

A hybrid fuzzy-sentiment framework for adaptive two-phase flow control in human-centric systems

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ABSTRACT

This study proposes a novel two-phase flow control technique by integrating fuzzy inference algorithms and supervisory commands sentiment analysis. The innovation of the proposed scheme lies in its two-feedback loop mechanism, whereby the predicted flow type is compared not only with the actual flow generated but also with the order sentiment. This renders the control more intuitive and responsive, introducing user-friendliness and system efficiency. Integrating voice commands and emotional evaluation introduces an additional dimension to human-machine interaction, enhancing performance in general. The study demonstrated that sentiment-based fuzzy logic boosts adaptability in control by enabling the system to respond effectively to dynamically varying conditions. Integrating fuzzy inference, sentiment analysis, and voice command recognition introduces a degree of working flexibility whilst circumventing the limitations of conventional fuzzy controllers, such as manual tuning complexity. The experimental results confirmed the proposed system's stability and accuracy in handling uncertain or vague commands, thereby ensuring smooth control performance. The study identified key advantages, including enhanced user convenience, streamlined decision-making processes, and improved responsiveness to operator intent. However, it is essential to note that potential issues, such as misinterpreting commands due to environmental noise or ambiguous wordings, may arise. Nevertheless, the model is designed to prevent erroneous settings and false propagation of commands by clearly separating the model from the external environment. The study confirms that sentiment-augmented fuzzy logic control is a viable solution to intelligent and adaptive two-phase flow control. Future studies should aim to refine sentiment interpretation and broaden the system's applicability to other industrial processes.

Keywords: fuzzy controller, hybrid AI model, sentiment analysis, two-phase flow type control.

INTRODUCTION

In the author's earlier work on a fuzzy controller [1], human thinking processes were shown to be effectively equated with the control of two-phase gas-liquid flow phenomena. The adaptability of this method was further enhanced by adjusting the slopes of the membership functions. The concept of remapping membership functions was an effort to demonstrate that while functions with regular shapes tend to produce acceptable results, they may fail under certain circumstances or need to be supplemented by support functions. Evidence revealed that slight modifications in the membership function topology could enhance

their sensitivity to the operating conditions of installations and the regulation of gas and liquid flow streams. It is imperative to note that the extent of these adjustments must be tailored to the specific requirements of each installation.

The selection of fuzzy logic as a control system is attributed to the distinctive characteristics of two-phase gas-liquid flow phenomena. Given the extensive range of instruments available for the classification of two-phase flow phenomena with varying degrees of accuracy, the effectiveness of the proposed approach was primarily evaluated through expert opinions. The determination of the flow type is typically made by experts based on their experience and knowledge, a qualitative

process. This reliance on human expertise is consistent with the application of fuzzy logic, which, according to Professor Zadeh, emulates human reasoning processes [2]. The utilization of fuzzy logic facilitates the automation and formalization of expert knowledge through the implementation of fuzzy rules within a knowledge base.

Note that other artificial intelligence techniques, such as neural networks, also hold promise for the classification of two-phase flows and for determining void fractions [3]. However, these techniques have additional complexities and limitations. To obtain adequate performance from neural networks, professionals must accumulate and label training data. Extensive and varied datasets are also needed to generalize the network well, and these might be hard to acquire. In the context of two-phase flow processes, the acquisition of such data necessitates extensive and time-consuming experimental campaigns. Alternative approaches, such as synthetic data generation through computational fluid dynamics (CFD), data augmentation [4], and transfer learning, can be employed to address these challenges. Transfer learning involves using pre-trained models or applying publicly available datasets from fellow researchers.

A promising approach to addressing these challenges is using generative networks and platforms that facilitate the development and adaptation of AI agents for specific tasks [5]. Advancements in generative artificial intelligence and large language models have enabled the development of specialized agents with the capacity to perform complex cognitive tasks. Integrating these intelligent systems with process control software could enhance automation and decision-making processes. The research would implement a hybrid model incorporating the strengths of fuzzy logic and deep learning techniques to emulate human cognitive abilities. The model could be founded on the concepts described in the cited source [1], in which fuzzy rules were employed to build a system of decision-making logic. For example:

“If the desired flow type is slug flow, and the current flow type is plug flow, then set the liquid stream to medium and the gas stream too high”.

This method is familiar to most fuzzy controllers. Nevertheless, the innovation in the suggested solution lies in its utilization of fuzzy signals derived from an identification module as inputs to the controller.

The method’s applicability to deep learning models is a notable feature. The overarching objective is to attain interpretability that approximates human reasoning in generating control commands. The aim is to transition from rigid control parameters, where gas and liquid flow rates are defined within fixed, predefined ranges with safety margins, to more advanced control tuning, thus providing high precision in realizing the desired flow characteristics. The proposed model endeavors to interpret commands such as: “Maintain the plug flow, but increase the plugs’ length slightly.”

