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FEEDBACK SYSTEM FOR REACTOR PROCESS ANALYSIS

SYSTEM ZE SPRZĘŻENIEM ZWROTNYM DO ANALIZY PROCESÓW TECHNOLOGICZNYCH W REAKTORZE

Abstract

The article discusses an approach to analyzing processes in industrial reactors using advanced systems with feedback. The authors describe the system preparation and image reconstruction algorithms of ultrasonic tomographs (USTs) that have applications in industry. The research presented in this paper focuses on developing effective strategies for controlling and monitoring chemical reaction processes in reactors. Using advanced data processing techniques, the authors propose systems with feedback that enable accurate analysis and optimization of reactor operating conditions. A key aspect is ultrasonic tomographic imaging, which provides precise data on the state of the process in the reactor. In summary, the paper presents a state-of-the-art approach to analyzing chemical reaction processes in industrial reactors using advanced feedback systems and ultrasonic imaging technologies. The proposed solutions are essential for improving efficiency and process control in the chemical industry.

Streszczenie

Artykuł omawia podejście do analizy procesów zachodzących w reaktorach przemysłowych poprzez wykorzystanie zaawansowanych systemów ze sprzężeniem zwrotnym. Autorzy opisują przygotowanie systemu oraz algorytmy rekonstrukcji obrazów ultradźwiękowych tomografów (UST), które mają zastosowanie w przemyśle. Przedstawione w artykule badania koncentrują się na rozwinięciu skutecznych strategii kontroli i monitorowania i sterowania procesów reakcji chemicznych w reaktorach. Wykorzystując zaawansowane techniki przetwarzania danych, autorzy proponują systemy ze sprzężeniem zwrotnym, które umożliwiają dokładną analizę oraz optymalizację warunków pracy reaktora. Kluczowym aspektem jest wykorzystanie obrazowania ultradźwiękowego tomografów, które dostarcza precyzyjnych danych dotyczących stanu procesu w reaktorze. Podsumowując, artykuł prezentuje nowoczesne podejście do analizy procesów reakcji chemicznych w reaktorach przemysłowych, wykorzystując zaawansowane systemy ze sprzężeniem zwrotnym oraz technologie obrazowania ultradźwiękowego. Proponowane rozwiązania mają istotne znaczenie dla poprawy efektywności oraz kontroli nad procesami w przemyśle chemicznym.

Keywords: *tomography, feedback system, process analysis, sensors, optimization, algorithms, image reconstruction, monitoring*

Słowa kluczowe: *tomografia, sprzężenie zwrotne, analiza procesów, sensory, optymalizacja, algorytmy, rekonstrukcja obrazu, monitoring*

Introduction

The embedded software of the feedback controller module includes both the control program and the communication interfaces. The control program is a set of instructions and algorithms responsible for collecting input data, processing it in real time, and issuing appropriate commands to the output devices. These complex algorithms involve various control techniques, such as PID (Proportional-Integral-Differential) control, predictive control, adaptive control, etc. The software must be optimized for speed of operation, reliability, and precision. Feedback refers to monitoring and comparing output values with expected or setpoint values. In the case of controller modules with feedback, feedback data is provided by sensors measuring various parameters such as speed, position, temperature, pressure, current, etc.

The controller module analyses this feedback data, compares it with target values, and takes appropriate corrective action to maintain system stability and accuracy. In addition, the feedback controller module's embedded software includes communication interfaces that allow data exchange between the controller and other devices or systems. These interfaces include RS485, RS232, and Ethernet. With these, the controller module can receive information from different devices, send diagnostic data and reports, or receive commands from central management systems. The software on the Unitronics PLC, which controls the agitators, peristaltic pump, and pH meter via the RS-232 communication protocol, enables comprehensive control and monitoring of mixing processes and pH measurement in various industrial applications.

With the integrated HMI, users have easy access to all PLC functions. This interface can include a color touchscreen panel enabling intuitive configuration and process control. The controller's communication methods with the mixers, pressure switch, pH meter, and peristaltic pump are developed based on various communication protocols and interfaces. The PLC uses multiple communication methods to control and monitor the equipment in the system. The mixer is controlled using an RS-232 interface, which allows data to be transmitted as an information stream. The controller sends the appropriate commands, such as speed and direction, to the agitator and reads the feedback data to monitor its status and operating parameters. The peristaltic pump is controlled via an

RS-485 interface using the Modbus protocol. The PLC communicates with the pump using the Modbus protocol, which allows it to send control commands such as on, off, speed setting, etc. The controller can also read feedback data from the pump, such as current speed, operating status, alarms, etc.

