Robust adaptive system identification of steam separator process in thermal power plants

Goran S. Kvaščev, Aleksandra Lj. Marjanović, and Željko M. Đurović

***Abstract*—Industrial practice imposes the problem of measuring physical quantities in terms of quality, which is the primary requirement of process control with good performance, and further processing of data in terms of application of algorithms to detect and isolate failures. In order to overcome the phenomenon of outliers, which is common in industrial practice, it is necessary to apply some of the techniques of robust identification. This paper presents a new approach to robust adaptive identification which was used to identify the parameters of steam separator. It would be possible to apply techniques for the failure detection and isolation based on the model of the process, as well as in terms of better process control. The comparison with the classical approach was carried out and demonstrated the efficacy proposed algorithm.**

***Index Terms*—Fault detection, robust process identification, steam separators, thermal power plants.**

I. Introduction

THE needs of modern industry are growing every day and the application of advanced process control techniques, modern equipment maintenance and servicing and energy efficiency is required. To satisfy these requirements it is necessary to know the process in terms of its characteristics and model, and it is very important to apply some procedure for early fault detection and isolation. Many of the methods which are dealing with these problems are based on the knowledge of a good process model, and therefore we can design modern process control, as well as FDI systems to quickly detect and isolate faults in complex systems.

In order to obtain a good process model special attention should be paid to the identification process, including the selection of an appropriate model, the process and model inputs, and identification methods. If the process is time variant, it is necessary to perform identification in real time, which further complicates the problem in terms of automation procedures without human supervision. In industrial practice, a large number of measurements are under the influence of high-level noise, which significantly reduces the performance of identification systems. A large number of methods assume that the measuring noise is with normal distribution and then it is possible to effectively estimate the parameters of the system. If the measurement noise does not have Gaussian distribution, it is necessary to apply more complex techniques to achieve satisfactory results. The paper presents a new robust adaptive parameters estimation procedure [1], [2] based on QQ-plot [3], [4] which can effectively deal with processes that have measurements with pulse noise, so called outliers.

For better performance and effective process control it is necessary to have reliable sensors and actuators. It is also of great importance to have a procedure that can efficiently detect not only the failures of individual components, but to monitor changes of their characteristics over time, so that timely servicing or calibration equipment facility can be done. Such a system should possess characteristics such as reliability and efficiency in terms of rapid and timely detection of failure, but also a small number of false alarms to avoid disfiguring the confidence in decisions made by the system.

The paper will show methods for M-robust estimation of system parameters that will be applied to a concrete example of the process of water steam separation in the steam power plant Kostolac TEKO B1. This example will illustrate the application of the algorithm on a process that has a measurement with a high degree of impulse noise (outliers), which significantly affects the recursive identification of parameters in real time, with which the standard identification methods cannot cope in terms of achieving performance. Results of identification can be used to monitor the system operation, to detect and isolate failures, as well as changes in the performance of individual components, such as water level and flow sensors in this case.

The paper is structured as follows: Following the Introduction, Section 2 contains a detailed description of the steam drum system in a thermal power plant boiler, as well as an explanation of relevant processes which take place in the system. Section 3 proposes a method for robust adaptive estimation of process parameters, which is extremely important for the identification of parameters of the analyzed subsystem, given the pulse noise present in the measurements. Finally, Section 4 discusses specific results of application of the proposed approach in a real steam separator system.

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II. Robust Adaptive System Identification Based on QQ Plots

Let us consider a linear, time invariant, discrete system defined as:

$$y(i) = -\sum_{k=1}^{n} a_k y(i-k) + \sum_{k=1}^{m} b_k u(i-k) + \xi(i) \tag{1}$$

where y(i), u(i), and ξ(i) are the system output, measurable input and noise, respectively. The linear regression form of (1) is given as:

$$y(i) = Z^T(i)\Theta + \xi(i) \tag{2}$$

where the regression vector is

$$Z^T(i) = \left[-y(i-1) \,...\, -y(i-n)\ u(i-1) ... u(i-m)\right] \tag{3}$$

and $\Theta^T = [a_1 \dots a_n\ b_1 \dots b_m]$ represents a vector of unknown system parameters.
System identification can be reduced to minimization of following criteria:

$$J_k(\Theta) = \frac{1}{k}\sum_{i=1}^{k} \rho(\nu(i,\Theta)) \tag{4}$$

where $\nu(i,\hat{\Theta}) = y(i) - \hat{y}(i|\Theta)$ is the output prediction error or measurement residual, and ρ(.) is a loss function, which for maximum likelihood is defined as $\rho(.) = -\ln p(.)$, where $p(.)$ is the probability density function. If the noise distribution is Gaussian, then minimization of (4) is classical least square method. If there is an impulse noise in measurements, then the application of this approach is inadequate because of poor performance. Huber recommended that the probability density function in such cases should be chosen as a normal distribution in the middle and exponential in the tails. For such a PDF, Huber's loss function is defined as:

$$\rho(x) = -\ln(p(x)) = \begin{cases} \dfrac{x^2}{2\sigma^2}, & if\ |x| \le k \\ \dfrac{k|x|}{\sigma^2} - \dfrac{k^2}{2\sigma^2}, & if\ |x| > k \end{cases} \tag{5}$$

A recursive M-robust estimation can be described with the following equations:

$$\Theta(i) = \Theta(i-1) + \Gamma(i)Z(i)\Psi\left[\nu(i,\Theta(i-1))\right];\ \Theta(0) = \Theta_0$$
$$\nu(i,\Theta) = y(i) - Z^T(i)\Theta \tag{6}$$
$$\Gamma(i) = \Gamma(i-1) - \frac{\Gamma(i-1)Z(i)Z^T(i)\Gamma(i-1)}{w^{-1} + Z^T(i)\Gamma(i-1)Z(i)};\ \Gamma(0) = \gamma^2 I$$

where the influence function is defined as:

$$\Psi(x) = \rho'(x) = \min\left(\max\left(\frac{x}{\sigma^2}, -\frac{k}{\sigma^2}\right), \frac{k}{\sigma^2}\right) \tag{7}$$

For ε-contaminated noise with probability density function:

$$p = (1-\varepsilon)N(0,\sigma^2) + \varepsilon N(0,\sigma_o^2) \tag{8}$$

where the outlier variance is much greater than noise variance, $\sigma_o^2 \gg \sigma^2$. Now, it is possible to define the M-robust influence function:

$$\Psi(\cdot) = \left[-\ln(p)\right]' \tag{9}$$

In order to apply this kind of recursive identification, it is necessary to estimate parameters of PDF that define the signal, using QQ diagrams and then construct a M-robust influence function (9), using the results of equation (8), shown in Fig. 1, for different parameters ε, σ and σ_o.

