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Study of the Influence of Optimization Methods on the Efficiency of an Extremal Control System Based on Acoustic Anomaly Detection

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Abstract

The paper investigates the influence of optimization methods on the efficiency of an extremal control system based on acoustic anomaly detection. The proposed system can detect abnormal equipment operating modes by analyzing sound characteristics and automatically adapting control parameters to new operating conditions. Using mathematical modeling, the operation of the system with different optimization algorithms (gradient descent, Momentum, Nesterov and RMSProp) was studied. The results show that RMSProp provides the fastest transition to steady state (103 s) with minimal overshoot (3%), but there are significant oscillations in the control signal. Classic gradient descent demonstrates an acceptable stabilization time (123 s) with moderate overshoot (23%). The Momentum and Nesterov methods are characterized by the longest settling time (173 and 160 s, respectively). The study confirms the feasibility of using extremal control systems with adaptive optimization to improve the reliability and efficiency of technological equipment under variable operating conditions.

Keywords: intelligent control system; optimization; mathematical modeling; transient process.

1. Definition of the problem to be solved

Today, in the synthesis and operation of automatic control systems, it is extremely important to consider the technical and operational condition of equipment, as its state directly affects the characteristics of technological processes occurring in the equipment. An example of equipment condition change can be the wear of bearings in rotating mechanisms, which causes additional load on the motor or other system components. Such changes cause alterations in the equipment sound, which can be recorded using a microphone and subsequently used as a trigger for reconfiguring the control system. The sound of equipment operation may not always directly depend on the equipment condition; it can change during operation under incorrect or atypical operating conditions, for example, overloading of a transport conveyor or feeding harder material into a crusher. Atypical operating conditions, in turn, affect the accuracy of the mathematical description of the control object, on the basis of which the synthesis and study of control systems take place.

Currently, there are various methods for determining equipment condition, namely: acoustic, visual, vibration analysis, and analysis using sensor arrays. The application of acoustic anomaly detection approaches allows for the analysis of the current technical and operational state of equipment based on audio data. This approach has a number of advantages, namely:

- relative affordability of sensors for data collection;
- possibility of use in hard-to-reach places and under difficult conditions.

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The application of the obtained technical and operational state of equipment allows for the identification of anomalous operating modes, which may be new technological regimes, for example, when the load on a motor changes and its characteristic operating sound changes, or potentially emergency situations. Therefore, when a new equipment operating mode is detected, it is necessary to reconfigure the controller according to the system's capabilities to reduce the risk of emergency situations or to return the equipment to a steady-state operating mode.

This work proposes a novel approach to building an extremal control system for solving the problem described above. The fundamental novelty of the proposed system lies in the use of an acoustic sensor unit for detecting an extremal point — the moment of entry into the control optimization algorithm. Unlike traditional approaches, where optimization occurs continuously or on a fixed schedule, the proposed system autonomously makes decisions about the need for reconfiguration based on acoustic data, which significantly reduces computational load and ensures rapid adaptation to changes in the technological object. The practical value of this approach lies in the ability to detect anomalies early and automatically trigger the control optimization procedure only when it is truly necessary, which is critically important for industrial systems with limited computational resources and strict response time requirements. However, for effective application of the proposed control system, it is necessary to conduct a series of studies, one of which is the investigation of the influence of optimization methods on the effectiveness of the proposed approach.

2. Analysis of the recent publications and research works on the problem

The article by Haoqian Wang et al. [1] is devoted to the study of stochastic optimization acceleration for Deep Neural Networks, with a special focus on the theoretical analysis of SGD-Momentum and Nesterov's accelerated gradient methods. The work consists of a mathematical investigation into the stability mechanisms of these algorithms and an evaluation of their convergence properties. The key scientific contribution is the identification and formalization of the "overshoot" phenomenon inherent in momentum-based approaches. The authors prove that because Momentum and Nesterov methods rely on the accumulation of historical gradients to accelerate training, they inevitably suffer from oscillatory behavior where parameters exceed their optimal target values. This discovery highlights a critical limitation in these standard algorithms: the reliance on past error information, while beneficial for speed, can destabilize the optimization path when the gradient direction changes rapidly. The authors further characterize Nesterov's method as a specific variation that applies a higher gain to the current gradient compared to classical Momentum, explaining its distinct convergence behavior.

