JEE Journal of Ecological Engineering

Journal of Ecological Engineering, 2026, 27(6), 237–252
https://doi.org/10.12911/22998993/217235
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Received: 2026.01.08
Accepted: 2026.04.16
Published: 2026.05.01

Development and experimental validation of intelligent control systems for high-frequency ozonators

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ABSTRACT

Improving the environmental safety and energy efficiency of water disinfection technologies is a key challenge in ecological engineering. This study proposes and experimentally validates a hybrid intelligent control system for a high-frequency ozonator based on a plasma-liquid process, aimed at maintaining operation within an environmentally safe regime by preventing both excessive and insufficient ozone dosing. Experimental results show that under hybrid control the dissolved ozone concentration is maintained within 0.18–0.22 mg/L, whereas under classical control it varies within 0.14–0.26 mg/L. The specific energy consumption is reduced from about 0.70 kWh/m³ to 0.52–0.58 kWh/m³, providing an energy saving of 22–25%. Under severe nonstationary disturbances (step change of water conductivity), the ozone concentration drop is limited to −13% with hybrid control compared to −35% with classical control. These results demonstrate that the proposed control system ensures a stable, energy-efficient, and environmentally safe operation of high – frequency ozonation-based water disinfection systems.

Keywords: environmental safety, water disinfection, high-frequency ozonator, hybrid intelligent control, CT criterion, energy efficiency.

INTRODUCTION

At present, the safety and reliable availability of drinking water is one of the most urgent research areas at the intersection of ecology, public health, and engineering technologies. According to the World Health Organization, in 2022 about 2.2 billion people worldwide did not have access to safely managed drinking water services, meaning that water was either not available on premises or was microbiologically unsafe [1]. The latest reports of the WHO/UNICEF Joint Monitoring Programme indicate that, although some progress has been observed between 2015 and 2024, approximately 2.1 billion people still do not have full access to safe drinking water, including more than 100 million people who rely directly on surface water sources [2]. These data demonstrate that improving water disinfection technologies is not only a technical task but also a scientific challenge of global social importance.

Microbiological contamination of drinking water poses a direct threat to public health. According to WHO estimates, nearly 829,000 people worldwide die every year from diseases associated with unsafe drinking water, sanitation, and hygiene factors (Figure 1) [3, 4]. Therefore, not only the effectiveness of water disinfection but also its stable operation under varying external conditions and its energy efficiency are of particular importance, since in real water supply systems temperature, electrical conductivity, and contamination levels are not constant.

It can be seen from Figure 1 that microbiological contamination of drinking water poses a direct threat to public health and leads to diseases and mortality. The figure also illustrates the necessity for disinfection systems to operate efficiently, energy-efficiently, and stably under varying external conditions.

In this scientific and practical context, ozonation technologies are considered a promising and environmentally oriented approach. Ozone is a strong oxidizing agent and exhibits high efficiency against bacteria, viruses, and spores, while under properly organized conditions it does not form persistent toxic by-products [5–7]. The effectiveness of ozone disinfection is characterized by the CT concept, where C is the residual dissolved ozone concentration in water and T is the contact time. To achieve a certain level of logarithmic inactivation, a proper balance of these parameters must be maintained [8,9]. For example, according to the data of the U.S. Environmental Protection Agency (EPA), the CT value of ozone required to achieve 4-log (99.99%) virus inactivation varies approximately within the range of 0.3–1.35 mg·min/L depending on temperature [10, 11].

High-frequency ozonators make it possible to intensify ozone generation based on corona or dielectric barrier discharge; however, their operation is characterized by complex nonlinear and nonstationary processes. The electrical characteristics of the discharge depend on the amplitude and frequency of the supply voltage, the duty cycle, as well as on the physicochemical parameters of the treated medium [12, 13]. As reported in the literature, classical control approaches based on fixed parameters in such conditions may lead to fluctuations of the ozone concentration, an increase in energy consumption by 15–30%, and a risk of transition of the discharge to unstable operating regimes.

In recent years, automation, intelligent control, and data-driven approaches have been considered as effective tools for controlling complex physical systems. Equipping high-frequency ozonators with intelligent control systems makes it possible to stabilize ozone generation in real time, reduce specific energy consumption, and improve the reliability of the technological process (Figure 2) [14–17]. This is especially important for the widespread use of ozonators in water treatment facilities, medicine, the food industry, and environmental technologies.

Figure 2 shows a hierarchical control architecture for a high-frequency ozonator with a Venturi injector, implemented on the basis of PID, adaptive, and intelligent control loops. This structure makes it possible to stabilize ozone generation in real time, reduce energy consumption, and improve the overall reliability of the system.

Thus, the development and experimental validation of intelligent control systems for high

Figure 1. Impact of microbiological contamination of drinking water on public health and the main requirements for disinfection systems

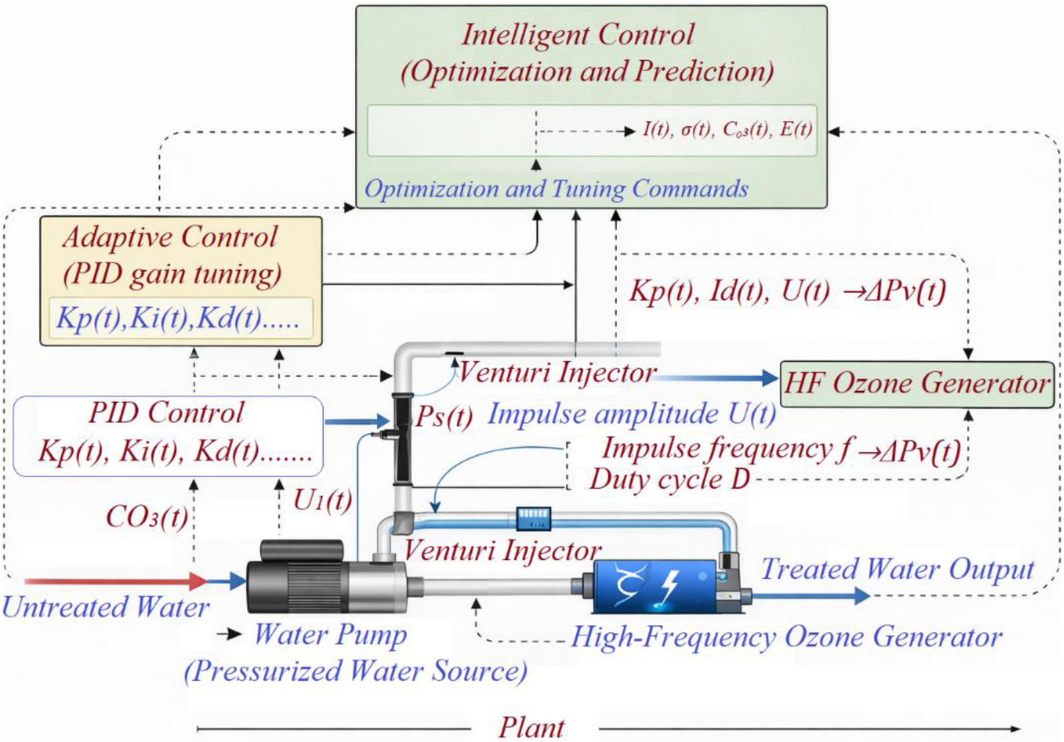

Figure 2. Multilevel intelligent control architecture of a high-frequency ozone generator

