

STUDY OF THE HAMMING NETWORK EFFICIENCY FOR THE SUCKER-ROD OIL PUMPING UNIT STATUS IDENTIFICATION

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Abstract: The oil extraction process requires continuous monitoring of the oil well equipment operation. One of the most effective methods of the on-line control of sucker-rod pumps operation is obtaining information from the force sensor in the polished rod or the current sensor of the pump jack driving motor. In many cases, timely troubleshooting and preventive repair allow saving large costs. Therefore, studies in the area of developing diagnostic systems and, on their basis, creating automated control systems for sucker-rod pumping units (SRPU) are of topical value.

The paper discusses the neural-network-based approach to solving the tasks of forecasting the technical status of jack pumps. The modified Hopfield network (Hamming network) was used as a neural network, for which an SRPU status identification algorithm was devised. Due to it, the identification process outputs not the sample curve itself, but only its number, which results in the faster neural network and smaller computing resources and memory required.

For testing the performance of the proposed identification algorithm, a laboratory bench simulating the operating SRPU status diagnostic system was created. The obtained experimental data show that the Hamming-network-based identification system can perform real-time diagnosing of the current status of the downhole equipment with the minimum error.

Key words: sucker-rod oil pumping unit, neural network, load curve, identification system.

1. Introduction

Sucker-rod oil pumping units (SRPU) make up a large part of Ukraine's oil production. Their operation conditions feature continuous variation of the oil-well flow rate, which is why a rational oil extraction mode needs to be set up. This can be done only subject to continuous monitoring of the technical status of the oil-extracting equipment using automated control systems [1]. Diagnosing SRPU operation is one of the oil extraction optimization components, since it makes it possible to detect not only the apparent oil-well equipment failures such as sucker rod breakage or plunger sticking, but to avert and

prevent some failures caused by the improper plunger fit, passing valves, insufficient fluid influx, etc. In such cases, adjustments in the oil extraction unit operation can be made in advance, which will extend the trouble-free running of the equipment and reduce costs.

The most popular method of diagnosing SRPU operation, especially for stripper wells, is measurement of the load on the polished rod for the whole period of the crank rotation [1–3]. In the modern control systems for oil-production, the load measurement results are recorded in the controller located near the SRPU or transmitted to the upper-level control system for a detailed analysis. The recorded load curve allows the experts to make conclusions about the operation of the downhole oil-well equipment. In this regard, designing the algorithms for program identification of the specific features of the deep-well oil-pumping unit is of considerable importance, since it will enable the automation of the oil production control and monitoring.

2. Selection of SRPU status identification method

There are a number of techniques available today that allow identifying the status of the oil extraction unit based on the load curve. The main approach in this case is to compare the recorded load curve with the template. The comparison relies on Fourier series or wavelet transforms [4, 5]. Another widely used method is based on detecting particular features (points) of the load curve [6] which are specific for each SRPU operation mode. Recently, new methods of oil well status identification have been widely implemented on the basis of neural networks [7, 8]. We believe that neural-network-based methods are most efficacious for load curve identification. To a large extent, this efficacy depends on the neural network type and the training algorithm. In [8], the authors analysed the most popular neural network types for their applicability in deep-well oil-pumping unit status identification systems based on the recorded load or current curves of the driving motor. Table 1 summarizes the results of the comparative analysis in the MATLAB environment.

Table 1

Training time for major neural network types

Neural network type	Training time for 10 images, s	Training time for 20 images, s
Single-Layer Perceptron	1.283	2.400
Multi-Layer Perceptron	4.851	6.740
Hopfield Network	0.385	0.540
Hamming Network	0.385	0.385

The table shows that the recurrent networks are better at solving images classification tasks and output a larger number of correct results in the severe conditions of SRPU operation. This allows using them in the real-time systems for SRPU control.

When selecting a specific type of network, the fact that the main drawback of the Hopfield network [9–11] is the lack of capacity to process a large amount of data is taken into account.