The dissertation by Olle Trollberg and Elling W. Jacobsen [2] is devoted to the study of extremal control methods with a special focus on the problem of multiple solutions and convergence speed. The work consists of two main parts and contains both theoretical research and practical applications. The key scientific contribution is the identification and investigation of the problem of multiple stationary solutions. The authors prove that even with a convex objective function, the classical ESC method can have multiple stationary points. This discovery refutes previous assumptions about the uniqueness of the solution when the conditions of existence and stability are met. Stationary solutions are characterized by a condition for local phase shift of the process, which can be satisfied at points not related to optimality. The authors show that the observed multiplicity of solutions is related to a certain type of bifurcation and provide conditions for their existence. Using the example of the CANON biochemical reactor process, it is demonstrated that the conditions for phase shift can be satisfied at operating points that are completely unrelated to optimal ones, which can lead to suboptimal system performance. Greedy ESC, a modification of the method for systems with multiscale dynamics, is considered separately. By optimizing only the fast dynamics of the system, significant performance improvements can be achieved while reducing computational complexity.

In the article Vytautas Kaminskas, Kęstutis Šidlauskas and Česlovas Tallat-Kelpša [3] examined a class of dynamic systems in which linear dynamic elements are combined with nonlinear static characteristics, and the output is distorted by random disturbances. Typical examples are fuel combustion and steam condensation processes at thermal power plants. The problem addressed in the article was the constant change in extreme characteristics due to equipment aging, surface contamination and uncontrollable factors. Therefore, a mechanism for automatic adaptation to changes in the system is needed. To solve this problem, the concept of self-tuning control was applied, which combines continuous parameter identification and control synthesis based on current estimates. The implementation includes an optimal predictor that forecasts the future output several steps ahead by decomposing the transfer function of disturbances using the Wiener-Hopf method into future (unpredictable) and past (known) components. The synthesis of the controller is based on the equality of the predicted and desired values, which gives a nonlinear equation with a square root. Periodic sign change before the root provides excitation of the system to improve identification. Constraints are taken into account by projecting the control to the admissible region. Identification uses a recursive least squares method in a component-by-component version. Prediction error updates parameter estimates through a covariance matrix without storing data history. A forgetting factor allows slow parameter changes to be tracked, giving more weight to fresh data.

An analysis of existing approaches shows that gradient-based optimization methods are most often used to solve extremal control problems due to their relative simplicity of implementation, low computational requirements, and ability to operate in real time. However, the literature presents various modifications of gradient methods—from classical gradient descent to adaptive algorithms with inertia (Momentum, Nesterov) and methods with adaptive learning rates (RMSProp, Adam). Each of these methods has specific features of convergence, noise resistance, and speed, which critically affect the efficiency of the control system in the context of anomaly detection. Therefore, it is advisable to investigate the possibility of using gradient-like optimization methods in control systems based on acoustic anomaly detection.

3. Formulation of the goal of the paper

The purpose of this work is to study the influence of optimization methods on the efficiency of an extremal control system based on acoustic anomaly detection. To achieve this goal, an experiment using mathematical modeling methods is proposed. The work will involve mathematical modeling of the operation of an extremal control system under identical conditions, using various optimization methods, namely: gradient-like, momentum, Nesterov, RMSProp.

4. Presentation and discussion of the research results

4.1. Description of the conditions for conducting the experiment

The experiment was conducted using mathematical modeling methods, which are described by a first-order differential equation:

$$\frac{dy}{dt} = -a \cdot y + b \cdot u, \tag{1}$$

where *y* is the output variable of the system; *u* is the control input; *b* is the amplification coefficient of the control input.

This model is typical for a wide class of technical systems, including thermal processes, hydraulic systems, and electrical circuits with capacitive loads.

Anomaly generation model

To simulate the occurrence of defects in the system, a stochastic model based on a normal (Gaussian) distribution was used:

$$\xi(t) \sim \mathcal{N}(\mu, \sigma^2), \tag{2}$$

where μ is the mathematical expectation; σ^2 is the variance of the random variable.

The choice of the normal distribution is justified by its ability to adequately describe the accumulation of small independent random effects, which corresponds to the nature of most technical malfunctions.

Experiment parameters

The parameters that were used for simulation are presented in Table 1. It includes simulation time, expected system output value and control value.

Table 1. Parameters of the experiment.