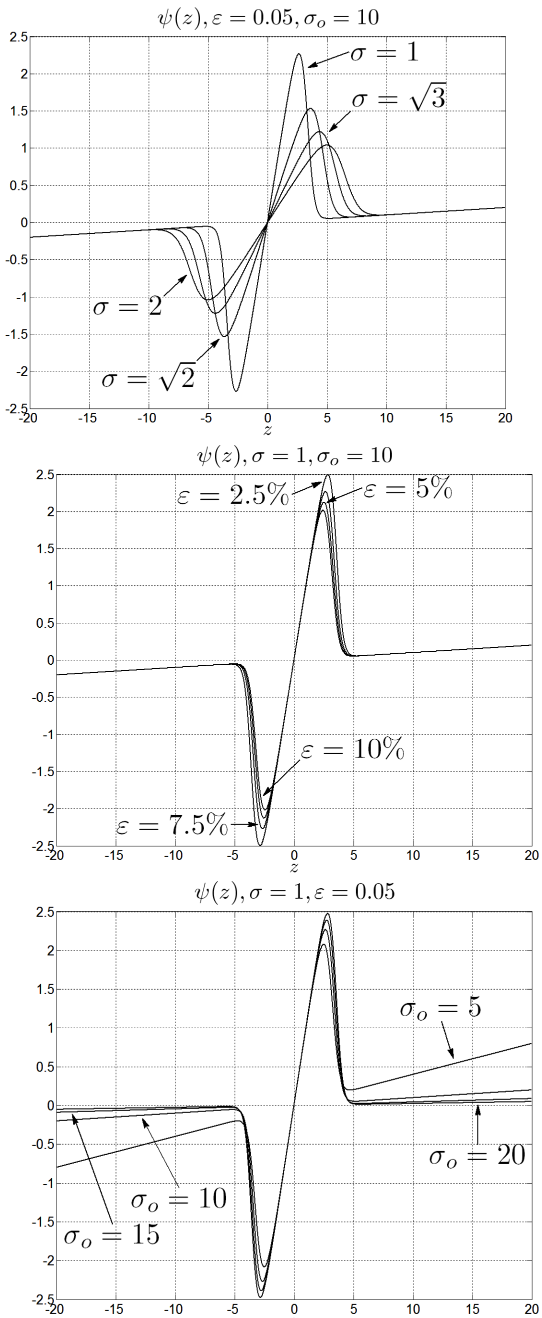

Fig. 1. Influence function for different parameters.

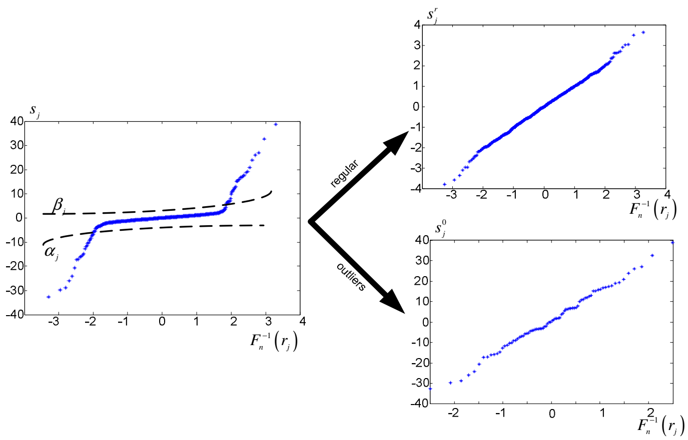

Fig. 2. Data classification (regular and impulse noise measurements). QQ-plot before and after data classification.

The algorithm consists of the following steps:

- classification of data into two categories, using QQ plot techniques, as shown in Fig. 2, the regular data and outliers. It is first necessary to determine curves α and β , and then it is easy to perform the classification of data,
- then perform the estimation of the parameters of statistics from equation (8), using the least squares method
- determine contamination degree ε , as a ratio between contamination of detected outlier and the total number of measurements on a particular window,
- then construct M-robust influence function obtained by including parameters in Equation (9)
- the final estimation is done using the parameters of the system in equations (6)

III. Steam Separator Parameter Identification of Thermal Powerplant Kostolac B1

Thermal power plants are the largest generators of electricity in Serbia, contributing more than 65% to the overall power supply. As such, their operational efficiency and stability needs to be maximized. Special emphasis is placed on reliable long-term operation in terms of negotiated delivery commitments, operation per design criteria for energy efficiency, and longevity of the facility. It is, therefore, extremely important to monitor vital subsystems and their individual components, such that early detection of any change in characteristics, or faults, will prevent accidents, down time, and substantial financial loss.

The paper addresses steam drums in thermal power plant boilers [5]-[7]. A boiler is a unit in which the chemical energy of fossil fuel is converted into heat energy of steam. Fig. 3 shows the basic structure of a steam boiler. An even number of mills (usually 6 or 8) break up and grind coal and then a mixture of coal and preheated air is routed to a furnace via a system of ducts. In parallel, the oxygen needed for combustion is provided by an air supply fan. On the way to the furnace, the air is additionally heated to enhance combustion. Temperatures inside the furnace are as high as 1400 ºC, such that all its parts need to be resistant to such temperatures.

