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# Diagnosing sucker-rod pumping units by means of a neural network module implemented on the basis of an oilwell controller

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## Quyunun idarə olunma kontrolleri bazasında yaradılmış neyroşəbəkə bloku vasitəsilə ştanqlı dərinlik nasos qurğularının diaqnostikası

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**Açar sözlər:** ştanqlı dərinlik nasosu, diaqnostika, qüsurlar, dinamoqram, nasazlıqların aşkarlanması.

Neft quyularının ştanqlı dərinlik nasoslarla (ŞDN) istismarı – neftçıxarmada ən əsas və geniş yayılmış üsullardan biridir. ŞDN-lə neftin çıxarılmasının optimallaşdırılması üçün RPC quyu kontrollerlərindən istifadə olunur. ŞDN qurğularının (ŞDNQ) diaqnostikası və nəzarətin əsas üsulu dinamometrləmədir – ştokda yükün onun yerləşməsindən asılılıq qrafiki qurulmaqla nasosun vəziyyətinin və iş rejiminin qiymətləndirilməsi. Dinamoqramın (DMQ) keyfiyyətli analizi diaqnostika, yəni ŞDNQ-nin hər hansı bir nasazlığının öyrənilməsi və əlamətlərinin təyin edilməsi deməkdir. Dinamoqramla nasazlıqların təyin edilməsi məsələsi kompüter analizində çətin hesab edildiyi üçün dinamoqramın qiymətləndirilməsi ixtisaslaşmış texnoloq tərəfindən həyata keçirilməlidir. Məqalədə alınan RPC dinamoqramlarla qüsurların təyin edilməsi üsulları və alqoritmlərinə baxılmışdır.

Bu üsulları analitik və neyroşəbəkə üsullarına ayırmaq olar. Analitik alqoritmlər DMQ qüsurlarını düstur və məntiqi asılılıqlarla təsvir edir. Neyroşəbəkə üsulları qüsurun tanınması məsələsinə bir biri ilə əlaqəsi olmayan məlumatların tanınması kimi yanaşır. Bu da ŞDNQ kimi, çoxlu sayda parametri olan sistemlə işləməyə kömək edir.

Naftamatika şirkəti əvvəlki yanaşmaların bütün mənfi və müsbət cəhətlərini nəzərə alıb öz neyroşəbəkə modelini işləyib hazırlamışdır. Modelin hazırlanması şəbəkənin tipinin seçilməsindən ibarətdir, təbəqələrin sayı, neyronların strukturunun yaradılması, şəbəkə öyrənmə şəraitinin formalaşdırılması və adekvat təlim nümunəsinin seçilməsi. Həlli WellSim kontrollerinə yerləşdirilmişdir. Kontrollerin təlimi üçün ayrı-ayrı qüsurlar və vəziyyətlərlə minlərlə dinamoqram yüklənmiş proqram istifadə edilib. Alqoritm 96 % dəqiqliklə az doldurulma, qaz faktoru və digər nasazlıqları uğurla aşkar edir.

## Диагностирование штанговых насосных установок с помощью нейросетевого блока, реализованного на базе контроллера управления скважиной

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**Ключевые слова:** штанговый глубинный насос, диагностика, дефекты, динамограмма, распознавание неисправностей.

Эксплуатация нефтяных скважин штанговыми глубинными насосами (ШГН) – один из основных и широко распространенных способов добычи нефти. Для оптимизации добычи с помощью ШГН используются скважинные контроллеры RPC. Основным методом диагностики и контроля установки ШГН (УШГН) является динамометрирование – оценка состояния и режима работы насоса с помощью построения графика зависимости нагрузки на штоке от его положения. Качественный анализ динамограммы (ДМГ) сводится к диагностике, которая изучает и определяет признаки той или иной неисправности УШГН в целом. Задача определения неисправностей по динамограмме считается сложной для компьютерного анализа и предполагает оценку динамограммы квалифицированным технологом. В данной статье рассмотрены методы и алгоритмы определения дефектов по полученным RPC динамограммам, реализуемые непосредственно в контроллере.

