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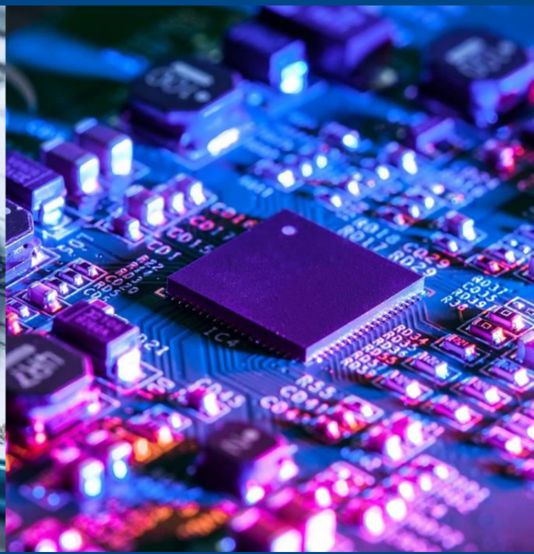

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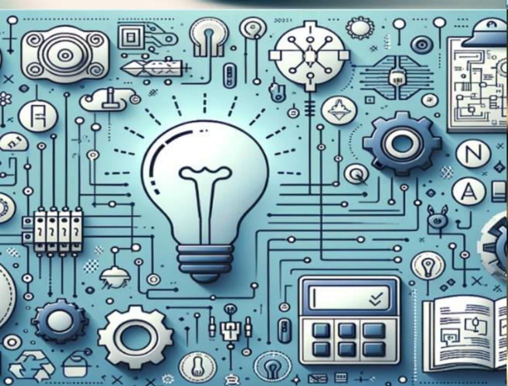

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Optimization and Control Strategies for Anti-Surge Valve Applications in Sour Gas Compressor Systems

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ABSTRACT: This study investigates advanced optimization and control strategies for anti-surge valve applications in sour gas compressor systems. To address the critical challenge of surge a phenomenon that can lead to operational instability, equipment damage, and safety hazards a robust, non-linear dynamic model of the compressor is developed. The model captures the irregular relationships between flow and head by incorporating higher-order terms and random perturbations that emulate real-world behaviour. In parallel, a surge prediction mechanism is implemented using a sliding window approach with quadratic polynomial fitting to forecast imminent surge events. The simulation framework, developed in MATLAB, not only replicates normal compressor performance but also identifies conditions under which surge is likely to occur. Comparative analysis between the simulation outputs and predictive results is provided, along with a discussion on next-generation solutions such as recurrent neural networks and model predictive control. The findings demonstrate that integrating advanced data-driven models with classical control approaches can significantly enhance system safety and operational efficiency in sour gas applications.

KEYWORDS: Anti-surge Control, Sour Gas Compressor, Surge Prediction, non-linear Dynamic Modelling, PID Controller, Optimization Strategies, Machine Learning, LSTM, Model Predictive Control (MPC) Digital Twin, Process Safety, Time-Series Forecasting

I. INTRODUCTION

The efficient operation of sour gas compressor systems is paramount to ensuring uninterrupted natural gas supply in increasingly demanding industrial applications. Centrifugal compressors, widely used in these systems, are subject to complex dynamic behaviour and often operate near their surge limit the point at which the compressor becomes unstable. Surge not only leads to a drastic decline in compressor performance but can also inflict severe mechanical damage, resulting in expensive downtime and hazardous operating conditions [1]. In sour gas environments, the presence of corrosive compounds exacerbates these risks, making surge prevention a critical aspect of system design [1].

Traditionally, compressor dynamics have been modelled using linear approximations to simplify analysis and controller design. However, real-world operating conditions are characterized by significant non-linearities arising from variations in gas composition, thermodynamic interactions, and mechanical wear [1]. These non-linear effects manifest as irregular relationships between key performance parameters such as flow rate (Q) and head (H). For instance, the compressor head may be better represented by a quadratic function:
H = a0 + a1 Q + a2 Q^2 + ϵ,

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where a0, a1, and a2 are coefficients derived from experimental data and ϵ denotes stochastic noise capturing measurement uncertainty.

