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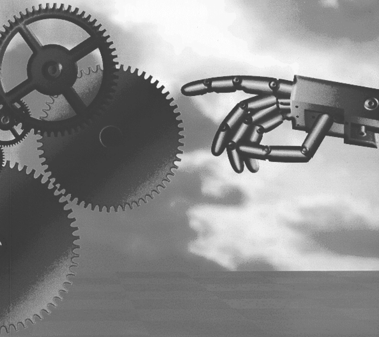

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Springer

Faults Identification of Oil Wells Using Neural Networks

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Abstract. Oil well diagnosis usually requires sophisticated tools and specialized sensors placed on the surface and in the bottom of the well. The purpose of this study is to identify oil well parameters based on the measurement the terminal characteristics of the electrical motor. The quality of the oil well could be monitored continuously and proper adjustments could be made. Such approach may lead to significant savings in electrical energy, which is required to pump the oil. With this approach, motors with smaller nominal power can be used instead of overrated motors operating at a fraction of their nominal power. The application of this new technology could lead to constant and effective monitoring of oil wells. These approach leads to better diagnosis, adjustment, choice of an optimum pumping rate, and more efficient use of energy.

1 Introduction

Several techniques are used for oil well diagnosis. These approaches usually require sophisticated tools and introduce specialized sensors placed on the surface and in the bottom of the well [1][2]. Recently, there is a significant interest in identifying characteristics of the oil well using neural networks [3]-[13]. Neural networks are also used for identifying faults of electrical motors, which are used to drive the oil pump. Such diagnosis of electrical motors, using their terminal parameters is already very advanced [14]-[20].

The purpose of this study is to identify oil well parameters based on the measurement of the terminal characteristics of the electrical motors. This approach does not require special instrumentation and can be used on any oil well with a pump driven by an induction motor. The quality of the oil well could be monitored continuously and proper adjustments could be made. Such approach may lead to significant savings in electrical energy required to pump the oil.

2 Oil well model

It would be very difficult and definitely very costly to introduce fault in real oil wells (Fig. 1). Therefore, a very complex model of an oil well was developed, so that all possible faults can be easily introduced. For the induction motor, the relatively simple, third order model was used. In addition to the three motor state variables, four state variables for the pumpjack were used: angular flywheel velocity, angular flywheel acceleration, beam angle, and beam angular velocity. Note that a relatively complex nonlinear relationship must be used between the angular position of the gear flywheel and the angular position of the pumpjack beam. For deep wells, the diameter of the sucker rod changes and this leads to different stiffness and different mass for every section of sucker rod. This distributed parameter system can be properly approximated by lumped six state variable systems representing displacement and velocities of sucker rod sections. Oil flow in the tube can be modeled by two additional state variables representing displacement and velocity. A three-dimensional model of oil flow through the formation can describe oil pressure distribution around the well. If radial uniformity is assumed, this problem can be reduced to a one-dimensional distributed parameter case, which can be well approximated with 10 state variables representing oil pressure for 10 different distances from the well. Overall the entire system is described by a 25-order system of differential equations and 25 state variables.

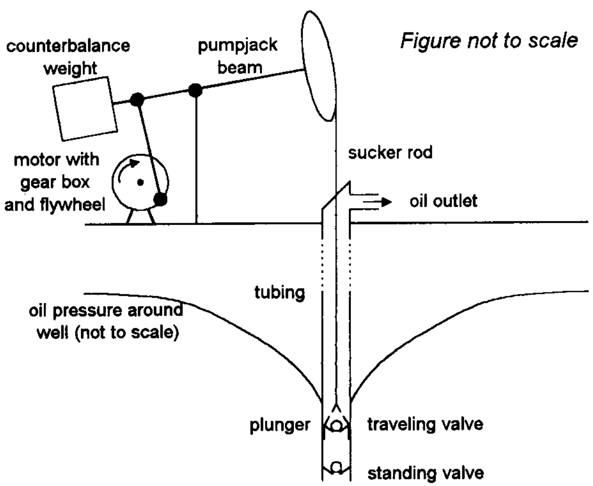


Fig. 1. Oil well with pump jack.

