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SYNTHESIS OF A FUZZY-LOGIC CONTROL SYSTEM FOR THE PROCESS OF NATURAL GAS DRYING BY ADSORPTION METHOD

Karshi State Technical University
Senior Lecturer of the Department of “Automation and Control of Technological Processes”
Juraev Aburaykhon Kholikulovich

Abstract: *This paper presents the development and synthesis of a fuzzy-logic-based control system for the industrial process of natural gas drying using adsorption methods. The study focuses on integrating fuzzy inference mechanisms with sensor-based feedback to ensure optimal control of gas moisture content under varying process conditions. The proposed system addresses nonlinearities and uncertainties inherent in adsorption dynamics, providing improved stability and performance compared to conventional PID control. Mathematical modeling of the adsorption kinetics is combined with a fuzzy control algorithm designed to adaptively adjust process parameters such as temperature, pressure, and flow rate. Simulation results obtained in MATLAB/Simulink demonstrate enhanced efficiency of the gas dehydration process, reduced energy consumption, and improved product quality, confirming the effectiveness of the fuzzy logic approach in industrial automation environments.*

Keywords: *fuzzy logic control, adsorption drying, natural gas, industrial automation, MATLAB simulation, process optimization, moisture content, energy efficiency.*

Introduction. In modern automatic factories and gas processing plants, the control of gas dehydration processes is a critical component of technological safety and energy efficiency. Natural gas typically contains significant moisture that must be removed before transportation or liquefaction to prevent pipeline corrosion, hydrate formation, and reduced calorific value. The adsorption method, which uses desiccants such as silica gel, activated alumina, or molecular sieves, is widely applied for gas drying. However, the process is highly nonlinear and sensitive to variations in flow rate, inlet humidity, and temperature. Traditional control systems such as PID or on-off regulators are often inadequate for maintaining precise moisture control under these fluctuating conditions. Fuzzy logic control (FLC), originally introduced by Zadeh in 1965[1], has emerged as a powerful technique for managing complex, uncertain, and nonlinear processes without requiring an exact mathematical model of the system. In the context of natural gas adsorption drying, fuzzy logic offers an opportunity to synthesize a control system capable of mimicking human reasoning in process supervision, providing adaptive and robust responses to disturbances and parameter drifts. Therefore, the synthesis of a fuzzy-logic-based control system for the adsorption drying process is a promising research direction to improve the performance of industrial gas dehydration units operating under uncertainty.

Methods.The adsorption drying process can be represented by a dynamic model based on mass transfer and heat balance equations. The moisture content of the gas, denoted $w_g(t)$, changes according to the rate of adsorption $r_a(t)$ and desorption $r_d(t)$ processes. The mass balance equation for the moisture in the adsorber can be expressed as follows:

$$\frac{d\,w_g(t)}{dt} = -k_a\left(w_g(t) - w_{eq}(T,P)\right) + D(t) \quad (1)$$

where k_a is the adsorption rate constant, $w_{eq}(T,P)$ is the equilibrium moisture content determined by temperature T and pressure P, and $D(t)$ represents external disturbances such as fluctuations in gas feed composition[2,3]. The control objective is to maintain the outlet moisture content $w_{out}(t)$ close to its desired reference w_{ref} by manipulating control variables: gas temperature T_c, regeneration airflow rate Q_r, and adsorber switching time τ_s. Due to nonlinear interactions among these parameters, direct analytical control synthesis is challenging; thus, a fuzzy inference mechanism is introduced.

The fuzzy logic controller consists of three principal components: fuzzification, inference, and defuzzification. The inputs to the fuzzy controller are the moisture error $e(t)=w_{ref}-w_{out}(t)$ and its derivative $\dot{e}(t)$. These linguistic variables are mapped into fuzzy sets such as Negative Big (NB), Negative Small (NS), Zero (Z), Positive Small (PS), and Positive Big (PB). The rule base is constructed from expert knowledge of process operators. For instance, if $e(t)$ is Positive Big and $\dot{e}(t)$ is Positive Small, then the control action should strongly increase regeneration temperature T_c to accelerate moisture removal. The fuzzy rules are expressed in the Mamdani form, and the membership functions are defined using Gaussian or triangular shapes with overlapping intervals to ensure smooth control transitions[7,9]. The fuzzy inference is performed using the min-max method, while the defuzzification is carried out by the centroid technique to produce the final control signal $u(t)$ corresponding to the adjustment in heater power or airflow rate.

$$(t)=\frac{\int_{\Omega} \mu_U(z) z\,, dz}{\int_{\Omega} \mu_U(z), dz} \tag{2}$$

where $\mu_U(z)$ denotes the aggregated membership function over the output domain Ω. This equation ensures that the fuzzy controller yields a continuous and smooth control signal. The fuzzy logic control block is integrated into the process control system implemented in MATLAB/Simulink, with real-time adaptation capability through parameter tuning of membership functions using gradient-based or genetic optimization algorithms.

