Acta Montanistica Slovaca
ISSN 1335-1788
actamont.tuke.sk

Development of Automated Analytics for Monitoring Gas Collection System and Early Detection of Gas Hydrate and Ice Complications

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How to cite this article:
Maximova, Y., Korotchenko, R., Zhironkin, V. and Zhironkin, S. (2025). Development of Automated Analytics for Monitoring Gas Collection System and Early Detection of Gas Hydrate and Ice Complications, *Acta Montanistica Slovaca*, Volume 30 (3), 571-580

DOI:
https://doi.org/10.46544/AMS.v30i3.02

Abstract
The transition to sustainable development and the movement towards carbon neutrality pose new challenges for the production of natural gas, which is considered both a "transitional" and a "stable" fuel. In the Arctic region, the formation of hydrates and ice plugs in gas collection and treatment systems is a significant unresolved problem. Implementing measures to prevent this can have a substantial impact on gas production operating costs. The aim of this work is to develop a prototype of an automated analytics system that detects pressure anomalies early, potentially signaling the onset of hydrate formation in the gas collection system. To solve this problem, the methods of searching for anomalies and averaging data (sliding window, moving average, threshold value) were used. The article highlights the shortcomings of existing approaches, which are associated with insufficient accuracy of modeling due to the complexity and multifactorial nature of hydrate formation, increased measurement error, imperfection of devices, and communication channels of sensors with the control panel. The study subject is a gas collection system. In the process of implementing the tasks, a decision-making algorithm was developed, and a mathematical model was developed at the first level of this algorithm, which is adaptive, flexible, and easily scalable for working with other types of time series of parameters (flow rate, temperature), as well as various types of gas collection systems. A mathematical description of the developed model was presented. The possibility of scaling and developing the idea was demonstrated, along with the feasibility and possibility of its implementation. The results of experimental verification are also given.

Keywords
natural gas, gas hydrate, ice plug, early detection, gas collection system, automation.

Introduction

Natural gas plays a significant role in the global energy sector due to its versatility of application – as an energy source (gas-fired power plants have high efficiency and quick start-up, which makes them ideal for covering peak loads and balancing power systems with a high share of renewable energy), as a mass source of heat (due to its high environmental friendliness – gas contains virtually no sulfur and particulate matter), as a raw material for the production of fertilizers and plastics, as a source of transport fuel alternative to gasoline and diesel fuel (Cherevko et al., 2024). Therefore, achieving the Sustainable Development Goals related to carbon neutrality and climate stability, coupled with ensuring universal access to cheap energy, inevitably preserves the role of natural gas as the main "transitional" fuel in the 21st century (Lukyanenok et al., 2023; Zonova et al., 2024). Therefore, investments in natural gas production have also increased by 8-11% annually over the past 2 decades (Gerasimova, 2024). At the same time, the growth of global gas consumption is obvious (Fig. 1), and existing forecasts indicate growth prospects by 2050 by 1.10-1.25 times, depending on the ″NetZero″ and ″Rational *t*echnological choice″ scenarios (Energy Insights, 2021).

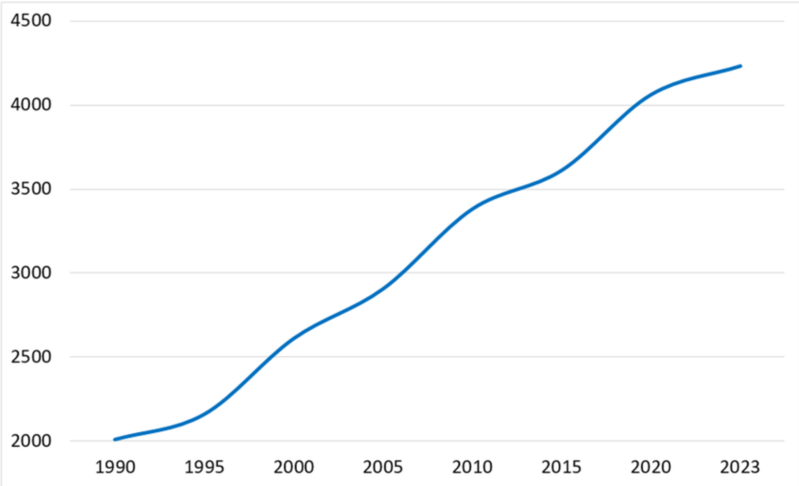

Fig. 1. World dynamics of natural gas production, bcm (World Energy & Climate Statistics, 2024)

The growth of global consumption of natural gas raises the question of developing reserves located in the Arctic and adjacent zones, with a proven volume of about 50 trillion cubic meters (Fig. 2).

