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Research on a Ground-Based Gas-Liquid Separation Control System Based on Virtual Observation and NMPC

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Abstract

To address the limitations of conventional technical solutions in surface testing operations for natural gas wells, this study identifies the deficiencies associated with the manual control of gas-liquid separators. A precision pressure control system for surface testing is investigated, integrated with virtual sensing (observation) and Nonlinear Model Predictive Control (NMPC). The mathematical model of a gravity-based gas-liquid separator is introduced, and a virtual observation method based on the Kalman filter is explored. Building upon these foundations, an intelligent control strategy for the separator is developed utilizing NMPC. Experimental results demonstrate that the proposed intelligent control approach, combining virtual sensing with NMPC, significantly enhances control performance and achieves robust stabilization of the gas-liquid separator.

Keywords

Well Testing; Gas-Liquid Separator; Virtual Observation; Nonlinear Model Predictive Control.

1. Introduction

In natural gas well surface testing operations, the gas-liquid separation process is critical for ensuring the accuracy of test data and operational safety [1]. Currently, widely adopted gravity separators, while structurally simple, exhibit numerous issues during actual operation [2]. Traditional separator control primarily relies on manual operation or rudimentary automated methods, which demonstrate significant limitations when confronting complex and variable operating conditions [3]. Operators must manually adjust valve openings based on experience. Due to the complexity of field conditions and the volatility of sensor signals, manual control often suffers from response delays and insufficient regulation precision, failing to meet the automation requirements of modern oil and gas fields [4, 5].

Existing automatic control schemes predominantly rely on PID control. Such linear control methods exhibit limited effectiveness in highly nonlinear systems like separators [6]. Particularly during sudden operational conditions such as plugging flow, conventional PID controllers often fail to adapt promptly to drastic changes in system parameters. This can lead to degraded control performance, manifesting as overshoot or oscillation phenomena. Although nonlinear control methods like sliding mode control enhance system robustness to some extent, their inherent chattering introduces new challenges. This not only compromises control accuracy but also accelerates mechanical wear on control valves, shortening equipment lifespan.

In terms of condition monitoring, existing technologies exhibit significant measurement blind spots. Direct measurement methods for gas-liquid flow at separator inlets are often lacking, yet this parameter is critical for achieving precise control. While inlet conditions can be inferred from outlet flow rates, the complexity of the separation process makes it difficult to guarantee the accuracy of such indirect measurement methods. Furthermore, when measuring critical parameters such as liquid level and pressure, existing sensors are constrained by installation locations and environmental interference. Measurement signals frequently contain noise and fluctuations, introducing additional uncertainty into control systems.

As oil and gas field development advances into deeper and more complex formations, surface testing operations face increasingly variable and intricate operating conditions, placing higher demands on the response speed, stability, and adaptability of separator control systems. Traditional control methods struggle to meet these demands, necessitating the development of novel intelligent control solutions. This paper proposes an intelligent control approach based on virtual observation and nonlinear model predictive control. By constructing a virtual observer using Kalman filtering, it enables real-time estimation of inlet gas-liquid flow rates while effectively suppressing sensor noise. Furthermore, employing nonlinear model predictive control with a high-precision predictive model achieves precise control of liquid level and pressure.

2. Mathematical Model of Gravity-Driven Gas-Liquid Separator

Gravity-type gas-liquid separators are the most critical equipment in separation systems. Based on their structural configurations, they can be categorized into four types: horizontal, vertical, spherical, and three-phase. Horizontal gravity-type gas-liquid separators are commonly used in natural gas processing operations, with a simplified operational diagram shown in Fig. 1. Mathematical models form the foundation of control strategies. Gas-phase behavior is typically described using the ideal gas equation of state, neglecting intermolecular forces in real gases. The liquid phase is assumed to be an incompressible fluid. The derivation process of the mathematical model is outlined below.

