

Список использованной литературы:

1. Методы классической и современной теории автоматического управления / под ред. К. А. Пупкова, Н. Д. Егупова. — М. : Изд-во МГТУ им. Г. Э. Баумана, 2004. — Т.1. Мат. модели, динамическое характеристики и анализ систем автоматического управления. — 656 с.: ил.
2. Михайлов Ф. А. Теория и методы исследования нестационарных линейных систем / Ф. А. Михайлов. — М. : Наука, 1986. — 319 с.
3. Верлань А. Ф. Интегральные уравнения: методы, алгоритмы, программы. Справочное пособие / А. Ф. Верлань, В. С. Сизиков. — К. : Наук. думка, 1986. — 544 с.

The article examines the questions of representation and the relationship of time and frequency integrated model which provides an effective apparatus for studying the characteristics of dynamic systems with variable and constant parameters.

Key words: *dynamic system, frequency form of integral models, time form of integral models.*

Отримано: 27.03.2015

O. Ustun*, Ass. Prof.,
M. Yilmaz**, Ass. Prof.,
P. Ali Zada***, Prof. Dr.,
R. N. Tuncay***, Prof. Dr.

*Istanbul Technical University, Istanbul, Turkey

**University of Illinois at Urbana-Champaign, IL, USA

***OKAN University, Akfirat Campus, Istanbul, Turkey

NOISES CANCELLING ADAPTIVE METHODS IN CONTROL TELEMETRY SYSTEMS OF OIL ELECTRICAL SUBMERSIBLE PUMPS

The main ideas of this paper are that only some from more than 10 *MATLAB* Adaptive Methods library may be useful and can be recommended to filter out High-Noise in similar Control Telemetry Channels of Electric Power Components like ESP Systems: only four of applied have shown successfully good results in the early prediction of the ESP motor real insulation disruption (like *Sign-error*, *Sign-data* and *Sign-sign* filters). The best among the ten analyzed adaptive filter algorithms was recognized to be, The Normalized LMS FIR filter algorithm — *adaptfilt.nlms*.

Key words: *signal, noise, adaptive methods, oil industry, submersible pump, communication-telemetry channels.*

Introduction. More than a thousand switchboards of Electro-submersible Pump (ESP) under different trademarks are running in the oil fields. There are complicated electronic complexes for installing oil well

boreholes for operational duty as well. To predetermine supporting parameters during oil production at well borehole simultaneously is the main problem. The ESP submersible telemetry system usually allows for the obtaining of information on the pump unit's intake pressure, temperature and most importantly for a submersible motor stator coil, its insulation resistance, for the successful exploitation of the oil complexes in the neighborhood of different types of heavy electromagnetic noises such as: random, pulsing, harmonic, etc. [1–3; 7–9; 23].

Increasing disturbance levels with corrupted analog telemetry result in an increasing noise level, but it's often still 'audible' or the control is still reliable. Digital telemetry technology is much better in suppressing disturbances but up to a certain level. With increasing disturbance levels, the analog signal will remain low, but audible. However, beyond a certain disturbance level, the digital telemetry and control stops abruptly. This, the so called 'digital cliff' (point *C*) makes it more complicated with digital telemetry to know as the disturbance critical level, before the digital telemetry and control unexpectedly stops. The analog signal after point *C* will be lower, but still audible, and the control system is still reliable [23].

Here, an analog signal processing implementation is studding for the detection of the most efficient adaptive noise-cancelling filters among dozens of well known in *MATLAB* for telemetry control of oil industry power complexes under severely noisy conditions. A useful approach to this filter-optimization problem is to minimize the mean square value of the error that is defined as the difference between some desired signal and the filter's actual output.

There are many noise cancellation methods and applications in industrial, civil, military, power systems telemetry and the control equipment's apparatus. But the success of these noise-cancelling methods and filters depend mostly on the noise factor (signal/noise ratio) and also on the control signal character under consideration: close to random, exponential, voice, sinusoidal, etc.

Due to the mentioned 'digital cliff,' the manufacturers of powerfully controlled electrical machines unfortunately still have to on some occasion work with analog signals and equipment. This paper deals with the oil industry ESP motor (see also ATACHMENTS), in particular with its control which is working close to, or in the neighborhood of, different heavy 'jam' of electromagnetic noises such as: random, pulsing, harmonic and so on, that overwhelm (engulf) the useful signals.

