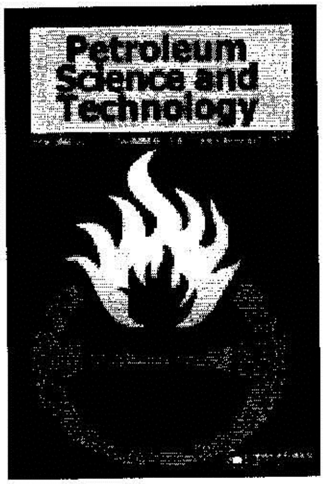

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The Identification of Data Distribution in Oil Production

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Abstract *This article suggests nonparametric criteria for diagnosing changes in process condition based on analysis of data variation.*

The developed criteria allow diagnosing changes in conditions of the studied process in cases of data distribution skewness, as well as cases when application of other criteria is not correct or complicated.

The suggested statistical criteria allow simplification of process diagnosis, which are described by multifractal, chaotic fluctuations, and their calculation algorithm can be easily realized.

The applicability of the diagnostic criteria has been proven both in modeled and practical examples of oil production.

Keywords diagnosing, distribution, nonparametric criteria, oil well, skewness, variations

1. Introduction

The complexity of dynamic systems and processes is related to infinite variation of their condition under outer and inner impacts (Haken, 2004). Many natural and technological processes fall under this definition, including oil and gas production processes (Mirzajanzadeh et al., 1997, 1999). These processes require permanent control of main technological data and timely reaction to variations in their condition.

With the development of IT, diagnostic methods were involved in the solution of such tasks, which help to effectively manage technological processes.

Methods of diagnosing dynamic processes can be divided into two main groups (Barkova, 1986): test methods, based on studying the reaction of a given process to artificial outer impacts, and functional diagnostic methods, based on studying natural passing of the process.

However, the use of test diagnostics may be associated with technical and technological difficulties, extra financial expenses, etc. The abovementioned predefines the necessity of using functional diagnostic methods, allowing assessment of both the condition and characteristics of the dynamic systems based on the production data (Mirzajanzadeh et al., 1997, 1999).

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One such method is the energetic method, which is based on measuring the power or amplitude of the controlled signal (Bendat and Piersol, 1971). Temperature, pressure, noise, vibration, and many other parameters may be used as diagnostic signals. Technology is built on measuring the degree of the signals in the controlled points and comparing them with threshold values.

A further development is amplitude–frequency technology (Bendat and Piersol, 1971), which offers allocation of measured signal constituents in a given frequency ranges and allows assessment of the condition and degree of nonequilibrium and self-organization of a reservoir formation system based on specific features of fluctuations as well as diagnosis of fluid movement, which aids in decision making regarding their management (Mirzadjanzadeh and Sultanov, 1995; Mirzajanzadeh et al., 1997, 1999).

In statistics, two types of criteria are used: parametric, based of statistical parameters of given sampling (such as dispersion, variation coefficient, normalized deviate, Theil criterion, etc.), and nonparametric, which are functions that are directly dependent on the values of studied data aggregates and their frequencies. Parametric criteria are used for verification of hypotheses regarding the aggregates parameters, which are distributed according to normal law, and nonparametric criteria are used for verification of hypotheses independent of the shape of the aggregate distribution (Jensen et al., 2000).

The use of parametric criteria (Mirzajanzadeh et al., 1997; Jensen et al., 2000) for analysis of natural processes is not always correct. Their use is valid only if the studied time series submits to a normal distribution. However, it is often difficult to discuss analyzed data subjugation to a definite distribution law (Mandelbrot, 1997).

The present work suggests nonparametric criteria for diagnosing the state of dynamic systems based on technological parameter fluctuation analysis.

2. Nonparametric Criterion of Identification of the Well Data Distribution

The principles of assessment of dynamic systems variation is based on the following. Let us assume that some dynamic process is being analyzed and is represented by n time series of some y parameter values.

Initial data are ranked in increasing order. Then the ratio of the square of the obtained curve deviation from a straight line distribution is determined, which connects points $(1, y_{\min})$ and $(n, y_{\max})$ to the square of abc triangle, with coordinates of $a(1, y_{\min})$, $b(n, y_{\max})$, and $c(n, y_{\min})$:

$$S = \frac{s_1 + s_2}{s_{\Delta abc}} = \frac{s_1 + s_2}{0.5 \cdot (y_{\max} - y_{\min}) \cdot (n - 1)} = \frac{2(s_1 + s_2)}{(y_{\max} - y_{\min}) \cdot (n - 1)},$$

where $y_{\max}$ is the maximum value of y; $y_{\min}$ is the minimum value of y; n is the number of values; s_1 and s_2 are the magnitudes of squares between ranked values of the studied parameter and an even straight line distribution; and $s_{\Delta abc}$ is the square of the abc triangle (Figure 1).