2.1. Derivation of the Liquid Level Change Model

After undergoing throttling and pressure reduction during ground testing, the liquid entering the separator has a lower pressure and can be considered an incompressible fluid, meaning its density remains constant. The calculation formulas are shown in Equations (1) to (3):

$$\frac{dV_L}{dt} = q_{L,in} - q_{L,out} \tag{1}$$

$$A_L = \frac{D^2 L}{4} arccos\left(\frac{D-2h_L}{D}\right) \tag{2}$$

$$\frac{dh_L}{dt} = \frac{dV_L}{dt}\frac{1}{2L\sqrt{h_L\left(D-h_L\right)}} \tag{3}$$

Where, $q_{L,in}$, $q_{L,out}$ - inlet and outlet liquid volume flow rate of the separator, m^3/s; A_L - total liquid cross-sectional area of the separator, m^2; V_L - separator liquid volume, m^3; D - separator diameter, m; L – separator length, m.

Equation (1) above expresses the relationship between changes in the liquid volume within the separator and changes in inlet and outlet flow rates; Equation (2) represents the cross-sectional area of the liquid calculated based on the liquid level height and the separator diameter; Equation (3) expresses the relationship between changes in liquid level and changes in liquid volume. Based on Equations (1) to (3), the relationship between changes in liquid level within the separator and changes in inlet and outlet flow rates can be derived, as shown in Equation (4):

$$\frac{dh_L}{dt} = \frac{q_{L,in} - q_{L,out}}{2L\sqrt{h_L\left(D-h_L\right)}} \tag{4}$$

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2.2. Derivation of the Pressure Variation Model

Using the ideal gas equations of state as shown in Equations (5), (6), and (7)

$$n = \frac{PV_G}{RT} \tag{5}$$

$$V_G \frac{dp}{dt} = RT\frac{dn}{dt} - p\frac{dV_G}{dt} \tag{6}$$

$$\frac{dn}{dt} = \left(q_{G,in} - q_{G,out}\right)\frac{\rho_G}{M_G} \tag{7}$$

Where, p - separator pressure, MPa; n – molarity, mol; V_G – gas volume, m^3; M_G - molar mass; T – temperature, K; V- separator total volume, m^3; R - molar constant, J/mol; ρ – density, kg/m^3. Equation (7) expresses the relationship between the change in the amount of gas in the separator and the gas flow rate. Since the total volume of the separator remains constant, as shown in Equation (8):

$$\frac{dV_G}{dt} = -\frac{VL}{dt} = -\left(q_{L,in} - q_{L,out}\right) \tag{8}$$

Substituting equations (7) and (8) into equation (6) yields equation (9), which expresses the variation in separator pressure with respect to changes in gas and liquid flow rates:

$$\frac{dp}{dt} = \frac{RT\left(q_{G,in} - q_{G,out}\right)\frac{\rho_G}{M_G} - p\left(q_{L,in} - q_{L,out}\right)}{V - V_L} \tag{9}$$

The flow rate of the control valve can be expressed by Equation (10).

$$q = 2.4\times10^{-4} xC_v\sqrt{p + \left(\rho_L g h_L \times 10^{-5} - p_1\right)} \tag{10}$$

Where, x – valve open, 0 - 1; C_v - valve flow coefficient.

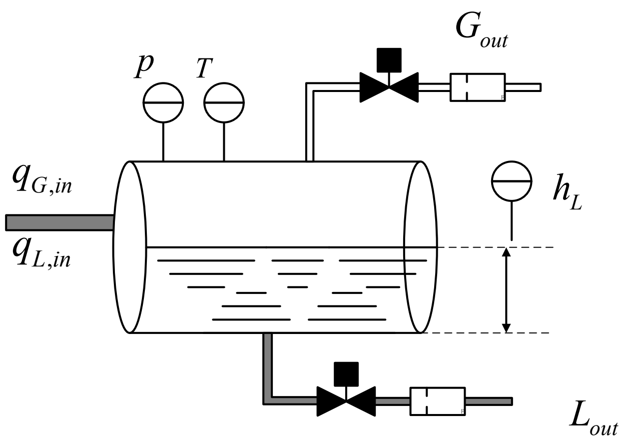

Fig 1. Schematic Diagram of Horizontal Gravity Gas-Liquid Separator Operation

3. Kalman Filter

Starting from the study of technical characteristics in separator control, establish and refine the relationship curves between the separation process model within the separator and the variations in relevant process parameters at its inlet and outlet. Based on a Kalman filter-based prediction process, develop a virtual metering model for the gas/liquid outlet flow rate of the separator.

