2021 IEEE Smart Information Systems and Technologies (SIST)
28-30 April, 2021, Nur-Sultan, Kazakhstan

Developing Predictive Oil Well Diagnostics Based on Intelligent Algorithms

Zhanar Omirbekova [1], Aslan Amangeldiyev [2], Daur Aktaukenov [3] Abdelrahman Abdallah[4]
[1] *Al-Farabi Kazakh National University, 71 al-Farabi Ave., Almaty, e-mail: zhanomir@gmail.com, https://www.kaznu.kz*
[2,3,4] Satbayev University, 22 Satbayev str., Almaty, email: reedgoody@gmail.com, dauraktaukenov@gmail.com, www.satbayev.university

***Abstract*— The current competitive market condition in the oil industry is so concentrated on companies' budgets that they require methods to extract oil from wells at the lowest possible cost. All pumping units, new or old, require regular preventive maintenance and constant inspection, and with 30 per cent of total oil production coming from sucker rod pumps, the cost of diagnostics must be reduced accordingly**

This article focuses on the intelligent diagnostics of the rod and borehole pump for preventive maintenance and monitoring during the life cycle of the well. The use of artificial intelligence methods for predictive diagnostics of equipment condition solves problems without production stoppages and without additional interventions from outside.

***Keywords*— Oil production, sucker rod pumps, artificial intelligent system, dynamograph, preventive diagnosis, machine learning.**

II. Introduction

The current state of the oil and gas industry in Kazakhstan is characterized by the fact that the vast majority of operations are at a late stage of development, characterized by increased water cut, reduced average flow rates from oil production wells, and higher costs per unit of oil produced. In addition, the oil and gas industry are just recovering from a severe downturn that led to significant operating losses for oil producers.

According to a 2019 report by the Oil and Gas Information and Analysis Centre of Kazakhstan, 90.4 million tons of oil were produced, of which 30% were produced using sucker-rod pumps [1, 2].

As is known, a sucker-rod pump (SRP) is a single-acting pump that converts the rotary mechanism of the motor into a vertical reciprocating motion to drive the pump shaft and is used to mechanically lift oil-bearing fluid from wells [].

According to Ambyint, it costs about $250,000 to install the SRP together with all the starting equipment, and up to $100,000 to repair or replace it [3]. This fact, with declining oil prices and decreasing profits, is forcing oil producers to use smart maintenance technologies to reduce costs, improve productivity and make their assets more profitable.

Various methods and tools are used for predictive fault diagnosis without having to stop the process, thereby reducing the cost of repair work

III. Diagnostic methods for sucker-rod pumps

A. The pump unit is connected to an electric or combustion engine via a torque box, which converts the rotary motion of the engine into a reciprocating motion of the pump rods. The pump rods in turn transfer the mechanical energy received at the surface to the down-hole pump. Some energy is lost to friction during this process. In figure 1 shows the main components of the SRP, namely the pump unit, the pump rod, and the pump itself.

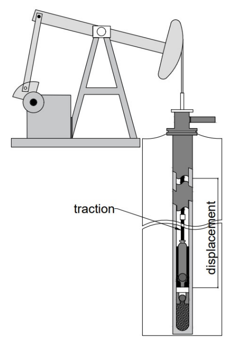

Figure 1 Mechanics of the sucker-rod pump

The depth pump, which is shown in figure 2, transfers the resulting mechanical energy into the multiphase fluid (oil, gas, sediment, and water).

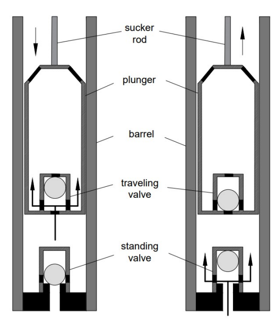

Figure 2. Depth pump working principle

The main components of a submersible pump are the plunger, casing, pressure valve and suction valve. Together they form a positive displacement pump system. When the plunger moves downwards, the pressure valve opens, and the suction valve closes. In this way, the volume of the oily liquid column is supported by the suction valve assembly and the liquid flows into the housing. The inside of the plunger is filled with oily liquid. Plunging the pump rods into the liquid causes a small discharge due to the volume that has been displaced.