The Modbus protocol and RS-485 interface ensure reliable communication between the controller and the pump. The pressure switch is connected to the controller via a 4-20 mA transmitter. An analog signal generated by the pressure switch, proportional to the measured pressure, is sent to the controller. The controller reads this signal and converts it to the corresponding pressure value, allowing monitoring and control decisions to be made depending on the set pressure thresholds. The mixer is controlled via an RS-232 interface, with communication via a data stream between the controller and the mixer. Using appropriate communication commands and protocols, the controller sends control signals to the agitator, such as speed, direction of rotation, duration of operation, etc. Feedback data from the stirrer, such as information on current operating parameters, can also be read out by the controller.

The pH meter is controlled similarly to an agitator via an RS-232 interface. The controller communicates with the pH meter via a data stream, sending commands and reading back data. The controller can send commands to calibrate the pH meter, read current pH values, control alarm points, etc. All this is done via communication protocols and commands defined for the pH meter. Through various communication methods, the PLC can effectively control the stirrers, pressure switch, pH meter, and peristaltic pump, providing precise control and monitoring of the parameters of these devices in the system.

Our study will focus on methods for measuring three important external parameters: pH, temperature, and pressure. In various fields such as industry, science, medicine, and many others, accurate measurements of these parameters are vital for process control, quality monitoring, and taking appropriate action. The measurement of pH is a technique used to determine the degree of acidity or alkalinity of a solution. It is an important phenomenon widely used in many fields, such as chemistry, biology, medicine, the food industry, and many others. The basis of pH measurement is using a pH electrode, which is sensitive to the concentration of hydrogen ions ($H+$) in a solution. A pH electrode consists of two main components: inner and outer electrodes. The inner electrode is made of a glass membrane selective for hydrogen ions. This membrane allows hydrogen ions to pass from the solution to the electrode. The outer electrode is a conductive material in contact with the solution under test.

When measuring pH, the pH electrode is placed in solution and is connected to a pH meter or other measuring device. An electrochemical reaction occurs between the inner electrode and the hydrogen ions in the solution. This reaction generates a potential difference proportional to the concentration of hydrogen ions in the solution. The pH meter measures this potential difference and converts it into a pH value using the appropriate calibrations. The pH scale is a logarithmic scale that indicates the concentration of hydrogen ions in a solution. pH 7 indicates neutrality, pH below 7 indicates an acid reaction, and pH above 7 indicates an alkaline reaction. Each pH unit on the scale represents a tenfold change in the concentration of hydrogen ions in the solution.

Accuracy and precision of pH measurement are crucial and require calibration of the pH electrode and maintenance of appropriate measurement conditions, such as temperature, flow, and solution purity. pH measurement is widely used in scientific research, industrial process control, water quality monitoring, medical diagnostics, and many other fields where accurate determination of acidity or alkalinity levels is essential. We will use the built-in temperature sensor in the pH probe for temperature measurement. This temperature measurement method is based on using a temperature sensor integrated directly into the pH probe. The pH probe has a pH electrode responsible for measuring the pH and a temperature sensor, which provides information about the current ambient temperature.

Thus, a temperature reading is also obtained simultaneously while measuring the pH. The temperature sensor in the pH probe reacts to changes in temperature and generates an electrical signal proportional to these changes. This way, we can simultaneously monitor and record pH and temperature in the medium under test. This temperature measurement method is convenient and efficient, as it does not require additional sensors and provides a simultaneous reading of both parameters. The read-out pH and temperature data are transferred to the relevant measuring devices or controllers, where they can be analyzed, monitored, and used for process control or decision-making depending on the application requirements. Pressure measurement using a digital pressure switch is a state-of-the-art technique for precise pressure monitoring and control in various industrial applications. Digital pressure switches use advanced pressure sensors and electronics to provide accurate pressure readings in real-time. A digital pressure switch works by measuring the change in electrical resistance as a function of pressure. The pressure sensor integrated into the pressure switch responds to changes in pressure and generates an electrical signal proportional to the pressure value. This signal is processed by the electronics in the pressure switch and converted into a pressure value in the appropriate units (e.g., bar, psi). Digital pressure switches have built-in calibration functions that allow readings to be adapted to the application's requirements. In addition to essential pressure measurement, digital pressure switches often offer additional functions such as alarms, relay outputs, or digital communication interfaces for integration into supervisory and control systems.

