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Alexey SAVOSTIN[1,2], Kayrat KOSHEKOV[1,3], Amandyk TULESHOV[1], Galina SAVOSTINA[2], Abay KOSHEKOV[3]

[1] *U. Joldasbekov Institute of Mechanics and Engineering, Republic of Kazakhstan*
[2] *M. Kozybayev North Kazakhstan University, Republic of Kazakhstan*
[3] *Civil Aviation Academy, Republic of Kazakhstan*

DEVELOPMENT OF REMOTE DIAGNOSTIC MONITORING SYSTEM FOR PUMPING EQUIPMENT WITH OPEN ARCHITECTURE

The study aim was *to develop a remote diagnostic monitoring system for pumping equipment with an open architecture to improve the reliability and efficiency of pump operation in various industrial sectors. The system is designed for the periodic collection and analysis of vibration and temperature signals, which allows for the prompt identification of potential equipment malfunctions and avoidance of emergency shutdowns during the production process.* ***The aim*** *of this study was to develop an effective open architecture for a diagnostic monitoring system for pumping equipment based on IoT technologies. The primary focus is on creating a system architecture that simplifies the installation and operation of equipment, ensures scalability and ease of integration with existing enterprise information systems, and reduces material implementation costs. To achieve this goal, the following* ***objectives*** *were addressed within the study: 1) selection of informative features from vibration signals that allow for the diagnosis of the most common faults in pumping equipment during periodic monitoring; 2) selection of hardware specifications that ensure the diagnostic monitoring system meets the stated requirements; and 3) development of a software and network architecture for the diagnostic monitoring system based on open hardware and software standards.* ***The results*** *of the experiments demonstrated that the developed system enables effective monitoring of the condition of pumping equipment and reduces the risk of emergency shutdowns, thereby optimizing operating costs. The incorporation of wireless technologies, open software products, and standards makes systems flexible and cost-effective, which is especially important for small and medium-sized industrial enterprises.* ***Conclusion.*** *The use of the proposed monitoring system improves the reliability of pumping equipment and maintenance management based on the current state data.*

Keywords: *pumping equipment; diagnostic monitoring; vibration signals; wireless technologies; open architecture.*

1. Introduction

1.1. Motivation

At the present stage of industrial production, pumping equipment is an integral part of many technological processes, ensuring the transportation of liquids and maintaining the stability of various systems. The reliable and uninterrupted operation of pumps is critically important for industries such as oil and gas, chemicals, energy, and utilities. In the context of increasing competition and requirements for reducing operating costs, increasing the reliability and efficiency of pumping equipment has become an urgent task.

The basis for increasing reliability is timely diagnosis of the pump condition, which allows the identification of potential faults at early stages [1, 2]. However, in most cases, the existing diagnostic methods used in the industry are limited to checking the condition of the equipment only at the commissioning stage [3] or after repair work [4]. This is due to the lack of qualified specialists, additional material costs, limited access to pumping units, and the complexity of organizing monitoring. Consequently, faults are often identified at late stages when the equipment already requires expensive repairs, and it becomes necessary to stop the production process [5].

The introduction of modern automatic monitoring technologies significantly improves the situation by providing continuous monitoring of key diagnostic parameters that reflect the current state of the pumps. Simultaneously, the operating features of the pumping equipment allow periodic monitoring, thus reducing the cost of organizing the infrastructure of the control system [6].

Among the many parameters used to assess equipment condition, vibration and temperature signals are the most informative [7, 8]. The analysis of vibration signals allows for the effective diagnosis of mechanical faults such as bearing wear, rotor imbalance, pump impeller imbalance, and other defects. Vibration parameters provide insights into the operation of mechanical components and allow for the early detection of deviations from the norm [9, 10].

The temperature signals complement the vibration analysis by reflecting the thermal characteristics of the pump. Monitoring the temperature of bearings and other components helps to detect problems with cooling, lubrication, or early wear, thus creating a comprehensive picture of the condition of the equipment [11].

In turn, it should be noted that temperature and vibration monitoring do not account for all possible emergency situations for a pumping unit, although they are distinguished by the simplicity of data recording and their obvious correlation with specified faults. More complete functional monitoring requires the use of additional sources of information (for example, the consumed power of an electric motor, pressure and movement of liquid, acoustic signals, etc.). In particular, the work [12] presented the principles of constructing diagnostic models that are capable of reflecting the complex relationship of a set of measured direct and indirect diagnostic features for the holistic control of the operability of complex systems.

However, using additional diagnostic parameters significantly complicates the architecture and operation of monitoring systems, increasing the costs associated with their development, installation, and operation. In contrast, using only vibration and temperature signals allows for creating simpler and more cost-effective solutions. Although these solutions are limited to the scope of the diagnosed faults, they enable timely detection of the most common issues. This approach achieves an optimal balance between system complexity and diagnostic capabilities, thus making monitoring accessible to various enterprises, including small and medium-sized businesses.

Therefore, the development of diagnostic monitoring systems using vibration and temperature data as informative features remains a pressing task in the field of industrial pump engineering. Particular attention should be paid to ensuring the simplicity of installation and maintenance of the monitoring system, minimization of the mechanical impacts on equipment, reduction of installation time costs, and the possibility of seamless integration with existing information and communication systems. At the same time, the open architecture of the system and the use of open-source software will allow for significant savings in material resources, as well as provide opportunities for scalability and future functionality expansion.

Considering the accumulated research experience, to form a detailed picture of the equipment conditions, this system must control a set of vibration signal parameters along three axes.

Based on the above, a diagnostic monitoring system for pumping equipment was developed that meets the stated requirements.

1.2. State of the art

Several well-known publications have focused on using vibration and temperature parameters to assess the condition of pumping equipment. In contemporary studies, authors have employed machine learning algorithms, such as multilayer perceptron, support vector machines [13], random forests [14], and artificial neural networks [14, 15], to construct informative features and address equipment fault classification. Additionally, statistical methods are used for these purposes, including linear regression [16] and hidden Markov models [17].

These approaches demonstrate high diagnostic problem solving efficiency, particularly when processing complex and multidimensional data. However, most of these studies did not adequately address the practical aspects of organizing the data collection process, simplifying the operation of monitoring systems, and optimizing their implementation costs. In addition, machine learning methods require substantial amounts of information to train models, which places significant demands on data collection infrastructure. This often necessitates the installation of complex sensor systems and the transmission of large volumes of data, thereby increasing the costs of system implementation and operation. Consequently, these studies tend to overlook strategies for reducing material costs associated with the creation and implementation of monitoring systems.