As the plunger moves upwards, the pressure valve closes, and the suction valve opens. The oily liquid moved by the plunger comes to the surface, while the body is filled through the suction valve. In this way, the volume of liquid in the pipe is transferred to the pump rod.

During continuous operation of the deep well pump, due to the reciprocating motion of the rods, the pumped oily liquid begins to fill the pump rod and rise to the surface.

There are three methods to diagnose the condition of the sucker-rod pump without stopping it and raising the plunger to the surface: the dynamometer method, the wattmeter method and using artificial intelligence based on the analysis of sucker-rod diagrams.

B. *Dynamometry*

Dynamometry of the rod pumping unit is the most important source of information about the performance of the rod pump, the rod string, the condition of the downhole hole, etc. It is carried out by means of special technical means [4]. It is carried out by means of special technical means [4]. Data from the dynamometer are transferred to a portable data acquisition module and then to a centralized upper-level system, or to a programmable controller installed at the well site and allowing to process, analyze and control operating modes of pumping equipment [5]. The dynamogram is a graph of load dependence, at the suspension point of the rod, on the movement of the polished rod. The theoretical dynamogram for normal pumping operation is based on gravity, elasticity, friction, and Archimedes' principle. Insufficient consideration of other influencing factors, such as the force of inertia and the properties of the pumped liquid, limits the capability of this method.

The dynamogram is shown in figure 3, which is a diagram of the rod load - p as a function of the polished rod stroke - s. The process can be divided into four steps. Point A in the dynamogram indicates the bottom-most position of the plunger and point C corresponds to the top-most position.

Stage 1 - polished rod and pump plunger move downwards. Line D1-A1 corresponds to the load difference from rod pressure and friction force P, the line is parallel to the zero line (s axis) of the dynamometer due to the constant rod pressure and friction force. Line D-A corresponds to the static pressure of the rod in the liquid Prod without friction force. Consequently, the friction of the rod against the liquid reduces the stroke length of the plunger and the suction valve closes at A1 (interval f ↓) instead of point A.

Stage 2 - the polished rod changes direction and moves upwards. When the direction of movement of the plunger is changed, the process is captured by the straight-line segment A-A2. Starting from point A2 the pump rod takes the load from the weight of the liquid column Pf. At point B1 the load is equal to the sum of the weight of the rod with the liquid and the friction forces. That is, at A2-B1 the pump rod stretches and the load increases, but the polished rod does not move and is still in the bottom end position of the plunger. At this point the pump suction valve opens and the oily liquid flows into the pump cylinder.

Stage 3 - polished rod and pump plunger move upwards which is described by the line B1-C1. The line is also parallel to the s-axis of the graph due to constant rod pressure and friction force.

Stage 4 - The polished rod changes direction and moves downwards, the friction force also changes its direction. The process is recorded by the straight-line C-C2. The load change corresponds to C2-D1 when the rod string is unloaded, and the pipes are loaded. Point D is the opening of the pump discharge valve and the start of the downward movement of the plunger.

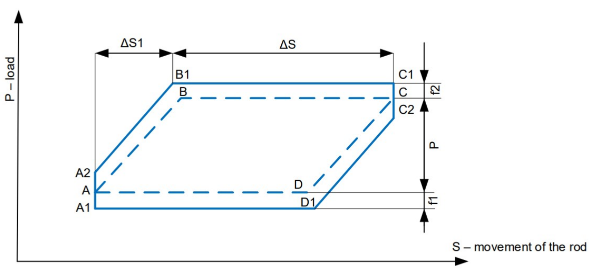

Figure 3. Dynamogram profile

The reading of the dynamograms allows quantitative and qualitative determination of the pump's performance loads and stresses in the polished rod, plunger and rod stroke lengths, degree of pump filling, tightness of the pump suction and pressure valves, gas impact, correct plunger fit, leaky tubing, rod or rod coupling turnovers and breakages, plunger jamming. The dynamometer can describe 30 different state parameters of the sucker-rod pumping equipment without lifting it. The transformation curve is a multi-resolution method that has been widely used to solve feature extraction problems [6,7,8].