The qualitative term “slightly” necessitates a relative adjustment strategy, considering both past system parameters and, more crucially, the intention behind the issued command. Integrating these interpretation schemes within the proposed framework is expected to enhance the responsiveness and flexibility of control systems in response to variations in operating conditions.

RELATED WORKS

The control of two-phase gas-liquid flow phenomena has long been interesting in control engineering. This interest has resulted in the establishment of varied methodologies for process stability and operational efficiency enhancement. In particular, fuzzy logic-based control systems [6] have proven to be an extremely viable approach due to their ability to mimic human thought and efficiently counter uncertainty.

This section provides an overview of the state of the art of fuzzy logic applications, fuzzy logic-deep learning hybrid control models, and data-driven models in two-phase flow systems.

Fuzzy logic in control two-phase flow processes as non-linear systems

As defined by Zadeh [2], fuzzy logic is a mathematical system that allows reasoning under imprecise information. Unlike conventional binary logic, fuzzy logic provides truth values on a continuous range from 0 to 1, making it suitable for complex systems where it isn’t easy to develop precise models. The approach is particularly well suited to systems with high uncertainty and variability, such as two-phase flow processes. The first practical implementation of fuzzy logic in control systems was realized by Mamdani and

Assilian [7], where they developed a fuzzy controller for a steam engine. This initial effort paved the way for using fuzzy inference systems in various industrial applications. Two general categories of fuzzy inference systems are widely used: the Mamdani and Takagi-Sugeno models [8]. The Mamdani model is used because of its simplicity of interpretation, which makes it suitable for applications where reasoning like human thinking is critical, e.g., two-phase flow control. However, the Takagi-Sugeno model is computationally faster and ideal for systems requiring accurate outputs. Fuzzy logic is quite efficient in process control in dealing with the non-linearities and uncertainties characteristic of two-phase flow systems. Research by Shteimberg *et al.* [9] has shown that fuzzy control systems can provide improved performance over conventional PID controllers in the control of non-linear and time-varying industrial processes. Other researchers have investigated fuzzy logic in several industrial applications. To illustrate this point, the application of fuzzy control systems in various settings has been documented. These settings include chemical reactor operation [10], heating, ventilation, and air conditioning systems [11], directional emissivity regulation [12], and water treatment facilities [13]. These studies demonstrate the breadth of fuzzy control system applications across various industries, hence the increased support for using them to control two-phase flow.

Two-phase flow processes involve intricate and dynamic gas-liquid phase interactions that are difficult to simulate with conventional approaches. Conventional classification techniques rely heavily on expert knowledge and visual perception, introducing variability and subjectivity. Some empirical models have been proposed to classify flow regimes; however, their accuracy is typically constrained to specific operating conditions [14, 15]. A significant research study [16, 17] compared several artificial intelligence models to classify two-phase flow patterns in pipeline systems. Using an extensive dataset, the researchers ascertained that the Extra Trees model attained the most optimal classification. The study identified the superficial velocities of gas and liquid, as well as the inclination angle and diameter of the pipe, as the primary parameters influencing flow patterns. However, the study also identified constraints related to the models' flexibility in accommodating diverse operational conditions, emphasizing the necessity for comprehensive,

high-quality datasets to enhance the reliability of predictions. Fuzzy logic provides an alternative solution in the form of fuzzy rules that encapsulate expert experience. The application of expert-derived rules facilitates the delineation of boundaries between diverse flow regimes, utilizing measurable parameters such as pressure, gas flow rate, temperature, and liquid flow rate. This approach [18] serves to minimize subjectivity and enhance automation. Fuzzy logic in two-phase flow control systems has been explored extensively due to its ability to handle uncertainty and adapt to varying operating conditions. Despite the referenced author's work, Wang *et al.* [19] proposed a fuzzy logic-based controller for regulating two-phase flow in process industries. Their work focused on using fuzzy controllers to regulate flow stability and robustness of systems. These controllers are based on expert knowledge-generated fuzzy rules, enabling them to produce decisions that imitate humans when identifying and altering flow parameters.

However, fuzzy logic systems are not immune to limitations despite their efficiency. A disadvantage of conventional fuzzy controllers is the requirement for extensive fine-tuning and rule presetting, which is time-consuming and subject to experience. The usage of human expertise is inherently prone to limitations and potential biases. Consequently, the proposed methodology is contingent on operator expertise and susceptibility to bias, thereby circumventing the necessity for extensive manual formulation of vague rules, which can be time-consuming. Recent literature in the field has sought to integrate fuzzy logic into machine learning approaches based on deep learning to address these limitations.