Anti-surge control systems are designed to maintain the compressor's operating point safely away from the surge region [1]. This is achieved by continuously monitoring process variables and modulating a recycle or anti-surge valve. The control strategy hinges on the accurate delineation of several critical boundaries: the Surge Limit Line (SLL), which defines the point of inherent instability; the Surge Control Line (SCL), a safety margin set above the SLL; and the Trip Line (RTL), an emergency threshold prompting immediate protective actions. Additionally, practical valve performance data often available as iterative measurements during operation play a key role in refining the control strategy [1].

Recent advances in predictive analytics have further enhanced surge control. By applying machine learning techniques, such as recurrent neural networks, it is now possible to predict surge events with greater accuracy and allow for proactive intervention. This study builds upon these innovations by integrating a sliding window polynomial fitting method for short-term surge prediction with traditional closed-loop PID control, setting the stage for future implementations of advanced predictive control strategies like Model Predictive Control (MPC) [2].

II. NORMAL SIMULATION OF COMPRESSOR PERFORMANCE

Non-Linear Dynamic Model

The compressor is modelled as a first-order system with a non-linear modification to account for real-world effects. The base transfer function is given by:

where:

$$G(s) = \frac{K}{Ts+1}$$

- K is the process gain,
- T is the time constant.

To better represent non-linear behaviour, the relationship between flow and head is modelled using a quadratic function:

$$H = c_0 + c_1 Q + c_2 Q^2$$

with coefficients c0, c1, and c2 determined from experimental or synthetic data. In our simulation, MATLAB was employed to generate the compressor performance map, overlaying the compressor curve with critical surge boundaries:

1. Surge Limit Line (SLL): The empirical boundary beyond which the compressor becomes unstable.
2. Surge Control Line (SCL): A conservative safety margin above the SLL.
3. Trip Line (RTL): An emergency threshold for triggering protective actions.

These curves are derived by applying offset adjustments and random perturbations to the compressor performance data to mimic field variability [2].

2.2 Simulation Output

1. Black Curve (Non-Linear Compressor Performance):
2. Based on fluctuating, irregular real-world data, rather than a smooth linear or quadratic model.
3. Red Dashed Line (SLL - Surge Limit Line):
4. Derived from test data with random variations to reflect uncertainty in surge behaviour.
5. Blue Dashed Line (SCL - Surge Control Line):
6. A 10-15% safety margin above SLL.
7. Green Dashed Line (RTL - Trip Line):
8. A 5-7% margin above SCL representing an emergency threshold.
9. Magenta Square (n2) & Cyan Circle (n3):

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10. Represent practical, measured valve performance points.
11. These points help in understanding how the anti-surge valve reacts at different operating conditions.

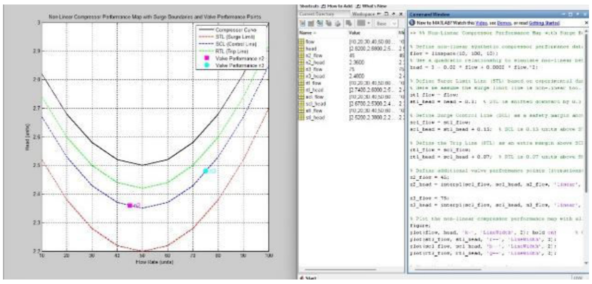

Fig.1. simulation of Nonlinear Dynamic model of Compressor Surge analysis

III. DETERMINING THE PERFECT SURGE LIMIT LINE

Due to the inherent noise and non-linear behaviour of real-world data, the experimentally derived SLL is often irregular. To create a more reliable boundary for analysis and control, curve fitting is used to smooth the SLL data [2].
Process:

1. Curve Fitting: A non-linear polynomial (in this case, a cubic fit) is applied to the SLL data points. This fitting process produces a continuous, smooth curve that best approximates the surge limit across the operating range.
2. Equation:
   The cubic polynomial is given by:

$$H_{\mathrm{STL}}(Q) = p_1 Q^3 + p_2 Q^2 + p_3 Q + p_4,$$

where P1, P2, P3 and P4 are the coefficients obtained from the fitting algorithm.

