **121** 265-284
[3] Bezerra M A D et al. 2009 Pattern Recognition for Downhole Dynamometer Card in Oil Rod Pump System using Arti-ficial Neural Networks. *Proceedings of the 11th International Conference on Enterprise Information Systems (ICEIS)* 351-355
[4] Kuzmin A N and Vyalykh I A 2016 Prediction of technical condition ofrod pumps based on neural network technology. *PNRPU Bulletin. Chemical Technology and Biotechnology* **3** 55
[5] Reges G D, Schnitman L and Reis R 2014 Identification of Valve Opening and Closing Points in Downhole Dynamometer Cards from Sucker Rod Pumping Systems based on Polygonal Approximation and Chain Code. *Rio Oil and Gas Expo and Conference* 654
[6] Urazakov K U et al. 2020 Test bed simulation stress loads on the sucker rod pump drive. *Petroleum engineering* **18(2)** 131-138
[7] Bakhtizin R N et al. 2019 A new approach of quantifying the technical condition of rod units with the solution of inverse dynamic problems by multidimensional optimization methods (Russian). *Oil Industry Journal* **07** 118-122
[8] Urazakov K U et al. 2017 Calculation of the theoretical dynamometer card of a differential sucker-rod pump when producing high-viscous oil. *Oborudovanie i tekhnologii dlya neftegazovogo kompleksa* **4** 41-47
[9] Jiang M et al. 2020 Fault diagnosis method of submersible screw pump based on random forest. *Plos one* **15(11)** e0242458
[10] Liu S et al. 2011 Automatic early fault detection for rod pump systems. *SPE annual technical conference and exhibition*. *Society of Petroleum Engineers* 755
[11] Hansen B et al. 2019 Model predictive automatic control of sucker rod pump system with simulation case study. *Computers & Chemical Engineering* **121** 265-284
[12] Aliev T M and Ter-Hachaturov A A 1988 *Automatic control and diagnostics of downhole sucker rod pumping units* (Moscow: Nedra) 232
[13] Dregotesku N D 1966 *Deep pumping oil production* (Moscow: Nedra) 294
[14] Krichke V O 1976 Measuring information system for wells equipped with pumping units IIS-SK. *Avtomatizaciya i telemekhanizaciya v neftyanoj promyshlennosti* **11** 16-18
[15] Svetlakova S V 2008 *Information and measuring system for dynamometry of wells equipped with sucker rod pumps* (Ufa: Ufa State Petroleum Technological University) 343
[16] Ruder S 2016 An overview of gradient descent optimization algorithms. *arXiv preprint* arXiv:**1609** 0474