S values vary in intervals from 0 to 1. Several dynamic processes comparison with various numbers of measurements allows using the following calculation algorithm of S criterion.

Initial data are ranked in increasing order and are normalized relative to maximum and minimum values of $Y_i = \frac{y_i - y_{\min}}{y_{\max} - y_{\min}}$, where $i = 1, 2, \ldots, n$. The numbers of N_i ranked

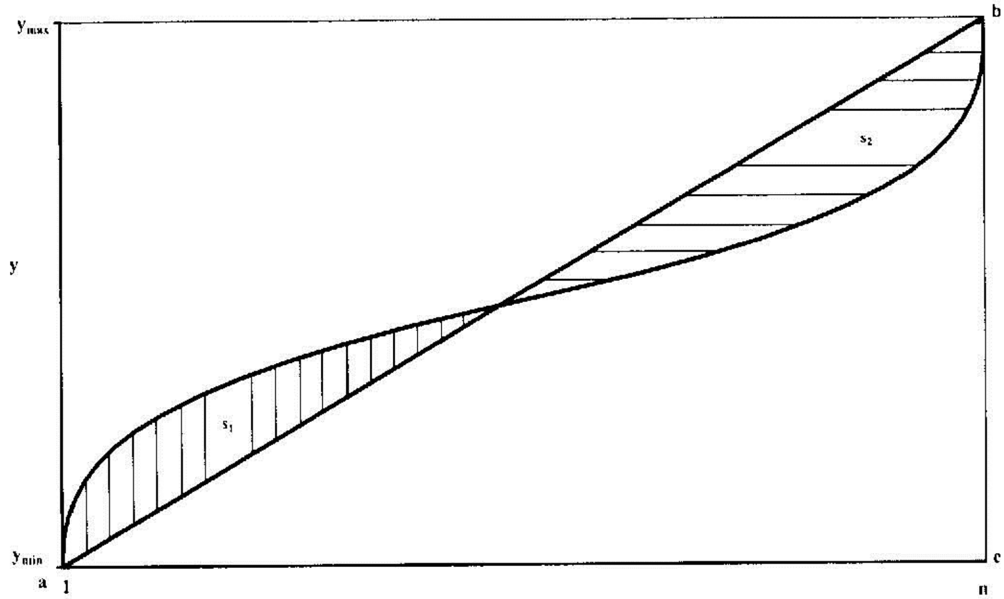

Figure 1. Ranked data curve.

values of are normalized in a similar way. Y_i and N_i values vary from 0 to 1 (Figure 2).

Such transformation (normalization) of initial data does not impact the shape of their distribution and allows visually presenting variations in the data distribution with different numbers of measurements and different maximum and minimum values.

Then the ratio of the square of the obtained curve deviation from a straight line distribution is determined, which connects points (0, 0) and (1, 1), to the square of the

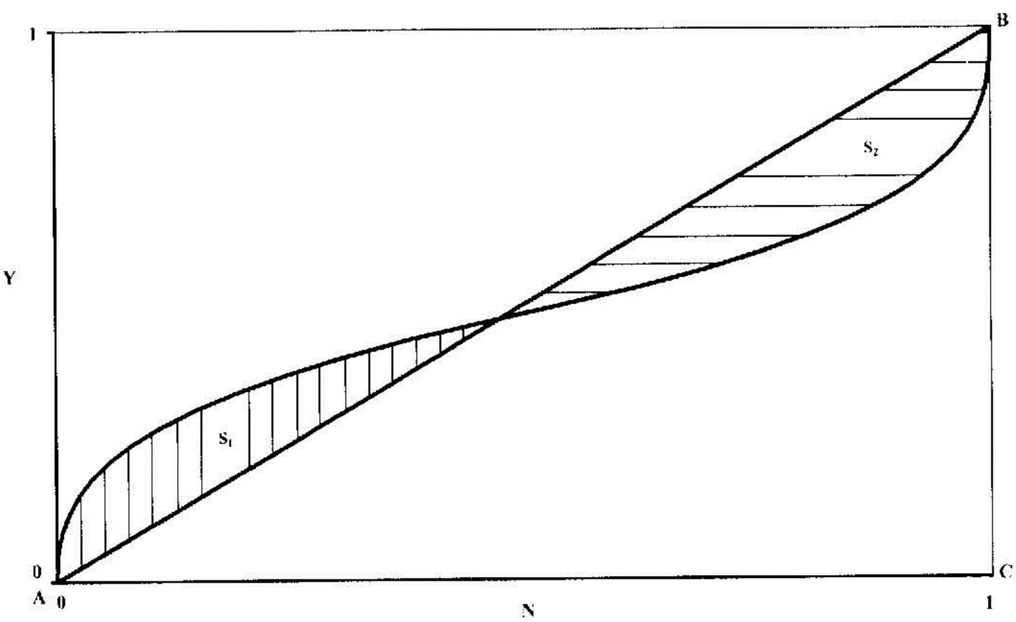

Figure 2. Normalized ranked data curve.