Эти методы можно разделить на аналитические и нейросетевые. Аналитические алгоритмы описывают дефект ДМГ в виде формул или логических зависимостей. Нейросетевые методы подходят к задаче распознавания дефекта как распознаванию набора не связанных между собой данных. Это помогает работать с системой с большим количеством параметров, такой как УШГН.

Компания Naftamatika учла плюсы и минусы предыдущих подходов и разработала свою нейросетевую модель. Разработка заключалась в подборе типа сети, количества её слоёв, создание пространственной структуры нейронов, формирование условий обучения сети и подбор адекватной обучающей выборки. Решение внедрено в контроллер WellSim. Для обучения контроллера использовалась программа, в которую были загружены тысячи динамограмм с различными дефектами и состояниями. Алгоритм успешно обнаруживает недостаточное заполнение, газовый фактор и прочие неисправности с точностью 96 %.

**Introduction**. Currently, sucker-rod pumping (SRP) units are widely used in oil wells, due to two important factors: costs and ease of use.

The main advantages of the SRP include independence from ground-based systems, relatively simple installation, a variety of types of operating modes, the ability to adapt to changing production conditions, etc. The disadvantages of SRP are the high wear of pump rods and tubing pipes, as well as the high labor intensity of operations during their repair and overhaul.

To optimize production using sucker rod pumps, well Rod Pump Controllers (RPC) have been used for more than 20 years. They provide control, monitoring and pumping unit metrology.

Today the main method of controlling the sucker-rod pumping unit is the analysis of dynagraph card (determination of the state and mode of operation of the pump based on the dependence of the rod's load on its position). At the same time, the analysis of the dynagraph makes it possible to reliably detect various equipment malfunctions, the deviation of the pumping mode from the optimal one, and to evaluate the performance of the SRP.

The qualitative analysis of a dynagraph comes down to diagnostics, which detects and identifies signs of possible malfunctions of the pump and the well as a whole. The goal of any qualitative analysis is to identify abnormalities in the pump operation, and then make recommendations for trouble-shooting.

Quantitative analysis serves as a means of monitoring the performance indicators of oil well pump and correcting the pumping mode. At the same time, a number of such quantities as the stroke length, pump intake and wellhead pressures, feed and fill ratios, plunger and rods friction, flow rates, etc. can be determined.

In many cases, timely detection of malfunctions and preventive maintenance make it possible to avoid fatal defects and are associated with high repair costs. It can be achieved only by means of real-time diagnostics of SRP, which also able to reduce equipment downtime and production costs.

To ensure quick response to emerging malfunctions and changing operating conditions, which allows receive the mentioned benefits, it is necessary to either maintain reliable and constant communication with the dispatcher or/and use on-site autonomous intelligent control system.

The task of determining malfunctions by a dynagraph is considered difficult for a computer analysis and involves the evaluation of a dynagraph card by a qualified technologist. But it is not possible to provide constant monitoring of numerous wells, and therefore the task of automatically detecting pump malfunctions is very relevant

This article discusses methods and algorithms for determining malfunctions from obtained RPC dynagraphs, implemented directly on base of the well controller.

Considerable attention is given to the task of interpreting dynagraph cards in the classical monographs and number of publications and articles [1, 2]. As for computer methods for recognizing malfunctions by a dynagraph, today they are implemented only on server systems (an example is Theta's XSPOC) or are laboratory-based [3, 4]. It is clear that malfunction diagnosis should be carried out in real time and on site in order to promptly adjust operation mode and avoid possible complications. That is why the task of detecting abnormalities of submersible equipment operation by means of RPC is extremely relevant.

**General overview**

In article [5], the authors review several analytical methods of pattern recognition by dynagraph card. The matrix representation of the dynagraph and the selection of relevant points on the card, as well as the application of the precedent method to the considered task should be noted among them.

