DEVELOPMENT OF A MODEL PREDICTIVE CONTROL FOR STABILIZATION OF A GAS LIFT OIL WELL

Felipo Doval Rojas Soares, Maurício Bezerra de Souza Jr., Argimiro Resende Secchi
Chemical Engineering Program, Universidade Federal do Rio de Janeiro, Brazil
Av. Horácio Macedo, 2030 - Cidade Universitária, Rio de Janeiro - RJ, 21941-901

Abstract Overview

A gas lift oil well is an oil well that uses high pressure gas to improve oil production. The injected gas reduces the density of the mixture inside the well and increases oil flow. This type of oil well is unstable if not enough gas is available for operation, a phenomenon called slugging. This work develops a Model Predictive Control for this gas lift oil well based on a simplified first principles model. The main challenges of the problem are unknown internal state, noisy measurements, unmeasurable disturbances, slugging and model mismatch. The main contributions of this study are the use of a more accurate process model than presented in literature, the use of non-gaussian and biased noise models and the evaluation of process-MPC model mismatch. To build the MPC we did a parameter estimation with data gathered using a 3 factor design of experiments. Using the internal states generated during the parameter estimation procedure, we trained a neural network to infer the internal state from sensor data. We tested the MPC against slugging, setpoint changes and unmeasurable disturbances. Estimation of the internal states by the neural network was accurate enough to allow for proper control. MPC was quite aggressive but successfully curbed slugging and kept the controlled variables around their setpoints.

Keywords

Gas lift oil well, NMPC, Neural networks, parameter estimation

Introduction

Gas lift oil wells (GLOW) work by using natural gas to reduce the density of the mixture in the tubing, lowering the pressure in the bottom hole, increasing production rate of the reservoir, as can be seen in Figure 1. Slugging occurs if the gas injection flowrate is too low. When injection rate is low the annulus loses more gas than enters, decreasing pressure, the pressure in the bottom of the annulus is lower than the bottom hole pressure. Natural gas stops flowing into the tubing and accumulates in the annulus, increasing the pressure. The output flow also reduces and both pressure and density of the mixture in tubing increases. When the pressure in the annulus gets higher than the bottom hole pressure gas resumes flowing into the tubing, there is a huge peak in the output flow and the density of the tubing rapidly decreases. Eventually the annulus loses more gas than is injected; both the pressure in the annulus and the tubing decreases to the point of the bottom hole pressure becomes higher than the pressure at the annulus bottom, so the process restarts (Eikrem et Al., 2004).

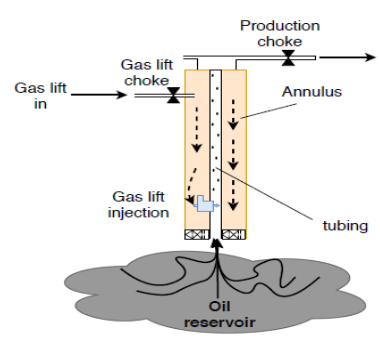

Figure 1. *Gas Lift Oil Well (Dias et al., 2019, reproduced with authorization)*

The purpose of this work is to develop a model predictive control for a gas lift oil well. The challenge of this work is to deal with: 1) unknown internal state; 2) noisy measurements; 3) unmeasurable disturbances; 4) slugging; 5) model mismatch. The gas lift oil well in this case is a mature well. Whatever sensors were installed in the bottom of the well have broken or discalibrated over the years, so those measurements do not exist or are unreliable. The internal states are the mass of gas in the annulus, the mass of gas in the tubing and the mass of oil in the tubing. It is not possible to measure directly any of those states (Jahanshahi et al., 2012).

Sources of disturbances are the natural gas pressure in the gas source, reservoir pressure (P_{res}), productivity index (PI) and gas oil rate (GOR). The natural gas source pressure depends on upstream processes, while the other disturbances are due to the inconstant nature of mature oil wells. GOR is exceptionally powerful in adding noise to the overall system. As these disturbances occur in the reservoir we cannot measure them.

Literature review

Model Predictive Control (MPC) works by using an internal model of the process to find the optimum set of control actions. Most MPCs use linear empirical models of the process (Nicolaou, 2001). In this work, we use a simplified first principles model, assuming ideal gas, no pressure drop from friction, homogeneous oil-gas mixture inside the oil well and no disturbances. The process model uses Peng-Robinson Equation of State (EoS) (Peng & Robinson, 1978), considers pressure drop from friction, linear profile of liquid fraction between the bottom and the top of the column and suffers from disturbances.