The shape of the dynamometer depends on the type of failure of the sucker-rod pump and can be used to identify the following types of failures in the sucker-rod pumping equipment: fluid leakage from the tubing and valves (suction and pressure); mechanical failures such as high and low plunger fit, rod breakage, plunger jamming, etc; other problems related to pumping liquids gas, sand, paraffin.

C. Wattmetrics process

Modern SRPs are driven by variable frequency drives, which provide control, speed adjustment and parameter control of the SRP. The method of watt metering is based on the power consumption of these variable frequency drives. Wattmetrics is the process of obtaining a watt-hour diagram which shows the relation between the power N(φ) consumed by the pump motor and the angle of the crankshaft, or the dependency of the power consumed by the installation on time [4]. The analysis of the wattmeter spectrum enables the detection of vibration and shock loads, which makes it possible to diagnose gearbox and bearing defects [9]. The difference between the Wattmeter and the dynamometer is that the dynamometer is mainly used for the submersible part of the shaft, while the Wattmeter is more informative for the above-ground part.

During the stroke, the pump rods are subjected to static and dynamic loads. The downward movement of the pump rods at the very end of the stroke causes a higher load, while the upward movement of the pump rods at the very end of the stroke causes a lower load. Since the pump rods are directly connected to the pump itself, these loads are transferred to the variable speed drive. Thus, information about the condition of the underground equipment is contained in the wattmeter spectrum. Experimentally, each state-specific wattmetergram can be linked to one of the various dynamometer classes, which are widely used in rod pump monitoring and diagnostics. This can enable rod pumps to be diagnosed directly from the wattmetrogram. Furthermore, rotor defects, static and dynamic eccentricities and bearing defects can be identified by the spectral power density.

A wattmeter diagram of a fully balanced and serviceable SRP is shown in Figure 4. For each full stroke of the boom the SRP has two half-periods with significant peaks corresponding to the horizontal position of the crank. According to the regulations, the difference in maximum power consumption by the drive motor of the pump unit during the lowering of the depth pump rod must not exceed 10% [15].

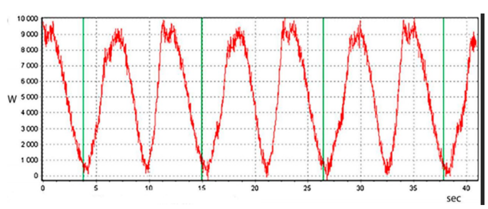

Figure 4. Wattmeter diagram of a fully balanced SRP

Insufficient amount of counter torque, created by cranked loads during lowering of sucker-rod pump column at unbalanced sucker-rod pump (fig. 5), leads to transition of drive motor to generator mode, and working stroke of pump rod is accompanied by increased loads on gearbox and pumping unit motor. The consequence of these processes is increase of specific energy consumption when lifting of formation fluid, high dynamics and exceeding of normative values of loads in elements of sucker-rod pump.

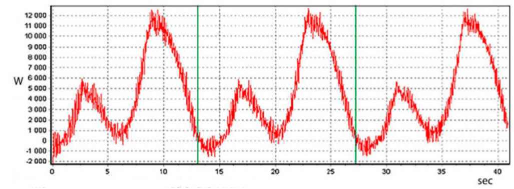

Figure 5. Wattmetrograms of unbalanced SRP (low load)

The analysis of wattmetrograms makes it possible to predict the most common faults of deep well pumps. [4] The classification of common faults can be solved by linear partitioning of the phase plane into parts, the appearance of each of which is determined by the presence or absence of certain faults. The classification features in the wavelet transform wattmetergram are determined by the equation [10]:

$$w(i,k)^n = a_0^{\frac{-i}{2}} \int_{-\infty}^{\infty} f(t)\varphi(a_0^{-i}t - kb_0)dt \qquad (1)$$

Where, φ(i,k) is the basis wavelet function;

f(t) is the wavelength function.

i,k ϵZ.

