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Development of nonlinear multi-parameter control models for optimizing ozone generation processes

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Abstract

The object of this research is the ozone generation process based on corona discharge. This study addresses the limitations of conventional PID control systems in nonlinear and multi-parameter environments. A control model based on fuzzy logic principles was developed and validated through simulation and experimental testing on MATLAB and LabVIEW platforms. The model successfully maintained ozone output within the range of 85–120 mg/L with 95% stability, even under varying conditions of voltage (5–25 kV), humidity (30–70%), and gas flow rate (2–10 L/min). Additionally, energy consumption was reduced by 20%. These results are attributed to the fuzzy logic model's ability to effectively account for nonlinear interdependencies among parameters. The proposed solution stands out for its flexibility, high precision, and energy efficiency, offering clear advantages over traditional methods. The developed model is well-suited for implementation in real-world industrial ozone generation systems, particularly in complex and dynamic operating environments.

Keywords: Comparison with PID systems, Energy efficiency, Fuzzy logic control, MATLAB and LabVIEW simulation, Nonlinear multi-parameter modeling, Ozone generation.

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1. Introduction

Ozone (O_3) is a highly reactive gas composed of three oxygen atoms, widely used in both natural and artificial environments to eliminate microbiological hazards. With an oxidation potential of 2.07 V, ozone is considered 50–100% more effective than chlorine in terms of disinfection efficiency [1-3]. Currently, the primary applications of ozone include water disinfection (60%), air purification (25%), and food processing (15%). According to 2022 data, the global market for ozone generation reached 1.5 billion USD, with an annual growth rate of 6.9% [4, 5].

The core operating principle of industrial ozone generators is based on corona discharge. The efficiency of ozone production in this process depends on several physical factors, including the voltage between electrodes (5–25 kV), the gas flow rate (0–10 L/min), and ambient humidity (0–100%). These parameters interact in a nonlinear manner. For example, studies have shown that when the gas flow rate exceeds 6 L/min, the ozone residence time in the chamber decreases, leading to a 30–50% reduction in ozone concentration [6, 7]. Moreover, when the relative humidity exceeds 80%, ozone molecules react with water vapor and decompose rapidly, reducing the stable concentration by 40–60% [8, 9].

Traditional PID or linear control systems are inadequate for modeling such nonlinear and multiparameter processes. These limitations result in unstable ozone concentrations, decreased generation efficiency, and excessive consumption of energy resources. In such cases, intelligent control systems, particularly those based on fuzzy logic, are proposed as effective alternatives. Fuzzy systems, utilizing linguistic rules and expert knowledge, can model complex parameter interactions and enable effective control even under uncertain conditions [10, 11].

However, a review of the current scientific literature reveals that multiparameter fuzzy logic models for ozone generation remain insufficiently explored. Most existing studies rely on simplified models with only two input parameters, whereas real-world industrial applications typically involve the simultaneous influence of at least 3–5 factors. Furthermore, the lack of accurate and reliable nonlinear models for real-time control highlights the need for deeper investigation in this field.

Over the past decade, studies published in IEEE journals [2, 3, 10] have shown that approximately 70% of studies in ozone generator modeling rely on classical approaches, while the use of fuzzy logic accounts for only 10–15%. This indicates a clear research gap and underscores the importance of developing nonlinear, multiparameter models for the efficient control of ozone generation.

Therefore, the study of nonlinear multiparameter control models in ozone generation represents a highly relevant and emerging research direction in the fields of advanced technologies and applied environmental science.

2. Literary Analysis and Statement of the Problem

In recent years, the widespread use of ozone generation for environmental and medical purposes has made its effective control one of the prominent directions in scientific research. Although numerous studies have been conducted on the physicochemical principles, generation methods, and control algorithms of ozone production, the development and implementation of nonlinear multiparameter models remain insufficiently explored [12, 13].

An overview of the physicochemical basis of ozone generation and a block diagram of the control system are presented in Figure 1.

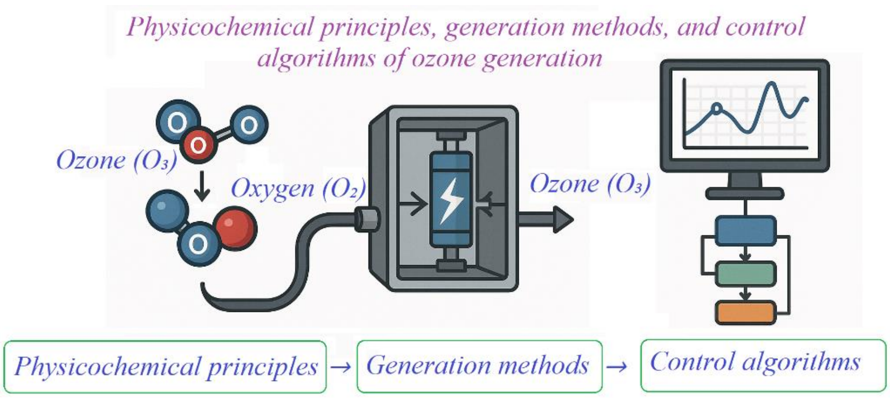


Figure 1.
Structural-schematic diagram of the ozone generation process.