Consider a linear stochastic system composed of a state equation and an observation equation, as shown in Equations (11) and (12):

$$X_{[k+1]} = AX_{[k]} + BU_{[k]} + GV_{[k]} \tag{11}$$

$$Y_{[k+1]} = CK_{[k+1]} + W_{[k+1]} \tag{12}$$

Where, X - State vector, h_L, p; U – process input, x_L, x_G; Y – measurement value, h_L, p; V, W - process noise and measurement noise.

Since the measurement value Y cannot fully describe the current state of the process, the Kalman filter provides an optimal state estimate X through a prediction-correction mechanism. For the pressure and liquid level prediction process, this filter consists of a state prediction equation and a measurement update equation.

3.1. State Prediction Equation

Based on equation (12) and the set of all measurements $y_{[k]} = \{Y_{[0]}, Y_{[1]}, \ldots, Y_{[k]})$ up to time step k, the predicted state value at time step k+1 is estimated. This prediction is derived from the state estimate $X_{e[k]}$ previously calculated at time step k. The state prediction equation is shown in Equation (13):

$$\begin{aligned} X_{p[k+1]} &= E\ [X_{[k+1]} \mid y_{[k]}] \\ &= AX_{e[k]} + BU_{[k]} \end{aligned} \tag{13}$$

The prediction error covariance update equation is shown in Equation (14):

$$\begin{aligned} P_{p[k+1]} &= E\ [\tilde{X}_{p[k+1]} \tilde{X}^t_{p[k+1]} \mid y_{[k]}] \\ &= AP_{e[k]} A^t + Q \end{aligned} \tag{14}$$

Equation (14) quantifies the uncertainty in the prediction result by propagating the current-time estimation error covariance $P_{e[k]}$ and superimposing the process noise covariance Q to obtain the prediction error covariance $P_{p[k+1]}$. The prediction error is defined as shown in Equation (15):

$$\tilde{X}_{p[k+1]} = X_{[k+1]} - X_{p[k+1]} \tag{15}$$

3.2. Measurement Update Equation

Measurement update equations are used to refine the estimate of the state prediction $P_{p[k+1]}$ using measurements available at time k+1. These equations minimize the combined effects of prediction error and measurement error by integrating the predicted state with new measurement information, thereby yielding a more accurate state estimate.

The measurement residual is calculated as shown in Equation (16):

$$\tilde{Y}_{p[k+1]} = Y_{[k+1]} - CX_{p[k+1]} \tag{16}$$

State estimation calibration is shown in Equation (17):

$$X_{e[k+1]} = X_{p[k+1]} + X_{[k+1]} \tilde{Y}_{p[k+1]} \tag{17}$$

This correction to the prediction is statistically optimal provided that the estimation error and the measurement residual are statistically orthogonal. Measurement residuals are sometimes referred to as measurement innovations. Through this approach, information about the current state value contained within the current measurement (but not conveyed by the preceding measurement set) is fully utilized to derive an estimate of the state.

4. Nonlinear Model Predictive Control

Based on the established predictive model, Nonlinear Model Predictive Control (NMPC) is employed to regulate separator pressure and liquid level. The core mechanism of NMPC involves acquiring states and observing disturbances at the start of each sampling cycle, followed by predicting future system dynamics using a discretized model. An optimal control

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sequence is then computed by solving a constrained optimization problem online. Compared to simpler control methods like PID or LQR, NMPC demonstrates superior capability in handling nonlinearity, multivariable coupling, and input/state constraints through its explicit model prediction and rolling optimization mechanism. Not only can it effectively handle complex process dynamics and stringent operational constraints, but by integrating efficient numerical optimization algorithms with disturbance observers (such as Kalman filters), it also partially overcomes the real-time application challenges posed by its high computational complexity.