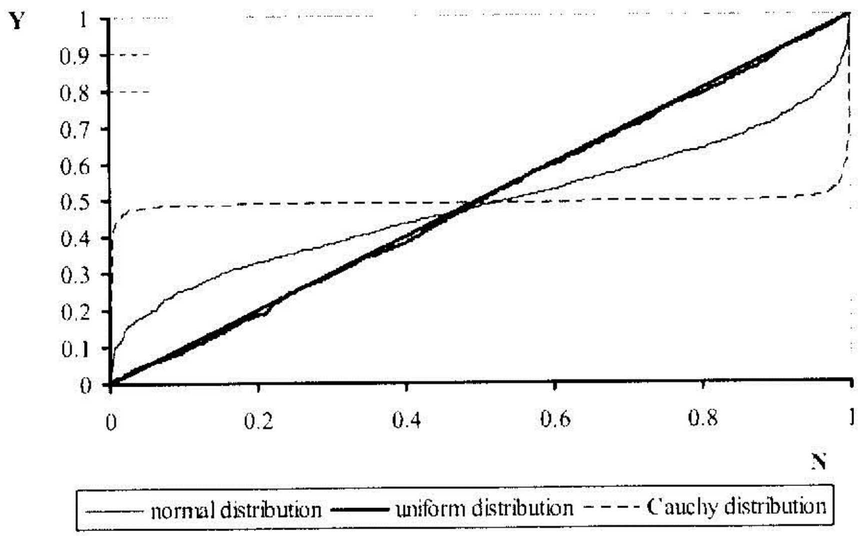

Figure 3. Ranked normalized data.

ABC triangle, with coordinates of $A(0, 0)$, $B(1, 1)$, and $C(0, 1)$:

$$S = \frac{S_1 + S_2}{S_{\Delta ABC}} = 2(S_1 + S_2),$$

where S_1 and S_2 are the magnitude of the squares between normalized ranked values of the studied parameter and an even straight line distribution; and $S_{\Delta ABC}$ is the *ABC* triangle square (Figure 2).

One can judge the variation of the dynamic system's condition based on variations in the S value. As an example of suggested criterion application, let us consider three types of data distribution: normal, uniform, and Cauchy distributions.

Figure 3 shows ranked data, which subjugate to normal, uniform, and Cauchy distribution functions. S criterion values are 0.215, 0.015, and 0.485, respectively. It is obvious from the given example that the suggested S criterion responds very well to the variations in distribution types.

The advantage of this approach is that it can be used for data that are transformed by different trend removal methods.

3. Assessment of Data Distribution Skewness

An important advantage of this approach in comparison with others (Klikushin, 2000) is that it can be used to analyze data with a skewed distribution.

The degree of skewness can be assessed using the following equation:

$$A_s = \frac{S_2 - S_1}{S_1 + S_2}$$

where S_1 and S_2 are the magnitude of the squares between the ranked normalized values of the studied parameter and an even straight line distribution (Figure 2).

The A_s value varies from -1 to 1. As an example, let us consider cases of nonsymmetrical distributions with right- and left-sided skewness. Figure 4 shows ranked data with right- and left-sided skewness, subjugating to same distribution law.

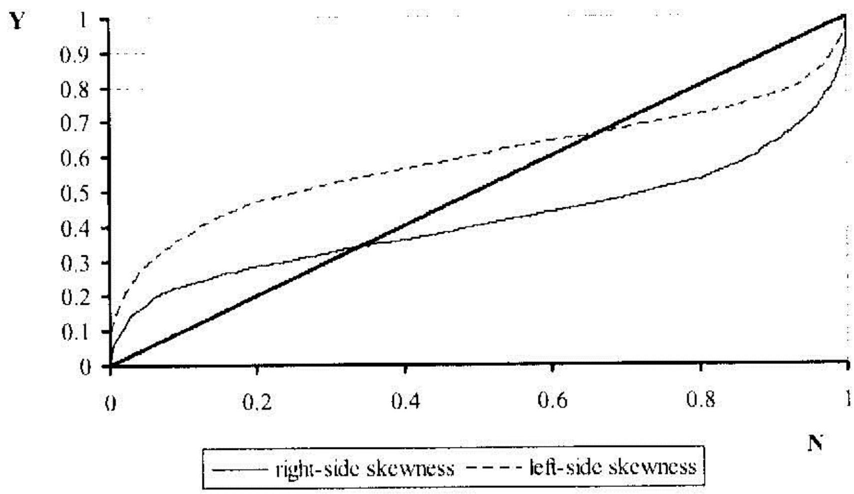

Figure 4. Ranked normalized data: 1, right-sided skewness; 2, left-sided skewness.