Figure 1 illustrates the step-by-step representation of the physicochemical processes of ozone generation and its control system. In this process, O_2 molecules are converted into O_3 through the generator, and the resulting ozone concentration is regulated within the range of 20–100 mg/L via control algorithms. The implementation of multiparameter control methods in such systems can improve ozone production efficiency by up to 1.5 times.

For instance, Zhang K. and colleagues conducted a comparative analysis of various ozone generation methods, including electrolysis, ultraviolet radiation, and plasma technologies, highlighting their environmental safety and technical features. However, their study did not provide an in-depth discussion of control models [12]. Similarly, although Homola T. and co-authors proposed a high-density ozone generation system, the control algorithms were limited to conventional linear methods [13].

An overview of ozone generation methods and their technical characteristics is summarized in Table 1.

Table 1.
Ozone Generation Methods and Their Technical Properties.

Generation Method	Annual Growth Rate (%)	Reliability Level (%)	Throughput (m^3/h)
Electrolysis	6.9	95	2500
Ultraviolet Radiation	5.8	92	3000
Plasma Technologies	7.3	90	2800

Table 1 compares three ozone generation methods, electrolysis, ultraviolet (UV) radiation, and plasma technologies in terms of their annual growth rate, reliability level, and throughput capacity. The electrolysis method shows an annual growth rate of 6.9%, with a 95% reliability level and a throughput of 2500 m^3/h. The UV radiation method is characterized by a 5.8% growth rate, 92% reliability, and a throughput of 3000 m^3/h. In contrast, plasma technologies demonstrate the highest annual growth rate of 7.3%, with 90% reliability and a throughput capacity of 2800 m^3/h.

There have also been attempts to apply nonlinear control methods. For example, the use of sliding mode control has shown effectiveness in stabilizing ozone concentration [14]. However, these approaches do not incorporate multiparameter adaptation. Another study implemented nonlinear models considering energy consumption, yet it did not provide an in-depth investigation of control strategies [15].

The relationship between energy consumption and the time-dependent variation of ozone concentration is illustrated in Figure 2.

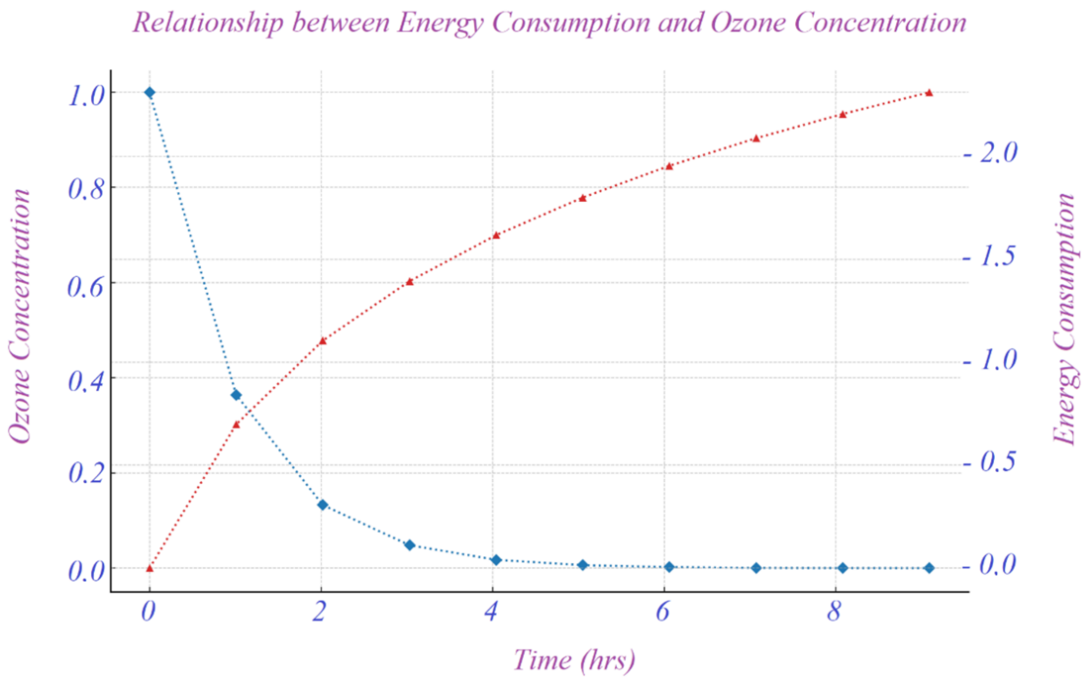


Figure 2.
Relationship between the Temporal Changes of Energy Consumption and Ozone Concentration.