In the context of the fourth industrial revolution, significant attention is being paid to the development and application of the concept of digital twins in modern pumping equipment monitoring tasks [18]. These virtual models enable real-time analysis of data from sensors, modeling of work processes, and prediction of fault development [19]. Digital twins offer a comprehensive approach to equipment diagnostics, as they consider not only current measured parameters such as vibration and temperature but also the interaction of various factors, including fluid characteristics, electric motor conditions, load conditions, and dynamic processes. With these capabilities, digital twins serve as an effective tool for ensuring high monitoring accuracy and optimizing pumping unit operation processes.

On the other hand, diagnostic monitoring systems that use digital twin models often require large amounts of data recorded in real time [11], which can be problematic in the absence of wired sensor interfaces.

Existing solutions primarily focus on servicing complex industrial facilities or specific equipment while considering operating conditions and unit locations [20, 21]. This focus is due to the fact that implementing digital twins requires significant resources, including highly qualified specialists, powerful computing systems, intricate data processing algorithms, and additional procedures for integrating digital twins into the existing infrastructure of enterprises [22].

Within Industry 4.0, IoT technologies are actively being developed [23], providing effective solutions for collecting diagnostic data [24]. A previous study [25] proposed an IoT-based system architecture for monitoring and diagnosing faults in centrifugal pumps. Despite the benefits of using IoT technologies, the architecture described in this paper has several shortcomings. It lacks detailed explanations of the interactions between the system components. In addition, insufficient information is available on the data processing algorithms used, which are critical to the system's performance. The issue of scalability when processing data from multiple sensors is also not addressed, and the user interface required by service personnel for effective monitoring and diagnostics of pump condition is not described.

In the study [26], the authors developed a structured methodology based on IoT solutions that combines key stages and tools for implementing predictive maintenance (PdM) for pump units. However, this study does not provide explicit information about the architecture of the monitoring system, such as system levels (sensors, gateways, servers), data transfer protocols, or user interaction interfaces.

The analysis of the existing literature shows that researchers are paying considerable attention to the development of machine learning algorithms for diagnosing pump unit faults. These approaches demonstrate high classification efficiency and processing multidimensional data; however, the practical implementation of such systems is often insufficiently addressed. The development of the concept of digital twins within the framework of Industry 4.0 opens up new prospects for monitoring pumping equipment, but their implementation requires high requirements for enterprise infrastructure and personnel training.

In addition, the methodology for using IoT technologies to monitor pumping equipment has certain limitations. Although these studies have provided IoT system architectures, the authors did not adequately address aspects related to the use of open technologies. Furthermore, there is a lack of information about the key components of the architecture, criteria for selecting data transfer protocols, and user interaction interfaces. In addition, insufficient attention is given to system scalability issues when integrating multiple sensors, data storage, and processing.

1.3. Objectives and the approach

An analysis of the current state of diagnostic monitoring systems for pumping equipment forms the goal of this study: to develop an effective open architecture for a diagnostic monitoring system based on IoT technologies. The system's effectiveness is defined by its ability to provide diagnostic information on the condition of pumps through vibration and temperature characteristics, as well as by facilitating installation, operation, and maintenance. In addition, it should offer flexibility, scalability, and an open architecture for integration into enterprise infrastructure.

Achieving this goal requires solving the following tasks:

1. Selecting informative features from vibration signals that enable the diagnosis of the most common faults in pumping equipment during periodic monitoring;
2. Selecting hardware characteristics to ensure that the diagnostic monitoring system meets these requirements;
3. development of software and network architectures for diagnostic monitoring systems based on open hardware and software standards.

The following issues were addressed in the following sections of this study. The second section provides information on the materials and research methods used to create the new open architecture for the diagnostic monitoring system of the pumping equipment. Methods for solving the research tasks are presented. The third section presents the results obtained by evaluating the experimental data. The fourth section draws conclusions based on the results of the study and presents directions for further development of the proposed approaches for diagnostic monitoring systems for pumping equipment.

2. Materials and methods of research

2.1. Selection of informative features of diagnostic signals

The applied standards for assessing the vibration states of pumping equipment [27] describe two main criteria that determine the operating mode of an installation. According to the first criterion, a comparison is made between the values of absolute vibration parameters in a wide frequency band (usually from 10 to 1000 Hz) and the established threshold values of the root mean square (RMS) of the vibration velocity V_{RMS} and/or the amplitude of the vibration displacement S_{PP}.

The RMS vibration velocity was measured in mm/s and was determined using the following expression:

$$V_{RMS} = \sqrt{\frac{1}{N}\sum_{i=1}^{N} v_i^2}, \quad (1)$$

where v_i – vibration velocity value at the i-th discrete measurement, N — total number of measurements. The frequency of discrete measurements f_S should be at least twice the maximum value of the studied frequency range of the vibration signal. That is $f_S \geq 2000$ Hz [28].

The second criterion for assessing the vibration state of pumps is the monitoring of the changes in the vibration parameters over time under the assumption of a possible deviation of these parameters from the initial normal values.

Note that in the existing standards and recommendations, the numerical values of the vibration parameters are defined only for equipment with a capacity exceeding 1 kW. At the same time, the recommended threshold values are not strictly fixed and can change depending on the type of equipment, as mutual agreement between the manufacturer and consumer. This is because the vibration level of the pumping equipment depends on its size, the dynamic characteristics of the vibrating elements, the installation method, and the purpose [27]. When selecting permissible vibration zones, it is necessary to consider the conditions that affect the vibration state of the unit.

Thus, the wide variability of pump unit designs requires the use of additional informative parameters when designing a functional diagnostic monitoring system that can provide a more comprehensive assessment of the operating equipment.

In particular, monitoring the acceleration of the RMS vibration allows additional control of the bearing condition [29, 30]. The crest factor is an indicative characteristic of the vibration signal [29]:

$$CF = \frac{A_P}{A_{RMS}}, \quad (2)$$

where $A_{RMS} = \sqrt{\frac{1}{N}\sum_{i=1}^{N} a_i^2}$ – RMS vibration acceleration, A_P – peak value.

The crest factor CF allows for evaluating the nature of the vibration signal. In other words, a high value of this coefficient indicates sharp spikes or pulses in the signal-probable signs of a mechanical failure.