As will be shown, for the ESP case, only a few of the *MATLAB* noise-cancelling methods — *Adaptive Filtering Methods* — present good real-time noise filtering results for the mentioned ESP severe noise cases. Every other apparatus case needs a special study to find the best filtering method for the particular equipment [4–6].

1. AN OBJECTIVE AND COMPARATIVE EVALUATION OF MATLAB NOISE-CANCELLING ADAPTIVE METHODS

For the comparative evaluation of MATLAB noise-cancelling (filtering) adaptive methods, here applies a twice heavier case for the study — voltages of the jam of accompanying harmonics $V_H = 10V$ each (not 3–5V) and random noise $V_{RN} = 1V$ (not 0.1–0.5V). As mentioned above, the controlled and very useful exponential variable — the parameter of the ESP motor cooling oil R-resistance signal can decay from 10V to 0.6V. All of the MATLAB Adaptive Filtering Methods presented below were one-by-one tested under the above-mentioned conditions for R-resistance decreasing exponentially the signal, corrupted by the jam of the accompanying useful signal harmonics and noises. Afterwards, the R-resistance signal is recognized and analyzed [15–18].

1.1. Analysis of Results

Thus, the signal types are: exponential, sinusoidal and random. The adaptive filter algorithms were applied to observe the value of the exponential variable parameter of the ESP motor cooling oil $R(t)$ -resistance signal — corrupted by the jam of accompanying interferences and noises. All methods were tested under a mixture of random noises and dominated harmonics for $f = 1; 2.5; 5 \text{ kHz}$.

There are two main zones in the below result curves:

1. The first zone — filter output signal at the beginning of the filter adaptation time $T_{AD} = 3 - 30$ days (not very important) which converge towards the desired exponential $R(t)$ -signal and then continuously controls it until the critical point.
2. The second zone — filter output signal at the end of the observing time — three and more months (up to a year), — till the very important critical point, when signal $R(t) \leq 0.6V$, which means that the ESP motor cooling oil resistance less than 30 kOhm — it is an extremely risky moment and the ESP must be switched off (from the maintenance instruction). It should be reminded here once again that any error in the interpretation of the $R(t)$ -signal critical point may bring a wrong and unreasonably early expensive lift of the ESP for the motor cooling oil removal and renewal service, or in the worst case of the $R(t)$ -signal critical point's late prediction — to short a circuit inside the motor, causing an emergency lift of the ESP for service and a very expensive restoration of the motor.

Unfortunately the characteristics of some of the adaptive filter algorithms have shown very low frequency ripple oscillation (like *Sign-error*, *Sign-data* and *Sign-sign filters*), which may bring additional errors in the late or early interpretations of the critical point issue. The less amplitude of this oscillation is, the better the adaptive filter algorithm (method). As

the best was recognized **Table 1** — *The Normalized LMS FIR filter algorithm adaptfilt.nlm5* [19–21].

1.2. Matlab Adaptive Filtering Methods And Their Results' Analyses

Table 1

Matlab Adaptive Filtering Methods and their results' analyses

Type of Adaptive Filter Methods	Harmonics Frequency (kHz)	Remarks
1. The Normalized LMS FIR filter algorithm (adaptfilt.nlm5)	1 ; 2.5 ; 5	The Best
2. The Sign-data LMS FIR filter algorithm (adaptfilt.sd)	2.5	Good
3. The Sign-error LMS FIR filter algorithm (adaptfilt.se)	2.5	Good
4. The Sign-sign LMS FIR filter algorithm (adaptfilt.ss)	2.5	Good
5. The Traditional LMS FIR filter algorithm (adaptfilt.lms)	2.5	Fair
6. The Delayed LMS FIR filter algorithm (adaptfilt.dlms)	2.5	Fair
7. The Adjoint LMS FIR filter algorithm (adaptfilt.adjlm5)	2.5	Very Bad
8. The FFT-based Block LMS FIR filter algorithm (adaptfilt.blmsfft)	2.5	Very Bad
9. The Filtered-x LMS FIR filter algorithm (adaptfilt.filtxlm5)	2.5	Very Bad
10. The Block LMS FIR adaptive filter algorithm (adaptfilt.blms)	2.5	Very Bad

