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ARTIFICIAL INTELLIGENCE-BASED AUTOMATIC CONTROL OF TECHNOLOGICAL PARAMETERS IN LABORATORY EQUIPMENT

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Annotation: This article discusses and analyzes the automatic control of technological parameters of laboratory equipment based on artificial intelligence. Modern scientific research and industrial testing rely heavily on the precision, reliability, and adaptability of laboratory equipment. Traditional control systems often fall short when dealing with dynamic, non-linear, and multi-variable technological parameters. By leveraging machine learning, neural networks, and computer vision, laboratory instruments can autonomously monitor, predict, and adjust their internal states in real time.

Keywords: artificial intelligence, automatic control, laboratory equipment, technological parameters, machine learning, neural networks, computer vision.

Introduction. Laboratory equipment serves as the cornerstone of innovation across various scientific domains, including chemistry, pharmacology, materials science, and biotechnology. The validity of experimental outcomes depends fundamentally on the strict maintenance of specific technological parameters such as temperature, pressure, fluid flow rates, chemical concentration, and environmental humidity. Historically, these variables were regulated using manual adjustments or conventional mechanical controllers[1].

While proportional-integral-derivative controllers have long been the standard for automated regulation, they struggle to adapt to sudden environmental fluctuations, equipment wear, or highly complex, non-linear chemical reactions. The emergence of artificial intelligence offers a transformative solution to these limitations. By embedding intelligent algorithms into laboratory control loops, systems can transition from passive feedback mechanisms to proactive, cognitive

[1] Astrom, K. J., Murray, R. M. Feedback Systems: An Introduction for Scientists and Engineers. Princeton University Press. Volume 2, 2021, 145–168.

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control architectures capable of managing intricate technological parameters without human intervention[2].

To understand the necessity of intelligent automation, one must evaluate the shortcomings of classical control methodologies. Conventional systems operate on fixed mathematical models. They require precise calibration based on predictable environmental conditions. However, real-world laboratory experiments are rarely perfectly predictable. For instance, an exothermic chemical reaction inside a reactor can cause rapid, localized temperature spikes that standard sensors and controllers cannot anticipate quickly enough, leading to compromised samples or hazardous situations.

Furthermore, traditional systems treat interconnected variables in isolation. In a multi-stage distillation process, changing the pressure directly influences the boiling points and vapor velocities of the substances involved. A standard controller often fails to balance these multi-variable dependencies simultaneously, causing system oscillations and lengthy stabilization times. Manual intervention by researchers remains a frequent requirement, which introduces subjective human error, limits the continuity of long-term experiments, and reduces overall laboratory efficiency.

The core computational layer utilizes machine learning models to interpret the incoming data streams. Unlike rigid algorithms, these models are trained on historical experimental datasets, allowing them to recognize complex patterns and anomalies. Once the artificial intelligence processes the current state of the parameters, it formulates an optimal response and transmits commands to the actuation layer. This layer includes automated valves, heating elements, micro-pumps, and robotic arms that adjust the physical state of the equipment with extreme precision. This continuous loop creates a self-optimizing ecosystem within the laboratory setup[3].

For example, during a prolonged microbiological cultivation process, maintaining exact dissolved oxygen levels is critical. A neural network can analyze the historical consumption rate of oxygen alongside current temperature and stirrer speed to forecast an impending drop in oxygen levels. The system then automatically increases the gas supply ahead of time, ensuring a perfectly stable environment for cellular growth. By shifting from a reactive posture to a predictive one, artificial intelligence eliminates the sharp fluctuations that frequently ruin delicate biological and chemical samples[4].

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2 Yusupbekov, N. R., Marakhimov, A. R., Igamberdiev, H. Z., Umarov, S. X. An Intelligent Control System for Technological Processes Based on Fuzzy Logic and Neural Networks. Chemical Technology. Control and Management, Volume 2020, Issue 3, 2020, 24–31.

3 Russell, S., Norvig, P. Artificial Intelligence: A Modern Approach. Pearson. 4th Edition, 2020, 581–610.

4 Siddikov, I. X., Khujamatov, H. E. Automation of Monitoring and Control of Technological Parameters of Industrial Enterprises Based on IoT and AI. Technical Science and Innovation, Volume 2022, Issue 2, 2022, 88–95.

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While traditional sensors measure quantifiable digital values like temperature or voltage, many qualitative technological parameters have historically required visual assessment by human scientists. Artificial intelligence bridges this gap through computer vision. High-resolution cameras combined with convolutional neural networks can continuously monitor visual indicators within laboratory devices.

In chemical synthesis, color changes, precipitation density, and bubble formation dynamics are critical indicators of reaction stages. Computer vision algorithms can detect micro-finesse changes in fluid color or crystallization patterns that are invisible to the naked eye. If a solution begins to change color faster than dictated by the experimental protocol, the intelligent system can instantly throttle the catalyst injection pump or modify the cooling jacket temperature. This visual automation extends the capabilities of control systems far beyond the scope of traditional thermal or mechanical sensors.

The replication crisis is a well-documented challenge in modern science, where independent researchers frequently struggle to replicate published experimental results. Often, this failure stems from micro-variations in laboratory environments or subtle differences in how human operators manage equipment parameters. Artificial intelligence eradicates this variability by enforcing absolute operational consistency. Every adjustment made by an intelligent controller is logged with microsecond precision, ensuring that the exact environmental and physical trajectory of an experiment can be recreated perfectly across different laboratories worldwide.

In addition to reproducibility, safety is profoundly enhanced. Laboratories often handle volatile compounds, biohazardous agents, or extreme thermal states. An artificial intelligence system equipped with anomaly detection can identify the earliest signatures of structural fatigue, thermal runaway, or pressure containment failures. By autonomously executing emergency shutdown protocols or isolating specific laboratory modules faster than human reaction times, the technology prevents catastrophic accidents and protects expensive infrastructure.

Despite the undeniable benefits, integrating artificial intelligence into laboratory control systems presents specific challenges. The primary obstacle is the requirement for substantial volumes of high-quality training data. Machine learning models must be exposed to various operational scenarios, including rare failure modes, to learn effectively. Developing standardized datasets for niche scientific experiments remains a demanding task. Additionally, retrofitting older, analog laboratory equipment with smart sensors and digital actuators requires significant initial financial investments and technical expertise[5].

Looking ahead, the future of laboratory automation lies in the convergence of artificial intelligence with edge computing and cloud-based scientific networks. Future laboratory devices will not operate as isolated intelligent units; instead, they will be interconnected globally. A control model optimized in one laboratory could instantly update the parameter control algorithms of identical

[5] Zheng, Y., Wang, H. Machine Learning Applications in Chemical Process Control and Laboratory Automation. Computers & Chemical Engineering, 2019, 222–235.

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devices in research facilities around the world via cloud networks. This collective intelligence will dramatically accelerate the pace of scientific discovery.

Conclusion. The automation of technological parameters through artificial intelligence represents a paradigm shift in laboratory instrumentation design. By superseding the limitations of traditional, rigid control mechanisms, intelligent systems introduce unprecedented levels of precision, adaptability, and foresight to scientific experimentation. Through the synergy of predictive neural networks, real-time sensor integration, and computer vision, laboratory equipment can now navigate complex, multi-variable environments autonomously. As these technologies mature and become more accessible, the fully autonomous laboratory will transition from a futuristic concept into an indispensable reality, significantly elevating the safety, efficiency, and reliability of global scientific breakthroughs.

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