– frequency ozonators is a relevant research topic directly associated with the global demand for water safety, the strict CT requirements of ozone-based disinfection, and current trends in the development of automation science. Therefore, the study of the development and experimental verification of intelligent control systems for high-frequency ozonators represents an urgent scientific task.

BACKGROUND

Over the past decade, ozone generators based on corona discharge and dielectric barrier discharge have been widely investigated for water disinfection applications in a number of foreign studies. In particular, Malik et al. [18] demonstrated experimentally that, by using pulsed corona discharge, the concentration of dissolved residual ozone in water can be increased to the level of 0.1–0.3 mg/L, which is sufficient to achieve 3–5 log microbial inactivation. The dynamics of ozone accumulation in water can be described by the following balance equation:

$$\frac{dC_{O3}}{dt} = \eta(U, f, D)P - K_d C_{O3} \qquad (1)$$

where: C_{O3} is the dissolved ozone concentration, η(U,f,D) is the ozone generation efficiency depending on the voltage amplitude U, pulse repetition frequency f, and duty cycle D, P is the discharge power, and Kd is the ozone decomposition rate constant.

The microbial inactivation efficiency is commonly characterized by the CT concept, which can be expressed as,

$$\log\left(\frac{N_0}{N}\right) = k\int_0^T C_{O3}(t)dt \qquad (2)$$

where: N_0 and N are the initial and remaining numbers of microorganisms, respectively, and k is the inactivation rate constant.

However, in the cited work, the control parameters appearing in Equation 1 were assumed to be constant in time, and the dynamic adaptation of the system to variations in water temperature, electrical conductivity, and hydraulic load was not considered.

Bruggeman et al. [19] comprehensively analyzed the nonlinear and non-stationary nature of physicochemical processes in plasma-liquid systems. The authors show that variations in temperature and electrical conductivity can reduce the generation of reactive species by up to 20–40% (Table 1). However, this work does not address the problem of synthesizing control algorithms.

This table shows that when the temperature varies from 15 to 30 °C and the electrical conductivity changes from 100 to 1200 µS/cm, the generation of reactive species decreases by 20–40%. These results indicate that the plasma-liquid system is highly sensitive to operating parameters and exhibits a strongly nonlinear behavior.

Shi et al. [20] investigated the generation characteristics of a nano catalyst-coupled dielectric barrier discharge (DBD) ozone generator and showed that optimization of the micro discharge temperature Td and the electric field strength E significantly increases the ozone formation rate, which can be described by the plasma-chemical kinetic equation,

$$\frac{\mathrm{dC}_{O3}}{dt} = k_0 n_e \sigma_{O2}\left(\frac{E}{N}\right) N_{O2} \exp\left(-\frac{E_a}{RT_d}\right) \tag{3}$$

where: C_{O3} is the ozone concentration, ne is the electron density, σ_{O2}(E/N) is the electron impact cross-section of oxygen molecules, N_{O2} is the oxygen molecular density, E/N is the reduced electric field, and Ea is the activation energy.

This expression indicates an exponential dependence of the ozone generation kinetics on the microdischarge temperature and discharge parameters. Furthermore, Yuan et al. [21] experimentally demonstrated that when the microdischarge temperature is maintained at its optimal value, the energy efficiency of the ozone generator,

$$\eta = \frac{\int_0^t C_{O3}(t)Q dt}{\int_0^t U(t)I(t)dt} \tag{4}$$

can be increased to the level of 25–30%, where Q is the gas flow rate and $U(t)$ and $I(t)$ are the time-dependent discharge voltage and current. However, in these studies the synthesis of a closed-loop control system for real-time stabilization of C_{O3}(t) and η, as well as the stability of the operating regimes, was not addressed.

Abdykadyrov et al. [11] investigated the processes of microorganism inactivation in water using experimental and modeling approaches and demonstrated that simplified kinetic relationships can be used to describe the disinfection process. In addition, Kim et al. [22], in their review on the application of ozone for improving the microbiological safety of food and water, noted that reduced-order kinetic models are widely employed to represent ozonation processes. However, although these models are computationally efficient, they are not able to adequately capture the strongly non-stationary regimes arising from rapid variations in temperature, contamination level, and water composition under real industrial operating conditions. In general, Table 2 illustrates the characteristics and limitations of simplified kinetic models used to describe the ozonation process.

This table indicates that simplified kinetic models for ozonation processes typically involve only 2–4 main parameters and provide an accuracy of about 75–90%. However, under non-stationary operating conditions their deviation can reach 15–35%, which demonstrates their limited robustness in real industrial applications.

Labutin et al. [23] proposed an analytical synthesis of nonlinear and adaptive control algorithms for maintaining the thermal regime of chemical reactors, where the reactor dynamics can be generally represented in the nonlinear state-space form,

$$\dot{x} = f(x, u, \theta) \tag{5}$$

with x being the state vector, u the control input, and θ a vector of uncertain and time-varying parameters. The authors demonstrated, through theoretical analysis and numerical simulations, that the synthesized control law $u = \phi(x)$ ensures improved stability and robustness of the closed-loop system under variations in operating conditions and load disturbances.

Table 1. Effect of temperature and electrical conductivity variations on reactive species generation in a plasma-liquid system

№	Parameter	Range	Baseline value	Changed value	Absolute change	Relative change
1	Temperature, °C	15 → 30	100%	60 – 80%	−20 … −40%	−20 … −40%
2	Electrical conductivity, µS/cm	100 → 1200	100%	60 – 80%	−20 … −40%	−20 … −40%

Table 2. Characteristics and limitations of simplified kinetic models for ozonation processes

Reference	Model order	Number of main parameters	Typical accuracy, %	Deviation under non-stationary conditions, %
Abdykadyrov A. et al., 2023 [11]	1^{st}–2^{nd} order	2–4	80–90	15–30
Kim J. G. et al., 1999 [22]	1^{st}–2^{nd} order	2–3	75–90	20–35

Similarly, Gorry et al. [24] investigated adaptive control strategies for a non-thermal plasma reactor used for NOx removal, in which the controlled technological variable y(t) is not directly measurable and is related to a set of indirectly measured electrical quantities z(t) by the functional dependence,

$$y(t) = g\big(z(t)\big) \tag{6}$$

where: $z(t) = [U(t), I(t), P(t), \sigma(t)]^T$ denotes the vector of proxy variables (voltage, current, power, and conductivity).