Digital pressure switches have many advantages over traditional analog pressure switches. They offer greater measurement accuracy and precision and more stable and repeatable readings. In addition, digital pressure switches often provide greater configuration flexibility and programmable functions, enabling customized operation to meet individual application needs. Pressure measurement with a digital pressure switch is used in many fields, such as the chemical, petrochemical, food and beverage, medical, and automation industries. With precise pressure measurement, monitoring processes, controlling process parameters, ensuring equipment safety, and optimizing system operation based on actual pressure values is possible.

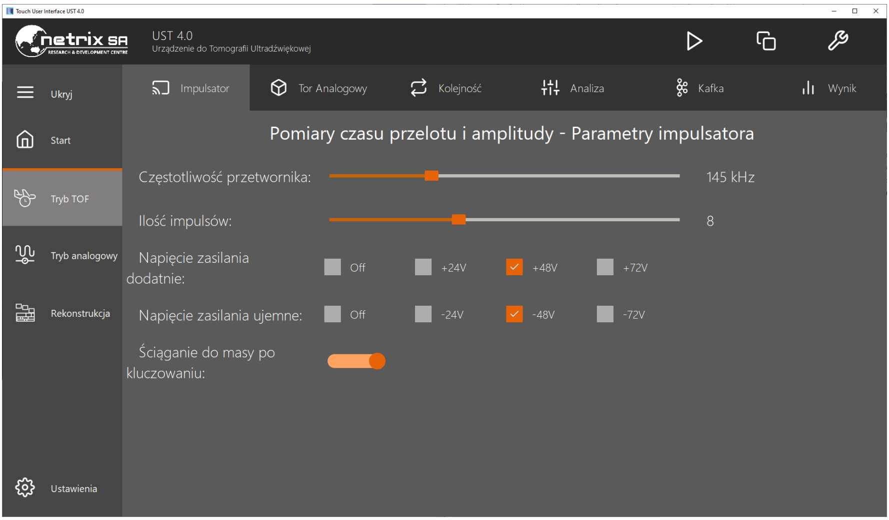
All these sensors and measuring devices must be appropriately calibrated and maintained to ensure accurate measurement results. Signals from pH, temperature, and pressure sensors can be transmitted to measuring devices, PLCs, or supervisory systems, where they are processed, monitored, and used for decision-making and process control. These measurements allow external parameters to be monitored, abnormalities identified, and system performance optimized according to application requirements.

Research Methodology

The device can control parameters. Application modules have been developed to control the device's parameters during measurements. Several operating modes of the device have been prepared, including the possibility of performing time-of-flight measurements and an analog mode allowing the user to visualize the entire sound pressure waveform recorded by the selected measurement sensor.

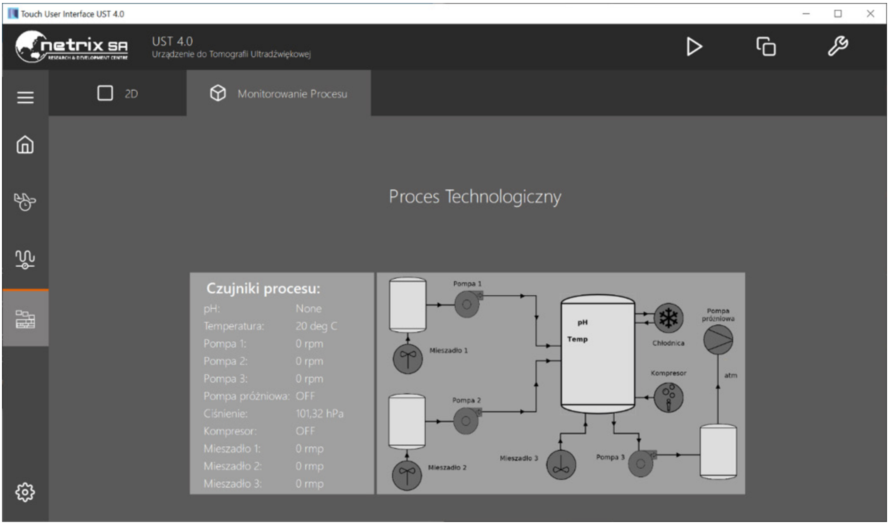
Figure 1 shows a user panel on which the pulsator parameters can be set. This panel allows the frequency of the transducers to be set, the number of excitation pulses, the voltage on the transducer for both polarities and the possibility of pulling down to the ground after keying.