The materials cited by the author testify to the satisfactory operability of the precedent method and the theoretical possibility of its application in industrial conditions.

This method is not implemented in RPC.

V.B. Sadov in the article [4] makes an extensive review of the methods of constructing and recognition of the dynagraphs.

The following should be highlighted among them:

1. Construction of the neural network malfunction recognition algorithm.

2. Analytical comparison with reference or defective dynagraph cards - by points and sections.

3. Analytical description of malfunction patterns in dynagraph cards with the reconstruction of a model of the malfunction.

4. Analysis of dynagraph cards using Fourier series or their analogues.

Summarizing all these methods, the author comes to the conclusion that the algorithm used for diagnostics should have a minimum dependence on the dynamic parameters of the well, minimal complexity and not require heavy computational processes. However, the main problem of analytical constructions related to dynagraph is a large number of technological parameters of the well and pumping unit, which on the one hand vary in a wide range of values, having a serious impact on the dynagraph card, and on the other hand, can dynamically change during pump operation, which requires fine-tuning of the algorithm for each specific well for stable operation. Based on an understanding of these difficulties, the authors propose solving the problem by creating a "lightweight" diagnostic program that determines the presence of a malfunction pattern on the dynagraph by using logical conditions in limited areas of the card. Such analytics module, due to the features described above, has a narrow scope of application.

Naftamatika has developed well simulator that is capable to determine the effectiveness of various mathematical models using its own library of industrial dynagraphs to test new algorithms.

One of these models is the construction of reference lines on the dynacard, which makes it possible to separate its "sensitive" areas or to establish the proportion between different parts that is characteristic to the pattern of defect.

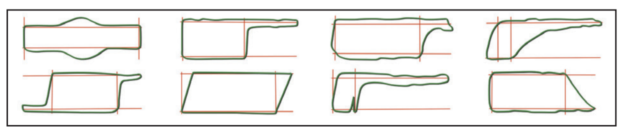

**Figure 1. Dynagraphs of well pumps with reference lines from book [7]**

Below (figure 1) are the results of diagnosing this model using the reference lines proposed in [2] and comments on the quality of the help search of this program.

In the below screenshots (figures 2) from the technological program, the correspondence of the studied dynagraph to the malfunction pattern is displayed in the form of a green scale with an illustration and sorted in descending order of pattern severity (pattern severity less than 1 % is hidden and displayed only by pressing the "+ More" button).

Based on the understanding of these difficulties, the authors propose to solve the problem of determining a malfunction by creating a "lightweight" diagnostic program that determines the presence