Feedwater pumps deliver partially heated water to the steam drum via an economizer, and then additional pumps discharge the water into a system of pipes where multi-stage heating takes place inside the boiler and the water is converted into steam. The steam drum also removes residual drops of water from the steam. The steam is then delivered to a multi-stage superheater where it is heated to about 540 ºC at a nominal pressure (usually 165-175 bars) before it leaves the boiler, and the superheated steam continues on to the turbine.

Specifically, at the TEKO B1 Unit of the Kostolac Thermal Power Plant, the diameter of the steam drum is 0.9 m and its height is about 24 m (Fig. 1(b)). Even a small water level variation inside the steam drum results in noticeable steam pressure fluctuations and affects the technical conditions of the process. If the water level is too high, emergency relief valves open to remove excess water and this improves the operational efficiency of the unit. However, if the water level is too low, after a certain time a boiler shutdown procedure is initiated automatically, to protect the piping from overheating. As a result, maintenance of the required water level is a very important control requirement.

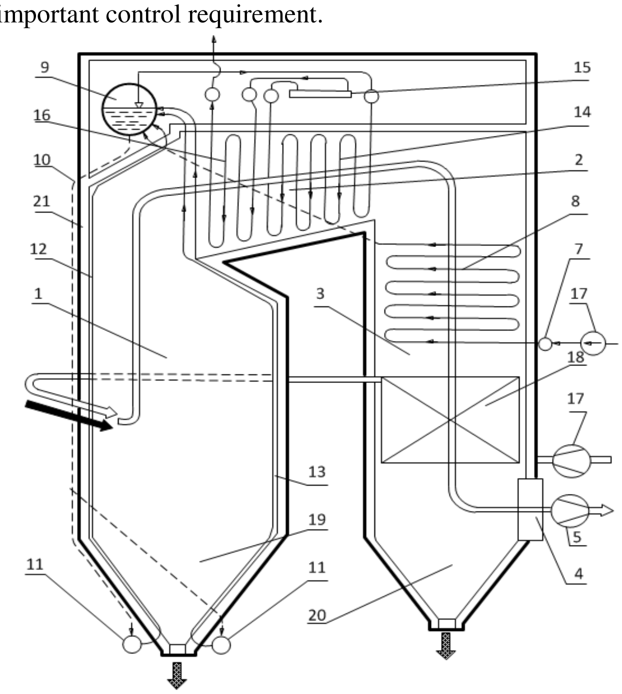

Fig. 3. Schematic of a typical boiler: 1-Exhaust fan, 2-Feedwater pumps, 3-Main feedwater control valve, 4-Economizer, 5-Steam drum, 6-Primary preheater, 7-Secondary preheater, 8-Air supply fan, 9-Air preheater.

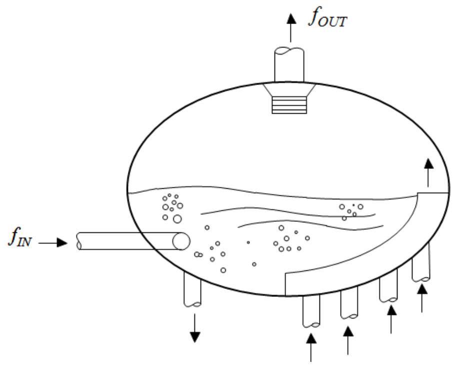

Fig. 4. Steam drum: f_{IN} - input feedwater flow, f_{OUT} - fresh steam output flow.

Given that the water level in the steam drum depends on the water flow to the drum and the steam flow from the drum, and since an integrating effect is inherent in the process, the following discrete separator model in the form of discrete transfer functions is proposed:

$$Y(z) = \frac{B_1(z)}{A(z)} f_{IN}(z) + \frac{B_2(z)}{A(z)} f_{OUT}(z) \tag{10}$$

where $Y(z)$ is water level in stem drum, $f_{IN}(z)$ feedwater flow, and $f_{OUT}(z)$ steam flow on the output (Fig. 4).