Figure 1. *Screenshot – Time-of-Flight Mode – Pulser Panel*



Process tomography is a handy tool for monitoring and optimizing industrial processes. Crystallization processes, such as the crystallization of chemicals in tanks, are critical steps in many industries, such as pharmaceuticals, chemicals, and food. To ensure the best possible crystallization quality and process efficiency, a monitoring module that generates optimal controller settings is necessary (Kłosowski, 2023).

Figure 2. *Screenshot of the app. A tab that allows you to display process parameters*



This report aims to present the process of developing a monitoring module to generate optimal controller settings for process tomography of the crystallization process in the tank. This module will monitor the parameters affecting the crystallization's quality and efficiency and then generate optimal controller settings to optimize the process. This is a relatively complex issue, as it requires considering all components of the process and its static and dynamic characteristics. For this purpose, it is necessary to use the knowledge of control theory and apply appropriate optimization algorithms.

Process elements that need to be taken into account when generating setpoints include:

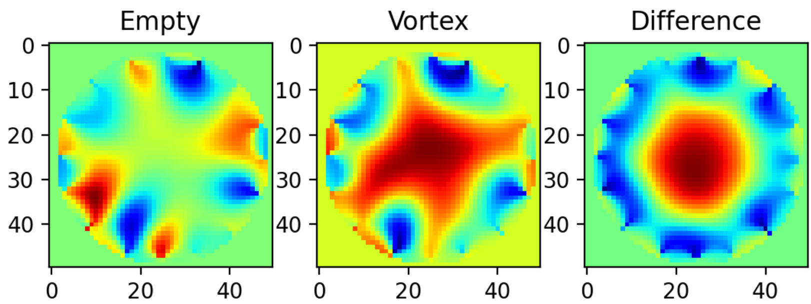
- pump rotation (in the case of the mixed tank process),
- rotation of agitators (in the primary and auxiliary tank),
- cooling water flow,
- cooling water temperature,
- temperature in the main tank,
- pH in the main tank,

Appropriate sensors should be used to monitor these parameters, which will transmit information to the monitoring module. Speed sensors should be used to rotate pumps and agitators, providing information about the current rotational speed. In the case of cooling water flow, a flow sensor should be used to give information on the current cooling water flow. In the case of pH in the main tank, a pH sensor should be used to provide information about the current pH in the main tank. In developing a monitoring module to generate optimal controller settings for process tomography of the crystallization process in the tank, it is essential to determine the appropriate target function. The goal function is vital in the optimization process, as it defines what criteria must be met to achieve optimal results.

A goal function is a mathematical expression that describes optimization criteria. In the case of crystallization process tomography, the target function can be defined as a combination of multiple parameters that affect crystallization quality. For example, the objective function might include minimizing the size of the crystals, maximizing their purity, and minimizing the degree of aggregation. It is also essential to consider process constraints, such as permissible temperature ranges, mixing speeds, or chemical concentrations. Developing the target function requires a thorough analysis of the crystallization process and identifying the parameters that significantly impact the crystallization quality. You then determine the weight of each of these parameters as a function of the goal to account for their relative importance. One of the components of the target function should be a value that is some form of aggregation of data from the reconstruction of the multimodal tomography image (Kłosowski, 2020; Rymarczyk, 2020; Kouluntzios, 2022). The figure below shows a reconstruction of a swirling liquid containing crystals.

Once you have prepared the target function, you must minimize it using an appropriate algorithm. In this case, we will use the rich database of algorithms included in the SciPy package for Python.