Diagnostic signs of sucker-rod failure are an increase in peak active power consumption by the motor when the sucker-rod head is lowered (the weight of the sucker-rod string does not compensate for the counteracting torque created by the crank). At the same time, the half-period of power increase is absent in the watt diagram during rod lowering, which is caused by absence of external load acting during lifting of formation fluid column of the borehole. Similarly, defects in the pressure valve of the submersible pump are shown. They consist in a significant decrease of power, consumed by the engine during the boom lift, because of leakage of most of formation fluid through the defective pressure piston valve back to the pump cylinder, and as a result, a significant drop in the point of suspension of the pump rods load. Uneven load growth during lowering of sucker-rod string, increase of dynamic force components at sucker-rod drive are the evidence of faulty sucker-rod pump valve.

The spectrum analysis of active power signal, shown on a figure 6, allows to reveal frequency components from 0 to 30 Hz, characterizing oscillations of kinematic chain "downhole pump - pump unit - reducer - driving motor". [4] Defects in working units and mechanical transmissions of sucker-rod drives determine occurrence of variable loads, that cause appearance of new spectral components. Periodic measurement of values in a power spectrum, characterizing concrete defects in the drive engine and mechanical transmission, allows to carry out estimation of technical condition of SRP in the simplest mode and, if necessary, to carry out repair actions for prevention of failures.

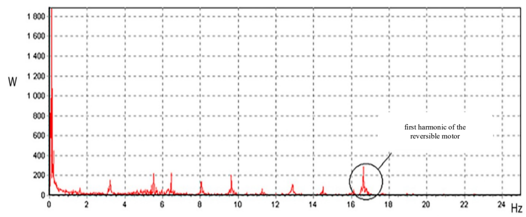

Figure 6. Wattmeter spectra in the presence of a pump-motor unit defect.

Spectral analysis of energy consumption records in asynchronous motors (Figure 6) can be used to detect defective electrical rotor parts, including rotor winding breaks and short circuits between layers; stator electrical parts, including power winding breaks and electrical asymmetry, short circuits between layers; static and rotating eccentricities; bearing defects resulting in fluctuating air gap shapes. Gearwheel faults, gear fit on the shaft, misalignment of driven shafts and their rotation supports, and defects in the V-belt transmission can be diagnosed by the nature of the change in the power signal spectrum.

D. *Artificial intelligence methods*

Dynamometry provides an exactly accurate indication of the condition of the SRP, but also requires intervention by workers, because a dynamograph will need to be installed and the instrument read. In Kazakhstan, dynamometer readings are taken once a month in oil wells, which means there is no continuous diagnostics of the SRP's condition, and it is impossible to predict its condition.

The disadvantages of this method of evaluating the technical condition of the SRPs with respect to their energy consumption include the difficulty in detecting several defects at the initial stage of development. Firstly, these are roller bearing failures, crankshaft rotation, wear, and destruction of connecting rod pins. The occurrence and development of these defects is accompanied by a change in the diagnostic signals of the spectra in the higher frequency range [16]. In real plant conditions, in the presence of liquid leaks in the pump, gas influences and other irregularities in the normal operation of the pump, the deciphering of the diagnostic readings becomes even more complicated and, as a rule, the influence of these irregularities is mixed and it is difficult to distinguish, in an explicit way, the influence of a single indicator on the pump malfunction and on its delivery [11]. The use of artificial intelligence techniques for predictive diagnosis of the condition of equipment can solve these problems without stopping production and without additional intervention from outside. One of the problems associated with pattern recognition is the so-called curse of dimensionality [12]. There are two reasons why the dimensionality of a feature vector cannot be too large: first, the computational complexity would become too great; second, increasing the size would eventually lead to a decrease in performance [13]. To reduce the dimensionality of the feature space, there are two different approaches. One is to discard certain elements of the feature vector and leave the most representative ones. This type of reduction is feature selection [14]. The other is called feature extraction, in which the original feature vector is converted into a new feature vector using a special transformation and the new features have much smaller dimensions