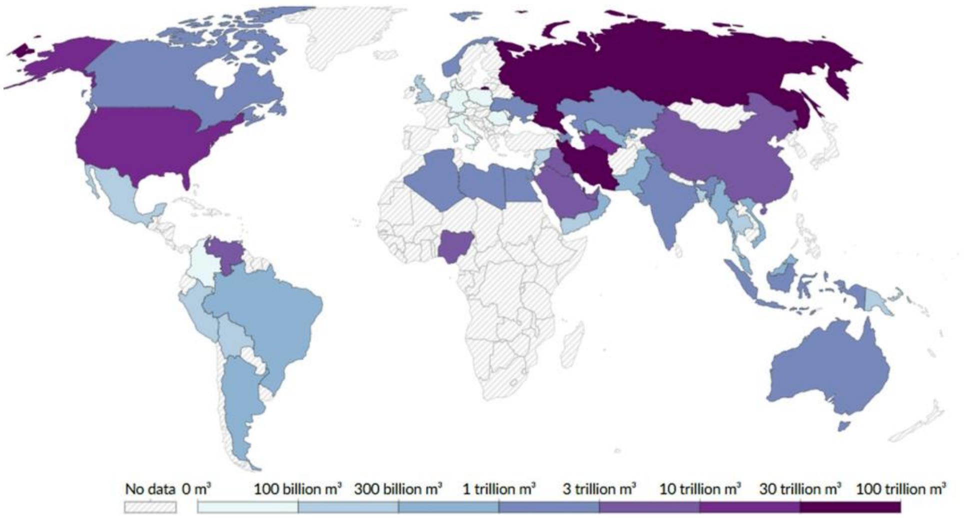

Fig. 2. World distribution of proven natural gas reserves, trillion cubic meters (Our World in Data, 2023)

Overall, the Arctic contains 13% of the world's probable oil reserves and 30% of natural gas, with 80% of the total hydrocarbons located offshore (Shutko et al., 2024). Given that the average annual temperature in the Arctic is -12 0C, greater attention will be paid to maintaining the operation of gas production equipment in low-temperature conditions.

In particular, the relevance of research on counteracting the process of hydrate formation in natural gas production systems is increasing, which includes two directions: preventing the formation of hydrates and eliminating those already formed (Makwashi et al., 2021).

Natural gas hydrates are solid crystalline compounds formed under certain thermobaric conditions from water and low molecular weight gas. The thermodynamics and kinetics of the hydrate formation process have been studied quite well (Rasoolzadeh et al., 2025). In general, the hydrate formation process consists of the appearance of the first signs of crystallization and the stage of sorption growth of the crystal around the nucleus. In Arctic conditions, the formation of hydrates and ice plugs in gas collection and treatment systems is one of the most significant and unresolved problems (Bogoyavlensky et al., 2019; Giustiniani et al., 2013; Marín-Moreno et al., 2016). Elimination of this complication is difficult, and the costs of measures to prevent it constitute a significant part of the cost of gas production (Sa et al., 2019).

Mathematical models describing the properties of hydrates, as well as the thermodynamics of their formation and growth, are quite complex and include many factors and conditions (Shostak, 2022; Musakaev et al., 2024).

The processes occurring in the collection and preparation system, including hydrate formation processes, are dynamic, and it can be added that the parameters for which operational information is available are extremely limited in field conditions and are reduced to monitoring the gas pressure at the well outlet, temperature, and gas flow at several well points along process communications of tens of kilometers. Wind speed in specific areas, wear of thermal insulation, the amount of deposits inside pipelines, and many other parameters remain unknown (Savenok et al., 2024).

There is measurement error, imperfection of devices, and communication channels of sensors with the control panel. Obviously, the combination of the described factors results in extremely limited capabilities for collecting data on the system as a whole, leading to a significant data error. In addition to the processes of hydrate formation itself in gas collection equipment, at the later stages of development, processes of ice formation occur directly (Xiao et al., 2023; Shahbazi et al., 2009), which introduces additional uncertainty when trying to model the processes occurring in the system. In this regard, it is extremely difficult to prevent the complication in question by means of forecasting based on physicochemical modeling of processes.