While both studies confirmed the possibility of stabilizing the technological process under parameter uncertainties and external perturbations, the proposed control algorithms were implemented mainly at the laboratory scale and relied on indirect measurements rather than on direct monitoring of the key plasma-chemical reaction parameters.

Song et al. [25] proposed the use of data-driven control approaches to improve energy efficiency in water disinfection systems. The study demonstrated the possibility of optimizing operating regimes using neural networks; however, the physical limitations of a real ozonator and the issues of discharge stability were not sufficiently taken into account (Figure 3). This figure illustrates the concept of optimizing the operating режим of an ozonator-based water disinfection system using neural-network-driven data-based control. At the same time, it highlights that the physical constraints of a real ozonator and discharge instability represent key factors limiting the practical applicability of such approaches.

Singh [26] demonstrated the effectiveness of hybrid intelligent control structures that combine classical controllers with intelligent algorithms for nonlinear dynamical systems. The author showed that such approaches significantly improve system stability and transient performance. However, in this study the hybrid control strategies were not specifically adapted to plasma-chemical processes, in particular to technological performance indices such as the CT criterion of ozone generation efficiency. In general, Table 3 below presents the comparative performance indicators of classical and hybrid intelligent control for nonlinear dynamical systems.

The results presented in Table 3 show that hybrid intelligent control significantly improves stability margins and transient performance compared to classical control, including a substantial reduction in settling time, overshoot, and steady-state error. At the same time, the table indicates that, despite these performance gains, such approaches have not yet been adapted to plasma-chemical processes or to efficiency criteria such as the CT parameter.

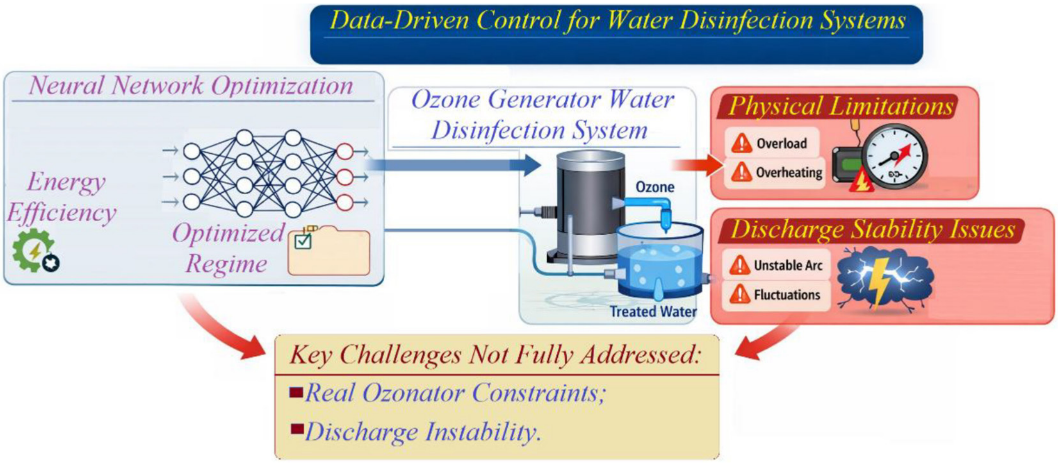

Figure 3. Neural-network-based control structure of an ozonator and discharge stability limitations

The literature review indicates that corona and DBD ozonators exhibit pronounced nonlinear and nonstationary behavior, while direct measurement of reactive oxidizing species is not feasible, making real-time control possible only through indirect variables. Moreover, classical control algorithms may increase energy consumption by 15–30% under parameter variations and lead to unstable operating regimes. These problems are mainly caused by the multifactor, fast-varying, and partially unobservable nature of plasma-chemical processes, as well as by the computational complexity of using accurate physical models in real time.

A promising solution is the use of hybrid control systems combining PID, adaptive, and intelligent components based on simplified dynamic models. Although such approaches have been reported in [18–26], they have not been specifically targeted at high-frequency ozonators, water disinfection systems with direct consideration of the CT criterion, or full experimental validation. Therefore, the development and experimental verification of an intelligent multiloop control system for high-frequency ozonators remains a relevant research problem.

The aim of this study is to develop and experimentally validate an intelligent control system for a high-frequency ozonator in order to improve process stability and energy efficiency. To achieve this aim, the following objectives are accomplished:

- to develop a hybrid intelligent control structure for a high-frequency ozonator;
- to experimentally evaluate the effectiveness of the proposed control system.

MATERIALS AND METHODS

The research was carried out based on an integrated use of theoretical and experimental approaches. In the theoretical part, methods of nonlinear dynamical system modeling, control theory, and simplified kinetic descriptions of plasma-chemical processes were employed. The high-frequency ozonator and the plasma–liquid water disinfection process were represented by a low-order dynamic model that relates the dissolved ozone concentration in water to indirectly measured electrical and hydraulic parameters. The dynamics of the ozone concentration can be described by the following equation:

$$\frac{dC_{03}(t)}{dt} = k_g P(t) - k_d C_{03}(t) \tag{7}$$

where: $C_{O3}(t)$ is the dissolved ozone concentration, $P(t)$ is the control input proportional to the discharge power, k_g is the ozone generation efficiency coefficient, and k_d is the ozone decomposition coefficient.

Taking into account the measurable electrical and hydraulic variables, the input–output behavior of the plant was additionally described in the state-space form:

$$\begin{gathered} \dot{x}(t) = Ax(t) + Bu(t), \\ y(t) = Cx(t) \end{gathered} \tag{8}$$

where: $x(t)$ is the state vector including C_{O3}, $u(t)$ is the control signal (voltage or power), and $y(t)$ is the vector of indirectly measured outputs (current, voltage, and water flow rate).