In turn, the peak value of the vibration acceleration (AP) can be used as an indicator of extreme vibration events. High signal spikes may indicate sharp impacts, impulse loads, or other dynamic effects that can damage equipment.

The statistical analysis of complex vibration signals can also provide useful informative features. In particular, it is possible to quantitatively assess the deviation of the real distribution of the studied vibration signal parameters from the normal distribution law $N(\mu, \sigma^2)$ [311]. Here, μ – is the mathematical expectation, a σ^2 – is the dispersion of the distribution. The deviation of the distribution from the normal distribution may indicate dominant harmonics in the signal spectrum, which can be caused, for example, by impact effects.

Thus, an informative statistical parameter of vibration acceleration is the asymmetry coefficient (Skewness), which is the third central standardized moment:

$$SKEW = \frac{\frac{\sum_{i=1}^{N}(a_i - \bar{a})^3}{N}}{\sigma^3}, \quad (3)$$

where $\bar{a}$– arithmetic mean of the vibration acceleration and σ – standard deviation [322].

From equation (3), it follows that SKEW ≈ 0 indicates a symmetric distribution of the vibration signal sample and normal operation of the equipment. Otherwise, large outliers in the distribution can be observed, which indicate rare but significant vibration events.

Another informative indicator is the coefficient of excess (Kurtosis), which is the fourth central standardized moment as follows:

$$m'_4 = \frac{m_4}{\sigma^4} = \frac{\frac{\sum_{i=1}^{N}(a_i - \bar{a})^4}{N}}{\sigma^4}. \quad (4)$$

Because the excess coefficient for the normal distribution is equal to three, formula (4) can be modernized as follows:

$$KURT = m'_4 - 3. \quad (5)$$

The advantage of the kurtosis coefficient (5) is that it allows one to assess the presence of outliers in a symmetrical distribution, which may not be evident in the mean or RMS. From the viewpoint of vibration diagnostics, KURT > 3 may indicate strong short-term vibrations or impacts. KURT < 3 indicates a flatter distribution, indicating uniform vibrations without sharp peaks.

Thus, the use of the proposed set of vibration parameters along the three axes for diagnostics of the pumping equipment condition allows obtaining a detailed and comprehensive picture of the system operation. Each of the described parameters provides

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unique information, and their combined use allows for a more accurate representation of the equipment conditions [33]. The selected parameters allow periodic monitoring of the pumping equipment without the need to transmit large amounts of data in real-time.

To simplify the analysis of the described criteria in the monitoring process, we used a single integral parameter obtained by forming an aggregating feature in the form of a technical condition index (TCI).

In addition to diagnostic vibration signals, the TCI may also include additional information, including quantitative features such as the total operating time of the equipment T_{Σ}, the power consumption of the pump electric motor P_1, the bearing temperature measured on the housing t, and nominal features such as the number of previously performed repairs and maintenance k, and operating conditions and others.

The TCI in the form of a quantitative one-dimensional feature characterizing the current state of the pump can be obtained using the Principal Component Analysis (PCA) method [34]. The proposed method is one of the most widely used algorithms for reducing the dimensionality of data, allowing us to identify the main features of the multidimensional set of features used. In this study, the TCI of the pump was determined based on the following parameters along the three axes: V_{RMS}, S_{PP}, CF, Skew, Kurt.

Let us have a data matrix X of size m×n, where m number of observations and n number of parameters characterizing the pump. To perform PCA, it is necessary to first center the data by subtracting the mean value of each parameter. After centering, the covariance matrix C of size n×n is calculated as follows:

$$C = \frac{1}{1-m}\hat{X}^{T}\hat{X}, \quad (6)$$

where $\hat{X}$ – centered data matrix. Next, to determine the principal components, it is necessary to calculate the eigenvectors v_i and the corresponding eigenvalues λ_i of the covariance matrix C:

$$Cv_i = v_i\lambda_i, i = 1, 2, \ldots, n, \quad (7)$$

where λ_i are ordered in such a way that $\lambda_1 \geq \lambda_2 \geq \ldots \geq \lambda_n$.

The principal components are linear combinations of the original parameters:

$$z_i = \hat{X}_i v_i, \ i = 1,2,\ldots,n, \quad (8)$$

where each main component z_i – it is a new feature containing the main information of the original dataset.

As a result, the first principal component z_1 can be
As a result, the first principal component z_1 can be
selected to form the TCI, which explains the greatest variance in the original data as follows:

$$\mathrm{TCI} = z_1. \quad (9)$$

Note that depending on the number and type of diagnostic features used, the first principal component may not be sufficient to determine the TCI. The number of principal components should be selected such that the level of explained variance is 90–95%.

Thus, TCI simplifies the understanding of the current state of equipment and can also be used for monitoring and forecasting the pump unit performance and making maintenance decisions. In addition, if necessary, forecasting the remaining resources can be performed using classical regression methods or machine-learning algorithms.

2.2. Selecting hardware

Owing to the clear balance between size, cost, and functionality, microelectromechanical systems (MEMS) accelerometers are increasingly being used as vibration sensors in modern measuring transducers. The vibration velocity and displacement signals are obtained from the vibration acceleration signal from integration [35]. In line with this, the use of MEMS accelerometers as vibration sensors is justified for the construction of diagnostic monitoring systems. Accordingly, the use of MEMS accelerometers with wireless data transmission channels as vibration sensors is justified for building diagnostic monitoring systems. In addition, to improve noise immunity, the measurement signals should be converted and transmitted in digital form. The use of digital systems increases the degree of integration of components and therefore makes it possible to place a temperature sensor in one housing to monitor the heating of bearings.

When choosing a protocol to transmit data from sensors in an information collection system, it is essential to consider the specific operational characteristics of the pumping units. The equipment being diagnosed is often situated in hard-to-reach areas or locations with increased risks, which makes regular inspections significantly challenging. In addition, laying extra signal lines is often undesirable because it complicates pump installation and maintenance, thereby increasing the risk of mechanical damage.

Moreover, installing wires incurs additional costs and effort, especially in difficult industrial environments. These challenges can be mitigated using wireless transmission systems. When periodic monitoring is organized, wireless technologies can lower installation and maintenance costs, minimize equipment downtime, and provide more flexible integration with the existing information infrastructure of the enterprise.

To select a wireless communication standard, we performed a comparative analysis of the most common and developed data transmission technologies presented in Table 1.