IV. SIMULATION

The simulation in the first stage is run-to-fail (RTF), which means that wells are maintained only after an accident occurs, and the goal of RTF simulation is to generate a large volume of telemetry and repair data. Machine learning (ML) models are then trained on the telemetry and repair logs to predict which production wells are likely to fail soon. Once the machine learning models are built, the simulation is repeated in predictive maintenance mode, which uses these machine learning models to mark those wells that are likely to fail soon and then assigns available service personnel to perform preventive maintenance on the marked wells.

A. *Initial Data*

The input data for the task is generated in the form of an excel spreadsheet with the following well parameters: number of SRPs, number of time steps, time interval each sensor has to wait before sending any telemetry, maintenance strategy used in the simulation, number of technicians available to service oil wells, and time needed for technicians to repair the well where an emergency failure has occurred.

B. *Simulation results and discussion*

Well flow rates decrease over time due to oil accumulation, and production is also interrupted when emergencies occur and they are repaired, as shown in the graph of well No. 123's production efficiency over time.

Figure 7. Processing capacity graph over time for machine 123

Different problems by design are more or less likely in different parts of the temperature, pressure and load parameter space, and the following scatter diagram shows that plough jamming is most likely to occur when the load on the pump rods becomes large.

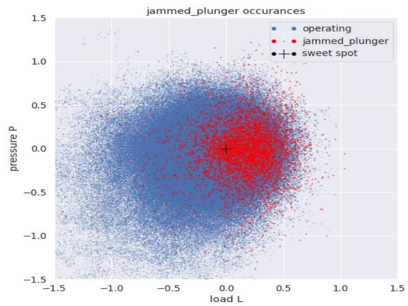

Figure 8 Scatter diagram of the "Plunger jamming" incident

The scatters of failures and deviations had to be compiled over the simulation period in terms of classify failures rapidly and accurately in the future

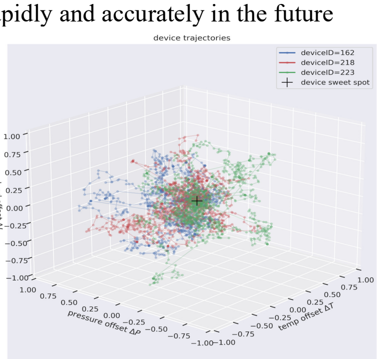

Figure 9 Load simulation results to process parameters

The result of the simulation is shown above, depending on the current process parameters during loading and the identification of the optimum parameter in the process, which ensures optimal operation of the pump in order to avoid failures.

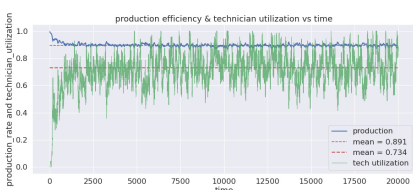

Figure 10. Production efficiency and the use of technicians with a predicate

As can be seen from the graph, the average use of technicians for repairs due to the failure of the SRP has decreased, and the average efficiency of production has also increased.

C. Testing and validation of simulation results

The quality of algorithm performance is verified by methods known in machine learning: MAPE, MSE, RMSE The mean absolute percentage error (MAPE), also known as the mean absolute percentage deviation (MAR), is a measure of prediction accuracy of a prediction method in statistics, such as in trend estimation, also used as a loss function for regression tasks in training an algorithm. It usually expresses accuracy as a percentage, and is defined by the equation:

$$\mathrm{MAPE} = \frac{1}{n}\sum_{1}^{n}\frac{\left|Y_i - \hat{Y}_i\right|}{Y_i} \qquad (2)$$

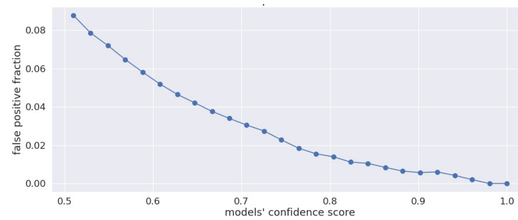

Figure 11 quality of the Simulation algorithms

The simulation result shows that we are able to reduce the MAPE error to 0.01 % (fig 11). At the same time, the number of training cycles can be reduced, as already after 10 training cycles, the model losses are no longer significant.