Our model comes from Jahanshahi et al. (2012), which model itself is an improvement of the model found in Eikrem et al. (2004). Jahanshahi et al. (2012) added pressure drop calculations in the tubing, which are important as the tube has more than 2 km; added a valve in the production choke, turning a SISO problem into a MIMO problem; and assumed that a gas lift valve is responsible for the gas inflow, while Eikrem et al. (2004) assumed gas inflow as the manipulated variable. We improved the model by changing the EoS from ideal gas to Peng-Robinson, as the pressure varies from 20 bar to 90 bar, a pressure range in which the deviation of the pressure calculation is considerable. We also use an exponential filter to estimate the reservoir mass flow used in pressure drop calculations.

Other authors also applied MPC to this problem. Ribeiro et al. (2012) added pressure drop calculations and controlled the process using an MPC based on linear models. Peixoto et al. (2015) used the same process and developed an MPC using Extremum Seeking Control. Regarding data based modeling, Jordanou et al. (2018) used an Echo State Network as internal model of an MPC of GLOW. The main advances introduced by the present work are: more complex MPC model, GLOW parameter estimation, internal states estimation, more realistic disturbances and noise, and improved process model.

In order to estimate the internal states of the MPC model, we use a neural network (NN) trained on the available sensor data and the estimated internal states obtained during parameter estimation.

Experimental procedure

The estimated parameters of the MPC model are the injection valve constant, productivity index, gas oil ratio and reservoir pressure.

Several step changes in the valve openings were applied to acquire data for the parameter estimation. A 3-factors design of experiments was used to determine the openings. In the last 3 experiments, slugging occurred in the process. The disturbances were gaussian noise for the pressure and random peaks for the GOR, representing bubbles on the reservoir. The process runs for 4 hours before each step.

The objective function of the parameter estimation was the weighted mean squared error between estimated sensor data and previously acquired data. The sum of square errors is weighted by the inverse of the variance of each measured sensor to account for the different scales and noise levels of each measured data point.

NN inputs were annulus top pressure, gas input flowrate, tubing top pressure, oil output flowrate, and output liquid fraction. The NN had 1 layer with 6 neurons, 10^{-3} weight decay term and trained with BFGS algorithm. The NN was developed with Matlab Neural Network toolbox (The MathWorks, Inc, 2015).

The controlled variables of the model are the input gas flowrate and output oil flowrate and the manipulated variables are input gas valve opening and output oil valve opening. The overall plant is sensitive to large variations of gas inflow (Jahanshahi et al., 2012), therefore, it is desired to keep it constant around 0.5 kg/s, and as previously mentioned, huge variations of output oil flowrate is not desirable for downstream processes so we control it around 20.5 kg/s.

MPC parameters were: sampling time of 10 seconds, control horizon and prediction horizon of 8 sampling times; valves lower and upper bounds of 0 and 1, respectively, and change in the control actions of ± 0.4. The Sequential Quadratic Programming algorithm was applied with maximum of 15 iterations and tolerance of 10^{-3}. The algorithm was implemented in Matlab Optimization Toolbox (The MathWorks, Inc, 2015).

Results

Parameter estimates were within error range of true values, with exception of GOR, which was expected as the noise is biased. Model mismatches are significant, as can be seen in Figure 2.

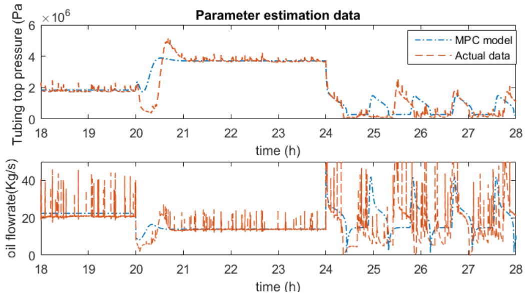

Figure 2. *Comparison between MPC and process models.*

The estimated noise regarding the NN training was reasonably successful, with a correlation coefficient of 94%. Most of the noise is due to slugging, for which the internal states estimation become worst. Without slugging R^2 increases to 99.6%. As the data during slugging is inaccurate, it is expected that the NN will not achieve a high-quality inference.