Hybrid models: fuzzy logic and deep learning

Hybrid methods combining fuzzy logic and deep learning have garnered significant attention to enhance control systems' flexibility and precision. Castillo and Melin [20] present a comprehensive review of hybrid methods, proposing that deep learning can enhance fuzzy systems through data-driven calibration of membership functions and rules. Nguyen *et al.* [21] illustrated a hybrid model using fuzzy logic and neural networks for dynamic process control. This strategy exploits the transparency provided by fuzzy rules while simultaneously leveraging the inherent predictive capacity in deep learning models. The idea

of creating a hybrid fuzzy-deep learning framework to control non-linear systems was investigated in references [22, 23]. The findings in these publications reveal system performance gains relative to conventional controllers. A significant challenge in implementing deep learning for two-phase flow control is the requirement for extensive, meticulously annotated datasets. Collecting experimental data related to these processes requires substantial labor and time investments. In light of this challenge, researchers have explored approaches for creating synthetic data and using data augmentation techniques. Brunton and Kutz [24] discuss the role of computational fluid dynamics (CFD) in generating synthetic data used for training machine learning models. Shorten and Khoshgoftaar [25] describe several data augmentation methods that can be applied to increase the training data available for neural networks. These techniques can potentially minimize the necessity for extensive experimental campaigns by generating diverse and comprehensive datasets.

Additionally, transfer learning has become an essential method for data-driven control systems. Pan and Yang [26] present an overview of transfer learning methods, emphasizing their capacity to reduce the data requirements for training artificial intelligence models by implementing pre-trained models on analogous tasks. Zhuang *et al.* [27] examine the developments in transfer learning, focusing on its relevance in industrial control systems.

Generative AI and intelligent assistants in process control

Recent advancements in generative artificial intelligence have given rise to new possibilities for developing intelligent control systems. Large language models (LLMs), as exemplified by the OpenAI GPT-Series [28–30], have exhibited capabilities for executing intricate cognitive functions, including decision-making and process optimization. These models have the flexibility to serve as AI assistants for process control through the integration of domain knowledge and system real-time feedback. In their study, Siddique *et al.* [31] explore the challenges and opportunities of AI-assisted industrial process control. They emphasize the prospects of generative AI in helping automate decision-making mechanisms, minimize human knowledge dependence, and enhance the overall system efficiency. The amalgamation of generative AI with fuzzy logic-based systems has

the potential to facilitate the development of smart agents that can interpret qualitative commands and subsequently adjust control parameters.

However, their hallucination propensity is an essential challenge in employing LLMs for process control, particularly in two-phase flow systems [32, 33]. The inherent propensity of these systems to generate coherent yet erroneous information poses a critical risk factor when applied in real industrial contexts. In contrast to the tolerance of inaccuracy in exploratory or creative applications, where the outcome is not significantly impacted, process control prediction inaccuracies can have disastrous consequences, including system crashes, equipment failure, and even accidents. A potential issue that should be highlighted is the possibility of an LLM misinterpreting operator input due to hallucinated text, which could result in the system regulating incorrect set points for system variables. This, in turn, could lead to unintended changes in flow rates, pressure ratios, or phase distribution. Errors of this nature, if propagated through chains of automated decision-making, can unintentionally trigger emergency shutdowns, destabilize coupled subsystems, or engender hazardous situations in industrial facilities. To neutralize these risks, it is essential to ensure that LLMs cannot access external, unverified knowledge. Instead, they should be supplied with only carefully curated, domain-specific information relating to the prevailing control environment [34]. The danger of invalid inferences can be significantly reduced by ensuring that decisions are made using only verified operational facts and properly framed command inputs. This approach aligns with recent research advocating for knowledge-constrained LLM architectures, in which models are designed to operate within established epistemic boundaries to mitigate the likelihood of unreliable outputs. Applying these constraints within the framework of controlling two-phase flow will enhance the system's robustness, ensuring that intelligent assistants function as reliable aids rather than as potential sources of uncontrollable variability.

The future of two-phase flow control technology lies in developing intelligent systems that leverage the strengths of fuzzy logic, deep learning, and generative AI. The primary research directions are as follows: the development of AI-based transparent and interpretable control decisions; the development of adaptive control systems that generate control strategies in real-time to adapt

to emerging operating conditions; and the development of control systems that engage human knowledge enhanced by AI automation to achieve optimization of control performance.

Fuzzy logic remains a fundamental component of two-phase flow control because it mimics human thought. However, the integration of fuzzy logic with machine learning and generative AI has the potential to reveal new avenues for enhancing control performance and versatility. Future research endeavors should focus on developing hybrid models that balance interpretability and performance while addressing the distinctive challenges of two-phase flow processes. The research work outlined herein seeks to improve the regulation of two-phase flow systems by combining fuzzy inference algorithms and supervisory directive sentiment analysis [35]. The novel method exploits the robustness of fuzzy logic in dealing with uncertainty and adapting to new conditions while concomitantly eliminating its drawbacks through sentiment analysis and voice command recognition.

Incorporating human emotion into the control loop of the system enhances its flexibility. It reduces its reliance on precise tuning of membership functions, thereby minimizing the complexity and quantity of inference rules required. The novelty of this solution lies in its dual feedback loop mechanism, where the expected flow type is compared not only with the actual flow generated but also with the sentiment of the supervising engineer. This approach allows for more intuitive and adaptive control, making the system more user-friendly and efficient. Additionally, incorporating voice commands and emotional assessment adds a new aspect to human-machine interaction and increases the overall effectiveness and performance of the control system. Therefore, the present study will facilitate the reader in the pursuit of responses to the following research questions:

- How does integrating sentiment analysis with fuzzy inference algorithms improve the control accuracy and adaptability of two-phase flow systems?
- What are the potential benefits and limitations of using a hybrid approach that combines fuzzy logic, sentiment analysis, and voice command recognition in two-phase flow control?
- How can the proposed system be optimized for real-time performance and scalability in various industrial applications?