Parameter	Value
Simulation duration	t∈[0;200] s
Number of discretization points	1000
Anomaly occurrence time	100 s
Target output value (y_target)	1.0
Initial control value (u_init)	0.5

The experimental study was conducted in five stages:

Stage 1. Simulation. The system functioned with nominal parameters ($a = 0.5, b = 0.5$). The adaptive controller learning rate was $\eta_{normal} = 0.01$. This allowed for obtaining the reference characteristics of the transient process and achieving a steady state.

Stage 2. Activation of the anomaly generator. At a defined moment in time, an additive disturbance was introduced into the system to model the occurrence of a defect. The intensity and nature of the disturbance were determined by the parameters of a Gaussian distribution

Stage 3. Anomaly detection. Monitoring of the output variable $y(t)$ was performed, and the deviation from the target value $y_{target} = 1.0$ was recorded. An anomaly was considered detected when the error exceeded the limits of the allowable band $\pm 2\%$.

Stage 4. Transition to a new steady state. The adaptive controller automatically adjusted the control input $u(t)$ to compensate for the changes in system parameters and return the output to the target value.

Stage 5. Analysis of the obtained results. For each optimization algorithm, the transient process quality indicators were calculated:

- settling time;
- overshoot;
- steady-state error.

The modeling time was 200 seconds. During the specified modeling period, an anomaly event was simulated, after which the control optimization procedure was launched. An extremal control system based on control optimization, using a gradient-like adaptation law [4], is considered as the basic control system solution:

$$u(t+1) = u(t) + \eta(y_{target} - y(t)). \tag{3}$$

The error, i.e. deviation from the current setpoint ($y_{target} - y(t)$) was used as the optimization criterion. The paper investigates the operation of the proposed control system based on the following optimization methods: the gradient-like optimization algorithm, the Momentum method, Nesterov (Nesterov Accelerated Gradient) method and RMSProp.

A gradient-like optimization algorithm, in particular gradient descent, is a first-order iterative method for finding the local minimum of a function. The principle of operation is that at each iteration, the gradient of the function at the current point is calculated, after which a step is taken in the direction opposite to the gradient, which contributes to a decrease in the value of the function.

The Momentum method [5] adds inertia to gradient descent. It considers not only the current gradient, but also the accumulated previous direction of movement (velocity). This allows you to speed up movement in stable directions and reduce fluctuations during optimization, especially in narrow “valleys” of the loss function.

Nesterov (Nesterov Accelerated Gradient) [6] is an improvement on Momentum and estimates the future position in advance to make more “far-sighted” steps. The key idea is to first move by inertia (as in Momentum) and then adjust the step based on the new gradient value at the point where inertia “leads.” This provides faster and more stable convergence, especially in convex optimization:

RMSProp (Root Mean Squared Propagation) [7] is an adaptive optimization method that applies different learning rates for each parameter. It uses a moving average of past gradients, which avoids overly small or large steps and stabilizes learning even in tasks with “noisy” or sparse gradients.

4.2. Results of the basic solution

Figure 1 shows the results of the acoustic anomaly detection system. In the figure, during the first 100 seconds, the probability of an anomaly in the equipment's operating mode does not exceed 0.2 (20%). After 100 seconds, the flaw detection system detected an anomaly. Since the anomaly is not peak, it is decided that this is a new operating mode, and the control optimization procedure for the new mode is started. After adaptation is complete, the current operating mode is accepted as the new nominal mode, which is why after 110 seconds, the probability of an anomaly is again below the threshold value.