A_s coefficient values for the presented data are 0.608 and −0.608, respectively, and S parameter values in both cases are 0.283.

4. Analysis of Technological Data

As a practical example, let us apply the suggested methods to retrospective analysis of dynamic of watercut of an oil well.

Watercut is the ratio of water produced compared to the volume of total liquids that come out of a producing well (Dake, 2001). The content of water in oil that comes out of an oil well has a negative impact on the production of oil and gas. Early time prediction of possible watercut allows proper management of the performance of a given well. Well testing methods help to estimate the movement of the water front to a given well; however, these methods are very expensive and are not always reasonable.

Figure 5 shows measurements of well head pressures of an oil well taken in July 2005 and July 2006.

The values of suggested parameter S for the given data significantly differ and equal 0.261 and 0.189, respectively (Figure 6). Skewness A_s equals 0.877 and −0.187, respectively.

Analysis of obtained results allowed assuming that qualitative changes were taking place in the reservoir–well system's behavior. Further production from the well indicated that fluctuations in this particular case were related to the start of water breakthrough.

Hence, on the basis of the application of the suggested methods for analysis of fluctuations of technological parameters it is possible to diagnose the changes in well performance.

5. Conclusions

The developed criteria allow diagnosing changes in conditions of the studied process in cases when application of other criteria are not correct as well as for cases of data distribution skewness.

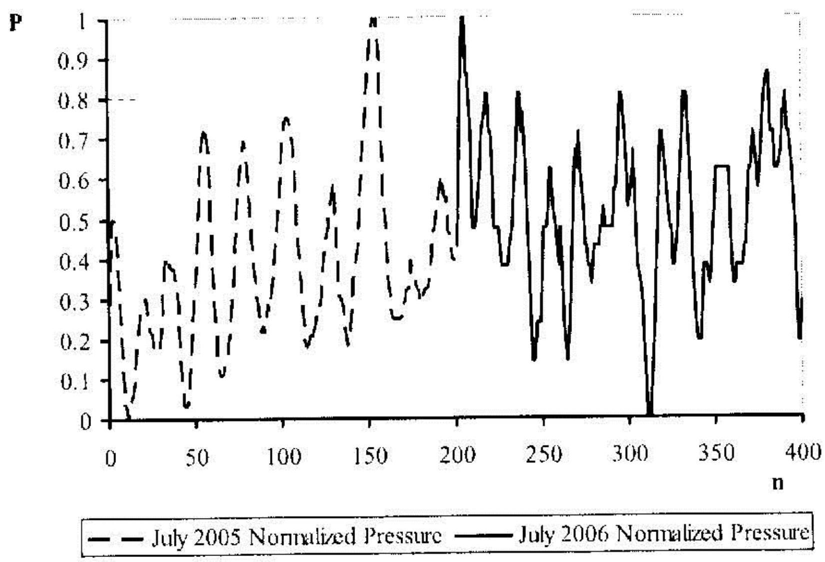

Figure 5. Dynamics of well head pressure (normalized).

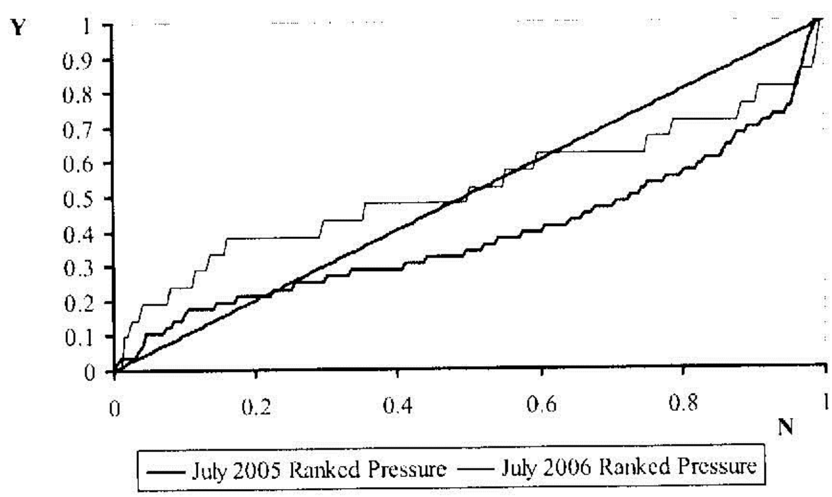

Figure 6. Ranked normalized well head pressure data.

The advantage of the suggested approach is that it can be used for data transformed by different methods of trend removal. Applicability of the diagnostic criteria has been proven in both modeled and practical examples of oil production.

The suggested statistical criteria allow simplifying the diagnosis of processes that are described by multifractal, chaotic fluctuations, and their calculation algorithm can be easily realized.

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