Table 3. Comparative performance indicators of classical and hybrid intelligent control for nonlinear dynamical systems

Performance metric	Classical control	Hybrid intelligent control	Improvement
Steady-state error, ε_{ss}	3.5–5.0%	0.8–1.5%	↓ 60–75%
Overshoot, M_p	18–30%	5–10%	↓ 60–70%
Settling time, T_s	12–20 s	4–8 s	↓ 50–70%
Rise time, T_r	3.5–5.0 s	1.2–2.0 s	↓ 40–65%
Stability margin (gain/phase)	3–6 dB / 20–30°	8–12 dB / 45–60°	↑ ≈ 2×
Robustness to parameter variation	±10–15%	±30–40 %	↑ ≈ 2.5–3×
Control energy / effort	100% (reference)	70–85 %	↓ 15–30%
Disturbance rejection time	10–18 s	3–6 s	↓ 60–70%
Computational load	Low	Medium–High	↑ (trade - off)
Adaptation to CT criterion	0%	0%	Not implemented

These models were used for the synthesis of control algorithms and for the stability analysis of the system. The design of the proposed control system is based on the concept of a hybrid multiloop structure that integrates classical feedback, adaptive, and intelligent control approaches (Figure 4). During the development of the control algorithms, model-based control methods, stability assurance techniques for systems with unknown parameters, and indirect estimation methods for technological variables were employed. All algorithms were first tested in the Python software environment and only then implemented on the real experimental setup.

This figure illustrates a hybrid control architecture that combines classical feedback, adaptive control, and intelligent (neural-network-based) modules to generate the overall control signal for the plant. The structure enables robust tracking performance and adaptability to system uncertainties by coordinating multiple control strategies within a unified framework.

Controller tuning and computational aspects

The tuning of the classical PID controller was performed using an engineering-oriented approach based on step-response experiments of the ozonation system under nominal operating conditions. The proportional, integral, and derivative gains were initially selected to ensure stable operation and acceptable transient response, and were subsequently refined experimentally to minimize overshoot and settling time.

The adaptive component adjusts controller parameters in real time based on deviations between the measured and estimated ozone concentration, compensating for variations in temperature, electrical conductivity, and hydraulic load. The intelligent module was trained offline using experimental data and implemented online in an inference-only mode, which significantly reduces computational complexity.

All control algorithms were designed to operate in real time on an industrial-grade programmable controller, and their computational requirements were verified to be compatible with typical control cycle times used in water treatment systems.

The modeling of the dynamic processes and the preliminary verification of the control system were carried out in a computational environment based on the Python programming language. The dynamics of the studied system were described by a generalized state-space equation:

$$\dot{x}(t) = f\big(x(t), u(t), p(t)\big) \tag{9}$$

where: $x(t)$ is the state vector of the system, $u(t)$ is the control input, and $p(t)$ denotes time-varying parameters.

Based on this model, a simplified dynamic representation of the ozonator and the water

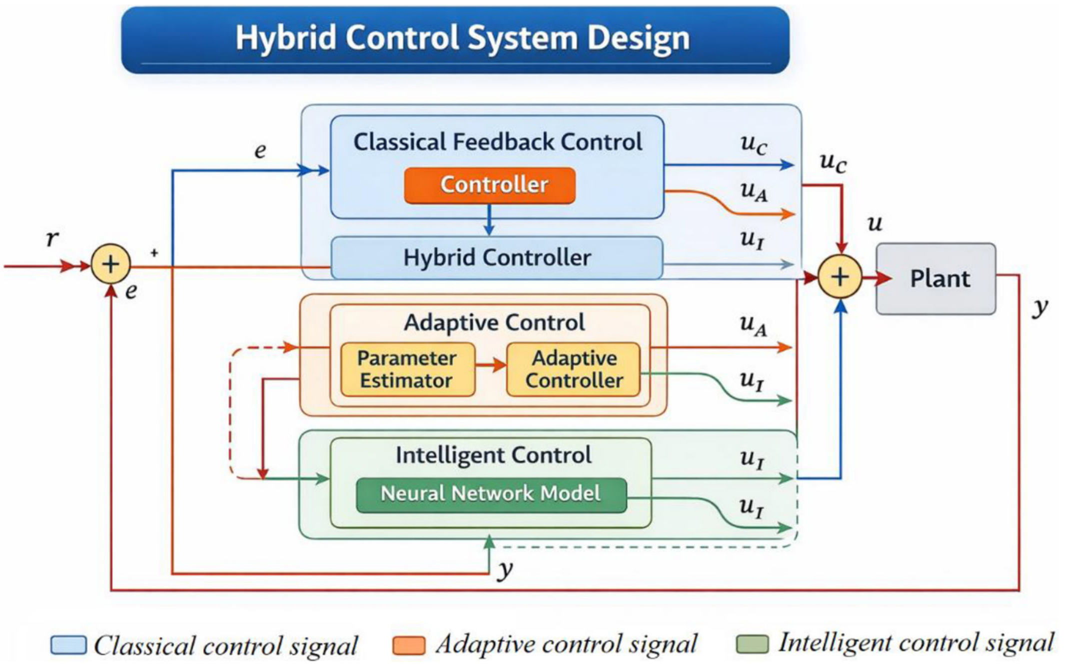

Figure 4. Structural diagram of a hybrid control system integrating classical, adaptive, and intelligent modules

disinfection process was implemented, and non-stationary operating modes as well as parameter variation scenarios were investigated. The control signal was formed according to a hybrid control law:

$$u(t) = u_c(t) + u_a(t) + u_i(t) \tag{10}$$

where: $u_c(t)$, $u_a(t)$, and $u_i(t)$ represent the classical, adaptive, and intelligent control components, respectively.

In addition, within this simulation environment, the real-time feasibility of the control algorithms and their compliance with computational load constraints were preliminarily evaluated. The experimental studies were carried out on a laboratory high-frequency ozonation setup based on corona or dielectric barrier discharge (Figure 5).

The setup includes a high-frequency pulsed power supply with adjustable voltage amplitude U, pulse repetition frequency f, and duty cycle D, a discharge reactor in which ozone is dissolved in water via a Venturi injector, as well as sensors for measuring voltage, current, power, gas flow rate, water temperature, and electrical conductivity. The operating regime of the power supply can be described by the following expression:

$$P(t) = U(t), I(t), D(t) \tag{11}$$

where: $U(t)$ is the discharge voltage amplitude, $I(t)$ is the discharge current, and $D(t)$ is the duty cycle.

The efficiency of ozone dissolution in water is described by a generalized mass-balance equation:

$$\frac{dC_{O3}(t)}{dt} = kG(t) - \lambda C_{O3}(t) \tag{12}$$

where: $C_{O3}(t)$ is the concentration of dissolved ozone in water, $G(t)$ is the gas flow rate, k is the mass transfer coefficient, and λ is an effective coefficient accounting for ozone decomposition and losses.