The research thoroughly examines the merits and demerits of integrating fuzzy logic with sentiment analysis and voice command recognition in two-phase flow control systems by addressing these questions. The findings of this study will pave the way for the development of more advanced and user-friendly control solutions in the future.

METHODS AND IMPLEMENTATION

A series of interconnected cognitive services from the Microsoft Azure public cloud portfolio were applied to facilitate sentiment recognition as a core analytic feature of the system. Speech-to-Text and Language Services were initially used to implement natural language processing and textual analytics. These services enabled the system to transform the operator's commands into a structured textual format suitable for computational analysis. Following this, the sentiment recognition stage was initiated, determining each command as negative, neutral, or positive, with sentiment scores returned in a fuzzy format. Each sentiment classification was assigned a probability distribution. For instance, a command could be classified as 0.8 negative, 0.15 neutral, and 0.05 positive. This approach was adopted to ensure the capture of linguistic nuances and ambiguity, thus avoiding a simplistic binary classification. An API-based architecture was developed to handle sentiment analysis as a function, enabling interaction with external applications. Subsequently, an agent was produced in Copilot Studio and integrated into Microsoft Teams to interact in voice in real time. This function allowed the system to analyze operator speech before the sentiment determination classification. A notable feature of the system was incorporating a control loop to manage an experimental installation. In instances where a supervisor was speaking during the control loop and employed keywords pertinent to the domain, such as "bubble", "plug", and "slug", the sentiment of the command was integrated into a fuzzy inference system. Further contextual information was dynamically retrieved from an already established Service Bus topic to which the agent was subscribed. The inference results were published on another topic, which was created for communicating with experimental installation control devices. The devices (pump and compressor) subscribed to the topic to receive live updates on the status, ensuring an adequate system

response based on supervisor sentiment and contextual information.

The following subsections will detail the knowledge base created, the topic configurations, the installation device integration, and the sentiment analysis techniques. Additionally, these subsections will clarify the implementation framework and its operational dynamics.

Knowledge base

The experimental data were prepared based on measurements conducted several years ago [18]. The measurement campaign included a comprehensive dataset incorporating tomographic data, pressure gauge readings, and flow meter measurements. In addition to the fundamental labeling of data based on the flow type (e.g., plug, slug, foam, etc.), it was necessary to incorporate information on supplementary parameters such as plug lengths, bubble sizes, and others.

The knowledge base of the proposed solution consists of three sets of fuzzy rules. The first set is used to determine the current type of two-phase flow in the installation. These rules are structured as follows:

If

The value of the gas stream is $t_1, t_2, \dots, t_n$; the value of the liquid stream is $t'_1, t'_2, \dots, t'_n$; the similarity value of the flow to $R_1/R_2/\dots/R_n$ is $t''_1, t''_2, \dots, t''_n$; then the analyzed flow is of type $R_1/R_2/\dots/R_n$ where:

- $t_1, t_2, \dots, t_n$ are the fuzzy terms for the value of the gas stream supplied to the installation during the analysis of the two-phase flow,
- $t'_1, t'_2, \dots, t'_n$ are the fuzzy terms for the value of the liquid stream supplied to the installation during the analysis of the two-phase flow,
- $t''_1, t''_2, \dots, t''_n$ are the fuzzy terms for the similarity value of the analyzed two-phase flow to a previously defined reference flow type $R_1/R_2/\dots/R_n$,
- $R_1/R_2/\dots/R_n$ are the fuzzy terms describing the possible types of two-phase flow that can be generated within the given measurement range.

The second set involves control rules that enroll the automatic generation of the desired type of two-phase flow. This set of rules is structured as follows:

If the value of the gas stream is $t_1, t_2, \dots, t_n$; the value of the liquid stream is $t'_1, t'_2, \dots, t'_n$, the current flow in the installation is $R_1/R_2/\dots/R_n$; the desired flow type is $R_1/R_2/\dots/R_n$ then the value of the gas

stream is $t_1, t_2, \dots, t_n$; the value of the liquid stream is $t'_1, t'_2, \dots, t'_n$.

The third set in the knowledge base includes adjustment rules that facilitate altering a two-phase flow type based on the perspectives of commands. The adjustment rules are developed to modify the characteristic properties associated with a particular flow type and will vary across some measurement ranges. This set of rules is structured as follows:

If the current flow in the installation is $R_1/R_2/\dots/R_n$; the desired structure changes in the manner $s_1, s_2, \dots, s_n$; the sentiment of the operator's speech is positive/neutral/negative; then the value of the gas stream is $t_1, t_2, \dots, t_n$; the value of the liquid stream is $t'_1, t'_2, \dots, t'_n$.