Figure 3 *Reconstruction of the vortex occurs when strong liquids are mixed with crystals*



Gradient Enhanced Classifier – UST – Transmission Mode

The feedback system allows analysis of the reactor processes based on reconstructions of the reactor interior using ultrasonic tomography imaging (Majerek, 2021). Reinforcement is a machine learning method. Initially, it was applied to classification problems. The concept of constructing a reinforcement method is to combine a set of weak classification trees to create a robust classifier (Kozłowski, 2020).

A training dataset is defined as

$$D=\{(x_i,y_i):x_i \in R^m,\ y_i \in \{-1,1\},\ 1\leq i \leq n\}.$$

Class membership is represented as $y_i \in \{0-1,1\}$ dla $1\leq i \leq n$. In the analyzed case, if the finite element belongs to the inclusion area, we assume $yi=1$. On the other hand, if the finite element belongs to the background, we assume $y_i=-1$.

Gradient-boosted classifier (GBC) (Hastie 2009) consists in the definition of a sequence of classification trees $\{\ T(x,\Theta_1\ ),T(x,\Theta_2),\ldots,T(x,\Theta_m\ )\ \ \}$, where the boosted classifier is defined as follows

$$f_m(x)=f_{m-1}(x)+T(x,\Theta_m)=\sum_{j=1}^{m} T\left(x,\Theta_j\right). \tag{1}$$

Reinforcing trees (1) are determined in stages, namely the classification tree $T(x,\Theta_m\ )$ is created for observations that have been misclassified by the amplified model $f_{m-1}(x)$. Every step of the way $j = 1, 2, \ldots, m$ the classification tree is defined as follows

$$T(x, \Theta_j) = \sum_{i=1}^{k_j} \gamma_{ij} I_{R_{ij}}(x), \tag{2}$$

where $R_{1j}, R_{2j}, \ldots, R_{kj,j}$ is a set of disjoint areas, and

$$I_A(x) = \begin{cases} 0, & x \neq A \\ 1, & x \in A \end{cases}$$

In view of the above, the sequence $\Theta_j = \{(\gamma_{1j}, R_{1j}), (\gamma_{2j}, R_{2j}), \ldots, (\gamma(k_{j,j}, R_{kj,j})\}$ specifies the parameters of the tree that was determined in the step j – th. For step j – go ($j > 1$) The parameters of the tree (2) are determined by solving the problem

$$\Theta_j = \underset{\Theta}{argmin} \sum_{l=1}^{n} L\left(y_l, f_{j-1}(x_l) + T(x_l, \Theta)\right)$$

where $L(.)$ denotes the loss function (Hastie 2009).

Algorithms have been developed based on the above assumptions, and the results of image reconstruction are presented in the images below.

Figure 4. *Given the distribution of material parameters (case I)*

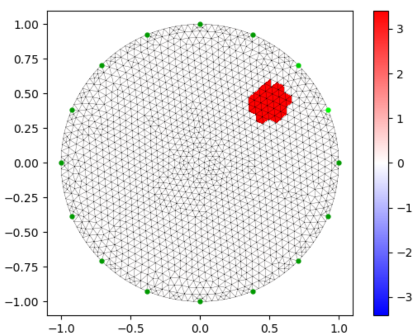


Figure 5. *Image reconstruction obtained using logistic regression (left) and using the GBC model (proper) (I case)*