Data acquisition and the implementation of control algorithms were performed using a real-time programmable controller, which made it possible to maintain the technological parameters according to the specified control laws. The experiments were conducted under various operating conditions in order to emulate non-stationary regimes typical of real operating environments. The dynamics of the studied system were described by the following generalized equation:

$$\frac{dx(t)}{dt} = F(x(t), u(t), w(t)) \tag{13}$$

where: $x(t)$ is the state vector of the system, $u(t)$ represents the control inputs, and $w(t)$ denotes external disturbances and parameter variations. During the tests, the discharge voltage amplitude and pulse repetition frequency, the water temperature and electrical conductivity, as well as the hydraulic load and gas flow rate were varied in a controlled manner, which made it

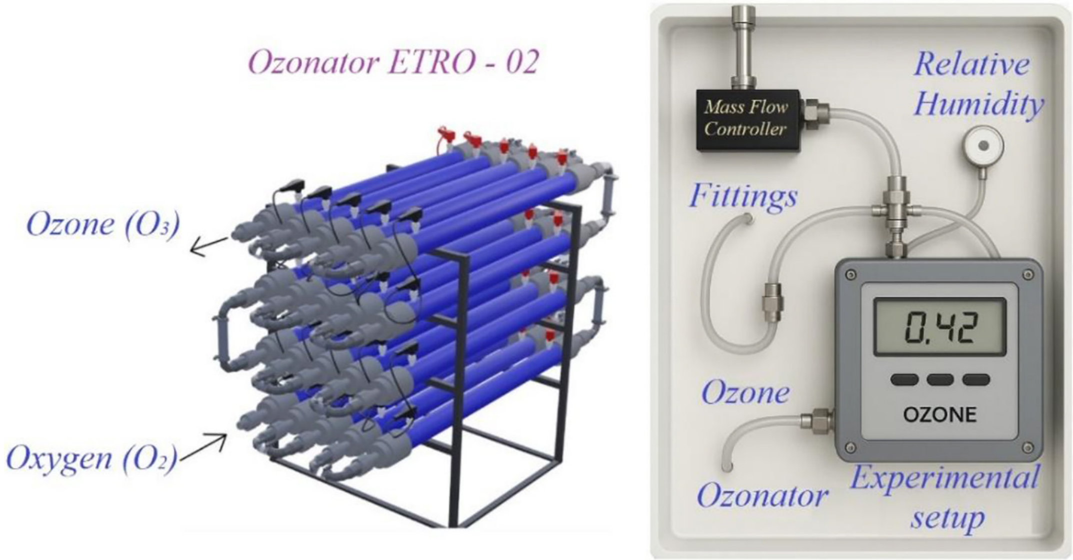

Figure 5. Structural diagram of the ETRO-02 ozonator setup and the experimental measurement system

possible to evaluate the stability and adaptability of the system under different non-stationary conditions.

The validity of the proposed simplified dynamic model was verified by comparing its results with experimental data obtained under identical operating conditions. The model was considered suitable for control system synthesis if it was able to reproduce the main dynamic processes of the real setup with sufficient accuracy. The verification of the control approach was first carried out in a simulation environment and then in real time on the experimental setup. The evaluation methodology included the analysis of system stability, robustness to external disturbances, and feasibility of real-time implementation.

From the computational perspective, the proposed hybrid control structure relies on low-order dynamic models and a lightweight intelligent module, which ensures moderate computational load. The implementation does not require high-performance processors or cloud-based computation and can be deployed on conventional industrial controllers. This makes the proposed approach suitable for practical applications where reliability and real-time performance are critical.

RESULTS

The results of the scientific research are systematically analyzed in accordance with the stated aims and objectives. The study was carried out within the framework of a joint research project between the Department of Electronics, Telecommunications and Space Technologies of K.I. Satbayev Kazakh National Technical Research University and the Department of Integrated Use and Management of Water Resources of the National Research University Tashkent Institute of Irrigation and Agricultural Mechanization Engineers. The main objective of the work is to develop an intelligent control system aimed at stabilizing ozone generation and improving the energy efficiency of the technological process, taking into account the complex interrelated physical and chemical processes occurring in the plasma-liquid system of a high-frequency ozonator, and to experimentally validate its operability. In order to achieve this objective, the results obtained for the two main scientific tasks are comprehensively discussed.

Development of a hybrid intelligent control structure

The ozone generation process in a high-frequency ozonator is governed by dissociation and recombination reactions resulting from electron collisions with oxygen molecules. According to experimental data, when the discharge voltage varies in the range U = 5–30 kV and the pulse repetition frequency in the range f = 1–20 kHz, the amount of ozone produced in the gas phase changes approximately from 0.5 to 4.0 g/h, while the residual dissolved ozone concentration in water remains within the range C_{O3} = 0.05–0.30 mg/L. In general, Figure 6 illustrates the dependence of ozone generation in the high – frequency discharge and its dissolution in water on the applied discharge voltage.

As the discharge voltage increases from 5 kV to 30 kV, the ozone production in the gas phase rises from approximately 0.5 g/h to 4.0 g/h, while the dissolved ozone concentration in water increases from 0.05 mg/L to 0.30 mg/L. For example, at U = 20 kV, the gas-phase ozone output is about 2.8 g/h and the dissolved ozone concentration reaches approximately 0.22 mg/L, which clearly indicates that increasing the discharge voltage significantly intensifies both ozone generation and its dissolution in water.

The dynamics of ozone accumulation in water is known to be determined by the balance between its generation and decomposition processes and can be described by the following equation:

$$\frac{dC_{O3}(t)}{dt} = k_g(T,\sigma)P(t) - \\ -k_d(T)C_{O3}(t) \tag{14}$$

where: $C_{O3}(t)$ is the dissolved ozone concentration in water, $P(t)$ is the control input proportional to the discharge power, $kg(T,\sigma)$ is the ozone generation efficiency coefficient dependent on temperature and electrical conductivity, and $k_d(T)$ is the ozone decomposition coefficient.