The issue of applicability and accuracy of predictive models based on physicochemical modeling of the hydrate formation process is raised in a number of studies (Karaköse et al., 2024; Niu, 2024). The authors of these works conclude that such modeling is unacceptable for solving the problem of operational hydrate detection in field conditions (Patri et al., 2014).

After reviewing the most common approaches, it is concluded that to date, no universal method has been found for predicting or early detection of hydrate formation in a pipeline that would provide very high accuracy with minimal costs for processing and obtaining information [Volovetskyi et al., 2023; Tang et al., 2024)

At the same time, systems working with empirical data in real time are being implemented at Arctic fields. Currently, a system for autonomous dosing of methanol is being successfully tested. The consumption of methanol depends on gas production indicators, which essentially constitutes an automated system for the early detection of changes in gas production parameters and an autonomous response to these changes (Prakhova et al., 2016).

The work on detection and elimination of gas hydrates and ice plugs is one of the key tasks for the process personnel of the facilities. This operation involves *personnel analyzing a large array of data from devices installed along the entire well production collection system to make informed decisions*. Due to the complexity and dynamism of the system, analytical work *focuses on the early detection of anomalies in pressure and temperature trends, as well as the interpretation of* detected deviations. Considering that all data is digital information, the idea of creating a model for automated analysis of the state of the gas collection system seems logical. The use of such an approach will allow moving away from unsuccessful attempts to create predictive physical and chemical models that are extremely demanding of the completeness and accuracy of information about the system. Instead, it is proposed to build a model that will work with statistical data, limited but sufficient for early detection of complications.

Considering this, the *research objective is to optimize the data processing processes of field gas collection systems by automating the technological process at* field "X".

Accordingly, the research object, the tasks that need to be solved include the following:

- develop algorithmic rules for the model's operation in the conditions of field data collection, based on real analytics.
- develop a mathematical model capable of performing operations for the early detection of data anomalies at the level of gas well operation.

The prototype of the mathematical model will demonstrate the fundamental possibility of implementing a full-fledged model of automated analytics of the entire gas collection system.

Formalization of the analytical process

To solve the first problem, it was necessary to determine which key actions of production personnel can be formalized and reduced to a strict algorithm. In solving this problem, several methods were employed, including observing personnel actions, synthesizing key aspects into a single system, abstracting from secondary tasks, classifying information, and using induction and deduction to establish logical connections in the final formal algorithm. In the course of the work, it became clear that data analytics is performed at different levels of the gas collection system. The first level of analysis is the level of gas well performance indicators, providing the bulk of the initial information. In the process, personnel identify abnormal changes in the time series of pressure and gas flow. By the nature of these changes, several causes of anomalies can be determined, including hydrate formation. If information at the well level is insufficient, a transition to a higher level of analysis is made – the level of a well cluster. At this level, a comparison of the parameters of gas wells located within the same cluster is performed. If the analysis at the well cluster level also does not allow the exact cause of the anomaly to be determined, the transition to two higher levels is performed – the gas collection manifold and the gas collection system. Ultimately, the exact cause of the anomaly will be determined at one of the levels.

The analytics described above is formalized and summarized in a single decision-making algorithm consisting of 4 levels: Level 1 – ″gas well ″, Level 2 – ″cluster of well ″, Level 3 – ″gas collection manifold″, Level 4 – ″gas collection system″ (Fig. 3). These levels reflect the hierarchy of the main operational blocks and all possible signals about the causes and prerequisites of anomalies (yellow and gray blocks).