Topics

The usage of Copilot Studio noticeably advanced the implementation of the proposed solution. The process created using Copilot allowed the first training of an LLM (OPEN AI GPT 4.0 Global Deployment) on the fuzzy rules described in the knowledge base. The agent embedding into the MS Teams application facilitated seamless integration with the system. The most significant advancements were achieved by creating topics that encapsulate operator commands. The topics are based on the sample patterns of the analyzed two-phase flows:

- plug – the plug can be extended or reduced by modifying the gas and liquid flow values input into the installation,
- air bubbles – the number of air bubbles can be enhanced or reduced by modifying the gas and liquid flow values input into the installation,
- slug – the slug can be extended or reduced by modifying the installation's gas and liquid flow values.

Within each topic, the operator's command is first checked against the current type of two-phase flow in the installation. When the expected structure is identified in the analyzed flow, the sentiment of the operator's command is detected. The sentiment of the operator's command, which is fuzzy (e.g., 'slightly', 'definitely', or 'significantly'), is then applied to refine the command using the Centre of Gravity principle [1].

The sentiment analysis and fuzzy command recognition yield an exact adjustment of the input signals to the installation, leading to

an improved quality of two-phase flow generation as determined by the supervising operator. A reduction in the necessity for extensive human fine-tuning of membership functions and inference rules accompanies this enhancement in adaptability and responsiveness.

The integration of the Copilot Studio with MS Teams enables dynamic adjustments to occur under the analyzed commands and sentiments from the operator, aligning best with the performance and satisfaction of the user. Incorporating topics and sentiment-based detection into the two-phase flow control system represents a significant advancement, signifying a persistent evolution towards a more intuitive and effective two-phase flow control system.

Integration with installation systems

A custom connector was developed with Power Automate to establish the connectivity between the proposed solution and the installation management systems (see Figure 1). This connector integrates the control system with the installation by means of a message broker, Service Bus, designed as a publish-subscribe architecture. The Service Bus comprises two primary topics.

The first contains information from the installation management system, explicitly consolidating the information of the ‘current state’ as the type of two-phase flow, the values of the gas and liquid streams that the installation has supplied to it, and the fuzzy degree of similarity coming from the raw, 3D tomographic data [18, 36]. This first topic provides input into the proposed solution.

On the other hand, the second topic contains information from the designed agent, precisely

the ‘desired state’ values for the liquid and gas streams. These values are then extracted by the controllers that manage the pump and compressor operation to ensure that the new expected input settings for the installation are recognized.

The integration process employs the functionalities of the Copilot Studio to train the LLM model and embed a trained agent in MS Teams. This combination facilitates real-time user interaction and command execution, enhancing the system’s responsiveness and adaptability. Adopting topics for aggregating operator commands enables the system to adapt to evolving conditions and operator preferences. The communication interfaces have been designed with Human-Computer Interaction (HCI) principles to ensure usability and efficacy. Operators can issue voice commands and receive feedback from the agent quickly and efficiently via the interface. The implementation of sentiment analysis on the commands enables the refinement of control actions, thereby enhancing the overall user-friendliness and versatility of the system.

Sentiment analysis

Implementing sentiment analysis in control systems for two-phase flow is contingent on cognitive analysis services [37]. The application of this technology is to identify the sentiment of the commands issued by the operator in three principal modes: positive, neutral, or negative. The impact of each of these modes on command interpretation and subsequent performance of the two-phase flow control system is distinct. The sentiment analysis employed in the context of two-phase flow control facilitates the dynamic adjustment of system