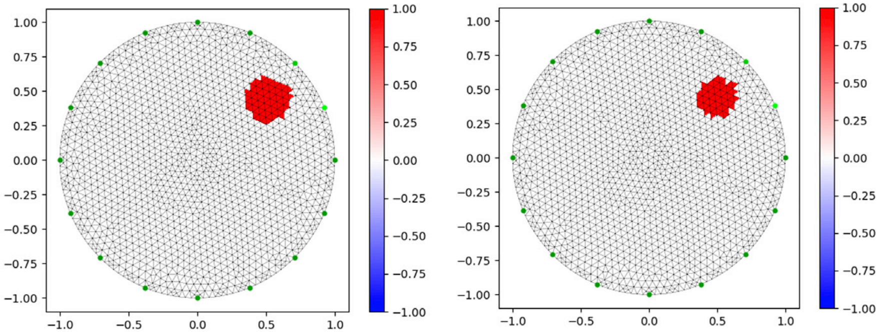


Figure 6. *Given the distribution of material parameters (case II)*

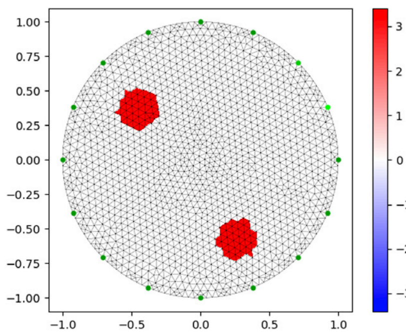


Figure 7. *Image reconstruction obtained using logistic regression (left) and using the GBC model (proper) (II case)*

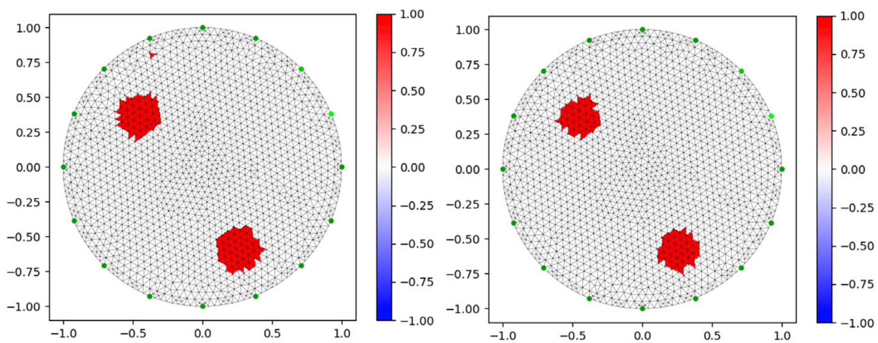


Figure 8. *Given the distribution of material parameters (case III)*

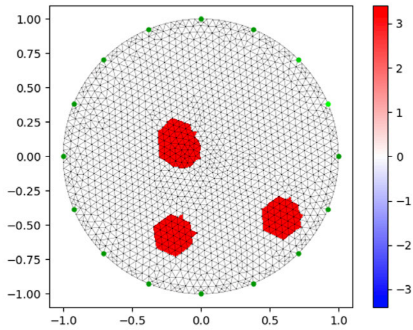


Figure 9. *Image reconstruction obtained using logistic regression (left) and using the GBC model (proper) (III case)*

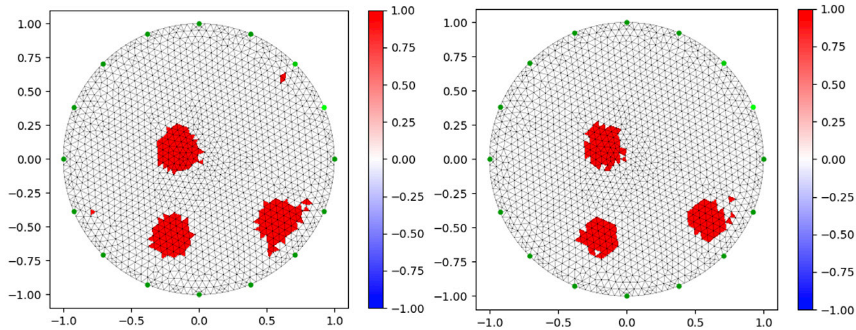


Figure 10. *Given the distribution of material parameters (case IV)*

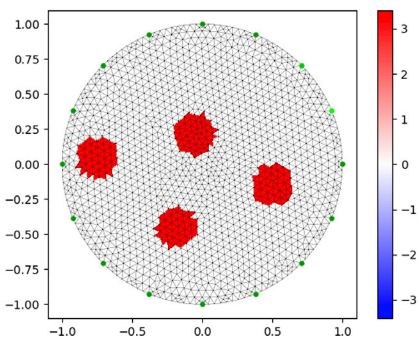


Figure 11. *Image reconstruction obtained using logistic regression (left) and using the GBC model (proper) (IV case)*