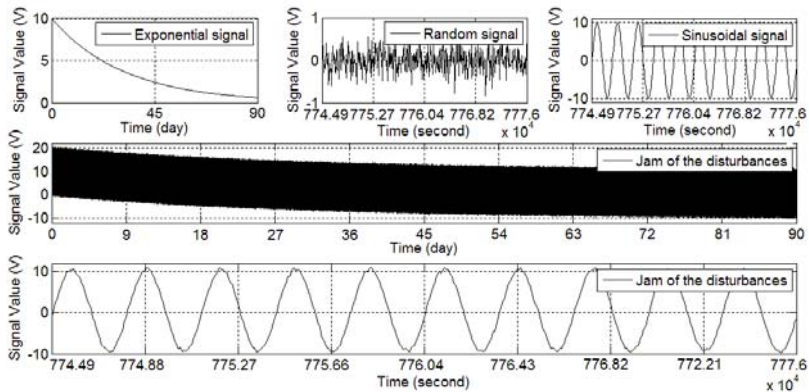


Fig. 1. Signals: useful exponential, which is corrupted by a jam of sinusoidal harmonics and random noises

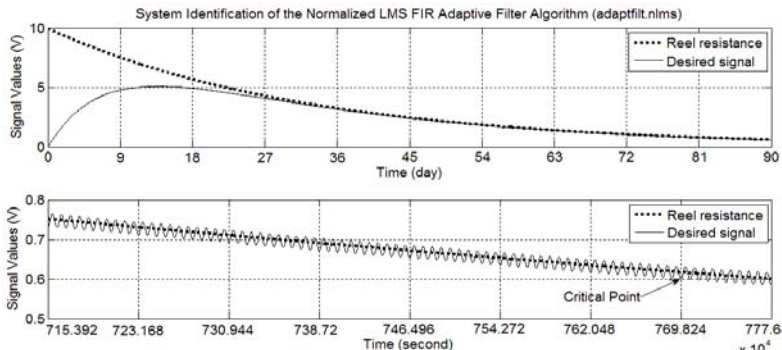


Fig. 2. The Normalized LMS FIR adaptive filter algorithm *adaptfilt.nlms* (1 kHz) (The Best)

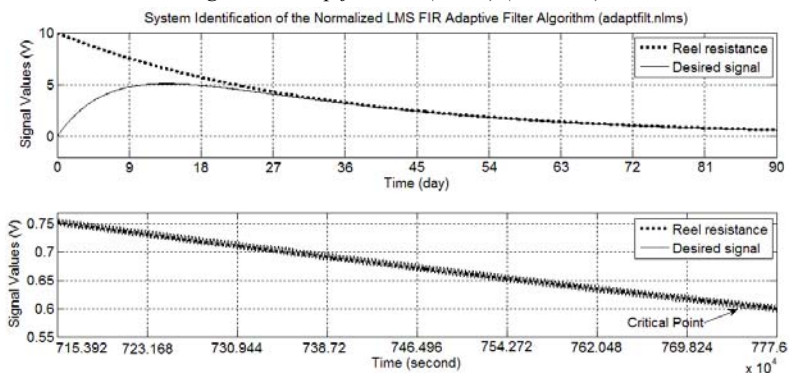


Fig. 3. The Normalized LMS FIR adaptive filter algorithm *adaptfilt.nlms* (2.5 kHz) (The Best)

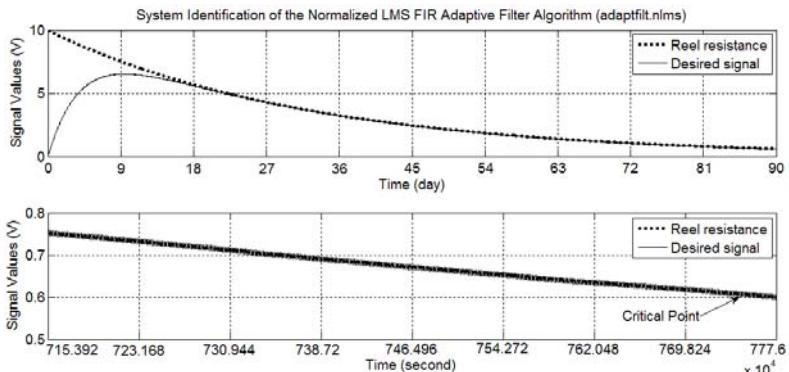


Fig. 4. The Normalized LMS FIR adaptive filter algorithm *adaptfilt.nlms* (5 kHz) (The Best)