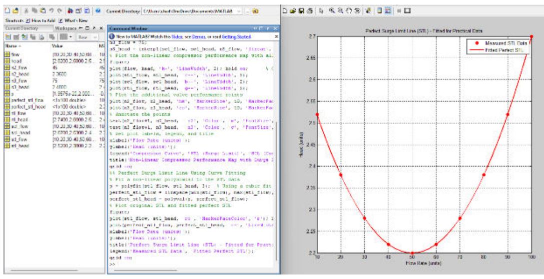

Fig.2. Determining the Perfect Surge Limit Line in MATLAB

MATLAB Implementation: The code fits the SLL data using the polyfit function and then evaluates the fitted curve using polyval. The original SLL data points are plotted alongside the fitted curve for visual verification [2].

IV. CONSOLIDATING PARAMETERS INTO A TABLE

Objective:
It is essential to summarize key system parameters in a concise format. This table provides a snapshot of the critical values that define compressor behaviour and surge boundaries, which can be used for further analysis and control tuning.

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Process:

1. Parameter Calculation: Parameters such as system gain K, time constant T, minimum surge flow, and the average head values at SLL, SCL, and RTL are calculated based on the synthetic data. These parameters are crucial for both dynamic modelling and controller design.
2. Presentation: The parameters are consolidated into a table, which facilitates easy comparison and reference in the research paper.

MATLAB Implementation:
The code calculates the mean values of the SLL, SCL, and RTL curves and combines these with predefined values for K, T, and the minimum surge flow into a cell array or table structure. This table is then displayed and saved for documentation.

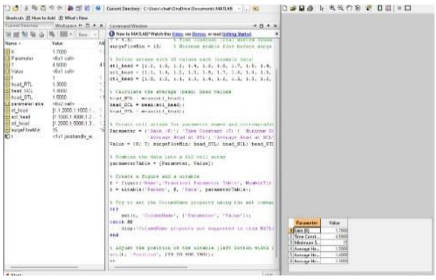

Fig.3. Closed-Loop Anti-Surge Control Simulation

IV. CLOSED-LOOP ANTI-SURGE CONTROL SIMULATION

PID Controller Design
A PID controller was implemented with the following control law:

$$u(t) = K_p e(t) + K_i \int_0^t e(\tau)\, d\tau + K_d \frac{de(t)}{dt}$$

In this equation, e(t) represents the error between the desired and actual system outputs, while Kp, Ki, and Kd are the proportional, integral, and derivative gains, respectively. These gains were meticulously tuned to achieve a stable closed-loop response [3].

Simulation Procedure
The simulation was executed using MATLAB, adhering to the following steps:

1. System Representation: The compressor's first-order transfer function was defined using MATLAB's transfer function.
2. Controller Design: A PID controller was designed and tuned to ensure system stability and optimal performance.
3. Closed-Loop Configuration: The closed-loop system was configured by integrating the compressor model with the PID controller using MATLAB's feedback function.
4. Response Analysis: Step responses of both the open-loop and closed-loop systems were simulated using the step function. The resulting plots were analysed to assess the effectiveness of the anti-surge control strategy.