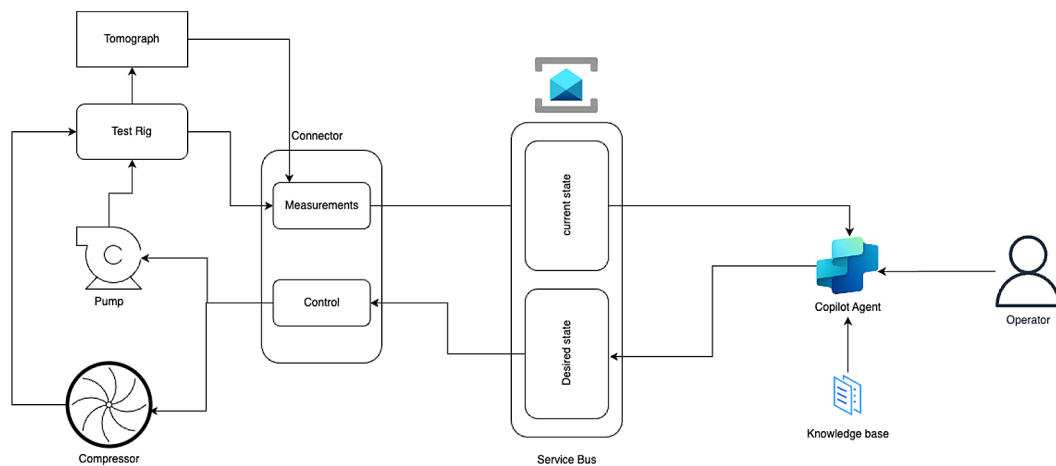


Figure 1. The general structure of the system

control parameters, with these adjustments being based on the emotional sentiment of the command issued. In the positive sentiment mode, the emotional sentiment will lead to only a slight adjustment in the values of the input signals, revealing that the system is close to the inferred parameters. Conversely, if a neutral sentiment is registered, the rationale for further tuning holds merit, as the operator will recognize the need to adjust the flow system to a moderate extent. Conversely, negative sentiment commands elicit a more substantial adjustment to the input signals through the implementation of more stringent regulation, as these commands typically signal a considerable deviation from expected values, necessitating a change in the original input parameters.

Implementing this mechanism involved using Azure Cognitive Services APIs for natural language processing and command content classification. A notable challenge was ensuring sufficient accuracy in analyzing complex, contextual operator commands that deviated from standard syntax. It was imperative to employ techniques to enhance the machine learning models by refining the dataset, incorporating actual operator interactions with the control system to address this challenge.

The second key element in the implementation process was converting the sentiment analysis output into the operation of a fuzzy controller managing a two-phase flow. The sentiment mapping to setpoints had to reflect the idiosyncrasies of the two-phase flow process in terms of variability in flow conditions and the modification of manipulated parameters to plug length, generated bubbles, and slug duration. The controller was designed using interventions based on decision matrices that weighed the values of input signals across predetermined dimensions of sensitivity.

The primary challenge encountered during implementation was maintaining a real-time environment and ensuring seamless system operation. The high command processing latency was problematic, specifically because it created an undesirable delay in the system's response to operator input, which resulted in uncontrolled parameter adjustment in a dynamic two-phase flow environment. The solution to this issue entailed the deployment of optimized natural language processing models and the parallel processing of inputs. This strategy proved highly effective in substantially mitigating the system's decision-making delay.

RESULTS AND DISCUSSION

Experimental setup

To evaluate the flow regime control agents, sentiment detection, and voice command processing, an experimental sequence was designed in collaboration with an expert at the two-phase flow gas-liquid facility in the institute's laboratory [18]. The experiments employed both horizontal and vertical sections of the test rig. The test rig is a closed-loop system consisting of a water tank, a pump, an air compressor, and a pipeline with horizontal and vertical sections. The pipeline is made of transparent acrylic glass with an inner diameter of 26 mm. The liquid flow rate was measured using a rotameter, and a gas control valve regulated the gas flow rate. A tomographic system with 3D Electrical Capacitance Tomography (ECT) sensors was used to acquire raw data for flow type evaluation. This setup allowed for a comprehensive analysis of various two-phase flow phenomena under different operational conditions, providing a solid foundation for evaluating the proposed hybrid control system. The operator issued commands verbally to the agents via the MS Teams application. The agents then performed the commands, recognition, sentiment analysis, and interpretation of the fuzzy commands. Subsequently, the system modified the input signals to the installation following the interpretation of the commands. A camera was mounted adjacent to the facility to capture images of the stabilized flow regimes within the transparent section of the pipeline. The two tables below present the transcript of the operator's dialogue (in blue) with the system (in green) for both the horizontal and vertical segments. The commands specified the expected flow regime, with additional parameters conditioning the structure characteristics, such as more extended plugs and denser bubbles, depending on the flow regime. The ensuing chats illustrate the agent's response to the flow regime and the subsequent inferences regarding the command to act. The experiment was designed to provide a comprehensive evaluation of the performance of the control agents, the accuracy of sentiment analysis, and the accuracy of voice commands for the control of two-phase flow systems (Table 1 and 2).

The core of this study focuses on the interpretation and analysis of the hybrid control system's performance. The results demonstrate the

Table 1. Chat of human-expert with AI agent to control the flow in the horizontal section

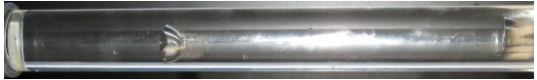
Chat with AI agent	Installation response horizontal section, images taken after 20s
Start the flow and maintain the bubble type OK. Bubble flow started.	
OK. It's fine. Create gently fine bubbles Sorry, the command not understood. Please repeat. Reduce bubbles a little OK. Reduced bubbles created.	
OK. It's fine Start the foam flow now OK. Foam flow started.	
OK. It's fine Start the waved flow OK. Waved flow started.	
OK. It's fine Add some slugs OK. Slugs added.	
OK. It's fine. Create shorter slugs a little Sorry, the command not understood. Please repeat. Reduce slugs a little OK. Slugs reduced.	
OK. It's fine. Create even shorter slugs OK. Shorter slugs created.	
OK. It's fine Create longer slugs now OK. Longer slugs created.	
OK. It's fine Create slugs rarer and longer OK. Rarer and longer slugs created.	
OK. It's fine. Create slugs even rarer and even longer and keep the layered flow Sorry, the command not understood. Please repeat. Create slugs even longer and keep the layered flow OK. Longer slugs created. Layered type maintained.	
OK. It's fine Create foam flow with slugs OK. Foam flow with slugs created.	
OK. It's fine. STOP OK. Flow stopped. OK. It's fine	