4.1. Dynamic System Modeling

For stable control of pressure and liquid level, it can be regarded as a tracking problem to the target value, as shown in Equation (18):

$$\dot{x} = f\left(x,u\right) \tag{18}$$

In the equation: x, u — state vector and input vector. The state vector is shown in Equation (19):

$$x = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} \tag{19}$$

In the equation: x_1 - liquid level height, m; x_2 - gas pressure, MPa; The input vector is:

$$u = \begin{bmatrix} u_1 \\ u_2 \\ u_3 \\ u_4 \end{bmatrix} \tag{20}$$

In the formula: u_1 - inlet liquid volumetric flow rate, m^3/s; u_2 — inlet gas volumetric flow rate, m^3/s; u_3 — liquid valve opening, 0-1; u_4 — gas valve opening, 0-1.

4.2. Cost Function

The core of NMPC lies in solving an optimal control problem (OCP) in a finite time domain for each sampling period k. This problem aims to find the optimal control input sequence for the next *Nc* steps, minimizing the predicted performance metric *J* while satisfying the constraints. The optimization objective *J* comprises two primary components:

Output tracking performance (y tracking y_{ref}): Minimize the cumulative deviation of the system outputs (level $y_1 = h_L$, pressure $y_2 = p$) from the setpoint (y_{ref}) within the predicted time domain (Np steps).

Control action smoothness: Minimize the magnitude of control increments Δu_k (valve opening changes) over the control time domain (Nc steps) to ensure smooth valve operation and reduce actuator wear.

The optimization objective *J* is expressed as in Equation (26):

$$J = \sum_{k=1}^{N_p} || y_k - y_{ref} ||_Q^2 + \sum_{k=0}^{N_{c-1}} || \mathrm{D}\ u_k ||_R^2 \tag{21}$$

At the same time, the following operational constraints in Equation (22) must be enforced during the optimization process:

$$\begin{cases} 0 \le y_{1,k} \le 2 \\ 6 \le y_{2,k} \le 10 \\ 0 \le u_{3,k} \le 1 \\ 0 \le u_{4,k} \le 1 \end{cases} \tag{22}$$

At each sampling instant, solving this optimization problem yields the optimal control input sequence $\{u_k, u_{k+1}, ..., u_{k+Nc-1}\}$, but only the first step control u_k is applied to the system. At the next instant, state estimation is performed based on new measurements, and a new optimization problem is solved iteratively.

4.3. Algorithm Verification

To evaluate the performance of the Kalman filter in flow prediction and assess its overall control effectiveness when combined with NMPC, simulation testing was conducted using Matlab. In this study, tracking capability and observation accuracy were adopted as evaluation metrics for observation performance, while response speed and stability served as metrics for control effectiveness. Prior to simulation initiation, detailed configuration of the simulation environment and relevant parameters is required. The physical parameters and settings of the separator employed in this simulation are listed in Table 1.

Table 1. Separator Physical Parameters and Settings

Parameters	Value	Units
Liquid Valve Flow Coefficient	865	m^3/h
Gas Valve Flow Coefficient	103.8	m^3/h
Liquid Density	8500	$Kg{\cdot}m^3$
Water Density	999.19	$Kg{\cdot}m^3$
Liquid Valve Downstream Pressure	0.6	MPa
Gas Valve Downstream Pressure	0.6	MPa
Gravitational Acceleration	9.81	m/s^2
Temperature	303.15	K
Separator Length	8	m
Separator Diameter	3	m
Separator total volume	56.52	m^3

The comparison between the Kalman filter observations and actual values is shown in Fig. 2. As illustrated in Fig. 2, the Kalman filter algorithm demonstrates superior responsiveness and stability in parameter adjustment for observing inlet liquid flow rate, gas flow rate, and gas-liquid ratio. It rapidly and accurately tracks actual values, exhibiting minimal deviation between observations and actual values, thereby demonstrating excellent tracking capability.