From Table 1, it follows that LoRaWAN [36], LTE-M, NB-IoT [37], and SigFox [38] technologies are optimal for the designed system to monitor the condition of pumping equipment in terms of range. These networks enable monitoring in remote and urban areas. However, the LTE-M and NB-IoT standards require cellular operator infrastructure. These technologies use licensed frequency ranges, and their operation is impossible without a connection to a base station. In addition, in terms of architectural openness, access to the specifications and settings of these standards is limited. Thus, in terms of the totality of characteristics, the LTE-M and NB-IoT technologies do not meet the requirements of the developed system.

When conducting periodic monitoring, the energy efficiency and data transfer rate of the LoRaWAN and SigFox standards satisfy the requirements of the designed system. Simultaneously, the LoRaWAN protocol has an open architecture because it was developed and managed by the LoRa Alliance, which made the specifications publicly available. The LoRaWAN transmission standard is open to use and supports various implementations, which contributes to its development and wide distribution.

However, the Sigfox architecture is closed because the network is managed only by Sigfox and its partners. Access to specifications is limited, and devices must meet strict requirements to operate on the SigFox network.

Thus, based on this analysis, LoRaWAN wireless data transmission technology can be an optimal choice for diagnostic monitoring systems. In particular, the long range (Table 1) allows LoRaWAN networks to cover a wide area of industrial facilities and all hard-to-reach locations without the need for additional repeaters. The low power consumption makes this standard ideal for autonomous sensors, ensuring a long service life without batteries, which is especially important when access to equipment is limited. LoRaWAN supports the transmission of small amounts of data at a low speed, which meets the needs of periodic monitoring and reduces operating costs. In addition, this communication is resistant to interference, which is critical in industrial conditions, and provides flexibility and scalability to the system, allowing new devices to be easily added as needed.

Table 2 presents the minimum technical requirements for vibration- and temperature-measuring transducers based on the selected diagnostic parameters and existing evaluation criteria [27].

The diagnostic signal features proposed in this study avoid complex data analysis methods, thereby simplifying the requirements for primary converters (Table 2. Thus, many sensors offered by vendors can be used as part of the developed diagnostic monitoring system. In addition, ready-made industrial solutions for vibration and temperature sensors can be used as part of the system.

Table 1

Comparison of wireless communication technologies

Network type	Range	Transfer speed	Energy efficiency	Ease of integration
Wi-Fi	Up to 100 m (indoors); up to 300 m (outdoors)	Up to 600 Mbps (802.11n); up to 3.5 Gbps (802.11ac)	Low	Very simple
Bluetooth	Up to 100 m	Up to 3 Mbps	High (especially in BLE)	Very simple
Zigbee	Up to 100 m (indoors); up to 300 m (outdoors)	Up to 250 kbps	High	Simple
LoRaWAN	Up to 15 km in open space; up to 5 km in urban environments	Up to 50 kbps	Very high	Simple
LTE-M	Up to 10 km (depending on cellular network coverage)	Up to 1 Gbps (depending on cellular network coverage)	Average	Simple
NB-IoT	Up to 10 km in open space; up to 2 km in urban environments	Up to 250 kbps	High	Simple
SigFox	Up to 50 km in open space; up to 10 km in urban environments	Up to 100 bps	High	Relatively simple

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Table 2
Technical characteristics of measuring transducers

Parameter	Meaning
Accelerometer	
Number of measurement axes	3 – x, y, z
Frequency range	10 – 1000 Hz
Amplitude range	± 16 g
Analog-to-digital converter bit depth	10 bit
Relative error	≤ 5 %
Nonlinearity	± 0,5 %
Temperature sensor	
Measurement range	-20°C – +120°C
Relative error	≤ 5 % throughout the entire measurement range

2.3. Development of an open software and network architecture for a diagnostic monitoring system

Fig. 1 shows the structure of the developed software and network architecture of the diagnostic monitoring system for pumping equipment. The proposed architecture uses a wireless channel to collect data from sensors using the LoRaWAN protocol, which is based on free software.

As shown in Fig. 1, in the developed system, the gateway serves as a bridge between the end nodes in the form of vibration and temperature sensors and the LoRaWAN network infrastructure. LoRa devices can send data over long distances, which are received by one or more gateways. Gateways collect data from all devices in the coverage area and forward them to the network server via a standard connection (e.g., Ethernet and LTE).

The network server is shown in Fig. 1 is the central part of the LoRaWAN infrastructure, and it manages the interaction of all network components. The server receives data from gateways, processes the data, and routes it to the application server.

The application server is responsible for data processing and user application interactions. Here, data are useful for monitoring tasks. In the proposed architecture, data processing is performed using an MQTT broker (message-queuing telemetry transport), as shown in Fig. 1. The broker publishes data received from sensors in the form of corresponding MQTT topics, allowing for easy integration of any number of sensors into the monitoring system.

The Telegraf software [39] acts as a "subscriber." This means to subscribe to the specific topics published by the MQTT broker. In other words, Telegraf acts as a data collection agent. The choice of this software was justified by the fact that Telegraf is lightweight and can operate in real time, which is important for the operational monitoring of equipment status.

The data obtained using Telegraf were transferred to the InfluxDB database [40] for storage and subsequent analysis (Fig. 1). InfluxDB is a high-performance database optimized for storing and analyzing time series.