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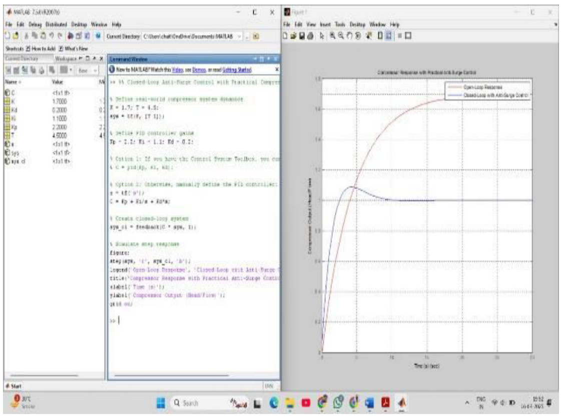

Fig.4. Surge Prediction Using Sliding Window Polynomial Fitting

V. SURGE PREDICTION USING SLIDING WINDOW POLYNOMIAL FITTING

1. Data Segmentation Using a Sliding Window

A sliding window technique is employed to extract the most recent N data points (e.g., the last 10 observations) from the compressor's operational history. This technique ensures that the prediction model always uses the latest available data, allowing for real-time forecasting [4].

Mathematical Representation
Given a historical time-series dataset:
(t1, Q1, H1), (t2, Q2, H2) ...., (tn, Qn, Hn)

where:

- ti represents the timestamp,
- Qi is the measured flow rate,
- Hi is the corresponding head value.

At any given time step tn , the algorithm selects a window of the last N observations:

$$(t_{n-N+1}, Q_{n-N+1}, H_{n-N+1}), \ldots, (t_n, Q_n, H_n)$$

This subset of data is used for predictive analysis.

2. Polynomial Fitting for Prediction Concept
To estimate the flow and head values for the next time step tn+1, a quadratic polynomial is fitted to the sliding window data. Quadratic fitting is chosen as it sufficiently captures the nonlinear behaviour of compressor performance trends [4].

Mathematical Model
A second-degree polynomial model is applied to both flow rate and head data:

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where:

$$\hat{Q}(t) = p_1 t^2 + p_2 t + p_3$$

$$\hat{H}(t) = q_1 t^2 + q_2 t + q_3$$

- p1, p2, p3 are the coefficients for flow rate prediction,
- q1, q2, q3 are the coefficients for head prediction.

Using MATLAB's polyfit function, these coefficients are calculated based on the most recent N data points [4].

Prediction for the Next Time Step

To estimate the values at tn+1:

$$\hat{Q}(t_{n+1}) = p_1 t_{n+1}^2 + p_2 t_{n+1} + p_3$$

$$\hat{H}(t_{n+1}) = q_1 t_{n+1}^2 + q_2 t_{n+1} + q_3$$

This provides the forecasted flow rate and head values for the upcoming time step.

3. Surge Prediction Rule

A surge event is predicted when the forecasted flow rate and head exceed predefined empirical thresholds. These thresholds are based on compressor specifications or experimental observations [5].

Mathematical Condition

Surge is predicted if:

$$\hat{Q}(t_{n+1}) < Q_{\text{crit}} \quad \text{and} \quad \hat{H}(t_{n+1}) > H_{\text{crit}}$$

where: Qcrit is the minimum flow rate before surge occurs. Hcrit is the head threshold beyond which instability is likely.

4. Graphical Visualization of Predictions

To provide an intuitive understanding of the surge prediction results, time-series plots are generated for both flow rate and head. The forecasted data points are highlighted, and predicted surge events are annotated [5].

MATLAB Implementation for Visualization

1. The historical flow and head data are plotted.
2. The predicted values for tn+1 are added to the plot.
3. If a surge is predicted, the corresponding point is marked in red.
4. A textbox annotation is included to indicate the prediction result.