The MPC removes most of the slugging as showed in Figure 3, when operating in this region, by injecting pulses of extra gas into the annulus. The system follows setpoint changes very closely. During the setpoint increase of gas input flow from 0.5 kg/s to 0.8 kg/s, the pulse injections are reduced. During the setpoint increase of oil output, the secondary objective of keeping gas input flow around 0.5 kg/s entered in conflict with the primary objective of keeping oil output flow around 25kg/s.

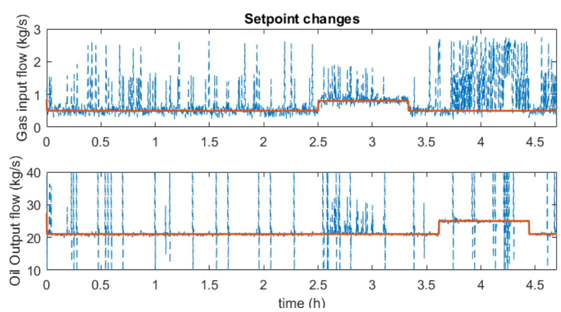

Figure 3. *MPC response to setpoint changes.*

The system also responded well regarding unmeasured disturbances, as can be seen in Figure 4. When reservoir pressure was reduced from 160 bar to 150 bar, the MPC responded by injecting more gas. When PI increased from 2×10^{-6} to 3×10^{-6} kg/(s Pa), the system responded by decreasing gas input flow pulses.

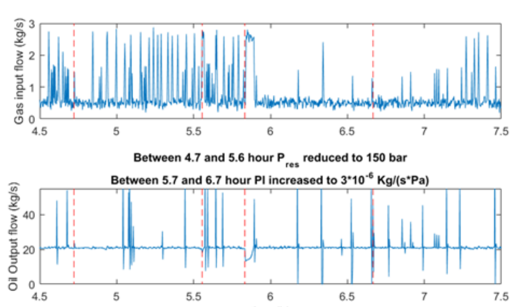

Figure 4. *MPC response to unmeasured disturbances.*

Conclusion

Model mismatch was significant and biased noise introduced a bias to the model. The NN worked well enough estimating the internal states and compensating the MPC model inaccuracies, given the low quality of available data.

The developed MPC was successful in stabilizing the system, dampening noise and disturbances. It reacted well to the disturbances forcing the system to stay on the setpoints.

Acknowledgements

This study was financed in part by the Coordenação de Aperfeiçoamento de Pessoal de Nível Superior - Brasil (CAPES) - Finance Code 001.

References

Dias, A. C. S. R. D., Rojas Soares, F. D., Jäschke, J., Bezerra de Souza, M. Jr., Pinto, J.C. (2019) Extracting Valuable Information from Big Data for Machine Learning Control: an Application for a Gas Lift Process. *Processes*, 7, 252.

Eikrem, G.O., Imsland, L., Foss, B. (2004). Stabilization of Gas Lifted Wells Based On State Estimation. In *IFAC International Symposium On Advanced Control Of Chemical Processes*. 37, 323, Hong Kong, China.

Jahanshahi, E., Skogestad, S. E Hansen, H. (2012) Control Structure Design For Stabilizing Unstable Gas-Lift Oil Wells, In *IFAC Proceedings Volumes*, 45, 93.

Jordanou, J.P., Camponogara, E., Antonelo E. A., Aguiar M. A. S (2018) Nonlinear Model Predictive Control of an Oil Well with Echo State Networks, *Proceedings Of The 3rd IFAC Workshop On Automatic Control In Offshore Oil And Gas Production*, 51, 13.

The MathWorks, Inc (2015) MATLAB, Optimization Toolbox Neural Network Toolbox Release 2015b, Natick, Massachusetts.

Nikolaou, M. (2001) Model Predictive Controllers: A Critical Synthesis of Theory and Industrial Needs, *Advances in Chemical Engineering, Academic Press,* 26, 131.

Peixoto, A. J., Pereira, D. D., Xaud A. F. S., Secchi, A. R., (2015) Modelling And Extremum Seeking Control Of Gas Lifted Oil Wells. In *2nd IFAC Workshop on Automatic Control in Offshore Oil and Gas Production.* 48, 21.

Peng, D. Y., Robinson, D. B., (1976). A New Two-Constant Equation of State. *Industrial And Engineering Chemistry: Fundamentals.* 15, 59.

Ribeiro, C.H.P., Miyoshi, S.C., Secchi, A.R., Bhaya, A., (2016) Model Predictive Control with Quality Requirements on Petroleum Production Platforms. *Journal of Petroleum Science and Engineering*, 137, 10.