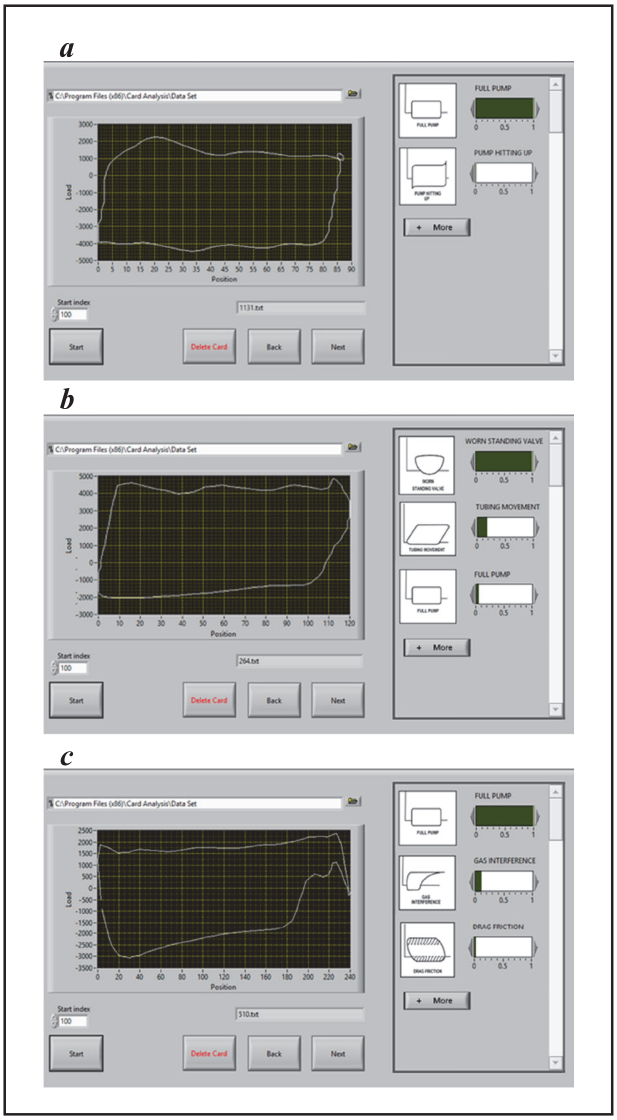


**Figure 2. Error in defect recognition when using analytical diagnostics: the simulator (running with analytical algorithm) shows the absence of a defect if the pump plunger is stuck when moving up (*a*). The simulator analytically diagnoses the wear of the standing valve, although the dynagraph does not show signs of defects, with the exception of possible sticking (*b*). Visually we can determine that the pump is not filling, but the simulator (running with analytical algorithm) does not show this (*c*)**

of a malfunction pattern in the dynagraph card by using logical conditions on specific sections of the dynagraph. Such product, considering problems described above, can't have the wide scope of appliance.

To determine the technological parameters of oil well by the downhole pump dynacard the construction of various reference lines or theoretical pump cards of different degrees of processing can be used.

Thus, using the analytical methods, it is possible to identify a particular well defect by the intersections between the pump card and the graph axes, by the slope, length and distances between them.

Due to the difficulties described above analytical approach often produces a large number of errors in practice, and become reliable only in rare case of perfect conditions.

Below are the diagnostic results of one of the industrial programs based on the principle of analytical fault determination using a pump map, and comments on the quality of malfunction patterns recognition by this program.

Based on the test results described above we can conclude that when using real dynagraphs with unique proportions analytical methods provide insufficient accuracy for industrial use.

Since the quantitative values of loads on dynagraph are not decisive for diagnostics (the technologist first evaluates the shape of the dynagraph card), the difficulties of analytical malfunction detection can be solved by using the pattern recognition neural network algorithm since the task of detecting a malfunction dynacard can be classified as an image recognition problem.

The first option of machine learning application is use of various types of highly developed networks for solving pattern recognition problem. These include such networks as VGG -16, ResNet - 34 and ResNext - 50. These networks are built on deep learning technologies, have high complexity and are designed for pattern recognition in images or photos. It is safe to say that this approach gives a positive result: these topics are discussed in detail in the article [5]. In [6], the possibility of using various networks of high complexity to solve the dynagraph card recognition problem is estimated. However, it should be noted that despite successful testing on real dynagraph cards, the solution of the problem of defect recognition can be achieved by a simpler and more specialized network solution: the high complexity of this networks implies high hardware requirements, which excludes the implementation of a system integrated on the basis RPC.

Thereby, it is worth noting the article [3], which reviews in details the second method of using machine learning for diagnostics, namely the construction of a special three-layer neural network to *recognize malfunction patterns in the* dynagraph cards. There A.M. Zyuzev shows the process of developing a diagnostic program based on the matrix representation of a dynagraph by creating and training a two-layer neural network.

The author notes: "The advantage of this solution lies in the generality of the approach to analyzing the entire variety of dynagraphs and the possibility of developing the system by parameterizing the selected structure with subsequent training."

It should be noted that this well-constructed system has a theoretical character (the author assumes only hypothetical implementation options, and the nomenclature of 9 malfunction patterns is insufficient), but it can serve as a starting point for the industrial implementation of a diagnostic system.