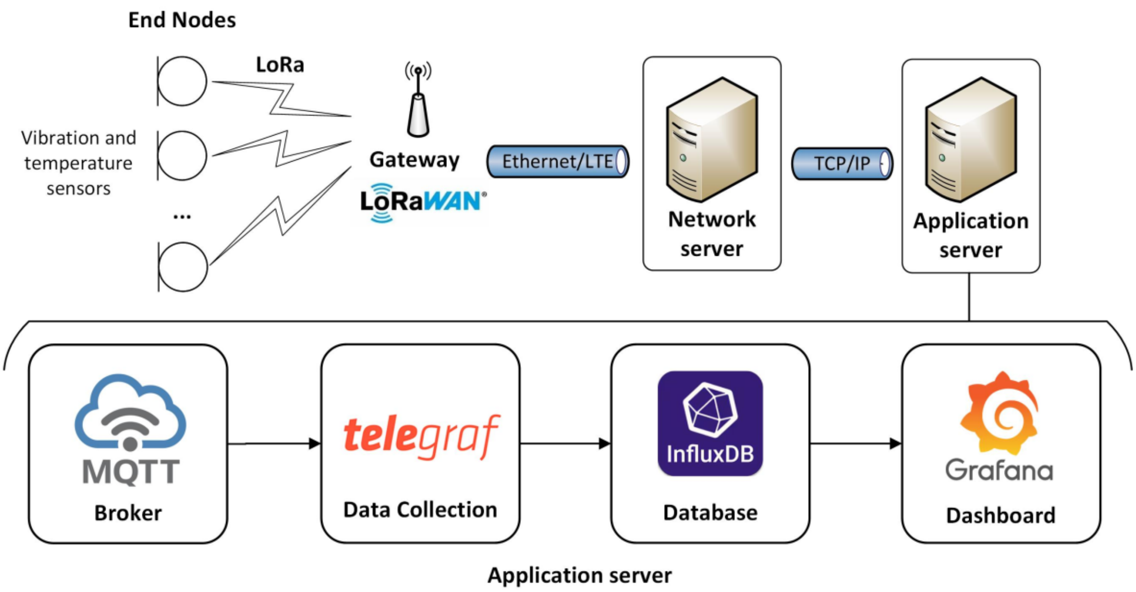

Fig. 1. Open software and network architecture of the diagnostic monitoring system

In the context of the developed system, it is used to store the vibration and temperature data received from sensors via Telegraf. InfluxDB has high speed for writing and reading data, which is important for scalable monitoring systems.

The Grafana data-visualization platform is used as a web application that provides a graphical user interface for monitoring tasks [41]. Grafana is integrated with InfluxDB, providing convenient tools to create dashboards and graphs. Using the Grafana platform allows support for various types of visualizations, including graphs, tables, histograms, and heat maps. Alerts and notifications can be set up, allowing prompt responses to data anomalies. In addition, it supports the use of various data sources, thereby making it flexible for integration into complex systems.

When deploying software on an application server (Fig. 1), Docker containerization technology is used [42]. This ensures the isolation and management of each element of the system separately to prevent dependency conflicts and ensure scalability. To launch all software components, Docker Compose was used, which allows the management of a group of containers as a single application.

Using Docker and Docker Compose allows for creating a modular and easily managed system that can be deployed on any platform that supports Docker. This significantly simplified the process of installing and maintaining the pumping equipment monitoring system. In addition, in accordance with the purpose of this study, all the software used is distributed under open-source licenses, which, together with the concept of building LoRa networks, ensures the openness of the software and network architecture of the diagnostic monitoring system.

3. Results and Discussion

The proposed diagnostic monitoring system was tested on the basis of an experimental rig for evaluating the operation of a centrifugal cantilever pump developed in the U.A. Dzholdasbekov Institute of Mechanical Engineering (Almaty, Kazakhstan). The experimental rig was a pump unit SNR of 32-160 (Karlskrona LLC, Kazakhstan) connected to an electric motor. The pump has the following main characteristics: 0.75 kW, 1500 rpm, a pressure of 5 m, and a flow rate of 8000 l/h. The rig also includes a control panel with a frequency-speed controller, a water flow meter, shut-off valves, and pressure gauges. The experimental stand is shown in Fig. 2.

The stand design allows the simulation of malfunctions in the operation of the mechanical and hydraulic parts of the equipment.

The equipment from Advantech, which meets the requirements listed in Table 2, the wireless vibration and temperature sensors WISE-2410 [43], and the industrial LoRaWAN gateway WISE-6610 [44], were used as measuring equipment for the monitoring system in the experimental studies.

Fig. 2. External appearance of the experimental stand

By programming the WISE-2410 sensors, it was possible to record the vibration parameters along the three axes defined in this study, as well as the temperature data. The sensor is fixed to the pump body using a magnetic mount. In addition, the WISE-6610 equipment is a comprehensive solution that combines a LoRaWAN gateway, a network server, and an application server in a single case (Fig. 1). However, in this study, the application server functionality was implemented separately on a personal computer with the Ubuntu 22.04 operating system and the following main characteristics: Intel Core i5, RAM 16 GB DDR 4, SSD 256 GB, HDD 1 TB, Ethernet 1 Gbps, and Wi-Fi.

A series of diagnostic monitoring system tests were performed on the specified equipment during normal pump operation and under cavitation conditions. For this purpose, the pressure at the pump inlet was reduced by partially closing the valve inlet. The pump was also operated at an increased speed to simulate cavitation. Experiments to record data on pump operation in normal mode and under cavitation conditions were carried out at different times, which made it possible to divide the obtained measurements into two classes: class $y = 0$ - normal operation mode and class $y = 1$ - mode with deviation from the norm.

As part of the tests conducted to demonstrate the openness and broad functional capabilities of the developed architecture, TCI calculation was performed by introducing an additional module into the overall software structure of the system, as shown in Fig. 3.

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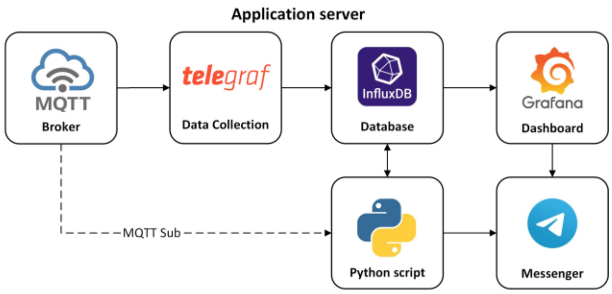

Fig. 3. Expanding the functionality of the monitoring system for PCA calculations

To calculate the TCI in the high-level language Python 3, a separate script was written that acted as an additional module in the system to perform PCA. The use of additional Python scripts will be justified in cases where the limitations of the Flux query language for InfluxDB do not allow the required manipulations with data to be performed.

As shown in Fig. 3, the Python script was programmed to read diagnostic parameters from the database for a specified time interval and apply the PCA algorithm to them to extract the first principal component (9). The script can also act as a subscriber to the MQTT broker and an independent data collection agent. The script frequency on the server was set using the cron daemon.

According to Fig. 3, a certain TCI parameter can be sent to the database and/or a corporate messenger to receive urgent notifications. As noted previously, the functionality of the Grafana software allows users to send notifications about registered events to the most common messengers.

To implement the PCA method in the Python script, the scikit-learn 1.5 library was used, and to work with the database, influxdb-client 1.47.0. Receiving MQTT messages is performed using the paho-mqtt 2.1.0 library, and the notifiers 1.3.3 library is responsible for sending notifications.

Fig. 4 gives the calculated principal component (9) values obtained from the recorded data. It can be seen that although there are some deviations by class, the data can be separated by setting threshold values close to zero. It is expected that the use of machine learning methods will enable a more accurate classification of pump operation by TCI.