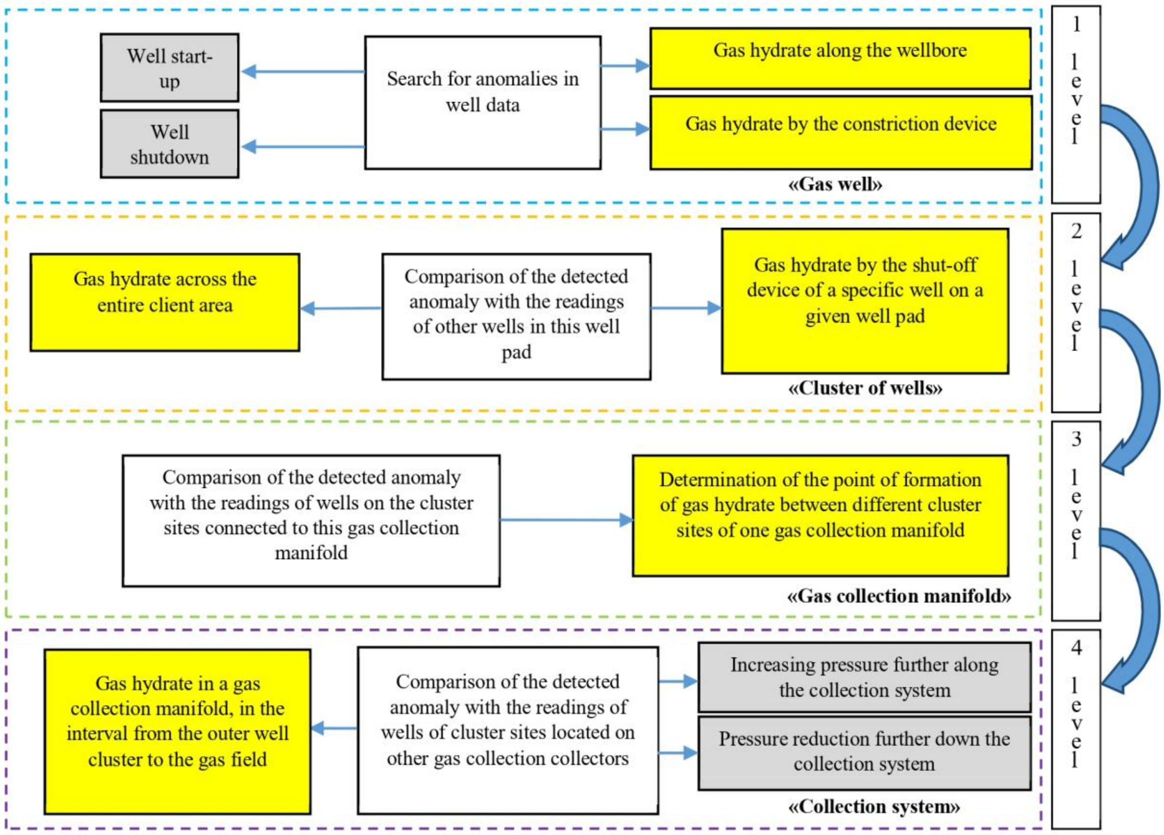

Fig. 3. Scheme of the solution algorithm and hierarchy of analysis levels

Development of a prototype of an automated analytics model

The implementation of the solution algorithm's steps must begin with developing a basic prototype – a starting mathematical model. Such a model could serve as a starting point for implementing a complex system and demonstrating the fundamental feasibility of a full-fledged project.

The first stage of well-level analysis is searching for anomalies in pressure and flow rate time series. In field conditions, this analysis is performed by visually viewing the relevant trends and finding sharp deviations. To create a mathematical description of this process, it is necessary to develop a model based on time series anomaly detection methods. In the process of developing the model, the difficulties associated with the dynamics of the gas gathering system were taken into account. The technological operating mode is constantly changing under the influence of seasonality, daily temperature differences, changes in system parameters as specified by the dispatcher, and other factors. In this regard, it was decided to reduce some of the data to relative values. It was decided to use the "sliding window" method to perform real-time data analysis. The threshold method was used to identify critical changes. In addition, the input data contains a high level of error, which leads to significant noise in the time series. To eliminate this problem, it is proposed to use the data smoothing method – "moving average", thereby creating a hybrid model for searching for anomalies in real time on noisy data in a dynamic system.

The model is designed for the analysis of pressure time series, but is equally applicable to the analysis of other time series coming to the control panel of the gas collection system. The model contains the following parameters:

Let's display some parameters of the model on the trend of an arbitrary pressure time series (Fig. 4):

- P_{cur} – measured pressure at the current time $t_{наст}$.
- T_{hist} – length of the historical interval (number of points used for averaging – empirically set).
- T_{buf} – buffer interval between historical and current data (empirically set).
- K_{crit} – critical anomaly threshold (empirically set).
- $P_{av}(t)$ – average pressure over the historical interval.
- $K_x(t)$ – anomaly coefficient determining the deviation of the current pressure from the norm.
- L – length of the verification interval (number of points analyzed after exceeding the threshold – empirically set).
- D – number of $K_x(t)$ values exceeding K_{crit} in interval L, at which the situation is classified as anomalous (empirically set).