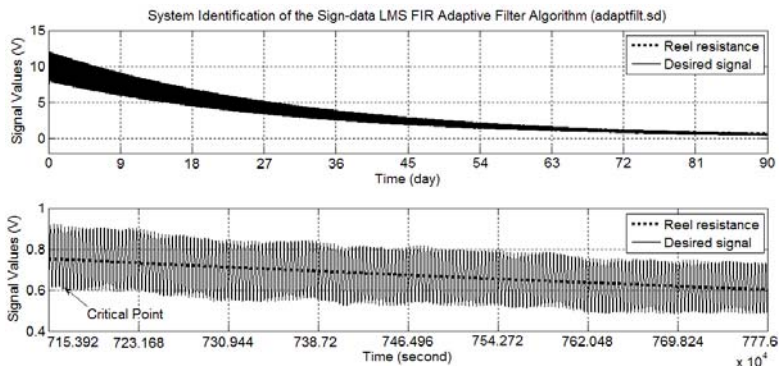


Fig. 5. The Sign-data LMS FIR adaptive filter algorithm *adaptfilt.sd* (2.5 kHz) (Very good)

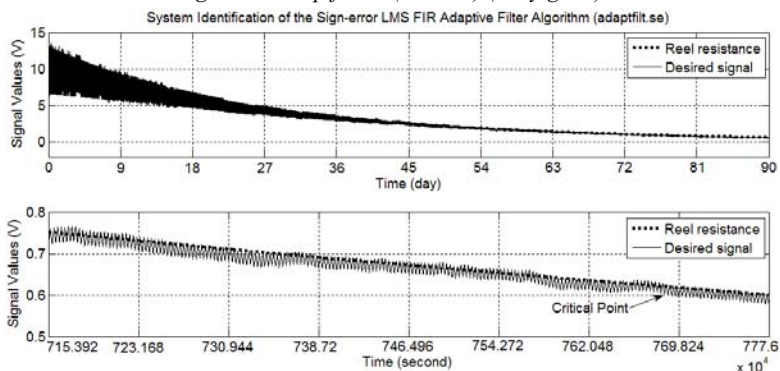


Fig. 6. The Sign-error LMS FIR adaptive filter algorithm *adaptfilt.se* (2.5 kHz) (Very good)

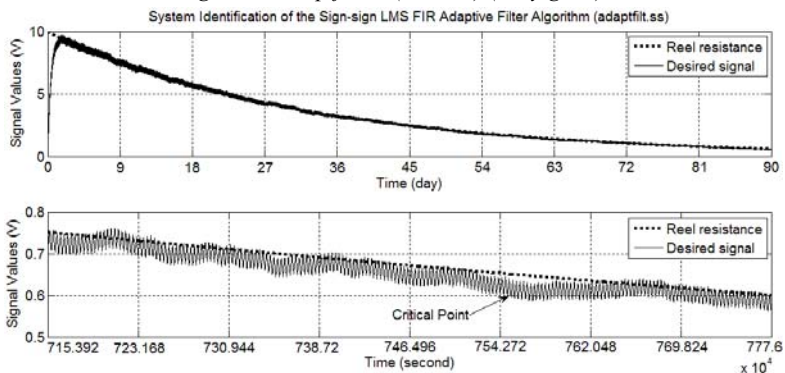


Fig. 7. The Sign-sign LMS FIR adaptive filter algorithm *adaptfilt.ss* (2.5 kHz) (Very good)

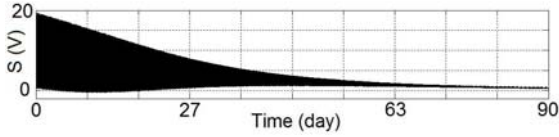


Fig. 8. The Traditional LMS FIR adaptive filter algorithm *adaptfilt.lms* (2.5 kHz) (Fair)