During the Hopfield network operation, the indicator of the pattern identification being complete is the moment when the network reaches a static state or a dynamic one. This final state of the network is its response to the input image. If at each subsequent step the output vector of the network is the same, we have a static state. In case of a dynamic state, two different output vectors alternate. The correct identification result is a steady state when the input vector (image) coincides with one of the vectors remembered during the learning.

However, under some conditions (in particular, when the number of input training images is too large) the work can result in a so-called false minimum consisting from parts of different images. Such a situation is erroneous and should be avoided.

This drawback has been overcome in the Hamming network [10–12] (Fig. 1) by adding a layer of neurons before the Hopfield network, which is why it is proposed that it should be further used in the SRPU status identification system.

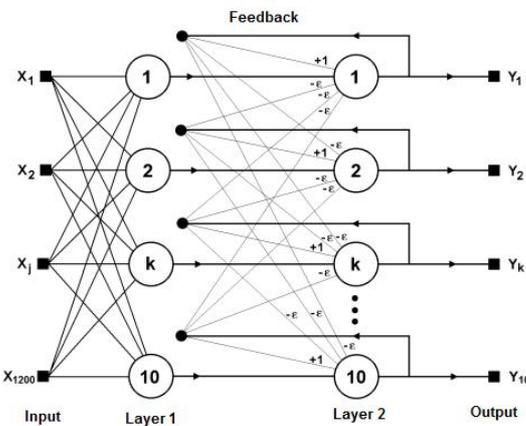


Fig. 1. Hamming Neural Network Architecture Feedback.

The selected neural network consists of two layers. Each layer is made up of 10 neurons, which corresponds to the number of classes of the selected template images. As the input image of the load curve is a 20×60 matrix, the Layer 1 neurons have 1200 synapses (inputs) each. Layer 1, the Hamming layer is a feed-forward neural network. This layer computes the degree of similarity (Hamming distance) between the input vector and the templates. The Hamming distance is the number of elements in the input image that differ from the template. This layer uses the linear activation function. Layer 2, the Hopfield layer contains 10 feedback neurons. All the feedbacks are negative. There is one positive feedback for each neuron that connects the neuron input and output. This is an all-to-all connected network with the sign activation function.

The operation principle of the selected network is based on calculating the degree of similarity between the input binary vector and the template (templates are memorized by the network in the course of training). In other words, the network is a classifier that outputs just a class number that the input image belongs to. This type of network is employed in cases when there is no need for the network to output the identified sample after the identification, as it is sufficient to have its number.

3. Neural network operation algorithm

According to the operation algorithm, an unknown binary vector is input into the neural network, on the basis of which Layer 1 weights are calculated. Then the transformed values are transferred to Layer 2. If Layer 2 outputs coincide with its inputs, the algorithm finishes; if not, then it goes back to Layer 2 inputs. The algorithm shows that Layer 1 is used only at the beginning and acts as a filter and archiver. Due to it, the network works faster and requires less computing resources and memory.

Fig. 2 shows the algorithm of the image identification system based on the Hamming neural network.

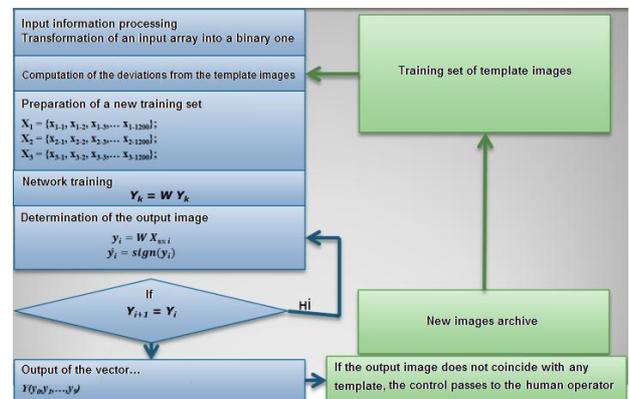


Fig. 2. Image Identification System Operation Algorithm.