There are very different time constants in the system. An induction motor operates at 60 Hz and typical time constants are of the order of 0.1 to 0.2 s. A pumpjack operates with cycles varying from 5 to 20 seconds. Transient responses in the well itself have time constants from several hours to several weeks, or even years, when the well capacity is considered. Significant differences in time constants make the system very stiff and difficult to analyze. Traditional forward Euler or Runge-Kuta methods would require the use of very small time steps and an unrealistically long simulation time. Such stiff dynamic systems require implicit integration methods. The key issue was to find an efficient method to simulate this very large set of nonlinear differential equations. It turned out that there is a very simple and efficient solution. Instead of developing dedicated code in FORTRAN or in C the entire system was simulated using the SPICE program, which has an excellently developed algorithm to handle very stiff dynamic systems with second order Gear integration scheme.

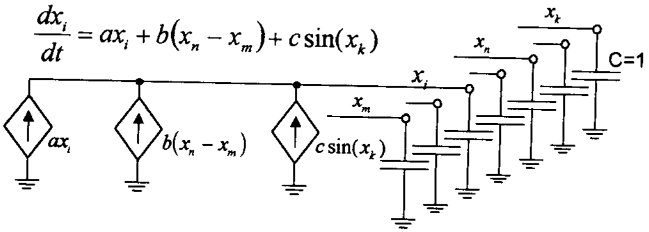


Fig. 2. Equivalent diagram for differential equation used in SPICE program. Voltage on each capacitor represents one state variable.

The approach is illustrated by the example with the equivalent circuit for an i-th differential equation for the state variable x_i is shown on Fig. 2. Note that recent versions of SPICE programs have nonlinear dependent sources. In the case shown in Fig. 2. three dependent current sources could also be combined into one, controlled by a nonlinear expression of many variables. The system of 25 differential equations is relatively complex, but the simulation time for one set of parameters is usually completed within 15-30 seconds on the Pentium 200MHz computer using PSPICE program version 7.1.

3 Data preprocessing and generation of training patterns

Sample results of oil well simulations using the complex model are shown in Fig. 3 and 4. Fig. 3 shows transient responses during operation in normal conditions and Fig. 4. shows the same responses with a leakage of the traveling valve. Note the significant differences, especially in Fig. 3 (d) and Fig. 4 (d). Unfortunately the measurement of such parameters at the bottom of the well is not easy. The purpose of this work was to identify oil well parameters by sole measurements of the terminal parameters of the induction motor and to use neural networks for data processing.