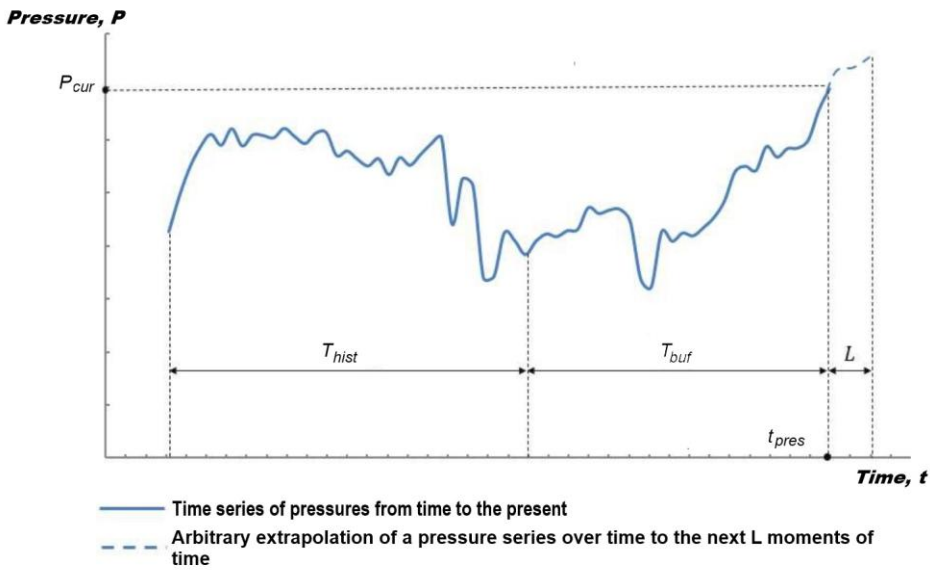

Fig. 4. Arbitrary time series of pressures with some model parameters indicated

Let the current pressure value P_{cur} at the present moment of time t_{pres} be divided by the average value $P_{av}(t)$ found in the historical interval t_{pres}. The historical interval t_{pres} is separated from the present moment of time t_{pres} by the buffer range of values T_{buf}. In the course of dividing P_{cur} by $P_{cp}(t)$, we obtain the coefficient $K_x(t)$. Then the obtained coefficient is compared with the critical (threshold) value $P_{av}(t)$. The values K_{crit} , t_{pres} , T_{buf} are determined empirically based on archive data during the analysis and adjustment of the model. Then, in the process of comparing K_x with K_{crit} , two options are possible:

1. If $K_x \leq K_{\text{crit}}$, then the mode is "standard".

In this case, the values and ranges are shifted one step to the right. The new $P_{av}(t)$ sliding is analyzed, the range windows T_{hist} , T_{buf} also slide to the right by one value. Thus, $K_x(t)$ is calculated and compared with K_{crit} in real time with continuous sliding to the right as new data is received with each new moment in time.

2. If $K_x(t) \geq K_{\text{crit}}$, then the mode is "check".

In this case, the sliding of the ranges T_{hist} , T_{buf} stops for a while, $P_{av}(t)$becomes fixed $P_{av\,fix}(t)$. In this case, the sliding of P_{cur} will continue in the interval of L of the following values. If, in the process of dividing the sliding P_{cur} by the fixed $P_{av\,fix}(t)$ in the interval of L, the following values, D values from the interval L, will be greater than or equal to K_{crit} , it is considered that there is an anomaly. Otherwise, it is considered that there is noise in the data, and there is no anomaly. The values of L and D are also determined empirically during the model tuning.

After executing the "check" mode, the model returns to the "standard" mode regardless of the check results, thus continuing to monitor the system in real time.