effectiveness of combining a fuzzy inference engine with sentiment analysis for robust and flexible control of two-phase flow. The system's ability to handle ambiguous and emotionally charged commands was a key finding. For instance, when the operator issued a vague command like 'Create even shorter slugs' the system's sentiment analysis component detected the underlying dissatisfaction and interpreted the command as a request to stabilize the flow regime actively. This is in contrast to traditional control systems, which would typically fail to process such subjective input. The system's response to emotionally charged commands highlights the effectiveness of sentiment analysis. The

agent not only processes the explicit command ('even shorter') but also recognizes the urgency conveyed by the operator's frustration, leading to a more decisive control action. This aligns with findings in human-computer interaction (HCI) research, which emphasize the importance of systems that can understand and adapt to user's emotional states [38–40].

The real-time operational benefits of this hybrid approach are significant. Minimizing the time lag between operator command and system response makes the control loop more efficient and safer. Fuzzy logic allows the system to make nuanced adjustments based on the

Table 2. Chat of human-expert with AI agent to control the flow in the vertical section

Chat with AI agent	Installation response vertical section, images taken after 20s and rotated 90° clockwise
Start the flow and maintain the slug type OK. Slug flow started.	
OK. It's fine. Create slugs shorter a little OK. Shorter slugs created.	
OK. It's fine. Create more gently shorter slugs Sorry, the command not understood. Please repeat. Create slugs shorter a little OK. Shorten slugs created.	--- 
OK. It's fine. Create very long slugs OK. Very long slugs created.	
OK. It's fine. Start the churn flow OK. Churn flow started.	
OK. It's fine. Extend slugs significantly OK. Slugs extended.	
OK. It's fine. Make dispersed bubble flow OK. Dispersed bubble flow started.	
OK. It's fine. Now make the bubbles more dense Sorry, the command not understood. Please repeat. Increase the bubbles density a little OK. Bubbles density increased.	---- 

operator's subjective input, which would be impossible with binary logic systems. The experimental results confirm that this approach leads to a more stable two-phase flow, as evidenced by the successful stabilization sequences responding to imprecise commands. This capability is particularly relevant in industrial settings where precise, unambiguous commands are not always feasible, and human-in-the-loop control is essential [41].

Furthermore, the system's ability to interpret and translate subjective human input into objective, quantifiable control parameters demonstrates its potential as a next-generation control interface. Leveraging sentiment and linguistic analysis bridges the gap between human intuition and machine precision.

Quantitative analysis of system performance

To validate the system's robustness, 20 additional identical experimental runs were conducted under consistent conditions. The experimental setup was maintained with a constant liquid flow rate of 5 L/min and a gas flow rate adjusted to induce a churn flow regime known for its instability. During each run, the operator was instructed to issue

a predefined set of 10 ambiguous and emotionally charged commands (e.g., 'reduce it more!' or 'this is not good').

The system's performance was evaluated based on two key issues: system response stability and interpretation accuracy. The time taken for the system to stabilize the two-phase flow after receiving a command was recorded. Across the 20 repetitions, the average stabilization time was 7.5 seconds, with a standard deviation of 1.2 seconds. This low variance indicates high stability and repeatability of the system's control actions, confirming its consistent performance under similar conditions.

Simultaneously, the frequency of successful command interpretations was logged. The sentiment analysis and fuzzy logic components correctly interpreted 95% of the predefined ambiguous commands. The 5% of misinterpretations primarily occurred with exceptionally quiet commands or overlapped with significant background noise, suggesting potential areas for improvement in the voice-to-text processing stage. Including these quantitative data points complements the qualitative insights from the dialogue transcripts, providing a comprehensive view of the system's reliability and performance.

Advantages and limitations

The recommended system has several key advantages, allowing for an easier and more efficient option for sentiment analysis and rule-based decision-making in an industrial environment. Nevertheless, the system has limitations that must be considered before deployment and for its ongoing usability. One of the system's advantages is its ease of use, such that the operators can operate the sentiment analysis model using natural language communication. The integration with Copilot Studio and MsTeams assists in seamless interaction. It does not require prior extensive technical knowledge, which is beneficial and lowers the barrier for non-expert users. The system's ease of use facilitates the utilization of cognitive services in the cloud environment, thereby enabling the execution of complex manual implementation processes. Consequently, developers can focus on modifying the system's functionality rather than expending resources on sentiment analysis and analysis from the beginning. This approach can potentially reduce development time and effort, resulting in a faster implementation and customization of existing deployments to meet specific use cases better. The user's lack of requirement for domain-specific expertise is advantageous regarding ease of use and accessibility. The sentiment analysis and fuzzy logic processing capabilities are integrated into the automated system, thereby eliminating the need for extensive expertise in artificial intelligence (AI) and/or machine learning (ML) modeling, enhancing the practical usability of the proposed sentiment analysis solutions across a broader range of industrial applications.