The Naftamatika took into account the pros and cons of previous approaches and developed its own neural network model. The development consisted of selecting the type of network, the number of its layers, creating a spatial structure of neurons, creating conditions for training the network and selecting an adequate training sample.

It is important to note the following feature of the construction of "hidden" layers located between the input and output: by construction the relationships between them, changing the "weight" of each of the neurons, we can create "events" within the algorithm, allowing for a more complex and in-depth analysis of patterns. Thus, malfunctions whose patterns are similar in appearance (gas interference and pump failure, for example) must be specially separated from each other when drawing conclusions about the condition of the well.

Other problem is recognizing a combination of several simultaneously existing malfunction patterns that develop in parallel at different rates. The solution for the latter case may not be an analysis of static dynacard, but a comparison of trends in the development of patterns on dynagraphs by using a neural network system on each oil well, as well as a comparison with reference trends of malfunction pattern development.

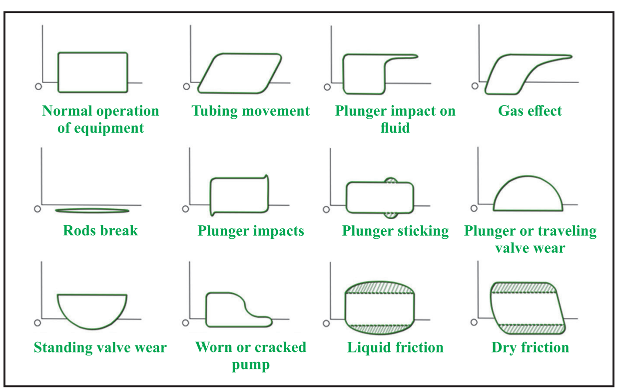


**Figure 3. Typical malfunctions patterns in dynagraph cards**

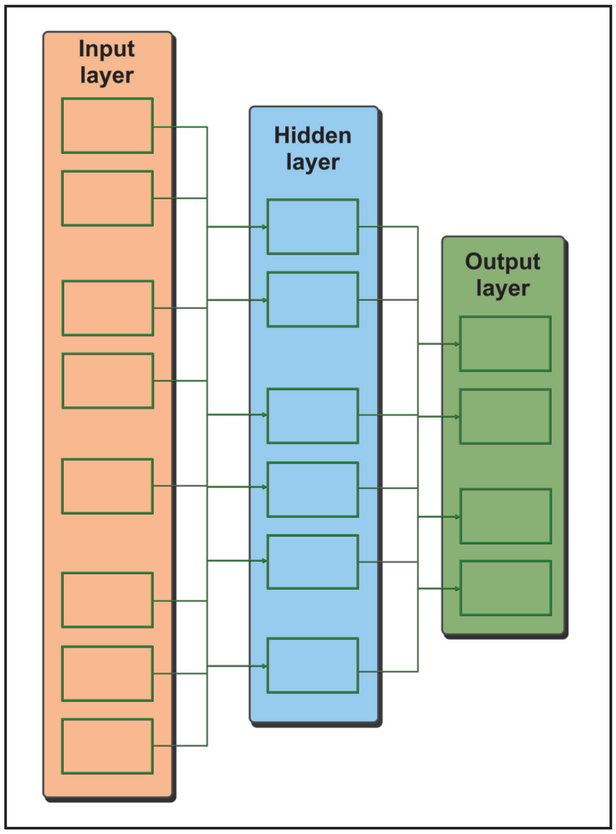


**Figure 4. An example of the structure of a three-layer neural network for the recognition of malfunction patterns by a dynagraph card**

Currently, the most common way to solve this problem is the pattern recognition method, which underlies all neural algorithms for working with images. Typical malfunctions patterns in dynagraph cards are on the figure 3 below. The pattern method consists of representing an image as a set of strings of logical values of «0» and «1».