An example of a model description using an arbitrary time series (Table 1):

Table 1. Conditional example of a pressure time series

Time, t	t_1	t_2	t_3	t_4	t_5	t_6	t_7	t_8	t_9	t_{10}
Pressure, P	P_1	P_2	P_3	P_4	P_5	P_6	P_7	P_8	P_9	P_{10}
Time, t	t_{11}	t_{12}	t_{13}	t_{14}	t_{15}	t_{16}	t_{17}	t_{18}	t_{19}	t_{20}
Pressure, P	P_{11}	P_{12}	P_{13}	P_{14}	P_{15}	P_{16}	P_{17}	P_{18}	P_{19}	P_{20}

1. "Standard" mode

1.1 For $t_{pres} = t_{15}$we define the ranges T_{hist} , T_{buf} and the value $P_{av}(t)$ on the interval T_{hist} :

$$T_{\text{hist}} = [t_1; t_{10}] \tag{1}$$

$$T_{\text{buf}} = [t_{11}; t_{14}] \tag{2}$$

$$P_{av}(t) = \frac{1}{10}\sum_{i=1}^{10} P_i \tag{3}$$

2. Calculate K_{15}:

$$K_{15} = \frac{P_{15}}{P_{av}(t)} \tag{4}$$

1.3 We compare $K_{15}$and K_{crit} . If $K_{15} \leq K_{\text{crit}}$, the model remains in the "standard" mode, and further checking of the values in the sliding window is performed. In this case, for the next $t_{pres} = t_{16}$, the new intervals T_{hist} and T_{buf} and the value $P_{av}(t)$ slide to the right by one value:

$$T_{\text{hist}} = [t_2; t_{11}] \tag{5}$$

$$T_{\text{buf}} = [t_{12}; t_{15}] \tag{6}$$

$$P_{av}(t) = \frac{1}{10}\sum_{i=2}^{11} P_i \tag{7}$$

$$K_{16} = \frac{P_{16}}{P_{cp}(t)} \tag{8}$$

2. "Check" mode

2.1 If $K_{15} \geq K_{\text{crit}}$, the model switches to the "check" mode. For the next $t_{\text{pres}} = t_{16}$, the ranges T_{hist} and T_{buf} stop sliding and $P_{av\,fix}(t)$ is fixed based on the results of the previous calculation:

$$P_{av\,fix}(t) = \frac{1}{10}\sum_{i=1}^{10} P_i \tag{9}$$

2.2 In this case P_{cur} continues to slide to the right for another L = 4 points. In this case $K_x(t)$ for $t_{16}, \ldots, t_{19}$ will be calculated as:

$$K_{16} = \frac{P_{16}}{P_{av\,fix}(t)}, \ldots, K_{19} = \frac{P_{19}}{P_{av\,fix}(t)} \tag{10}$$

2.3 If at least *D* = 2 coefficients $K_x(t)$from the interval *L* = 4 exceed K_{crit} , the anomaly is confirmed.

3. After performing the check (regardless of the result), a return to the "standard" mode occurs. New $t_{\text{pres}} = t_{20}$:

$$T_{\text{hist}} = [t_6; t_{15}] \tag{11}$$

$$T_{\text{buf}} = [t_6; t_{19}] \tag{12}$$

$$P_{av}(t) = \frac{1}{10}\sum_{i=6}^{15} P_i \tag{13}$$

$$K_{20} = \frac{P_{20}}{P_{cp}(t)} \tag{14}$$

Results and Discussion

The model was implemented experimentally in Python using the Pandas and Matplotlib libraries. Testing was performed on synthetic data similar to real data, simulating the dynamics of changes in the pressure time series with an interval of 15 minutes. The testing time range is one month. The automated system, developed based on the model prototype, identified 32 clusters of anomalies in the gas pressure time series. Clusters were formed by adjacent anomalous indicators within 2 hours (necessary to isolate the anomaly ranges instead of identifying a set of closely spaced anomalous points). In the process of setting up the model, the following parameters were defined: $T_{\text{buf}} = 15$, $T_{\text{hist}} = 15$, $L = 4$, $D = 2$, $K_{\text{crit}} = 1.0015$. The model successfully identified early signs of anomalies in the pressure time series. The monitoring range of the latest input data, $L = 4$, corresponds to a data analysis and decision-making time of 1 hour. As a result of the experiment and model tuning, it turned out that this time is the minimum required analysis window when making decisions in model conditions. In real-world fields, the analysis window is approximately 1 hour or 4 last input values of the time series (4 values of 15 minutes equal 1 hour). Thus, it can be assumed that the efficiency of analysis, speed, and accuracy of anomaly detection by the model should not be inferior to the efficiency and accuracy of anomaly detection by a person. Visualization of the experiment is presented in Fig. 5.