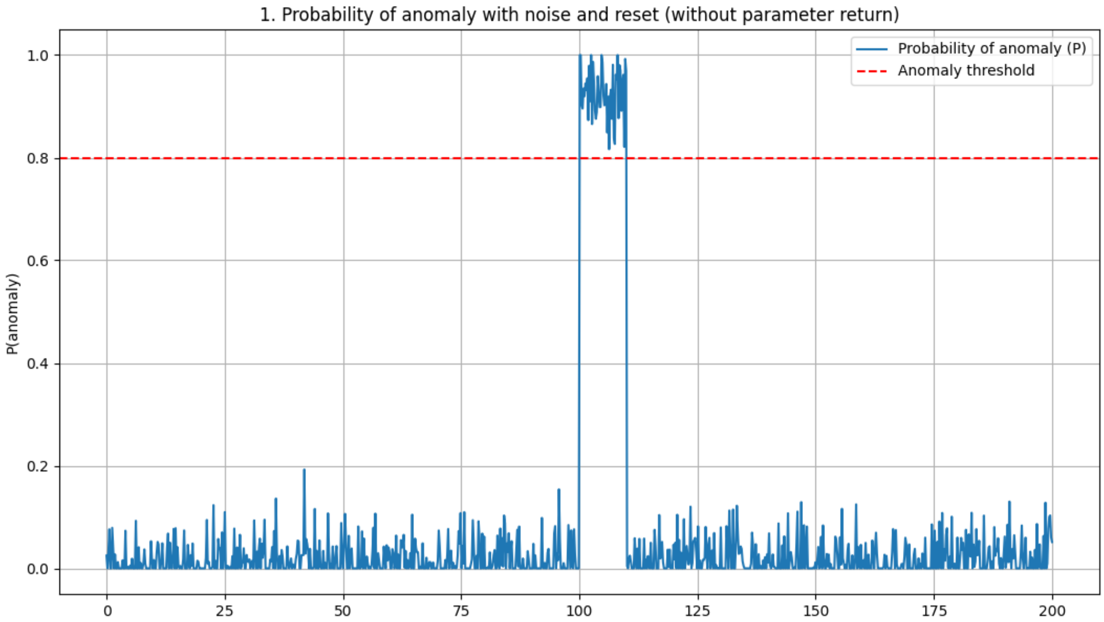

Fig. 1. Graph showing the probability of an audio-based defect.

Figure 2 shows a graph of the deviation from the set value. The time to reach a steady state is approximately 50–60 seconds. After 100 seconds, there is a short-term jump in the error, indicating the presence of an anomaly that requires optimization of the object control under new conditions. In this case, optimization is performed using the gradient descent method. The error after 150 seconds is almost zero, which indicates effective optimization and the ability of the system to adapt.

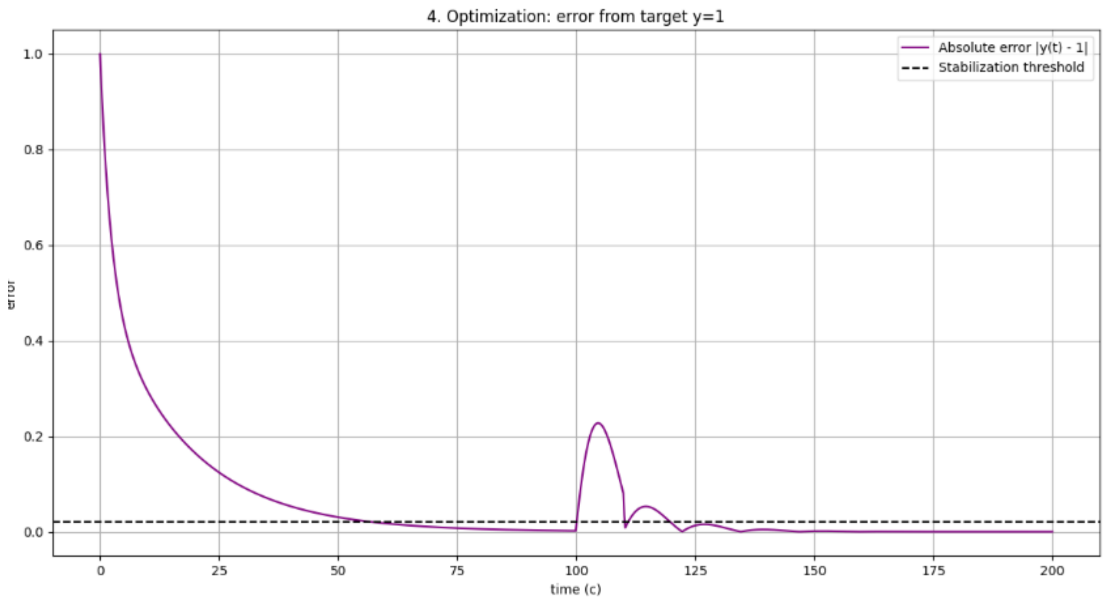

Fig. 2. Graph of deviation from the set value.

The results of the proposed system are shown in Figure 3. The adaptive system quickly reaches the target level y=1 and maintains it with high accuracy. When an anomaly occurs, there is a short-term overshoot with an amplitude of about 0.2 and damped oscillations. Thanks to its adaptive properties, the output stabilizes and returns to the set value. This indicates the stability of the system and its ability to compensate for disturbances.