For the diagnostic monitoring system based on the Grafana software, a dashboard was developed as a web application, consisting of the following monitoring panels: sensor status and signal transmission parameters panel (Device Status), temperature panel (temperature), vibration signal monitoring panel (accelerometer), and statistical characteristics panel (accelerometer statistics). The following parameters were monitored in the panels: V_{RMS}, S_{PP}, A_{RMS}, A_P, CF, σ, Skew, Kurt, t (bearing temperature measured on the housing).

Fig. 5 displays the Device Status panel. The panel displays the LSNR (LoRa Signal-to-Noise Ratio) and RSSI (Received Signal Strength Indicator) parameters to monitor the status of the LoRa transmission channel.

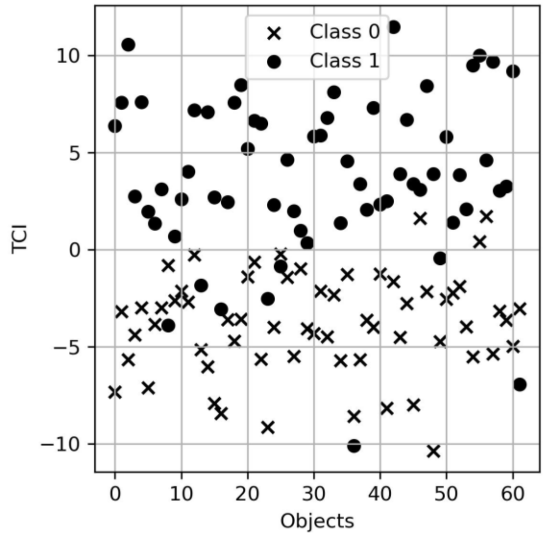

Fig. 4. Distribution of pump operating modes by class using principal component method

The experimental environment during system testing was organized such that the pumping unit with measuring sensors was located in the basement of the building. The receiving equipment was located on the first floor at a considerable distance from the pumping unit, so that several monolithic load-bearing walls and technical rooms were in the path of the radio signal. In other words, unfavorable conditions for signal transmission were intentionally created. At the same time, as shown in Fig. 5, the SNR = 10 dB. Therefore, it can be concluded that the received signal is slightly distorted and that there is still a significant reserve in the transmission range.

The RSSI parameter also shows the power of the received signal, which is measured in decibels relative to milliwatt-dBm. The RSSI value in Fig. 5 is -79 dBm, which is acceptable according to the LoRa standard.

In addition, the Device Status panel (Fig. 5) displays the status of the Device Status sensor (OK, the sensor is operating in normal mode), a graph of the change in the frequency of the transmission channel frequency, the type and voltage of the sensor's Power Source (in this case, from the battery – battery), and the number of transmitted and lost FCNT packets. The information content of this panel was determined from the data provided by the WISE-2410 sensor during operation. The data collection frequency was set to 10 s.

Fig. 5. Device Status panel

Fig. 6 shows the temperature control panel. As can be seen from the (Fig. 5), information is provided on the sensor operability (Sensor Status), the current bearing temperature value measured on the housing, and the temperature measurement in dynamics over the analyzed period of time.

In addition, the ability to control the set temperature threshold value was implemented using the Alarm Status window and Temperature Event time scale.

Fig. 7 (a) A part of the developed monitoring panel responsible for notifying the service personnel when the specified vibration acceleration thresholds are exceeded along the three axes. In addition, threshold values for all monitored parameters can be set using Grafana software with the ability to send notifications to e-mail or to a corporate chat (Fig. 3).

Fig. 7 (b) shows the time data of the V_{RMS}, vibration velocity measurement as an element of the vibration-signal monitoring panel. The graph shows the measured values of the parameters along the three axes. In addition to the graphs of the changes in the monitored parameters, the minimum, maximum, and last measured values of the vibration characteristics for the displayed period of time, as well as the average value, standard deviation, and signal amplitude for this period.

Fig. 7(c) shows a portion of the statistical characteristics panel with the calculated values for the kurtosis coefficient (4) and the skewness coefficient (3).

Thus, the monitoring system can assess the condition of the pumping equipment according to the criteria presented in regulatory documents [27, 45] and by using the additional parameters proposed in this work. The system provides flexible options for setting the threshold values of the vibration and temperature parameters, with the ability to change them for different types of pumps.

The indication of alarm signals and the sending of corresponding notifications to personnel are supported, which increases the efficiency of response to potential malfunctions. The system functionality also provides additional modules to calculate and monitor the necessary parameters. The presented version of the implementation of the additional functionality of the TCI monitoring system demonstrated the effectiveness of the proposed integrated assessment of the condition of the pumping unit based on the experimental setup.