We must note that the values on the vertical pressure axis are not displayed, as they may be related to a commercial secret. In the simulation, relative values were used, reflecting only the dynamics of changes. Within the framework of the model, such an approach is acceptable, since the calculation of the main parameters of the model is carried out through relative values.

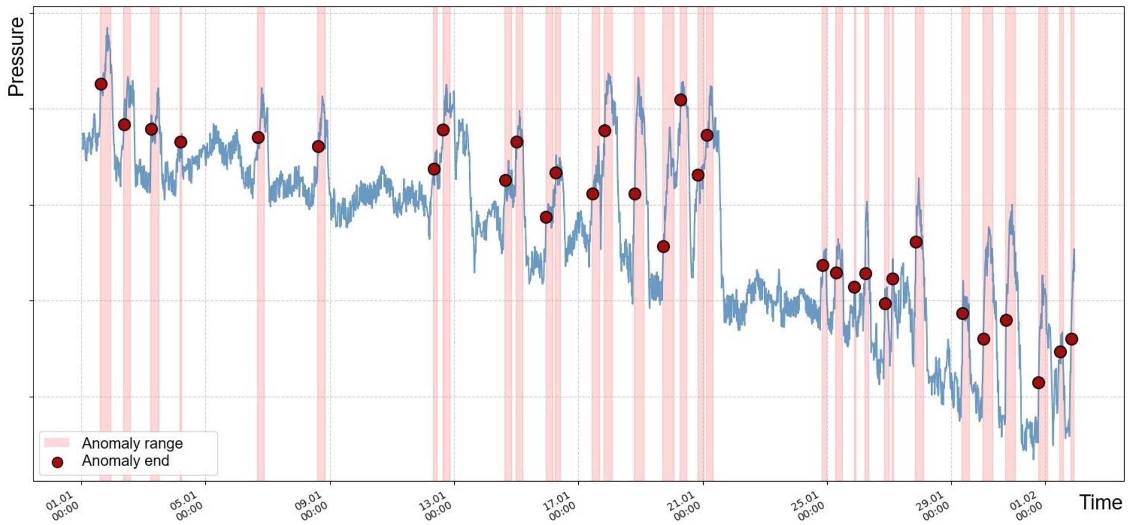

Fig. 5. Visualization of the anomaly detection model in pressure data in Python

The anomalous ranges in Fig. 5 are highlighted with red areas. The beginnings of the anomalous zones are marked with dots. The moments of anomaly detection and their duration are presented in Table 2

Table 2. Time ranges and duration of detected anomalous zones

No	*Date/time of the anomaly start*	*Date/time of end of anomaly*	*Duration of anomalous zone (min)*	*No*	*Date/time of the anomaly start*	*Date/time of end of anomaly*	*Duration of anomalous zone (min)*
1	*01.01/15:03*	*01.01/22:03*	*420*	*17*	*20.01/06:48*	*20.01/10:48*	*240*
2	*02.01/09:03*	*02.01/13:33*	*270*	*18*	*20.01/20:18*	*21.01/00:18*	*240*
3	*03.01/06:03*	*03.01/11:33*	*330*	*19*	*21.01/03:03*	*21.01/07:18*	*255*
4	*04.01/04:33*	*04.01/04:48*	*15*	*20*	*24.01/20:33*	*24.01/22:48*	*135*
5	*06.01/16:33*	*06.01/20:48*	*255*	*21*	*25.01/06:48*	*25.01/10:48*	*240*