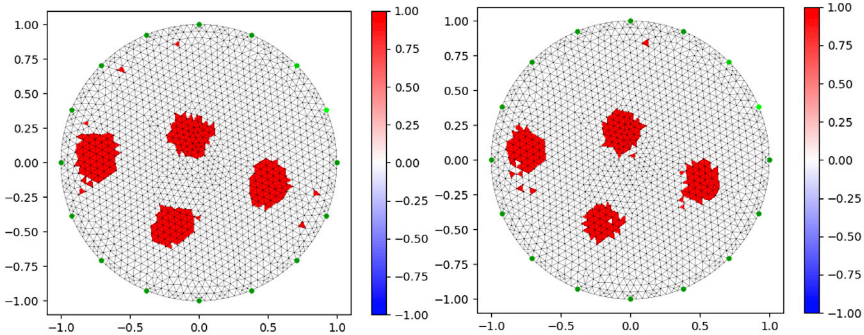


Figure 12. *Given the distribution of material parameter (case V)*

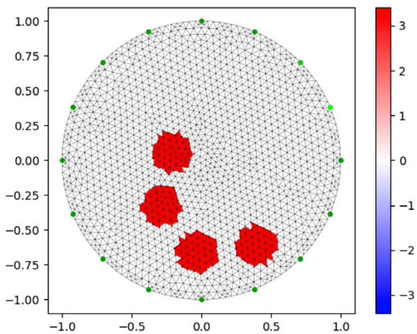


Figure 13. *Image reconstruction obtained using logistic regression (left) and using the GBC model (proper) (V case)*

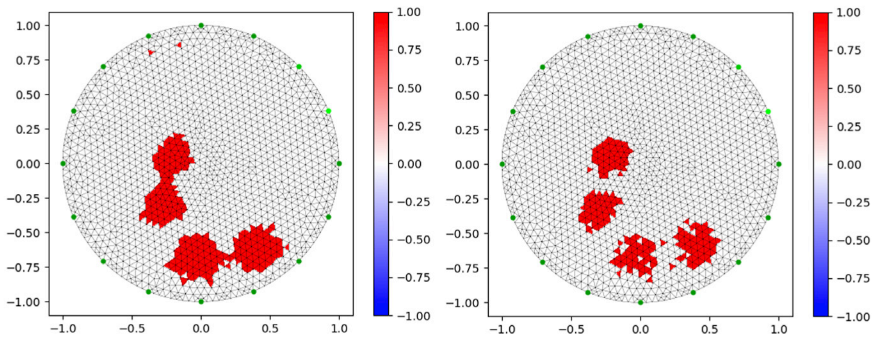


Table 1. *Parameters characterizing the quality of image reconstruction – logistic regression*

Example	Accuracy	Precision	Recall	F1	SSIM
I	0,99490	0,79167	1,00000	0,88372	0,97083
II	0,99320	0,85507	1,00000	0,92188	0,96400
III	0,98503	0,83966	0,97073	0,90045	0,92091
IV	0,97891	0,81848	0,97255	0,88889	0,89954
V	0,96939	0,75949	0,94488	0,84211	0,84836

Table 2. *Parameters characterizing the quality of image reconstruction – GBC*

Example	Accuracy	Precision	Recall	F1	SSIM
I	0,99762	0,94643	0,92982	0,93805	0,98511
II	0,99694	0,97391	0,94915	0,96137	0,98174
III	0,98946	0,97283	0,87317	0,92031	0,95220
IV	0,98333	0,91870	0,88627	0,90220	0,89522
V	0,97551	0,88235	0,82677	0,85366	0,84802

Conclusions

This paper presents research into the design of a feedback system for reactor process analysis. The primary research problem was designing and constructing a feedback system and a complex system based on ultrasonic transmission and reflection tomography. The selection of methods to analyze the obtained measurement results by solving inverse problems was also performed. Based on reconstructed acoustic parameters, the internal structure of the investigated area can be visualized. The imaging is based on the differences in the local values of the individual acoustic parameters. The image obtained by the tomograph is presented. Due to the process's time-varying, non-linear, and irregular nature, it isn't easy to define an accurate mathematical model of these processes, which requires continuous ones. Effective process monitoring is essential to ensure high reliability and trouble-free operation. The main problem in ultrasonic tomography has been the difficulty in building a physical model considering the full complexity of acoustic phenomena occurring in a relatively small space. The proposed tomographic solution allows the reconstruction of images regardless of the size, shape, location, or number of inclusions hidden in the studied object.

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