Using comparative analysis of models of different order, it was concluded that the minimum order model that adequately describes the system is three, and the proposed forms of polynomials in the numerator and denominator are:

$$A(z) = 1 + a_1 z^{-1} + a_2 z^{-2} + a_3 z^{-3}$$
$$B_1(z) = b_{11} z^{-1} + b_{12} z^{-2} + b_{13} z^{-3} \tag{11}$$
$$B_2(z) = b_{21} z^{-1} + b_{22} z^{-2} + b_{23} z^{-3}$$

This model is not adequate for modeling the dynamics of the system. Taking this into account, and that the process is integrator type, a priori information was implemented into the model as:

$$\mathrm{Y(z)} = \frac{\mathrm{B_1(z)}}{\mathrm{A(z)(1 - z^{-1})}} \mathrm{f_{IN}(z)} + \frac{\mathrm{B_2(z)}}{\mathrm{A(z)(1 - z^{-1})}} \mathrm{f_{OUT}(z)} \tag{12}$$

In time domain nine parameters model is presented as:

$$\mathbf{dh[k]} = -\sum_{i=1}^{3} \mathbf{a_i dh[k-i]} + \sum_{i=1}^{3} \mathbf{b_{1i} f_{in}[k-i]} + \sum_{i=1}^{3} \mathbf{b_{2i} f_{out}[k-i]} \tag{13}$$

where $\mathbf{dh[k] = h[k] - h[k-1]}$ is the level difference in two time sample.

The water-level signal noise cannot be modeled in the usual manner, with Gaussian zero-mean distribution. Such a measurement sequence includes sporadic high-intensity noise, or outliers. This can be attributed to the fluid level measurement procedure which involves differential pressure measurements in the steam drum, where a large liquid and steam fluctuations produce measurement noise. Pulse noise originates from sudden evaporation and the appearance of large steam bubbles inside the vessel, which rapidly separate on the surface and create a pressure disturbance. This nature of the measurement noise prevents the application of standard identification procedures, so the paper proposes robust adaptive parameter estimation which is highly efficient in the case of measurements with pulse noise.

Proposed procedure is applied and the results of estimation of level and measured levels are presented, in Fig. 5, for 24 hour time period without system fault. Estimation of level is satisfactory, and this is a verification of the proposed procedure, as well as the order of adopted model. Fig. 6 shows the movements of the model parameters (13) in time. It is obvious that the contribution of robust estimation is significant, in the sense that the occurrence of impulsive noise does not affect the procedure as significantly as a disturbance.

The Figs 7 and 8 show the estimation of water level in the water/steam separator in the system when there is a failure, which is modeled as a multiplicative failure (30%) measuring the water level and water flow.

During the real time recursive estimation it is necessary to determine the forgetting factor, as the balance between the speed of detection of parameter changes and the quality of identification. As the appearance of impulse noise significantly affects the deterioration of estimation, it is necessary to increase the forgetting factor, and thus slow down the detection of changes in the state system. As the proposed procedure significantly reduces the impact of poor impulse measurements, the forgetting factor may have a low value and thus affect the reduced time to detect failures.

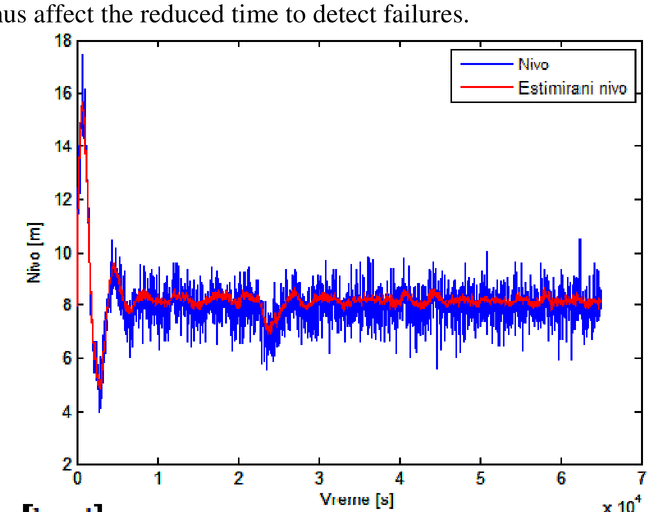

Fig. 5. Estimated water level (red) and measured water level (blue) in steam drum without fault.