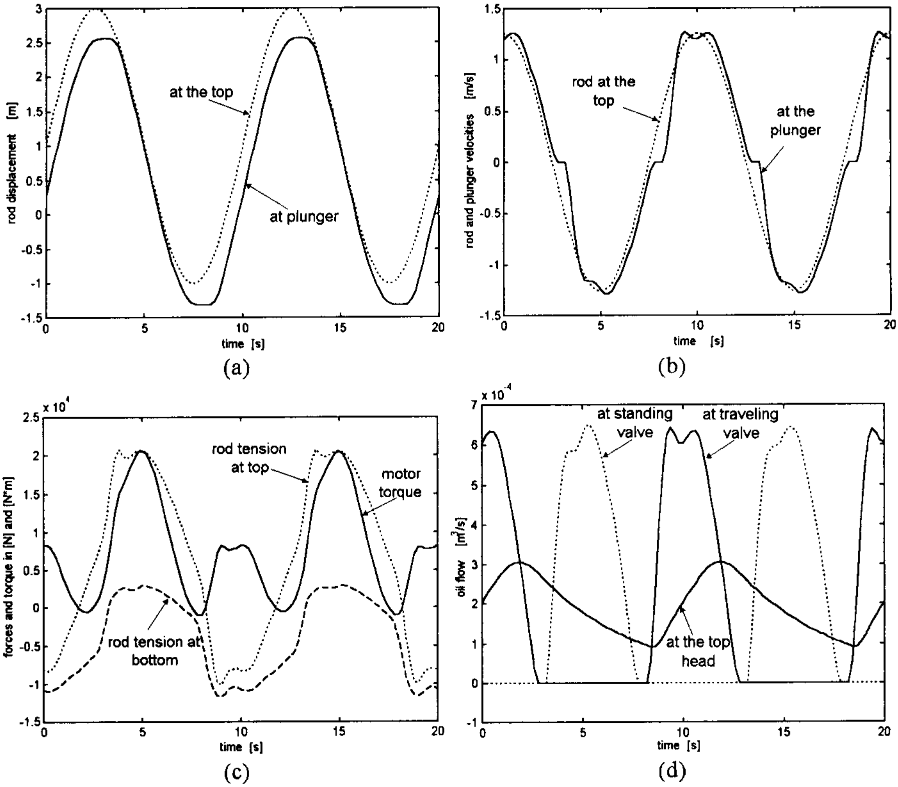
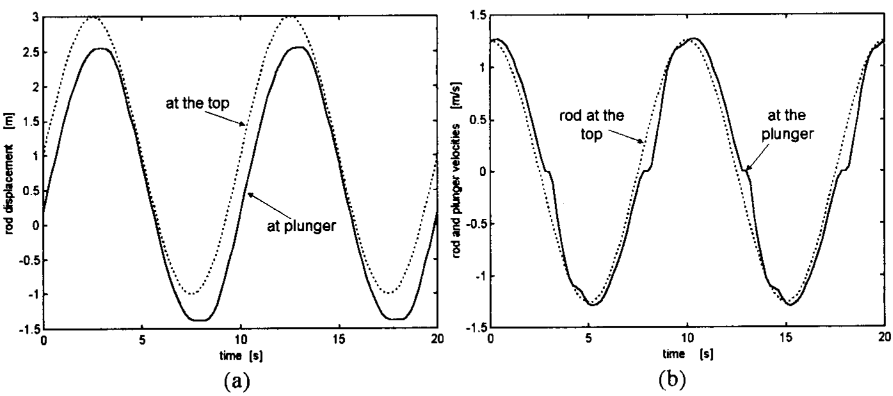
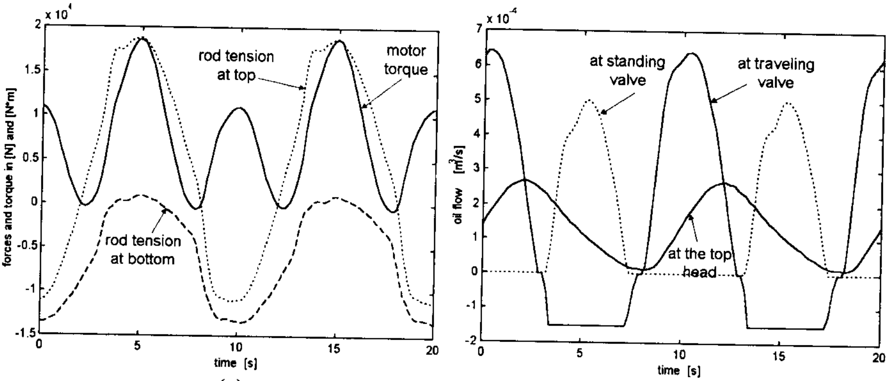


Fig. 3. Results of simulation of the 1500m deep oil well in normal condition (a) sucker rod displacements, (b) sucker rod velocities, (c) forces and torques, and (d) oil flow.

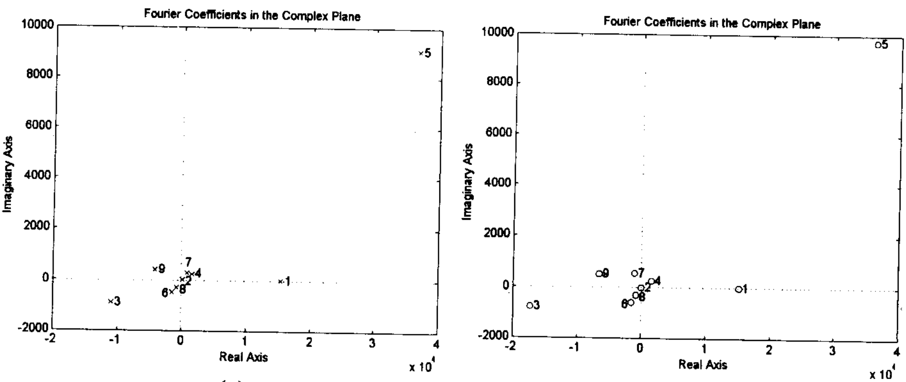




(c) (d)

Fig. 4. Results of simulation of the 1500m deep oil well with leaking traveling valve (a) sucker rod displacements, (b) sucker rod velocities, (c) forces and torques, and (d) oil flow.