Fig. 5. Surge Prediction logic

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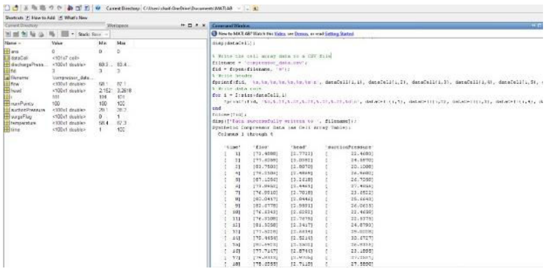

Fig.6. Make Compressor.csv file and store data

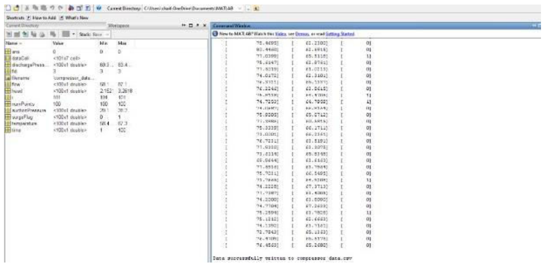

Fig.7. Calling Compressor.csv file output window

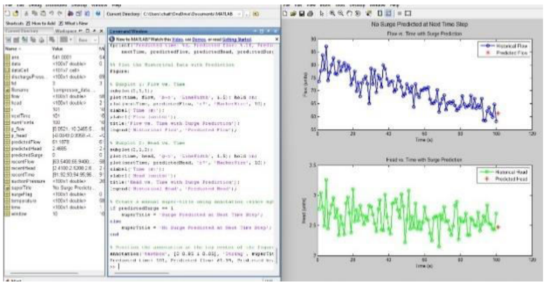

Fig.8. No Surge Predicted at Next Time-step

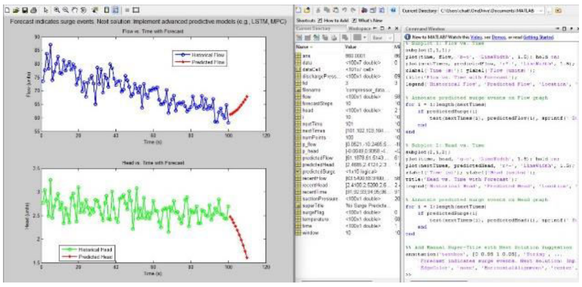

Fig.9. Forecast indicates surge events

VI. SHUTDOWN-LOGIC OF ANTI-SURGE CONTROLLER & VALVE

1. Shutdown Initiation
   - Manual shutdown command received (e.g., operator command).
   - Emergency shutdown (ESD) signal from the control system.
   - Process shutdown due to external interlocks or trips [6].

2. Surge Protection Activation
   - The Anti-surge controller immediately opens the Anti-surge valve to prevent surge.
   - The controller checks current compressor operating conditions (flow vs. pressure ratio) [6].

3. Ramp Down of Compressor Speed
   - The controller initiates a controlled speed reduction.
   - The pressure decay rate is monitored to avoid sudden pressure drops [6].

4. Blow-off or Recycle Flow Management
   - The Anti-surge valve remains open to recycle flow and maintain safe conditions.
   - The control system ensures the discharge pressure remains within safe limits [6].

5. Final Shutdown & Valve Closure
   - Once the compressor stops completely and pressures are equalized, the Anti-surge valve starts closing gradually [6].
   - The Anti-surge controller resets and goes to standby mode [6].

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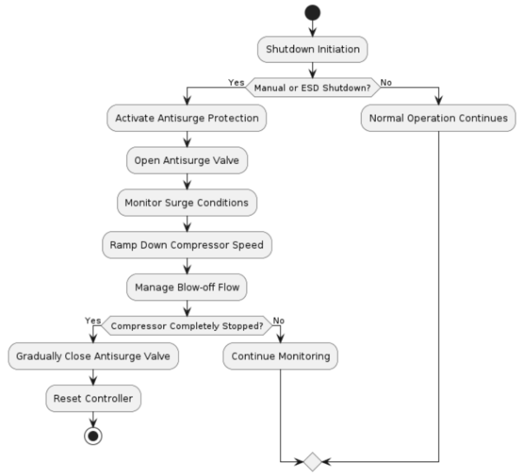