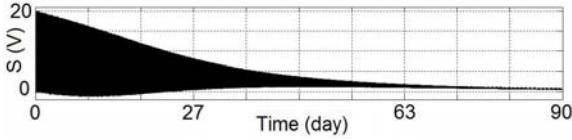


Fig. 9. The Delayed LMS FIR adaptive filter algorithm *adaptfilt.dlms* (2.5 kHz) (Fair)

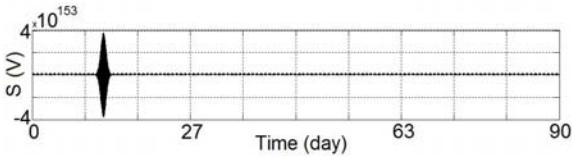


Fig. 10. The Adjoint LMS FIR adaptive filter algorithm *adaptfilt.adjlms* (2.5 kHz) (Very Bad)

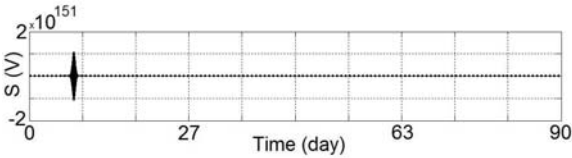


Fig. 11. The Block LMS FIR adaptive filter algorithm *adaptfilt.blms* (2.5 kHz) (Very Bad)

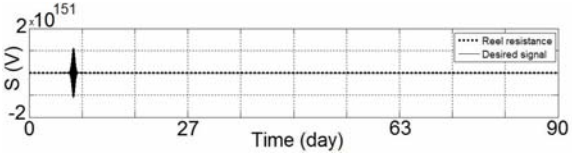


Fig. 12. The FFT-based Block LMS FIR adaptive filter algorithm *adaptfilt.blmsfft* (2.5 kHz) (Very Bad)

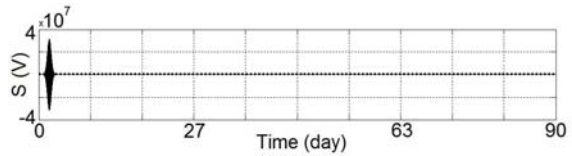


Fig. 13. The Filtered-x LMS FIR adaptive filter algorithm *adaptfilt.filtxlms* (2.5 kHz) (Very Bad)

Conclusion. This article is the addendum to the authors paper: Ali-Zade P., Yilmaz M. et al, «*Extended Kalman filter application for high-noise cancelation in control telemetry channels of oil electric submersible pump*», that was published in Journal of Petroleum Science and Engineering (PS&E), Dec. 2013” [23], which has been downloaded or viewed more than 200 times since publication (PS&E Journal information).

In this paper several MATLAB Adaptive Filter algorithms have been applied to solve in real time the problem of early prediction of disruptions in the oil industry Electro Submersible Pump (ESP) motor. From the analysis of the results, it is possible to claim that the start of trouble is predictable within a very long time interval of practical interest. Unfortunately, some of the adaptive filter algorithms have shown bad (4) and fair (2) results, which may bring additional errors in the late or false early interpretation of the critical point of the ESP motor insulation disruption issue. Some of the adaptive filter algorithms have shown successful and very good results of the early prediction of the ESP motor real insulation disruption (like Sign-error, Sign-data and Sign-sign filters). The best among the ten analyzed adaptive filter algorithms (methods) for application in ESP telemetry was recognized as — The Normalized LMS FIR filter algorithm — `adaptfilt.nlms`.

References:

1. Mohn F. Electric Submersible Pumps / F. Mohn. — Bergen, Norway : AS Oil & Gas, Division, Frank Mohn AS, 1994.
2. William C. Lyons, Gary J. Plisga, Standard handbook of petroleum and natural gas engineering, Gulf Professional Publishing, 2005.
3. Smart tools for oil industry. The leading manufacturer of the oil surface equipment industry in Russia. — Mode access: www.electon.ru.
4. Shynk J. J. Frequency-Domain and Multirate Adaptive Filtering / J. J. Shynk // IEEE Signal Processing Magazine. — 1992. — Vol. 9. — № 1. — P. 14–37.
5. Hayes M. Statistical Digital Signal Processing and Modeling / M. Hayes. — New York : Wiley, 1996.
6. Poularikas A. D. Adaptive Filtering Primer with Matlab / A. D. Poularikas, M. Zayed, I. K. Ramadan // International Pvt. Ltd. — 2006.
7. Ali-Zade P. G., Kulizade P. K. Method of electro submersible pump motor insulation checking. Patent USSR, AC SU 271644. — 1968/1970.
8. IEEE Recommended Practice for Specifying Electric Submersible Pump Cable-Ethylene-Propylene Rubber Insulation, IEEE Std 1018™, IEEE Industry Applications Society, New York, NY 10016-5997, USA, 13 April 2005.
9. Dillard S. M. Transient Voltage Protection for Induction Motors Including Electrical Submersible Pumps / S. M. Dillard, T. D. Greiner // IEEE Transactions on Industry Applications. — 1987. — Vol. IA-23. — Issue. 2. — P. 365–370.
10. Boldea I. Electric Drives. Boca Raton / I Boldea, S. A. Nasar. — Florida : CRC Press, 1999.
11. Bose B. K. Modern Power Electronics and AC Drives. Upper Saddle River / B. K. Bose. — NJ. : Prentice-Hall, 2002.

12. International Telegraph and Telephone Consultative Committee (CCITT). — Mode access: www.itu.int/net/about/history.aspx.
13. Bell Telephone Company and Edison Electrical Institute. — Mode access: www.edisonfoundation.net/iee/reports/index.htm.
14. Inter branch rules on a labor safety (rules) at operations of electro-installations. ПИОТ PM-016-2001, PEEP and PUE (in Russian). — Mode access: <http://www.enerkomp.ru/documents/need.html>.
15. Moschner J. L. Adaptive Filter with Clipped Input Data : Ph.D. thesis / J. L. Moschner. — Stanford, CA, 1970.
16. Gersho A. Adaptive Filtering With Binary Reinforcement / A. Gersho // IEEE Trans. Information Theory. — 1984. — Vol. IT-30. — P. 191–199.
17. Cowan C. F. N. Adaptive Filters, Prentice Hall Signal Processing Series / C. F. N. Cowan, P. F. Adams, P. M. Grant // Englewood Cliffs. — 1985.
18. Wan E. Adjoint LMS: An Alternative to Filtered-X LMS and Multiple Error LMS / E. Wan // Proceedings of the International Conf. on Acoustics, Speech, and Signal Processing (ICASSP). — 1997. — P. 1841–1845.
19. Mallat S. Tour of Signal Processing / S. Mallat, A Wavelet. — Cambridge : Academic Press, 1999.
20. Yilmaz M. A wavelet study of sensorless control of brushless DC motor through rapid prototyping approach / M. Yilmaz, R. N. Tuncay, O. Ustun // IEEE International Conference on Mechatronics, ICM 2004.
21. Yilmaz M. Sensorless Control of Brushless DC Motor Based on Wavelet Theory, Electric Power Components & Systems / M. Yilmaz, R. N. Tuncay, O. Ustun, T. P. Krein //, Taylor & Francis. — 2009. — Vol. 37. — № 10.
22. Consider the silent treatment, Noise control in Alberta // Pipeline & Gas Journal. — 2012. — Vol. 239. — № 4.
23. Ali-Zade P. Extended Kalman filter application for high-noise cancelation in control telemetry channels of oil electric submersible pump / P. Ali-Zade, C. Hajiyev, U. Hajiyeva, M. Yilmaz // Journal of Petroleum Science and Engineering. — 2013. — Mode access: <http://authors.elsevier.com/ffprints/-PETROL2503/0a000ac002d9a8d3a5282e6565f6d7b1>

Основная идея этой работы заключается в выборе наиболее эффективных адаптивных методов фильтрации сигналов, которые реализованы в MATLAB (из числа более десяти). Сигналы характеризуются высоким содержанием шумов, поскольку они передаются по каналам электропитания погружных электронасосов ПЭД. Исследования показали эффективность применения четырех библиотек адаптивных методов при решении задач прогнозирования состояния изоляции двигателя с целью предотвращения возможных разрушений. Наиболее эффективным адаптивным алгоритмом фильтрации для рассматриваемых задач является Normalized LMS FIR filter algorithm — `adaptfilt.nlms`.

Ключевые слова: *сигнал, шум, адаптивные методы, нефтяная промышленность, погружной насос, телеметрические каналы связи.*

Отримано: 18.03.2015