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## Robust Extremum Seeking Control with application to Gas Lifted Oil Wells

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**Abstract:** Classical extremum seeking control (ESC), when applied to systems with disturbances, can be subject to large deviations during transients caused by abrupt changes in the disturbances. In oil and gas production applications, such deviations can make ESC impractical. This paper presents a simple yet practical extension to the classical gradient-based extremum seeking control to make it robust to such disturbances, by removing the effect of the disturbance with a priori information of the disturbance model. Modelling and robustness of the disturbance models are discussed. The proposed method is demonstrated by a simulation-based study on gas lift optimization of a single well in oil and gas production.

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## 1. INTRODUCTION

Extremum seeking controller (ESC) is a class of datadriven adaptive control methods, where the steady state performance of the system is optimised in real time by applying constant perturbation to the system. The concept of extremum seeking control was first introduced in 1922, but gained steady interest only in the last decade after a rigorous proof of the classical ESC was provided in Krstic and Wang (2000). Various techniques have since then been developed to improve the performance of the extremum seeking control. The most popular ESC approach is the gradient-based approach due to its simplicity and guaranteed local convergence. The classical ESC identifies the extremum by estimating the gradient of input-output map by correlating the input perturbation signal with the measured performance function. The system is then driven towards the extremum by simply integrating the estimated gradient continuously, see Ariyur and Krstic (2003).

In many practical applications, the system is subject to disturbances which may change the performance function and the corresponding input-output map. A relatively fast and abrupt change of a disturbance and the corresponding effect on the performance function, can cause fast and large deviations in the estimated gradient and hence in the optimising parameter. Although the extremum seeking controller may eventually converge to the optimum after the disturbance has reached its new constant value as shown in Krstic (2000), the resulting transients may be far too large and long for practical applications. In some cases, this can even cause the ESC to converge to other stationary points that are no longer optimal, see Trollberg and Jacobsen (2013).

The data based disturbance feedforward method presented in Marinkov et al. (2014) addresses this issue by extending the classical ESC with additional blocks that detect abrupt changes in the performance function. The detected events are then used to stop the perturbation and wait for a predefined time to allow the disturbance or transients to damp out before starting the extremum search again. This method however may not be very practical for slow processes, where the waiting time maybe too long, or if the process is frequently subject to disturbances, where the extremum seeking scheme may spend a lot of time waiting for the transients from the disturbances to damp out.

Many applications in the oil and gas industry have slow system dynamics and may be subjected to disturbances often. The method proposed in Marinkov et al. (2014) may therefore not be very practical for such processes. In this paper we propose an alternative solution that addresses this problem for processes with slow dynamics. The method introduces robustness to disturbances by rejecting the effect of the disturbance from the performance function without stopping the perturbation or adaptation of the optimising parameter. Therefore the algorithm continuously seeks the extremum value without being affected by the disturbance nor waiting for the transients due to the disturbances to die out. The problem motivation and the proposed method are demonstrated through an application example of gas lift optimisation using extremum seeking control, as suggested in Peixoto et al. (2015).

The paper is organised as follows. Section 2 illustrates the issues with the classical gradient-based extremum seeking control using the gas lift optimisation example. Section 3 describes the problem formulation. Section 4 describes the proposed extremum seeking scheme with discussions on modelling the disturbance rejection block. Section 5 shows the results of the simulation example, before concluding the paper in section 6.

## 2. MOTIVATING EXAMPLE

In many oil production wells, when the reservoir pressure is not sufficient to lift the oil from the reservoir, artificial lift methods are employed. One commonly used method is

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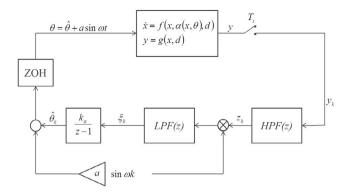


Fig. 1. Classic extremum seeking scheme

the gas lift method, where compressed gas is injected at the bottom of the well. As a result the fluid density decreases, thereby decreasing the hydrostatic pressure drop over the well. The pressure at the well bottom decreases and the inflow rate from the reservoir increases thus increasing the oil flow rate to the surface. However, injecting too much gas increases the frictional pressure drop which has an opposite effect on the flow rate. At some point the frictional drop becomes dominant over reduction of the hydrostatic pressure drop and causes the flow rate from the reservoir to decrease. Hence there exists an optimal gas lift injection rate that maximises the oil rate. The relation between the oil rate and the lift gas injection rate are called gas-lift performance curves, which have an optimum, see Golan and Whitson (1991) and Rashid et al. (2012).