Based on the results of the ML training experiments, model number 3 can be selected for further testing on online data in the SCADA system. For this purpose, the model was saved on TensorFlowServing. New data are fed to the model by means of API requests in JSON format and the result from the trained model was fed back to any SCADA, where graphs were already built based on previous readings and predicted values.

ACKNOWLEDGMENT

This research was conducted during the master's and PhD thesis of Satbayev University and the focus in simulation thanks to open data access and the support of al-Farabi Kazakh National University

REFERENCES

[1] Oil and Gas Information and Analysis Centre. Infographics // Nur-Sultan, 2020.

[2] NC Kazmunaigas JSC. Annual Report 2019 // Nur-Sultan, 2020.

[3] David Wethe 'Nodding donkeys' challenged to pump oil from horizontal wells // Bloomberg Dec. 15, 2017

[4] Shinyakov Y., Sukhorukov M., Torgaeva D., Soldatov A. Methods and means of control of the rod pump operation // International Journal of Engineering and Technology, 2018

[5] V.D. Kovshov, M.E. Sidorov, S.V. Svetlakova, Dynamometry, modelling and diagnostics of the deep rod pumping unit condition //

[6] D.O. Bruno, M.Z.D. Nascimento, R.P. Ramos, V.R. Batista, L.A. Neves and A.S. Martins, LBP operators on curvelet coefficients as an algorithm to describe texture in breast cancer tissues, Expert Systems with Applications. 55 (2016) 329–340.

[7] F. Li, F. Fang and G. Zhang, Unsupervised change detection in SAR images using curvelet and L1-norm based soft segmentation, International Journal of Remote Sensing. 37 (14) (2016) 3232–3254.

[8] Y. Li, Q. Yang and R. Jiao, Image compression scheme based on curvelet transform and support vector machine, Expert Systems with Applications. 37 (4) (2010) 3063–3069.

[9] Khakimyanov M.I., Pachin M.G., Monitoring of sucker-rod pumping units condition by the results of wattmetrogram analysis // Electronic scientific journal "Oil and Gas Business" № 5, 2011
[10] Dunayev I.V., Diagnostics and monitoring of downhole sucker-rod pumping unit condition on the basis of dynamometry and neural network technologies // Department of Technical Cybernetics at Ufa State Aviation Technical University, 2007[in Russian]
[11] A.G.Rzaev, S.R.Rasulov, A.M.Abdurakhmanova // Research of deep pump condition diagnostics, Institute of Control Systems, Azerbaijan State University of Oil and Industry, 2016
[12] K. Feng, Z. Jiang, W. He and B. Ma, A recognition and novelty detection approach based on Curvelet transform nonlinear PCA and SVM with application to indicator diagram diagnosis, Expert Systems with Applications. 38 (10) (2011) 12721-12729.
[13] van der Heijden, F., Duin, R., De Ridder, D., & Tax, D.. (2004). Classification parameter estimation and state estimation: An engineering approach using MATLAB. John Wiley & Sons Inc.
[14] Theodoridis, S., & Koutroumbas, K. (2003). Pattern recognition. New York: Academic Press.
[15] Bubnov M., Zuzev A. Means of diagnosing equipment of rod deep-well pump installations // Proceedings of the First Scientific and Technical Conference of Young Scientists of the Ural Power Engineering Institute. Yekaterinburg, 2016. [in Russian]
[16] Barkov A., Barkova N., Borisov A. Methods for diagnostics of mechanisms by electric current consumption // North-West Educational Center. Saint Petersburg, 2012.)[in Russian]