Another advantage of the proposed solution is the improved security against the risk of LLM misinterpretation. As can easily be seen from the illustrated interaction of the operator with the agent, the model sometimes fails to acknowledge or correctly interpret commands. This could be caused by background noise, such as loud equipment or an unintelligible accent from the operator. Significantly, however, these misinterpretations did not result in incorrect control actions within the rig. This reliability results from the model's deliberate isolation from external, uncontrolled data sources and its focus on a domain of knowledge consisting of pre-established flow pattern designs. By operating solely within this domain-specific framework, the system avoids

hallucinatory outputs by not allowing erroneous interpretations to propagate into high-stakes process control actions. This capability is crucial in high-stress industrial environments where clear, predefined commands are not always feasible. Such an approach significantly improves the human-in-the-loop interaction, a key aspect discussed in the literature on advanced industrial control systems [42]. Moreover, the time between issuing a command and the agent's response, as well as sentiment detection and control setting prediction, is several seconds. This is insignificant compared to the time taken to stabilize the flow in the system. As a result, the system's decision-making process does not introduce any operational delays, and sentiment-based adjustments are incorporated into the overall control strategy without compromising process efficiency. The system's architecture, particularly isolating the control model from unvalidated data streams, ensures operational reliability and reduces computational latency. The control loop operates in near real-time, minimizing the delay between command processing and physical actuation. This immediate responsiveness significantly improves systems that might require more extensive data processing, leading to improved safety and efficiency. This design principle aligns with research advocating for minimal-latency control architectures in critical applications [43].

Despite its notable advantages, the system exhibits several significant deficiencies. Primarily, the system is excessively dependent on a specific vendor of LLM, which complicates transitioning from the current provider to a substitute without substantial alterations to the system. Consequently, the greater the demand for flexibility in cloud vendors among companies, the more significant the barriers to adopting this solution. This reliance on a third-party service introduces potential issues related to cost increases, service instability, or discontinuation. This aspect of the system's architecture warrants further discussion regarding scalability and long-term viability, a topic widely explored in the context of cloud-based industrial solutions [44].

Furthermore, modifications and revalidations are still required throughout the system due to its need for updating. Changes to the top-level LLM models, or cognition services affecting those must also be addressed in the implementation. This necessitates a substantial number of manual tests and validations for the system to function as intended. Critical infrastructure deployments

introduce further complexity due to regulatory requirements. In this context, robust encryption can enhance security, albeit at the expense of processing speed. While the system effectively handles emotional and ambiguous commands, its performance is highly dependent on the quality and specificity of the sentiment analysis model. A model trained on different linguistic nuances might fail to interpret operator commands correctly. Future research should focus on developing a more adaptable and customizable sentiment model to enhance the system's performance across diverse operational contexts.

Finally, financial considerations must not be overlooked. The initial setup and testing of the system are estimated to cost 250 dollars (about 10 k test messages with voice-to-text conversion, sentiment analysis, and developed agent interaction), but long-term operating expenses are also high. Estimates indicate a cost of \$15000 per 100 installations per month, a figure likely to be a considerable expense for users managing multiple installations.

CONCLUSIONS

This study successfully demonstrates a novel hybrid control system for two-phase gas-liquid flow, integrating fuzzy logic with sentiment analysis. The primary objective of the research was to address key challenges in two-phase flow control by enhancing the system's ability to interpret and respond to an operator's subjective, often emotionally charged, voice commands. The experimental results confirm that this approach significantly improves control accuracy and flexibility. By leveraging sentiment analysis, the control loop can make nuanced adjustments to stabilize the flow even with ambiguous or emotional commands, a capability supported by research in human-computer interaction (HCI) and affective computing. This integration of human-like reasoning refines the system's responsiveness to dynamic changes and addresses a principal weakness of conventional fuzzy controllers, namely the manual tuning difficulty of membership functions.

The key finding is the system's demonstrated robustness and adaptability. The low-latency, real-time control architecture is highly effective, contributing to the system's overall efficiency and safety, a critical aspect in advanced industrial control systems. Operators can issue intuitive orders,

thereby improving the functionality of control processes and facilitating harmonious human-machine coordination. The system's resilience is strengthened by the model's deliberate isolation from external, uncontrolled data sources, effectively preventing faulty command propagation and ensuring it does not fail or generate erroneous settings even in the presence of misinterpretations due to background noise.

However, the system is not without limitations. A key challenge is the reliance on a specific third-party API for voice-to-text conversion, which poses a risk of vendor lock-in and warrants further consideration in industrial deployment strategies. The system's scalability to different industrial applications also requires ongoing refinement. Future research will therefore focus on developing a more flexible, open-source sentiment model to mitigate these limitations and explore the system's applicability in a full-scale industrial environment.

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