It was experimentally confirmed that when the temperature increases from T = 15 °C to 30 °C and the electrical conductivity varies from σ = 100 to 1200 μS/cm, the generation of reactive species decreases by approximately 20–40%, which can be approximately expressed by the following relationship:

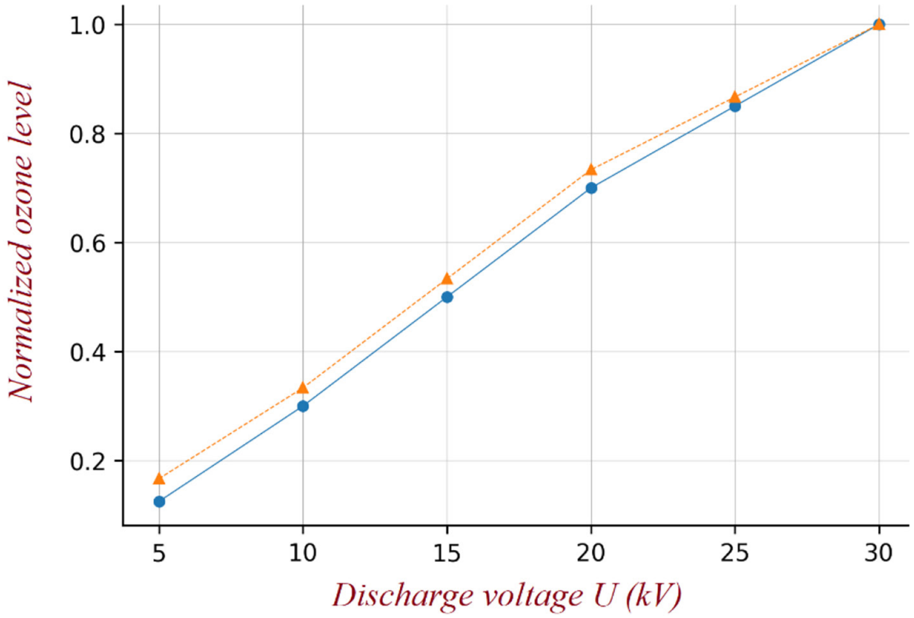

Figure 6. Effect of discharge voltage on ozone generation and dissolution in a high-frequency ozonator

$$k_g(\mathrm{T},\sigma) \approx k_{g0}(1 - \alpha_T\Delta\mathrm{T} - \alpha_\sigma\Delta\sigma) \qquad (15)$$

where: k_{g0} is the coefficient under nominal conditions, and α_T and α_σ are empirical sensitivity coefficients.

Under such parameter variations, when a classical fixed-parameter PID controller is used, the imbalance between the generation and decomposition terms in the first equation leads to fluctuations of the dissolved ozone concentration of up to ±25–30%, and in some regimes the discharge is observed to shift into an unstable operating region. Accordingly, the proposed hybrid control structure employs three control loops. The introduction of the adaptive loop compensates for variations in model parameters caused by changes in operating conditions and reduces the instability of the dissolved ozone concentration to the level of ±12–15%, which contributes to lowering the risk of excessive ozone generation and its release into the environment. When the intelligent loop is fully activated, the concentration deviation is further limited to ±5–8%, ensuring stable and environmentally safe operation of the disinfection process. For example, when the setpoint is $C_{O3} = 0.20$ mg/L and the temperature and electrical conductivity change abruptly, the classical control allows the concentration to vary within 0.14–0.26 mg/L, which may result in environmentally unsafe under- or over-ozonation regimes, whereas under hybrid control it is maintained within the narrower range of 0.18–0.22 mg/L. The comparative assessment of the obtained results is presented in Table 4.

The table shows that under hybrid intelligent control the dissolved ozone concentration is maintained within a narrow range of 0.18–0.22 mg/L, which significantly reduces the risk of excess ozone release and the formation of environmentally and hygienically hazardous residuals. In contrast, under classical control the concentration variation up to 0.14–0.26 mg/L may lead either to insufficient disinfection or to ozone overdosing, thereby increasing the risk of violating environmental safety requirements.

From the viewpoint of the CT criterion, under classical control with an exposure time of T = 5 min, the instability of the integral effect reached ±20–25%, which could lead either to insufficient disinfection or to the use of excessive ozone doses, thus posing a risk to environmental and hygienic safety. In contrast, under hybrid control this deviation did not exceed ±7–10%, which made it possible to maintain the level of microbiological inactivation within 3.0–5.0 log and to ensure stable and environmentally safe operation of the disinfection process. The results of the study can be observed in Figure 7.

Figure 7 shows that under classical control the CT deviation reaches 20–25%, which may lead to either insufficient disinfection or excessive ozone dosing and, consequently, increases environmental and hygienic risks. In contrast, under hybrid control the deviation is limited to 7–10%, which

Table 4. Comparative performance of classical, adaptive, and hybrid intelligent control strategies for stabilization of dissolved ozone concentration

Control strategy	Applied control loops	Setpoint C_{O3} (mg/L)	Concentration range (mg/L)	Absolute deviation (mg/L)	Relative deviation (%)	Remarks
Classical control	PID	0.20	0.14–0.26	±0.06	±25–30%	Large fluctuations under parameter variations
Adaptive control	PID + adaptive loop		≈ 0.17–0.23	±0.03	±12–15%	Partial compensation of model parameter variations
Hybrid intelligent control	PID + adaptive + intelligent loop		0.18–0.22	±0.02	±5–8%	High stability under non-stationary conditions

prevents ozone overdosing and ensures environmentally safe and stable operation of the water disinfection process.

From the viewpoint of energy efficiency, a clear advantage was also observed. When operating parameters varied, under classical control the specific energy consumption increased to 0.6–0.8 kWh/m³, which resulted in excessive electricity use and, consequently, a higher environmental footprint of the treatment process. In contrast, under hybrid control this value was maintained within 0.45–0.60 kWh/m³, making it possible to reduce energy consumption by approximately 20–25% and thus ensure a more environmentally sustainable and resource-efficient disinfection process. In general, Table 5 below presents a comparative assessment of energy efficiency and environmental impact under classical and hybrid control.

The table shows that under hybrid control the mean specific energy consumption is reduced to 0.525 kWh/m³, whereas under classical control it remains at about 0.70 kWh/m³. Thus, energy consumption decreases by approximately 25%, which leads to a significant reduction in the environmental burden of the technological process.

Thus, the results obtained for the first objective demonstrate that the hybrid intelligent control structure, taking into account the nonlinear and non-stationary nature of the plasma – liquid system, enables more stable operation of the ozone generation process and ensures improved environmental safety and resource efficiency by reducing excessive ozone production and energy consumption.