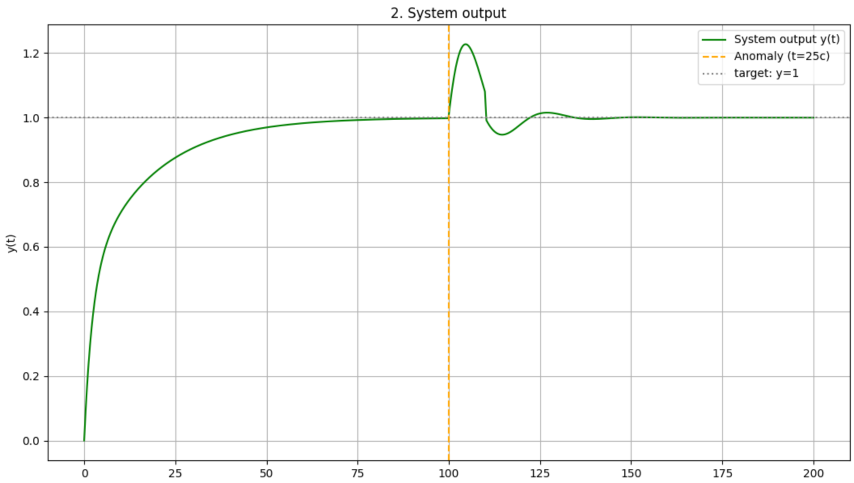

Fig. 3. Transition process of the proposed control system.

4.3. Study of the impact of quality criteria on the efficiency

Figure 4 shows a comparison of the performance of different optimizers in this system. All methods quickly reduce the absolute error to a level close to the target but differ in their response dynamics. RMSProp demonstrates the fastest error reduction and the smallest fluctuations after an anomaly, while Momentum and Nesterov have more pronounced overshoots. Conventional gradient descent (GD) stabilizes more slowly but provides relatively smooth dynamics. In general, all algorithms can return the system within the stabilization threshold (±2%), which, in our case, is reaching a steady state, but the effectiveness of their response to perturbations varies significantly.

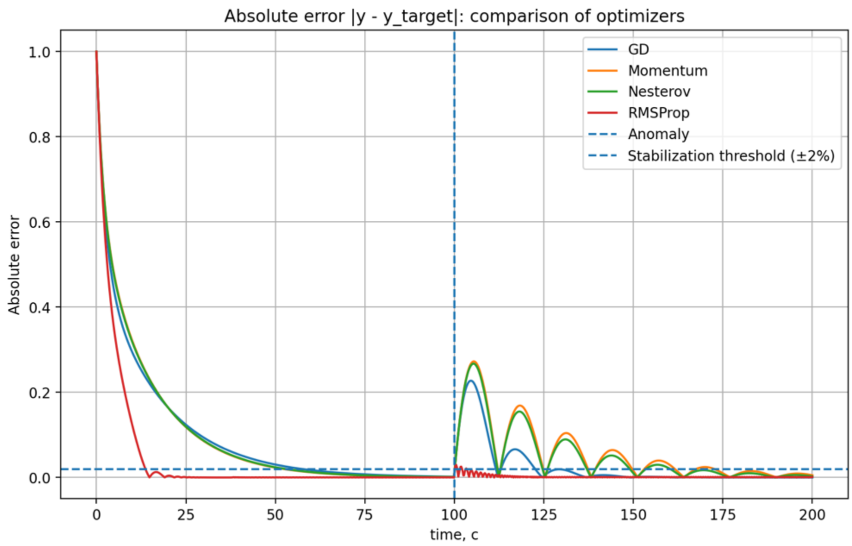

Fig. 4. Transition process of the proposed control system

Figure 5 shows a comparison of control signals obtained using different optimizers. In the initial phase, all methods gradually increase the control influence, but RMSProp forms more pronounced fluctuations even before the anomaly occurs. After the disturbance (t≈100 s), GD, Momentum, and Nesterov provide a smoother response with gradual attenuation of fluctuations, while RMSProp exhibits significant high-frequency fluctuations, indicating its less stable behavior. In conclusion, it can be noted that classical methods (GD, Momentum, Nesterov) provide more stable and predictable control, while RMSProp is fast but unstable in its response to external influences. Figure 6 shows the system output when using different optimization methods. All optimizers achieve the target level, but the dynamics differ. RMSProp reaches steady state faster than other methods, but its response is accompanied by slight fluctuations.