The gas lift performance curves, however, change with changes in the wellhead pressure, injection gas pressure, reservoir productivity etc., which can considered as disturbances to the system. For example, the gas lift performance curves and their gradients for two different wellhead pressures are shown in Figure 3(red and blue lines). The goal of the controller is then to find the optimal gas lift injection rate (optimising input) that leads to maximum oil rate (performance function), see Peixoto et al. (2015).

In Figure 1, we show the block diagram of a classical gradient based extremum seeking scheme in discrete time with a sampling time  $T_s$  that is applied to such a process as suggested in Peixoto et al. (2015). To briefly explain the scheme, for the moment, we assume the disturbance is a constant. The scheme uses a sinusoidal dither signal  $a \sin \omega k$  to perturb the optimising input(gas lift injection rate), which makes the performance function(oil rate) to vary according to the gradient of the gas-lift performance curve around the operating point. In essence, it is from the oscillating value of the performance function and that of the dither signal, that we are able to figure out how to move the value of the optimising input to maximise the performance function.

In discrete time setting, the gradient information is extracted in the stated scheme at each time step k via the following steps: remove the low frequency part of the output using a high-pass filter as shown in (1); correlate the outcome with the dither signal; apply a low-pass filter to the correlated signal as shown in (2). The estimated gradient is then used to update the optimising variable  $\hat{\theta}_k$ (3). The filter cut-off time constants  $T_h$  and  $T_l$ , adaptation gain  $k_a$  and the dither amplitude a are tuning parameters

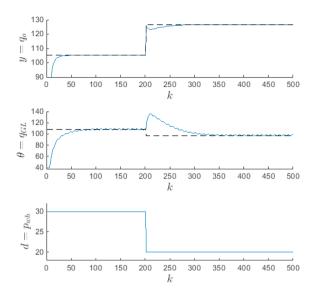


Fig. 2. Simulation results showing the effect of disturbance on the ESC

for the extremum seeking controller. For guidelines on parameter tuning, see Nesic (2009) and Tan et al. (2010).

$$z_k = \frac{T_h}{T_s + T_h} \left[ z_{k-1} + y_k - y_{k-1} \right]$$
(1)

$$\xi_k = \left(1 - \frac{T_s}{T_s + T_l}\right)\xi_{k-1} + \frac{T_s}{T_s + T_l}z_k a\sin\omega k \quad (2)$$

$$\hat{\theta}_k = \hat{\theta}_{k-1} + T_s k_a \xi_k \tag{3}$$

So the classic extremum seeking scheme works fine for the cases in which the disturbance d is constant. However, when the disturbance changes abruptly and/or frequently with large magnitudes, the scheme may lead to quite undesirable outcomes. Briefly speaking, this is because a change in disturbance causes a change in the performance function, in addition to the change caused by the dither signal. Therefore, in this period it is no longer possible to extract reliably the information of the gradient w.r.t. the optimising input from the measured performance function. This results in wrong gradient estimation and hence driving the optimising input in a wrong direction during the transient period.

This point is further demonstrated using the simulation results from the gas-lift process mentioned above. The optimising parameter here is gas injection rate  $q_{GL}$ , the performance function (output) is oil production rate  $q_o$ and disturbance is wellhead pressure  $p_{wh}$ . Figure 3 shows the gas-lift performance curves for  $d = d_1$  and  $d = d_2$ with  $d_1 > d_2$ . When the disturbance changes from  $d_1$  to  $d_2$  abruptly, a steep rise in the oil rate occurs, i.e., the value of the performance function increases sharply. At the same time, if it happens that the dither signal  $a \sin \omega t$ is positive, the extremum seeking scheme "thinks" that the small magnitude of increase in the optimising parameter could lead to large increase in the output. Therefore, the scheme increases the value of  $q_{GL}$  drastically making it deviate far away from where it should be. This transition is simulated in Figure 2. Note that the direction and the magnitude of the deviation in the optimising input  $q_{GL}$ 

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