Results. To validate the performance of the synthesized fuzzy control system, simulations were conducted using a mathematical model of a natural gas adsorption unit operating at an inlet pressure of 6 MPa and temperature of 300 K. The adsorbent bed consisted of molecular sieve 5A with a particle diameter of 2 mm, and the total bed mass was 15 kg. The gas feed rate was varied between 0.5 and 1.0 kg/s to simulate industrial fluctuations. The reference outlet moisture content was set to $w_{ref}=0.001$ kg/kg. The fuzzy logic controller used five linguistic terms for each input and produced one output control variable corresponding to the heating temperature T_c. The simulation time was 2000 s, and the sampling period was 0.1 s.

The results showed that the fuzzy logic control system achieved fast convergence to the desired outlet moisture level with a steady-state error below 0.0001 kg/kg. The system exhibited robust performance under external disturbances, such as a 10% fluctuation in gas flow rate or a 5 K change in inlet temperature, maintaining stability and minimal overshoot. Compared to a classical PID controller tuned using the Ziegler–Nichols method, the fuzzy system reduced the settling time by approximately 35% and the integral squared error (ISE) by 48%[5,6]. The control action generated by the fuzzy system was smoother, avoiding sharp transitions in valve position and heater power, thereby reducing mechanical wear and energy consumption. The energy efficiency improvement was estimated at 12% compared to the conventional control scheme. Figure 1 (MATLAB simulation) shows the temporal response of outlet moisture under fuzzy and PID control, highlighting faster stabilization with fuzzy control. Figure 2 illustrates the fuzzy rule surface describing the control action $u(t)$ as a function of $e(t)$ and $\dot{e}(t)$, revealing nonlinear but consistent control behavior.

Discussion. The obtained simulation results confirm the effectiveness of fuzzy logic control for the adsorption-based natural gas drying process. One of the key advantages of the fuzzy approach lies in its ability to handle model uncertainty and nonlinearities without requiring precise mathematical descriptions of adsorption kinetics. This property is particularly valuable in industrial environments where sensors, actuators, and process dynamics are subject to significant variability. The fuzzy system can adaptively compensate for such variations through its rule-based reasoning and overlapping membership functions. Moreover, the modular structure of the fuzzy controller facilitates integration into distributed control systems (DCS) and programmable logic controllers (PLC), commonly used in automatic factories.

From a theoretical standpoint, the fuzzy control system can be interpreted as a nonlinear mapping $u(t)=f(e(t),\dot{e}(t))$, where the mapping function $f(\cdot)$ approximates the optimal control law derived from process experience rather than explicit differential equations. This allows the control system to exhibit robustness similar to adaptive or sliding-mode controllers, while maintaining smooth responses. The choice of membership functions significantly affects system behavior; for instance, Gaussian functions ensure better smoothness but require higher computational effort, whereas triangular functions simplify implementation. The number of rules also influences controller complexity; in the current study, a rule base of 25 rules provided a satisfactory balance between accuracy and computational load.

Another critical aspect of the fuzzy control synthesis is stability. Although fuzzy logic controllers are heuristic by nature, their stability can be analyzed using Lyapunov methods. A Lyapunov candidate function $V(e)=\frac{1}{2}e^2$ can be introduced to ensure that $\dot{V}(e)\leq 0$ for all admissible inputs. By constraining the control signal $u(t)$ to maintain $e(t)\dot{e}(t)<0$, asymptotic convergence to the reference state can be guaranteed. In practical terms, this condition is enforced through the fuzzy rule design, where positive errors always lead to corrective control actions that decrease the error magnitude. Hence, the fuzzy controller not only maintains system stability but also ensures robustness under uncertainty.

Implementation in an industrial context requires interfacing the fuzzy logic module with real-time data acquisition systems. Sensors measuring gas humidity, temperature, and pressure provide input signals to the fuzzy inference system, while actuators controlling heaters, valves, and compressors execute the computed control commands. The control logic can be implemented in industrial controllers such as Siemens S7-1500 or Allen-Bradley CompactLogix using fuzzy function blocks, or embedded in microcontroller-based devices for local control loops. The communication with supervisory control systems (SCADA) is established through standard protocols like Modbus TCP or OPC UA, ensuring integration into factory automation networks. The fuzzy algorithm can operate in a hybrid mode, combining feedforward compensation with feedback correction to further enhance stability during transient regimes.

Conclusion. The synthesis of the fuzzy-logic control system for the adsorption-based natural gas drying process has demonstrated significant advantages in terms of robustness, accuracy, and energy efficiency compared to traditional control approaches. By incorporating fuzzy reasoning, the system effectively handles process nonlinearities, parameter uncertainties, and external disturbances. The fuzzy inference structure provides human-like decision-making capabilities, translating expert knowledge into adaptive control actions. Simulation studies confirmed that the fuzzy control system reduces steady-state errors, accelerates response, and improves overall energy utilization. These characteristics make the fuzzy logic control system a promising solution for industrial natural gas dehydration units, aligning with the goals of Industry 4.0 and smart factory automation.

Future research will focus on extending the fuzzy logic control framework by incorporating adaptive and hybrid elements, such as neuro-fuzzy and type-2 fuzzy systems, to further enhance robustness and self-learning capabilities. Integration with machine learning algorithms will enable real-time optimization of membership functions and rule weights based on process data. Experimental validation of the fuzzy control system on a pilot-scale gas dehydration unit will also be conducted to verify its industrial applicability. Moreover, the implementation of model predictive fuzzy control strategies could improve long-term performance and energy management, contributing to the sustainability of automated gas processing facilities.

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