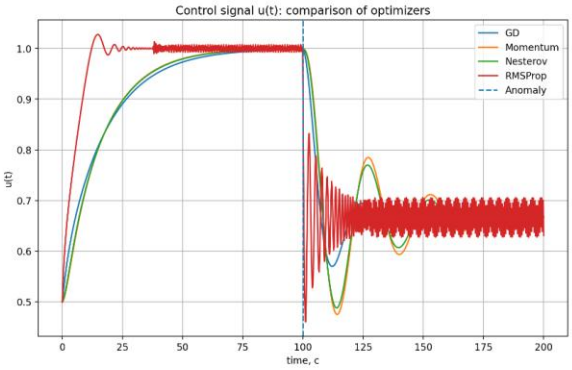

Fig. 5. Control signal.

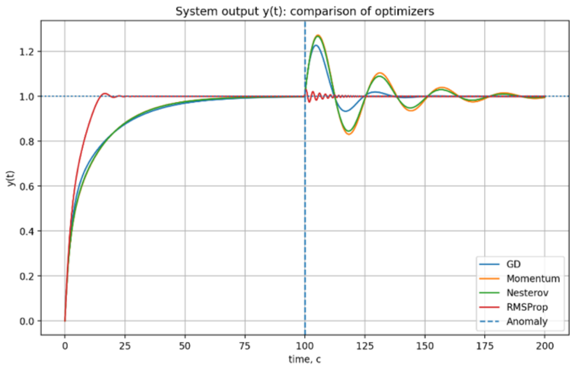

Fig. 6. Comparison of system output.

A comparative description is provided in Table 2. This table shows the time that system needs to reach steady state, the overshoot and the system error across different optimization methods.

Table 2. Optimization methods comparison.

Method	Time, s	Overshoot, %	Steady state error
GD	122.7	22.7	2.05e-05
Momentum	172.7	27.2	0.0069
Nesterov	160.3	26.7	0.0043
RMSProp	103.5	2.9	1.908e-05

5. Conclusion

The extremal control systems using optimization methods have shown high efficiency in achieving and maintaining target values. Despite the presence of disturbances and anomalies, the system stably restores the steady state and keeps the output within the acceptable error threshold. This confirms the feasibility of applying such approaches in real technical objects, where it is important to ensure stability and quick response to changing conditions.

RMSProp demonstrated the best results: minimum time to reach the stabilization threshold (~103 s), very low overshoot percentage (~3%), and virtually no error in steady state. This indicates its high stability and suitability for use in systems of this type. However, this optimization method leads to significant oscillatory processes, which can result in excessive load on the actuator. Gradient Descent (GD) showed acceptable stabilization time (~123 s) and insignificant steady state error, but has a significant overshoot (~23%). It provides relatively smooth dynamics, but is inferior to RMSProp in terms of speed and stability. Momentum and Nesterov are characterized by the longest settling times (173 and 160 seconds) and higher overshoot percentages (~27%), making them less effective for high-speed systems. They also guarantee low steady-state error, so they can be useful in conditions where a longer transition process is acceptable.

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Дослідження впливу методів оптимізації на ефективність екстремальної системи керування на основі аудіальної дефектоскопії

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Анотація

У роботі досліджується вплив методів оптимізації на ефективність екстремальної системи керування на основі аудіальної дефектоскопії. Запропонована система здатна виявляти аномальні режими роботи обладнання шляхом аналізу звукових характеристик та автоматично адаптувати параметри керування під нові умови експлуатації. Методом математичного моделювання досліджено роботу системи з різними алгоритмами оптимізації: градієнтним спуском, Momentum, Nesterov та RMSProp. Результати показують, що RMSProp забезпечує найшвидший вихід на усталений режим (103 секунди) з мінімальним перерегулюванням (3%), проте супроводжується значними коливаннями керуючого сигналу. Класичний градієнтний спуск демонструє прийнятний час стабілізації (123 секунди) з помірним перерегулюванням (23%). Методи Momentum та Nesterov характеризуються найдовшим часом встановлення (173 та 160 секунд відповідно). Дослідження підтверджує доцільність застосування екстремальних систем керування з адаптивною оптимізацією для підвищення надійності та ефективності роботи технологічного обладнання в умовах змінних режимів експлуатації.

Ключові слова: інтелектуальна система керування; оптимізація; математичне моделювання; перехідний процес.