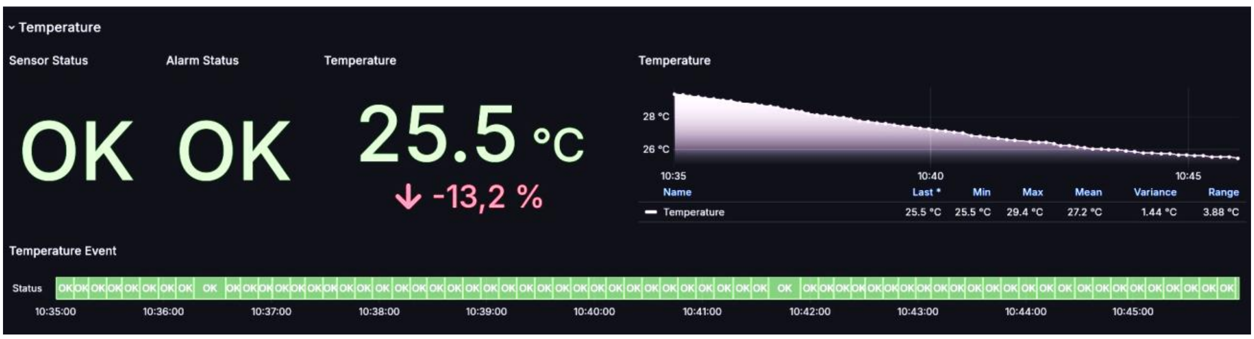

Fig. 6. The temperature monitoring panel

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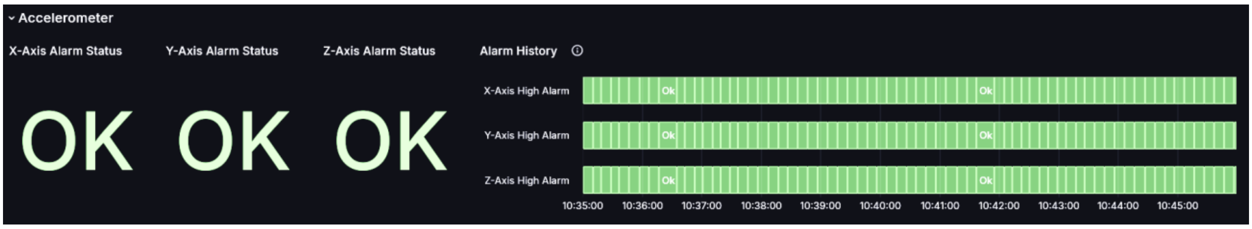
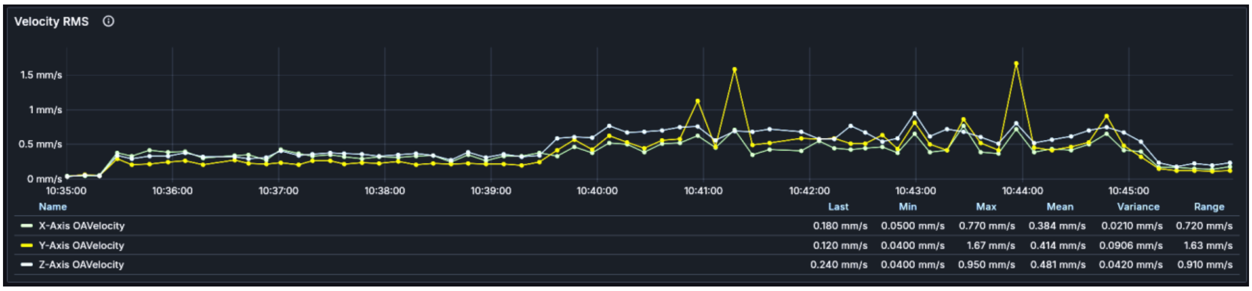
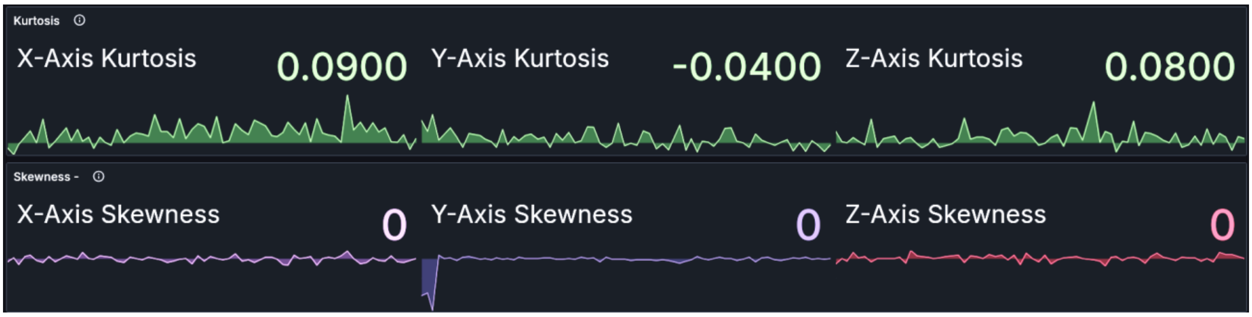


a



b



c

Fig. 7. Elements of the developed monitoring system dashboard

A limitation of the proposed solution is that it is important to specify that diagnosis is restricted to pump unit faults that clearly correlate with the informative features presented in the study. Bearing wear is expected to manifest as an increase in A_{RMS} vibration acceleration, the peak factor CF and the excess factor KURT. Rotor and impeller imbalances are indicated by an increase in the vibration displacement S_{PP} and a change in the asymmetry coefficient SKEW. Shaft misalignment results in an increased vibration velocity V_{RMS}, whereas cavitation affects both - KURT and CF. Shaft defects and the failure of support elements are characterized by an increase in low-frequency vibration and instability.

Additionally, the placement of a temperature sensor in the monitoring setup allows the determination of pump temperature at the installation site.

However, positioning the sensor on the bearing support enables the detection of inadequate or contaminated lubricant, bearing wear, increased mechanical loads, and cooling system malfunctions due to temperature increases.

4. Conclusions

In this article, we propose a remote diagnostic monitoring system for pumping equipment that features an open architecture and uses wireless data transmission via the LoRaWAN protocol. The article outlines the selection criteria and required characteristics for the system's hardware and software components. Scalability is achieved by integrating data collection technology using the LoRaWAN protocol and application server software, which form part of the overall software and network architecture. The proposed software products facilitate the integration of additional functional components into the system, as demonstrated by the example of calculating the TCI of a pump. A judicious choice of the wireless communication standard simplifies system installation, extends the geographical monitoring range, and enables the use of hardware from various manufacturers, thereby allowing a network to be built without dependence on a specific vendor.

In addition, the use of open standards and open-source software enables the architecture of the proposed diagnostic monitoring system to be integrated into the existing infrastructure of industrial facilities. This will ensure accessibility to various users, including small and medium enterprises. Furthermore, the selected informative features, which consist of vibration and temperature signals, facilitate this integration. This choice balances the informativeness of the system with its infrastructural complexity.

Based on the proposed vibration parameters, this work demonstrates the potential of periodic monitoring to diagnose cavitation processes in a pump. It can be concluded that the proposed signal characteristics can effectively identify the most significant and common faults in pump units, which are correlated with the vibration and temperature data.

Experimental testing of the system based on a centrifugal pump demonstrated its operability and efficiency under simulated operating conditions, including both normal and abnormal scenarios. In addition, the proposed technical condition index, which is calculated using the principal component method, can help generalize diagnostic parameters and simplify equipment condition monitoring. To enhance convenience and accessibility for service personnel, specialized monitoring panels were designed to present information about the condition of the research object in an easily perceivable format, with options for customization and notification.

Thus, the proposed monitoring system has significant potential for use in industrial enterprises, where reliable and uninterrupted operation of pumping units is crucial. Adopting open architectures and standards reduces the barrier to implementing such solutions. In the future, as the system operates and accumulates a sufficient volume of diagnostic data, its functionality can be enhanced by incorporating machine learning methods to predict the remaining lifespan of the equipment and improve diagnostic accuracy.