To implement this method, a compact three-layer neural network (figure 4) was used, combining the features of networks described in [4]. One might say that this method represents a rethinking and development of the A.M. Zyuzev's methodology from [3]. The size of the first layer was determined by the number of points of the dynagraph card: 200 neurons of the first layer, 28 neurons of the hidden layer, and 16 neurons of the output layer. The increased number of input points (200 instead of 112) is based on the company's regular dynagraph data presentation and gives better resolution than the method from [3]. The 16 neurons of the output layer correspond to the extended range of malfunction patterns. The choice of the number of neurons in the intermediate «hidden» layer is dictated by the optimization requirements and, as a rule, is determined by an expert method from practical learning results.

Here the number of neurons in the input layer corresponds to the number of points of the analyzed dynagraph, the number of neurons in the output layer corresponds to the number of recognizable defects. The number of neurons in the intermediate layer, the choice of the activation function and the method of learning are determined by experimental testing.

The neural network is trained using the back-propagation algorithm, neurons are activated by the function $y = 1 / \exp(-x)$. The purpose of this function is to activate a neuron, thereby putting into work the necessary chain of connections. The selected function is continuous over the interval 0..1, has an order of smoothness $c^8$ and allows the use of the gradient descent method for optimization.

The back-propagation error algorithm transmits changes from the output of the algorithm to the inner layers, thereby helping to correctly adjust the weights of the connections between all layers of the neural network, allowing to achieve its stable operation. That algorithm is one of the most popular in the field of building convolutional neural networks, and despite the need to avoid