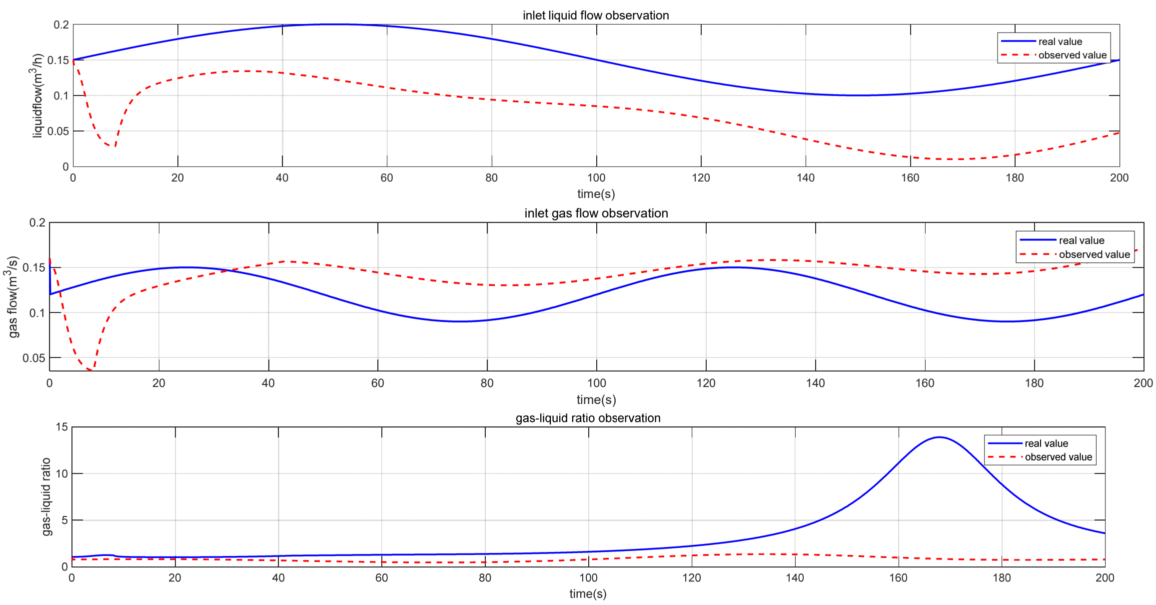

Fig 2. Comparison of Kalman Filter Observables and Actual Values

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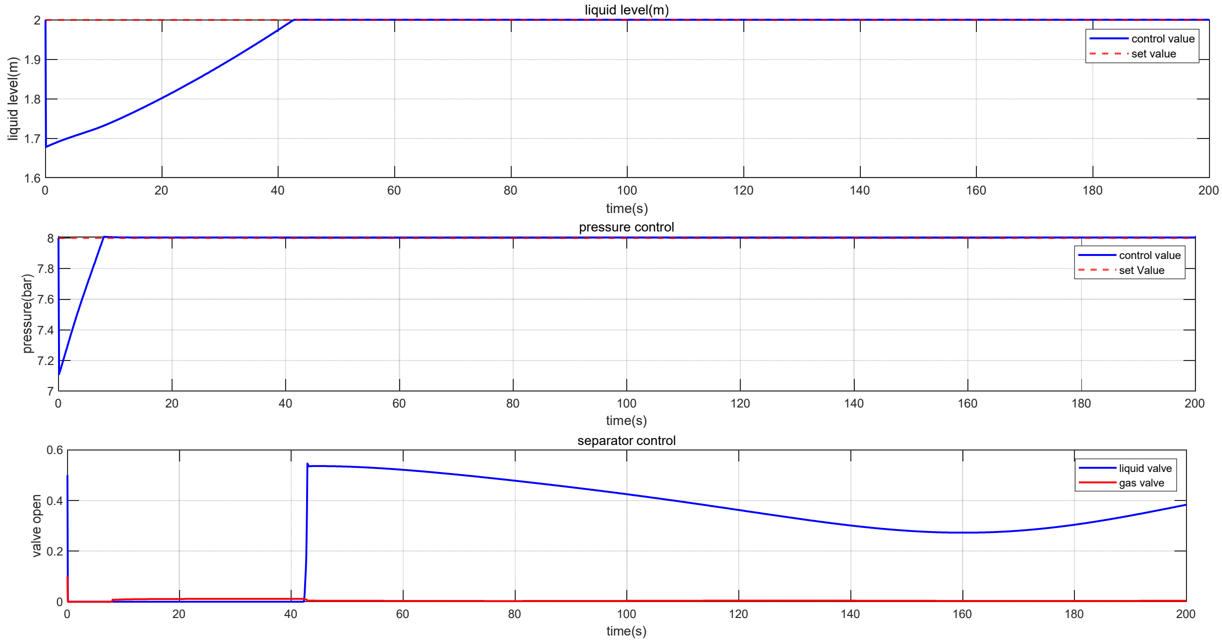