Contributions of authors: conceptualization, methodology – **Alexey Savostin, Kayrat Koshekov**; formulation of tasks, analysis – **Amandyk Tuleshov, Galina Savostina**; development of model, software, verification – **Alexey Savostin, Galina Savostina, Abay Koshekov**; analysis of results, visualization – **Galina Savostina, Abay Koshekov**; writing – original draft preparation – **Alexey Savostin, Amandyk Tuleshov**, writing – review and editing – **Kayrat Koshekov**.

Conflict of Interest

The authors declare that they have no conflict of interest in relation to this research, whether financial, personal, authorship or otherwise, that could affect the research and its results presented in this paper.

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Data Availability

The code for launching the developed diagnostic monitoring system is available at the link https://github.com/alex21582/advantech-data-monitoring.

Use of Artificial Intelligence

The authors confirm that they did not use artificial intelligence methods while creating the presented work.

All the authors have read and agreed to the publication of the final version of this manuscript.

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РОЗРОБКА СИСТЕМИ ДИСТАНЦІЙНОГО ДІАГНОСТИЧНОГО МОНІТОРИНГУ НАСОСНОГО ОБЛАДНАННЯ З ВІДКРИТОЮ АРХІТЕКТУРОЮ

О. О. Савостін, К. Т. Кошеков, А. К. Тулешова,
Г. А. Савостіна, А. К. Кошеков

Об'єктом дослідження в даній роботі є система дистанційного діагностичного моніторингу насосного обладнання з відкритою архітектурою, розроблена для підвищення надійності та ефективності експлуатації насосів у різних промислових галузях. Система призначена для періодичного збору та аналізу вібраційних і температурних сигналів, що дає змогу оперативно виявляти потенційні несправності обладнання та уникати аварійних зупинок виробничого процесу. **Метою** даного дослідження є розробка ефективної відкритої архітектури системи діагностичного моніторингу насосного обладнання, що базується на технологіях IoT. Основну увагу приділено розробленню такої архітектури системи, яка дасть змогу спростити монтаж і експлуатацію обладнання, забезпечити масштабованість і простоту інтеграції з наявними інформаційними системами підприємств, а також знизити матеріальні витрати на її впровадження. Для досягнення мети в рамках дослідження вирішено такі **завдання**: 1) добір інформативних ознак сигналів вібрації, що дають змогу діагностувати найпоширеніші несправності насосного обладнання під час періодичного моніторингу; 2) вибір характеристик апаратної частини, які забезпечують відповідність системи діагностичного моніторингу пред'явленим вимогам; 3) розробка програмно-мережевої архітектури системи діагностичного моніторингу, яка базується на відкритих стандартах апаратного та програмного забезпечення. **Результати** проведених експериментів засвідчили, що розроблена система дає змогу ефективно контролювати стан насосного обладнання та знижує ризик аварійних зупинок, оптимізуючи у такий спосіб експлуатаційні витрати. Застосування бездротових технологій, відкритих програмних продуктів і стандартів робить систему гнучкою та економічно ефективною, що особливо важливо для промислових підприємств малого та середнього масштабу. **Висновок**: використання запропонованої системи моніторингу дозволить підвищити надійність роботи насосного обладнання та поліпшити управління їх технічним обслуговуванням.

Ключові слова: насосне обладнання; діагностичний моніторинг; вібросигнали; бездротові технології; відкрита архітектура.

Савостін Олексій Олександрович – канд. техн. наук, доц., вед. наук. співроб. Інституту механіки та машинознавства ім. У. А. Джолдасбекова, Алмати, Республіка Казахстан; проф. каф. енергетики і радіоелектроніки Північно-Казахстанського університету ім. М. Козибаєва, Петропавловськ, Республіка Казахстан.

Кошеков Кайрат Темірбаєвич – д-р техн. наук, проф., голов. наук. співроб. Інституту механіки і машинознавства ім. У. А. Джолдасбекова, Алмати, Республіка Казахстан; проф. каф. авіаційної техніки і технологій Академії цивільної авіації, Алмати, Республіка Казахстан.

Тулешов Амандик Куатович – д-р техн. наук, проф., кер. лаб. Інтелектуальних робототехнічних систем, Інститут механіки і машинознавства ім. У. А. Джолдасбекова, Алмати, Республіка Казахстан.

Савостіна Галина Володимирівна - PhD, асоц. проф. каф. енергетики і радіоелектроніки Північно-Казахстанського університету ім. М. Козибаєва, Петропавловськ, Республіка Казахстан.

Кошеков Абай Кайратович – PhD, асоц. проф. каф. авіаційної техніки і технологій Академії цивільної авіації, Алмати, Республіка Казахстан.

Alexey Savostin – Candidate of Technical Sciences, Leading Researcher of U. Joldasbekov Institute of Mechanics and Engineering; Professor at the Department of Energetic and Radioelectronics, M. Kozybayev North Kazakhstan University, Petropavlovsk, Republic of Kazakhstan,
e-mail: asavostin@ku.edu.kz, ORCID: 0000-0002-5057-2942, Scopus Author ID: 57190305485.

Kayrat Koshekov – Doctor of Technical Sciences, Chief Researcher of U. Joldasbekov Institute of Mechanics and Engineering, Professor at the Department of Aviation Technique and Technologies, Civil Aviation Academy, Almaty, Republic of Kazakhstan,
e-mail: kkoshekov@mail.ru, ORCID: 0000-0002-9586-2310, Scopus Author ID: 56150300500.

Amandyk Tuleshov – Doctor of Technical Sciences, Professor, Head of laboratory, U. Joldasbekov Institute of Mechanics and Engineering, Laboratory of Intelligent Robotic Systems, Almaty, Republic of Kazakhstan,
e-mail: aman_58@mail.ru, ORCID: 0000-0001-9775-3049, Scopus Author ID: 42062588900.

Galina Savostina – PhD, Associated Professor at the Department of Energetic and Radioelectronics, M. Kozybayev North Kazakhstan University, Petropavlovsk, Republic of Kazakhstan,
e-mail: gvshubina@ku.edu.kz, ORCID: 0000-0001-7042-4480, Scopus Author ID: 57202745019.

Abay Koshekov – PhD, Associated Professor at the Department of Aviation Technique and Technologies, Civil Aviation Academy, Almaty, Republic of Kazakhstan,
e-mail: a.k.koshekov@gmail.com, ORCID: 0000-0001-7373-1494, Scopus Author ID: 57192438940.