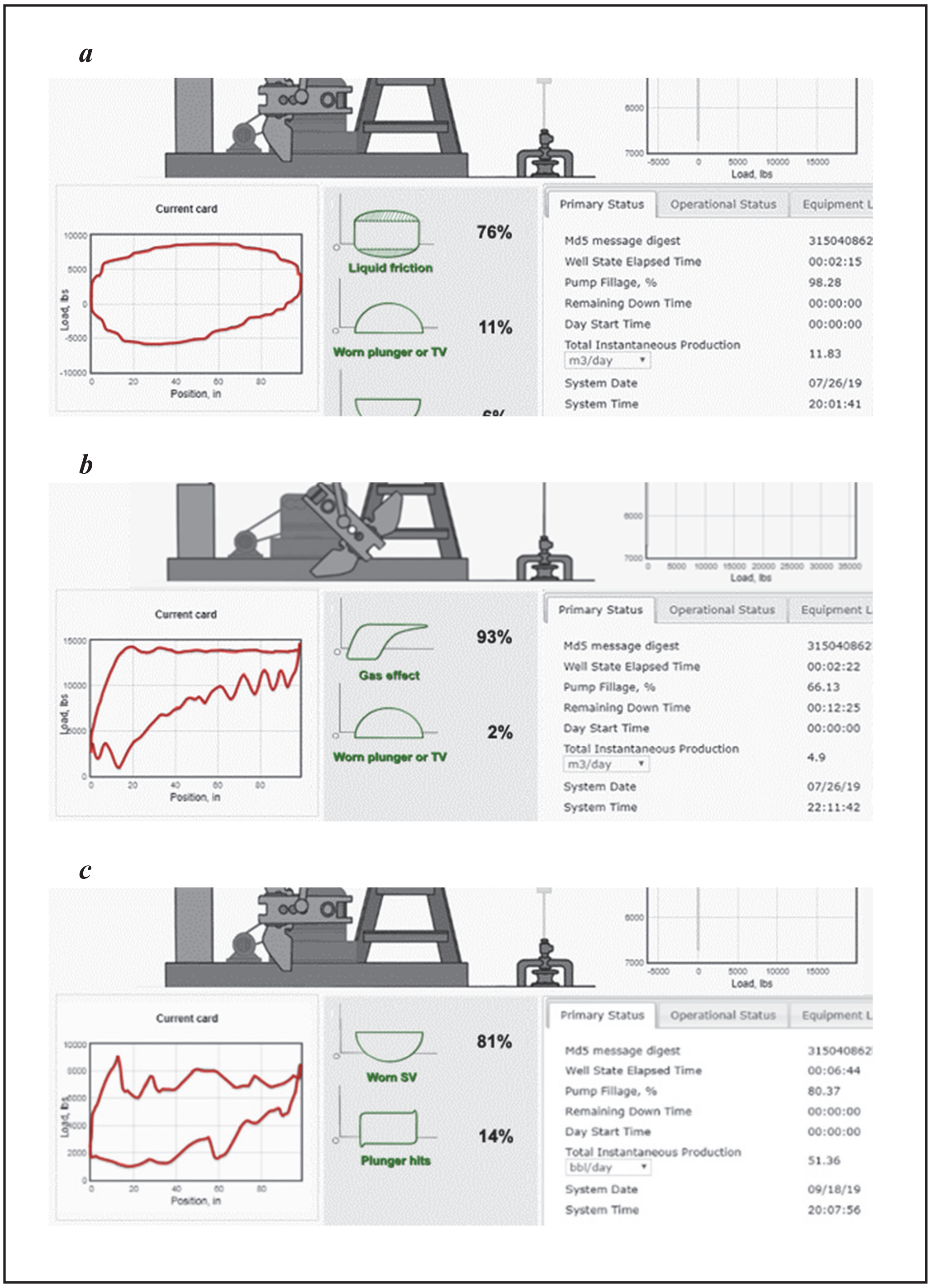


**Figure 5. Automatic recognition of worn plunger (*a*), of gas interference (*b*), of multiple simultaneous defects (*c*)**

retraining and falling into local minima, it is quite effective.

The structure of the network and the choice of elements used in it is consistent with the solutions used for solving problems of similar type from other areas. This network is implemented in a Wellsim pump controller, which provides sufficient performance, the algorithm successfully detects insufficient filling, gas factor and other faults with an accuracy of 96 %.

Examples of automatic malfunction patterns recognition by using a neural network integrated into the RPC firmware are given below (figures 5).

Wide implementation of the AI system, in particular at the oil fields of Belorusneft, showed in 2023 a serious increase in the overhaul interval and, accordingly, an increase in production and a decrease in costs.

Due to various customer requirements, the following options for using neural network technologies in the field of oil production are available:

a) Implementation of the algorithm on the well controller. This option was implemented by Naftamatika engineers. Its advantages include autonomy, high performance, the ability to customize for a specific well, as well as stable autonomous operation of a single RPC.

b) Application of a neural network for diagnosing wells on the basis of a SCADA. The obvious disadvantage is delays in decision making.

c) An intermediate option, in which the neural network system is preinstalled both on the server and on individual RPC, which allows new recognition solutions (for example, in case of errors in the operation of the algorithm) to be “dispatched” from the top level to the controllers for the purpose of additional training and correction of a sample of characteristic dynagraphs.

## Conclusion

Machine learning is a very promising direction in any industry, one way or another connected with the solution of complex, difficultly parameterized tasks. Since at present a significant experience has been gained in the use of neural networks in related areas, the transfer of techniques to the field of dynagraphs or wattmetergraphs may raise the diagnosis of SRP malfunctions to a new level. Often, the use of relatively simple tools that were previously used for image recognition and that has shown themselves well, makes it possible to obtain an impressive result with minimal development costs.

The neural network method gives high recognition accuracy more than 95 % with a sufficient amount of training sample. The main concern with its use is the requirement of computational resource and a large amount of data for training. The use of complex neural networks for pattern recognition [6, 7] is hardly advisable in RPC due to the relative simplicity of this task. Therefore, in our opinion, the problem of malfunction patterns recognition should be solved using a simple method with the creation of a 3-layer neural network, which is perfectly implemented on our RPC, but also having trained the neural network on a sufficient number of verified dynagraph cards from various sources (first of all, we use our own database from thousands of real dynagraphs with malfunction patterns), limiting at the initial stage up to 16 typical malfunctions. Using the above tools, it was possible to achieve more than 96 % probability of identifying malfunctions directly on site by means of the RPC.

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