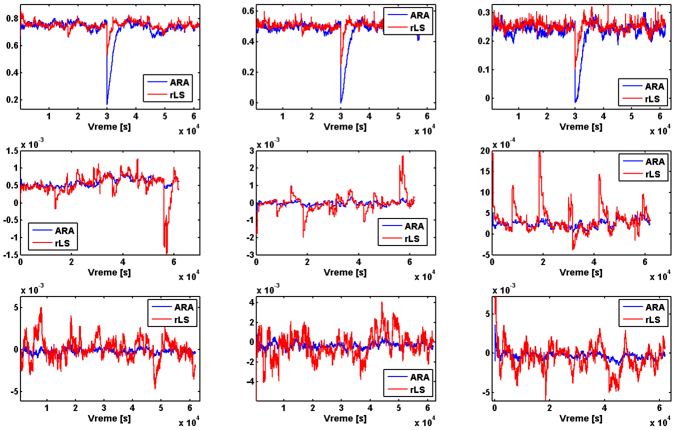

Fig. 6. Movement of estimated parameters in time: proposed method (blue) and recursive least squared method (red).

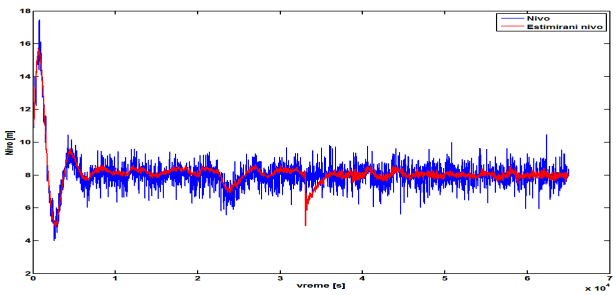

Fig. 7. Estimated level (red) and measured water level (blue) in steam drum with level sensor fault.

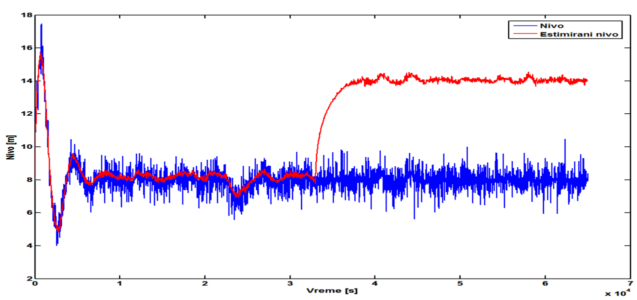

Fig. 8. Estimated level (red) and measured water level (blue) in steam drum with feedwater flow sensor fault.

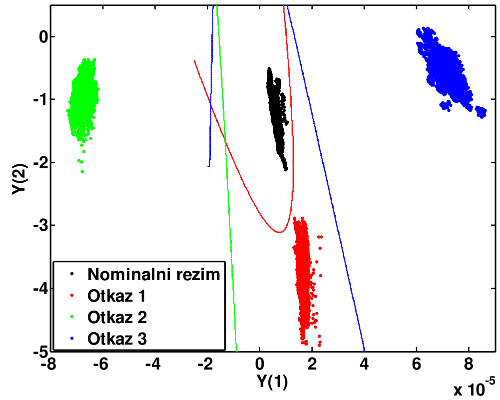

Fig. 9. Classes of operating regimes after dimension reduction: nominal regime without fault (black), level sensor fault (red), feedwater flow sensor fault(blue), steam flow sensor fault (green).

IV. Conclusion

In this paper an adaptive method for robust estimation of system parameters based on QQ-plots and its application on a system of power plant steam separator TEKO Kostolac B1 320~MW nominal power has been presented.

A comparison with the classical recursive least squares method has been done, and the significant improvement in the estimation of parameters of the system has been shown. These results become usable for better process control, and they can be applied also to detect failures in the steam separator system, after using techniques for dimension reduction as shown in Fig. 9.

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