At the first stage, the Hamming distance as the number of elements in the input image that differ from the template is found. Table 2 offers the graphical representation of such calculation.

Table 2

Hamming distance

	Hamming distance = 0
	Hamming distance = 2
	Hamming distance = 5

In the classical case, this is Layer 1 of the feed-forward neural network that deals with computing the Hamming distance. This approach requires significant computing resources. As the training set is fairly large and extends in the process of the oil-pumping unit operation, this layer will need continuous modification and increase in the neuron number. This causes the complication of the algorithm by the adaptive function and, as a result, larger errors and reduced probability of correct identification of the oil well status.

Therefore, we decided to replace Layer 1 in the Hamming network with the algorithm of the bit-by-bit arrays comparison. It is based on a fast search of the database for elements [11, 12], due to which it takes only a few iterations to output the result. This solution significantly simplifies the program part of the control system. After comparing the input vector with all the templates, we obtain a 10-element vector. Out of these ten values we choose the three lowest ones with the smallest Hamming distances. This will be a training set for the next layer of the network (Hopfield network).

$$\begin{aligned} \mathbf{X}_1 &= \{x_{11}, x_{12}, x_{13}, x_{14}, \dots, x_{1\ 1200}\}; \\ \mathbf{X}_2 &= \{x_{21}, x_{22}, x_{23}, x_{24}, \dots, x_{2\ 1200}\}; \\ \mathbf{X}_3 &= \{x_{31}, x_{32}, x_{33}, x_{34}, \dots, x_{3\ 1200}\}. \end{aligned} \quad (1)$$

In Layer 2, according to the learning rules for the Hopfield network, the training vector is multiplied by this same vector transposed. Thus, we obtain three square matrices (2). These matrices are added, and the diagonal of the resulting matrix is replaced with zeroes for a better strength of the network $W_{ij} = 0$, for $i=j$ [11, 12].

$$\begin{aligned} \mathbf{W}_1 &= \mathbf{X}_1 \times \mathbf{X}_1^T; \\ \mathbf{W}_2 &= \mathbf{X}_2 \times \mathbf{X}_2^T; \\ \mathbf{W}_3 &= \mathbf{X}_3 \times \mathbf{X}_3^T; \\ \mathbf{W} &= \mathbf{W}_1 + \mathbf{W}_2 + \mathbf{W}_3. \end{aligned} \quad (2)$$

Then the resulting matrix \mathbf{W} (Fig.1) is multiplied by the transposed vector of the input image \mathbf{X}_i^T ($i = 1, 2, 3$). As a result, we obtain the vector \mathbf{y} , which is processed using the sign activation function. This function replaces each element of the vector with 1 or -1 according to the rules (if $x_i < 0$, then $x_i = -1$, if not, then $x_i = 1$). The resulting vector \mathbf{Y}_{i+1} is compared with the vector \mathbf{Y}_i from the previous iteration (if this is the first iteration, then with the input vector). If the vectors differ, we go back to the previous step, choosing another vector \mathbf{X}_i^T . If not, the obtained vector is compared with the template and the appropriate vector is chosen. Should there be no appropriate vector, a new sample is created, which the human operator can add to the existing template base.

The network works fast. The model uses one of the simplest algorithms of forming synaptic weights and biases of the network, hence it is always convergent. In contrast to the Hopfield network, the Hamming network capacity is independent of the dimension of the input signal; it is determined by the number of template images. The Hamming network has the advantage of a small number of the weighted links between the neurons. The major drawback is that the network cannot work with binary data only. Besides, if the input vector is very noisy (the Hamming distance exceeds 60 % of the total number of elements), the identification rate decreases considerably, while the number of false actuations increases.

For testing the Hamming network in the task of the sucker-rod oil pumping unit status identification, a laboratory bench was created on the basis of the signal microprocessor ARM Cortex M3 STM32F107 [13] from ST Microelectronics (Fig. 3). The network was trained on the set of load and current curves obtained for different volumetric efficiencies of the deep-well oil pump. For recording the test set, a mechanism of downloading the load and current curves via the COM PORT using the MATLAB environment was developed.