Measurement of currents and voltages at terminals of the three-phase induction motor operating at 60Hz leads to the collection of tremendous amounts of data. It turns out that most of the important information is contained in the instantaneous power of the induction motor [18]. The data for the transient waveform of the instantaneous power is processed with FFT (Fast Fourier Transform). The Fourier coefficients on the complex plane are generated, as shown in Fig. 5. Since this mechanical system includes several large masses with inertia the system works as high order low-pass filter, therefore, only the first nine Fourier components is used. As a result, each instantaneous power waveform is represented by 19 numeric values: 9 real, 9 imaginary, and one representing the dc offset. These 19 values were used as the input pattern for the neural network

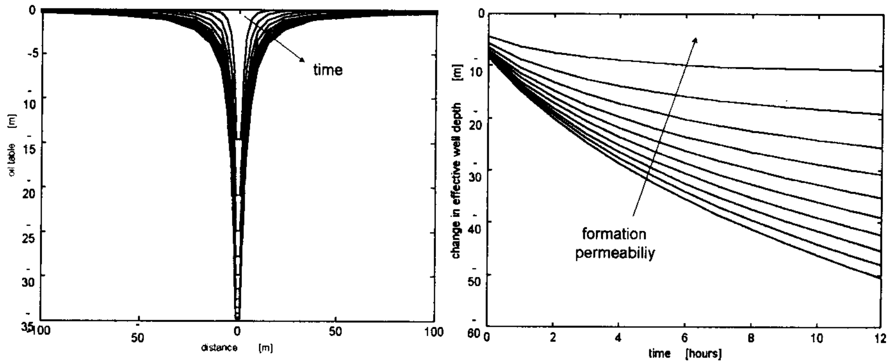


(a) (b)

Fig. 5. Conversion of instantaneous power waveform into Fourier coefficients: (a) case with normal operation and (b) case with leaking traveling valve.

4 Neural network architecture and training

All neural network processing was done using SNNS software, which can be acquired free of charge from http://www.informatik.uni-stuttgart.de/ipvr/bv/projekte/snns/snns.html Various feedforward architectures were explored with one pattern file used for training and with another pattern file used for verification. All input and output patterns were scaled in such a way that input and output values changed within the -1 to +1 range. Good results were obtained using a two hidden layer neural network with full connections across layers with 5 neurons in each hidden layer. Several different training algorithms were explored such as Backpropagation [22], Quickprop[23], RPROP[24], Backpercolation[25], and Conjugate Gradient Method[26]. It turned out that for this case the most efficient was the RPROP algorithm.



(a) (b)

Fig. 6. Oil pressure distribution in vicinity of the well: (a) spatial distribution around well with pumping time as parameter and (b) transient response of the pressure in the well with soil permeability as parameter.

The leakage of the traveling valve, the leakage of the standing valve, the effective oil depth, and the location of balance mass on the beam, were four outputs of the neural network. Initially, both training patterns and verification patterns were generated in such way that for each pattern only one variable (for example, leakage of the traveling valve) was modified and the remaining parameters had normal values. In this case the neural network was able to identify the correct fault in 100% cases. More importantly the neural network was also able to identify how much a certain parameter has deteriorated. For example, what is the leakage, what is the effective depth, or what is the location of the balance mass. The accuracy of this identification varied from 10 %, in the case of the effective oil depth, to 50%, in the case of the standing valve leakage.

For the next experiment all four faults were introduced simultaneously by randomly chosen values. In this experiment correct results were obtained only if there was one clearly dominant fault. When several faults were present, then the neural network was often confused and misidentified faults. This means that there are strong interactions of a nonlinear nature between the parameters.

Fortunately, three of four of the investigated parameters (the leakages and the mass location) can be assumed constant during experiments, which leads to the identification of formation permeability and reservoir capacity. As Fig. 6 (a) shows the pressure distribution around a well changes with the pumping time. The only parameter, which can be observed in the wellbore, is the effective depth of the oil table. Fig. 6 (b) shows how the effective oil depth changes with time for different values of the formation permeability. From such transient responses it is possible, using well-established techniques [27][28], to estimate formation permeability and drainage-area pressure, the reservoir heterogeneity or boundaries.

5 Conclusion

The terminal parameters of the induction motor contain significant information about the oil well, which can be extracted using neural networks. This information is not only about the condition of the oil reservoir, but it may lead to better adjustments of the pump and its ballast so the pumping can be done more efficiently. With this approach, motors with smaller nominal power can be used instead of overrated motors operating in a fraction of their nominal power. The application of this new technology could lead to constant and effective monitoring of oil wells. Measurements may lead to better diagnosis, adjustment, choice of the optimum pumping rate, and more efficient use of energy.

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