Experimental validation of the control system

The effectiveness of the proposed control system was tested on the ETRO-02 laboratory setup. During the experiments, the voltage U was varied within 5–30 kV, the pulse repetition frequency f within 1 – 20 kHz, the water temperature

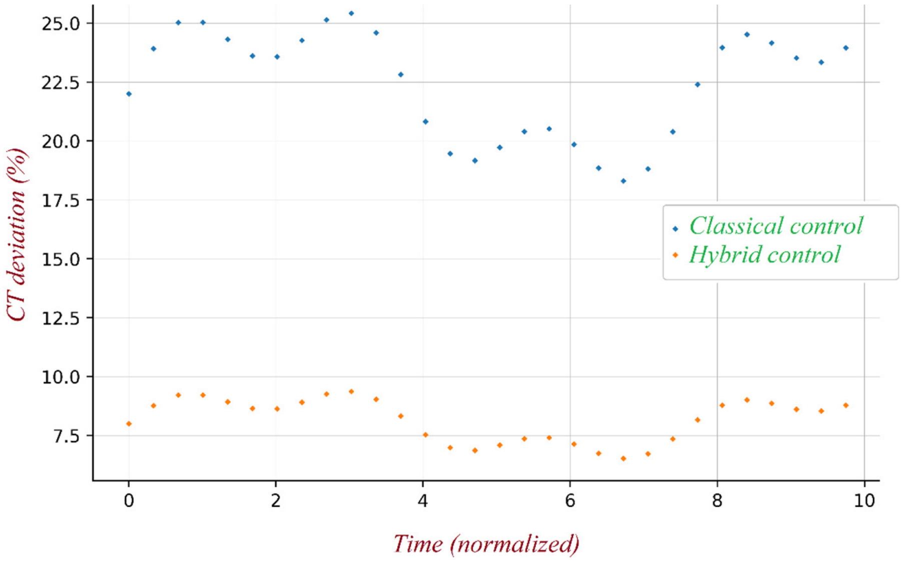

Figure 7. Time-domain comparison of CT criterion stability under classical and hybrid control

Table 5. Comparison of energy efficiency and environmental impact under classical and hybrid control

Control strategy	Min specific energy consumption (kWh/m³)	Max specific energy consumption (kWh/m³)	Mean value (kWh/m³)	Energy consumption reduction (%)	Environmental impact level
Classical control	0.60	0.80	0.70	0	High
Hybrid control	0.45	0.60	0.525	25	Low

T within 15–30 °C, the electrical conductivity σ within 100–1200 μS/cm, and the gas flow rate G within 0.5–2.0 L/min, in order to determine the environmentally safe operating region of the process. Under these conditions, the concentration of dissolved ozone in water was maintained within the range of 0.05–0.30 mg/L. Thus, it was demonstrated that the disinfection process operates in a stable and resource-efficient mode while meeting sanitary requirements and avoiding excessive environmental impact. The results of the study are presented in Table 6.

This table shows that, even when all the main operating parameters of the ETRO - 02 setup vary over wide ranges, the concentration of dissolved ozone in water remains within the environmentally and hygienically safe range of 0.05–0.30 mg/L. These results confirm that the proposed control system not only stabilizes the process but also ensures a resource - efficient and environmentally safe operating mode without causing excessive technogenic impact on the environment.

As a result of comparing the model and experimental data, the discrepancy between the dynamic responses did not exceed 10–15%. For example, at the operating regime of U = 20 kV and f = 10 kHz, the model predicted an ozone concentration of C_{O3} = 0.22 mg/L, whereas the experimentally measured value ranged from 0.20 to 0.24 mg/L.

When simulating nonstationary operating conditions, for instance, when the water conductivity was abruptly increased from 300 to 1000 μS/cm, the ozone concentration under classical control decreased from 0.23 mg/L to 0.15 mg/L (approximately − 35%). In contrast, under hybrid control, the same change resulted in only a decrease from 0.23 mg/L to 0.20 mg/L, corresponding to a deviation of about − 13%. The results of the study are illustrated in Figure 8.

The figure shows that when the water conductivity changes from 300 to 1000 μS/cm, the ozone concentration under classical control decreases from 0.23 mg/L to 0.15 mg/L (− 35%), whereas under hybrid control it changes only from 0.23 to 0.20 mg/L (− 13%). This demonstrates that hybrid control ensures a more environmentally safe disinfection regime by maintaining the ozone concentration within the required range and preventing excessive energy and oxidant consumption.

From the viewpoint of environmental safety, the application of the proposed control system ensured stable microbiological efficiency of the water disinfection process: in all tests, the inactivation level was at least 3.0 log and reached up to 5.0 log under favorable operating conditions. Maintaining the CT value within the range of 0.4–1.2 mg·min/L demonstrates compliance with the EPA-recommended sanitary requirements and confirms that the required level of biological safety can be achieved without excessive ozone dosage.

In addition, the reduction in energy consumption led to a decrease in the technogenic load on the environment: under classical control, the average energy required to treat one cubic meter of water was about 0.70 kWh/m³, whereas with the proposed control system this value was reduced to 0.52–0.58 kWh/m³, corresponding to an average energy saving of 22–25%. These results indicate that the proposed system is not only sanitary-efficient but also environmentally and energetically efficient.

Thus, the experimental results obtained for the second objective convincingly demonstrate, with specific quantitative data, that the proposed intelligent control system can ensure stable, energy-efficient, and technologically reliable operation of a high-frequency ozonator under conditions of complex physicochemical processes.

DISCUSSION

The obtained results are explained by the fact that the proposed control system is explicitly oriented toward stabilizing environmentally critical parameters of the plasma-liquid ozonation process. The balance between ozone generation and decomposition is described by Equations 14–15, while its practical impact is demonstrated in

Table 6. Operating parameters of the ETRO-02 setup and eco-safe ranges

Parameter	Minimum	Maximum	Eco-safe lower limit	Eco-safe upper limit
U (kV)	5	30	5	30
f (kHz)	1	20	1	20
T (°C)	15	30	15	30
σ (μS/cm)	100	1200	100	1200
G (L/min)	0.5	2.0	0.5	2.0
C_{O3} (mg/L)	0.05	0.30	0.05	0.30