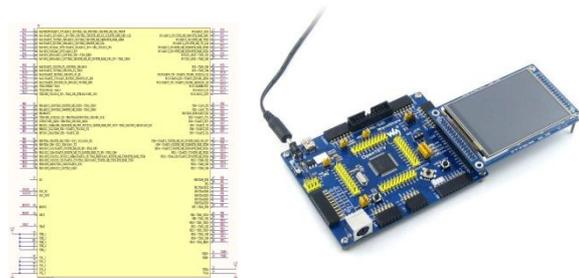


Fig. 3. STM32f107 diagram and view of the chip with the processor and display.

To form the load torque of the induction motor controlled by the frequency converter, a typical laboratory bench motor-generator was set up. A DC machine was used as the generator. The specificity of the design is a special scheme of the generator load formation. The load is formed in such a way that it can simulate the change of the force in the SRPU polished rod. The power circuit of the laboratory bench is shown in Fig. 4. This scheme enables regulation of the current within the range 70–100 % of the rated value, which reflects the real change of the load in SRPU.

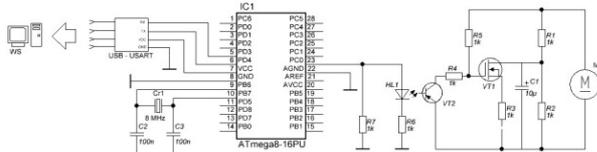


Fig. 4. Load formation scheme.

4. Experimental results

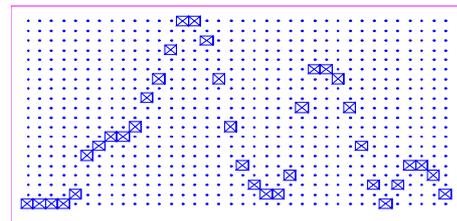
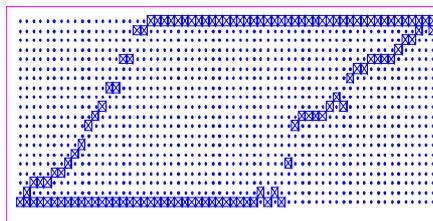
Let us consider the operation stages of the identification system. At the first stage, an array of

values of the load or current curve for one crank revolution is downloaded. Then this array is processed, and the message about the successful download is displayed (Fig. 5).

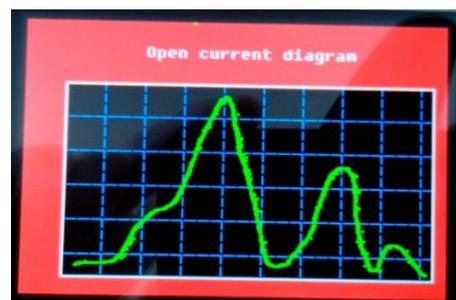


Fig. 5. Display of data array download on LCD.

During the next stage, the downloaded array is analysed and the task of forming the image for further identification is launched. According to the developed algorithm, the force on the rod or the RMS current is converted into the relative units and a binary matrix is built. The result is shown on the screen (Fig. 6, a, b) and input into the neural network.



a



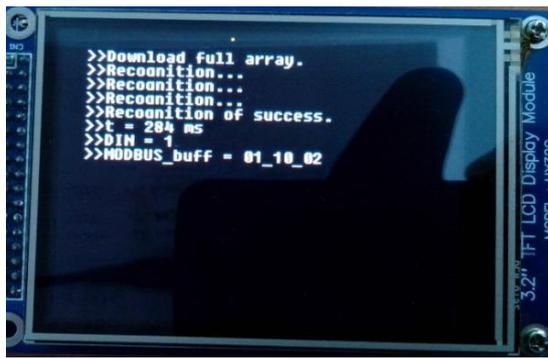
b

Fig. 6. Display of the binary matrices and load curve for the coefficient of pump filling of 1 (a), and the current curve for the coefficient of pump filling of 0.7 (b).