Fig 3. Schematic of Control Performance Combining Kalman Filtering and NMPC

The control performance of the Kalman filter combined with NMPC is shown in Fig. 3. As seen in Fig. 3, the combined use of Kalman filtering and NMPC demonstrates excellent control performance: in liquid level control, the actual value rapidly reaches the setpoint and remains stable, indicating that the Kalman filter effectively tracks the liquid level setpoint; in pressure control, the actual value similarly reaches and stabilizes at the setpoint quickly, demonstrating good pressure control performance. For the separator's intelligent control, the opening degrees of the liquid and gas valves adjust rapidly during the initial phase before gradually stabilizing. This indicates that the valve opening adjustments effectively control the system's liquid level and pressure.

5. Summary

This paper investigates the gas-liquid separation control system for natural gas surface testing. Based on the MATLAB simulation platform, an observer model and intelligent control model for the separator were constructed. A NMPC-based approach was employed to achieve coordinated optimization control of liquid level and pressure. The performance of the Kalman filter as a state observer within the NMPC framework was evaluated. Results demonstrate that the Kalman filter offers significant advantages in enhancing liquid level tracking accuracy, strengthening system disturbance rejection capabilities, and improving gas-liquid separation stability, making it suitable for high-dynamic separation process control. This research provides an effective solution for intelligent regulation of multiphase flow separation equipment. By integrating NMPC with the Kalman filter observer, it significantly enhances the operational performance and control quality of separators under variable operating conditions. This holds significant importance for advancing the automation and precision of separation processes in the process industry.

References

[1] Gao Feng. Key Technologies and Experimental Study of Deepwater Gravity Subsea Separator System[D]. Harbin: Harbin Engineering University, 2017.

[2] Ma Yaojian. Design and Flow Field Analysis of Oil-Gas-Water Three-Phase Separator for Offshore Platforms[D]. Harbin: Harbin Institute of Technology, 2019.

[3] Dong Tianyi. Research on Gas-Liquid Separation Device and Control System of Subsea Separator[D]. Harbin: Harbin Engineering University, 2018.

[4] Lu Hongjie, Qi Chuanguo, Ma Yupeng, et al. Research and Application of Well Testing Technology for Ultra-High Pressure and High Temperature Deep Wells: A Case Study of Jida X Well in Kalajida Structure[J]. Journal of Jianghan Petroleum University of Staff and Workers, 2011,24(1): 11-15.

[5] Wang Qiang. Study on Optimal Liquid Level Height and Control Process of Horizontal Three-Phase Separator[D]. Xi'an: Xi'an Shiyou University, 2019.

[6] Dai Jin. Design and Experimental Study on Control System of Subsea Separator[D]. Harbin: Harbin Engineering University, 2015.