6	*08.01/14:48*	*08.01/19:33*	*285*	*22*	*25.01/21:03*	*25.01/21:18*	*15*
7	*12.01/08:18*	*12.01/10:18*	*120*	*23*	*26.01/05:18*	*26.01/07:33*	*135*
8	*12.01/15:33*	*12.01/20:03*	*270*	*24*	*26.01/20:33*	*26.01/22:48*	*135*
9	*14.01/15:33*	*14.01/19:33*	*240*	*25*	*27.01/02:18*	*27.01/02:48*	*30*
10	*15.01/00:18*	*15.01/04:33*	*255*	*26*	*27.01/20:33*	*28.01/01:33*	*300*
11	*15.01/23:03*	*16.01/03:48*	*285*	*27*	*29.01/08:33*	*29.01/13:03*	*270*
12	*16.01/06:33*	*16.01/09:18*	*165*	*28*	*30.01/00:33*	*30.01/07:18*	*405*
13	*17.01/10:33*	*17.01/15:33*	*300*	*29*	*30.01/18:03*	*31.01/00:33*	*390*
14	*17.01/20:03*	*18.01/01:33*	*330*	*30*	*31.01/19:18*	*01.02/01:18*	*360*
15	*18.01/19:03*	*19.01/01:48*	*405*	*31*	*01.02/12:03*	*01.02/13:33*	*90*
16	*19.01/17:33*	*20.01/01:03*	*450*	*32*	*01.02/20:18*	*01.02/22:03*	*105*

Although the model quickly and accurately identified all the existing anomalies in the modeled data, it has a number of limitations. Some of the detected anomalies may not be signs of hydrate formation in the system. They may be associated with technological reasons, such as well starts and stops, and pressure redistribution in the system as a whole. In its current form, the model cannot be used to classify anomalies by the cause of the anomalies found. In essence, at the moment, the model performs the task of the "search for anomalies in well data" block of the first level of data analysis of the decision-making algorithm presented in Fig. 3. However, it is obvious that the model, even in its current form, has the potential for scaling.

To implement automated analysis of the entire first level, it is necessary to add additional critical coefficients for starting and stopping the well, and apply the model to the time series of flow rates. At the next levels of the algorithm, it is necessary to add methods for comparing the parameters of time series with each other and finding correlations between the series. Within the framework of the existing data specifics, the time series of neighboring wells have a similar value profile. However, if anomalies are present, they may exhibit a shift in their signs over time or a different rate of development of anomalous indicators. In these conditions, one of the most promising methods for finding correlations is the method of dynamic transformation of the time scale (DTW). The use of this method and other approaches to comparing time series data seems to be a completely feasible task.

Prospects for using machine learning to upgrade an existing model or create an alternative one

Currently, the possibility of upgrading the presented model by using machine learning or even creating an alternative solution to the stages of the formal algorithm shown in Fig. 3 is being considered. Artificial intelligence can quite well solve problems related to the analysis of time series and provide the required solutions in various fields of application, including the oil and gas sector (Qin et al., 2019; Hanga et al., 2019; Paltrinieri et al., 2019). Obviously, the methods for optimizing the parameters T_{buf}, T_{hist}, D, L, which are now set empirically, based on statistics and expert estimates, can be applied to this model. In addition, the threshold method for determining anomalies through K_{crit} can be replaced by machine learning algorithms capable of identifying complex patterns. In general, the use of machine learning, at least at some stages of the implementation of the developed formal algorithm, looks like a fairly promising solution.

Conclusion

This paper addresses the problem of hydrate formation in gas collection systems of gas fields. According to the hypothesis and arguments presented, the most promising solution is to create a model of automated analytics for the gas collection system, based on the principle of early problem detection. The purpose of the work was to create a prototype of such a system. In the process of implementing the set tasks, it was possible to develop a decision-making algorithm and create a mathematical model at the first level of this algorithm.

The proposed mathematical module performs early detection of pressure anomalies, which may be a signal about the beginning of the hydrate formation process in the gas collection system. Calculation of the moving average value, use of the buffer interval, and introduction of the interval for confirming anomalies make the model resistant to noise and false alarms. At the same time, the use of the sliding window method allows for analyzing the system in real time. The model is adaptive, flexible, and easily scalable for working with other types of time series (flow rate, temperature) and various types of gas collection systems. Adaptability and versatility are achieved due to the ability to adjust the ranges T_{buf}, T_{hist}, D, L, as well as setting the parameter K_{crit}. In addition, the model is quite simple to implement, does not require large computing power or deep modernization of equipment. The efficiency and scalability of the presented model are arguments confirming the possibility and economic feasibility of developing a comprehensive system for analyzing processes in gas collection equipment. A possible option for developing the idea is to use machine learning to create a hybrid method or even an alternative approach.

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