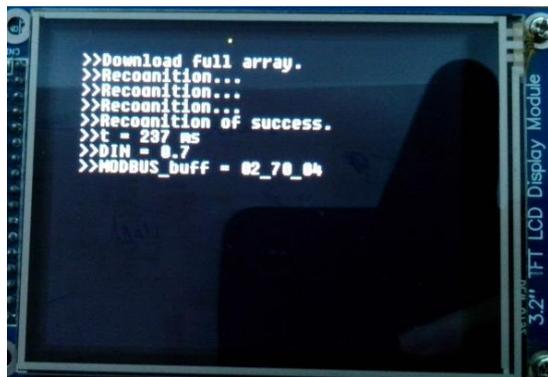
The result of the neural network operation is the correctly identified input image and the number of the class it belongs to (Fig. 7, a, b).

The obtained result is conveyed to the SRPU control system, which makes a conclusion about the current status of the unit (regular operation, emergency operation, standard operating conditions with a corrected

task for the frequency converter). If the neural network received a very noisy sample or a sample corresponding to an unknown mode of operation, the control passes to the human operator who assigns this sample to the existing class or sets up a new class. This solution allows increasing the percentage of correct identifications of the images in the process of the scheme operation.



a



b

Fig. 7. Identification results for the load curve for the coefficient of pump filling of 1(a) and the current curve for the coefficient of pump filling of 0.7 (b).

5. Conclusion

The designed laboratory bench of the SRPU status identification system makes it possible to fully simulate all the operation modes of the oil well. The system tests showed that the scheme is good at processing the input data both for the load curved and for the current curves.

A series of experiments with different noise levels of the input data were conducted. It was established that the network ensures correct identification of the images for which the Hamming distance does not exceed 60 % of the total number of elements in the input vector.

The microcontroller speed and properly selected software enable simultaneous operation of the frequency converter, a set of sensors, the database, a GSM modem, an LCD and a keyboard. As the system can be retrained in the course of operation, it can adjust to work with various SRPU types using the same hardware and software.

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ДОСЛІДЖЕННЯ ЕФЕКТИВНОСТІ НЕЙРОННОЇ МЕРЕЖІ ХЕМІНГА ДЛЯ ЗАДАЧ РОЗПІЗНАВАННЯ СТАНУ ГЛИБИННОПОМПОВОЇ УСТАНОВКИ

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Процес нафтовидобутку нафти потребує проведення постійного моніторингу роботи обладнання свердловин. Одним з найдієвіших методів оперативного контролю роботи штангових глибинних насосів є отримання інформації від давача зусилля в полірованому штоці або давача струму привідного двигуна верстата-гойдалки. У багатьох випадках завчасне розпізнавання неполадок і здійснення профілактичного ремонту дають змогу уникати великих матеріальних витрат. У зв'язку з цим актуальними є дослідження, пов'язані з розробленням систем діагностики та створення на їхній основі автоматизованих систем керування ШГПУ.

Розглянуто підхід до вирішення завдання прогнозування технічного стану штангових глибинних насосів з використанням нейромережових технологій. Як нейронну мережу використано модифіковану мережу Хопфілда – мережу Хемінга. Для неї створено алгоритм ідентифікації стану ШГПУ, завдяки якому результатом розпізнавання є не сам зразок, а тільки його номер. У результаті прискорюється робота мережі і витрачаються менші обчислювальні ресурси та пам'ять.

Для тестування працездатності запропонованого алгоритму розпізнавання створено лабораторний стенд, який імітує роботу системи діагностики стану ШГПУ. Отримані експериментальні результати показали, що система ідентифікації на основі мережі Хемінга може в реальному часі та з мінімальними похибками розпізнавати поточний стан глибиннопомпового обладнання.



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