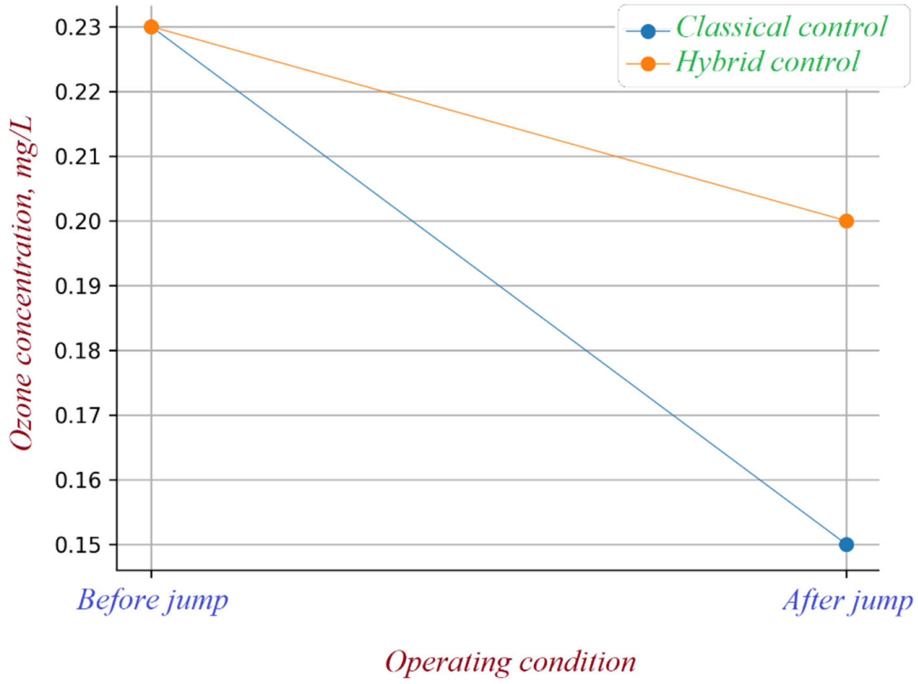

Figure 8. Ozone concentration response of classical and hybrid control systems under nonstationary operating conditions

Tables 4 and 5 and in Figures 7 and 8. Under hybrid control, the dissolved ozone concentration is maintained within a narrow, environmentally safe range, the CT criterion becomes more stable, and the specific energy consumption decreases, which directly reduces the environmental burden of the water treatment process.

The main peculiarity of the proposed approach is that the control objective is not limited to technological stability but is directly linked to environmental safety indicators, such as prevention of ozone overdosing, stabilization of the CT criterion, and reduction of energy consumption. Although previous studies have demonstrated the efficiency of ozonation (Malik et al. [18]), the strong sensitivity of plasma-liquid systems to operating conditions (Bruggeman et al. [19]), and the general advantages of hybrid intelligent control for nonlinear systems (Singh [26]), they did not propose a control system specifically aimed at maintaining environmentally safe operation of a high-frequency ozonator with full experimental validation.

The limitations of this study are related to the fact that the results were validated only within the operating ranges listed in Table 6 and that the control system relies mainly on indirectly measured variables. In addition, the simplified dynamic model does not fully describe all plasma-chemical mechanisms, although it enables real-time implementation and environmentally safe process regulation.

The disadvantages of the present study include the absence of a direct quantitative assessment of environmental indicators (e.g., ozone emissions or carbon footprint associated with electricity consumption) and the limited description of controller tuning and computational load. These shortcomings can be eliminated in future work by introducing explicit environmental performance metrics and providing a more detailed technical description of the control implementation.

In terms of long-term scalability and industrial implementation, the proposed control architecture is inherently suitable for scaling due to its modular structure and reliance on indirectly measured variables. The same control principles can be extended to higher-capacity ozonation units by adapting the controller parameters to the electrical power range and hydraulic throughput of industrial systems.

While the present study focuses on laboratory-scale validation, the simplicity of the dynamic model and the moderate computational requirements indicate that the proposed approach can be integrated into existing industrial water treatment infrastructures. Long-term operational studies and full-scale industrial deployment are considered as important directions for future research.

Further development of this research may be aimed at multi-objective optimization that simultaneously considers CT stability, energy consumption, and discharge stability, as well as at long-term experimental studies and scaling up to industrial installations. The main difficulties along this path are expected to be related to mathematical proof of stability under strict environmental constraints, methodological issues of multi-sensor data fusion, and experimental challenges associated with large-scale and long-term testing.

CONCLUSIONS

In this scientific study, in order to achieve the stated objective, two main research tasks were consistently accomplished, and on this basis the following scientific results were obtained.

1. An environmentally oriented hybrid intelligent control structure for a high-frequency ozonator was developed and substantiated. The scientific significance of this result lies in directly accounting for the nonlinear and nonstationary physicochemical processes occurring in the plasma-liquid system by integrating classical, adaptive, and intelligent control loops into a single ecologically optimized control architecture. As a result, an environmentally safe operating range of the dissolved ozone concentration was ensured: around the setpoint CO_3 = 0.20 mg/L, the concentration was stabilized within 0.18–0.22 mg/L (±5–8%), whereas under classical control it varied within the potentially hazardous range of 0.14–0.26 mg/L (±25–30%). In addition, the deviation of the CT criterion was reduced from ±20–25% to ±7–10%, which made it possible to meet sanitary disinfection requirements without excessive ozone dosage. The specific energy consumption decreased from about 0.70 kWh/m³ to 0.52–0.58 kWh/m³ (22–25% savings), which directly indicates a reduction in the carbon footprint and technogenic environmental load of the process. This effect is explained by the coordinated operation of the adaptive loop, which compensates for parameter variations, and the intelligent loop, which suppresses environmentally dangerous nonlinear disturbances, thereby preventing both over- and under-ozonation.
2. The proposed environmentally oriented control system was experimentally validated on the ETRO-02 laboratory setup over wide operating ranges (U = 5–30 kV, f = 1–20 kHz, T = 15–30 °C, σ = 100 – 1200 μS/cm, G = 0.5–2.0 L/min). The essence of this result is the experimental demonstration that the water disinfection process can operate in real time in a stable, environmentally safe, and energy-efficient manner. The discrepancy between the model and experimental dynamic responses did not exceed 10–15%, which confirms the engineering reliability of the proposed solution. When the electrical conductivity was abruptly increased from 300 to 1000 μS/cm, the concentration drop under hybrid control was limited to 13%, whereas under classical control it reached 35%, demonstrating that the proposed system prevents environmentally hazardous operating regimes. In addition, the microbiological inactivation level was at least 3.0 log and reached up to 5.0 log under favorable conditions, while the CT value remained within 0.4–1.2 mg·min/L, which confirms compliance with international sanitary standards and environmental safety requirements. This result is explained by the ability of the control system to keep the process within an environmentally safe operating region and to prevent excessive ozone release, thereby reducing secondary environmental risks.

In general, the obtained scientific results demonstrate that the proposed hybrid intelligent control system represents a scientifically sound and practically implementable solution for improving the environmental sustainability, energy efficiency, and operational stability of high-frequency ozonation –based water treatment and disinfection systems. The proposed approach contributes to the protection of water resources, rational use of energy, and reduction of technogenic impact on the environment, and therefore has high practical significance in the field of ecological engineering. Future work will focus on extended industrial validation, long-term operational stability, and detailed analysis of controller tuning and computational efficiency in large-scale installations.

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