Fig.10 Shutdown-logic-I of Anti-surge valve & Controller Using ESD

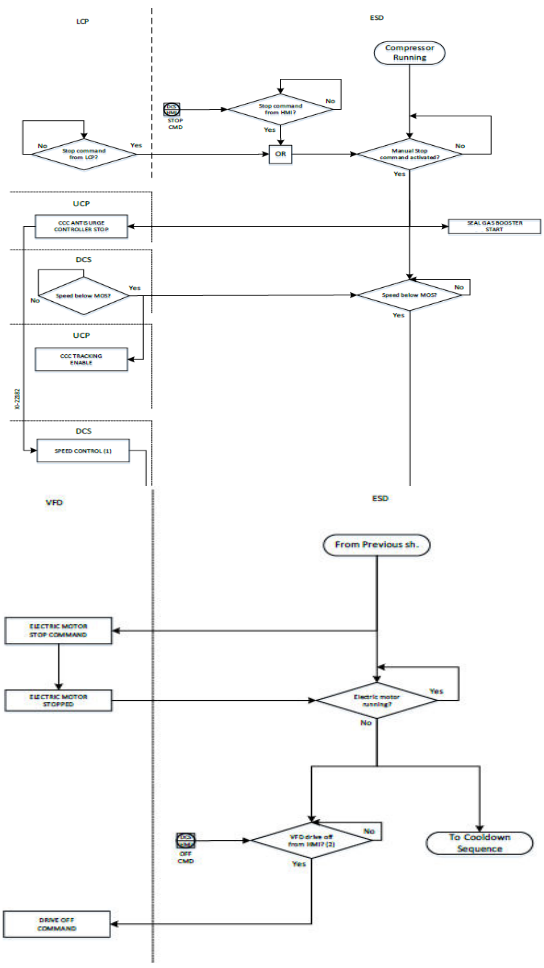

Fig.11 Shutdown-logic-II of Anti-surge valve & Controller Using ESD.

VII. PRIMARY CAUSES OF COMPRESSOR SURGE:

1. Low Flow Conditions: Operating the compressor at flow rates below its design capacity reduces the momentum of the working fluid, leading to an unstable operating point where flow reversal may occur [7].
2. Rapid Changes in Operating Conditions:
    - Inlet Temperature Variations: Sudden fluctuations in the inlet temperature alter the density of the gas, which can destabilize the compressor's performance.
    - Pressure Fluctuations: Abrupt changes in either suction or discharge pressures can drive the compressor into unstable regions, increasing the risk of surge.
3. Improper System Design:
    - Piping and Ductwork: Poorly designed piping networks or unfavourable duct geometries can create adverse pressure gradients, reducing the effective surge margin [7].
    - Insufficient Surge Margin: Inadequate consideration of surge margins during the design phase may result in the compressor operating too close to the surge line.

4. Control System Failures: Ineffective or delayed control actions due to sensor inaccuracies, slow response times, or faulty control logic can prevent timely corrective measures, allowing the compressor to enter surge conditions [7].

5. Fouling and Mechanical Deterioration:Accumulation of deposits on compressor components or physical wear and damage can alter the aerodynamic characteristics, thereby reducing performance and triggering surge [7].

VIII. CONCLUSION

Compressor surge, characterized by oscillations and flow reversals, poses significant risks to compressor integrity. To mitigate this, a closed-loop simulation utilizing a PID controller was implemented to regulate the anti-surge valve, effectively maintaining the compressor's operating point away from the surge region. Additionally, a predictive algorithm employing polynomial fitting was developed to forecast imminent surge events, enabling proactive interventions. Understanding the primary causes of surge including low flow conditions, rapid operational changes, improper system design, control system failures, and mechanical issues is crucial. Implementing robust control strategies and predictive maintenance can significantly enhance compressor reliability and efficiency.

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