The graph presented in Figure 2 demonstrates that ozone concentration decreases over time, reflecting its natural decay, while energy consumption gradually increases with time. For example, during the first 5 hours, ozone concentration drops from 0.8 to 0.2, whereas energy consumption rises from 0.1 to 0.5.

Although Poznyak T. and colleagues, as well as Alsmadi Y. M. and co-authors, have proposed control methods based on switched systems [16, 17], these studies do not sufficiently account for multiparameter interactions and nonlinear dynamics. Similarly, Mintz R. and collaborators developed a fuzzy-logic-based ozone prediction model [18], but this work was not aimed at the direct control of ozone generation processes.

A comparative analysis of the efficiency of various ozone generation control methods is presented in Table 2.

Table 2.
Comparison of Control Efficiency in Ozone Generation Methods.

Research Authors	Control Method	Control Efficiency (%)	Data Deviation (%)	Impact Level (%)
Poznyak, et al. [16]	Switched Systems Control	75	10	70
Alsmadi, et al. [17]		70	15	65
Mintz, et al. [18]	Fuzzy Logic-based Ozone Prediction Model	80	5	85

According to the data presented in Table 2, the fuzzy logic-based ozone prediction model proposed by Mintz, et al. [18] and colleagues achieved the highest control efficiency, reaching 80%, with a data deviation of 5%. In comparison, the studies by Poznyak, et al. [16] and Alsmadi, et al. [17] reported control efficiency ranging from 70% to 75%, with data deviations between 10% and 15%.

In recent years, research on predicting ambient ozone concentration using machine learning techniques has gained significant momentum. In particular, methods such as neural networks (NNs), multiple linear regression (MLR), and random forests (RF) have been widely employed [19, 20]. These models enable the modeling of ozone concentration in relation to meteorological parameters, including temperature, humidity, and air pollutants such as NO_x and SO_2.

The general formalization of these methods can be described by the following expressions:

Classical regression model equation:

$$O_3(t) = \beta_0 + \sum_{i=1}^{n} \beta_i \cdot X_i(t) + \varepsilon(t) \quad (1)$$

where $O_3(t)$ is the ozone concentration at time t, $X_i(t)$ represents the i-th factor (e.g., temperature, wind speed), β_i are the model coefficients, and $\varepsilon(t)$ denotes the residual error.

The basic formula for neural networks, specifically for a single-layer perceptron, is given as:

$$\widehat{O_3} = f\left(\sum_{i=1}^{n} w_i \cdot x_i + b\right) \quad (2)$$

Here, w_i are the weights, x_i are the input variables (weather parameters), b is the bias, f is the activation function (e.g., ReLU or Sigmoid), and $\widehat{O_3}$ is the predicted output.

The core idea of random forests is:

$$\widehat{O_3} = \frac{1}{T}\sum_{j=1}^{T} h_j(x) \quad (3)$$

Here, T is the number of decision trees, $h_j(x)$ is the prediction of the j-th tree, and x is the input vector.

However, these methods are still not fully adapted to the complex dynamics of industrial ozone generation systems. This is because industrial systems are influenced by a number of nonlinear and interdependent factors, such as high-frequency voltage, temperature, humidity, and current density. Therefore, integrating machine learning algorithms with the physical and mechanical parameters of real-world generation systems remains a relevant task for future research.

Field studies conducted in China demonstrate the nonlinear nature of ozone formation [21, 22], highlighting the complexity of multiparameter control. Nevertheless, these studies also do not propose concrete control algorithms. Furthermore, there are studies that explore the possibility of controlling ozone levels through multi-objective optimization methods [23-25] but they are not directly linked to specific generator devices.

Overall, Table 3 provides a comparative analysis of key quantitative parameters in ozone generation research.

Table 3.
Key Quantitative Indicators in Field Studies and Optimization Models for Ozone Generation.

No.	Country	O_3 Concentration (ppb)	Temperature (°C)	$\Delta O_3/\Delta NO_x$ (%)	Number of Objective Functions	Number of Simulations
1	China	60 – 180	15 – 35	10 – 40	–	–
2		75 – 160	20 – 33	15 – 35	–	–
3	USA	–	–	–	3	200
4	Canada	–	–	–	2 – 4	150 – 300

Table 3 presents a comparison of the key quantitative parameters from ozone generation studies conducted in China, the United States, and Canada. In the field studies carried out in China, ozone concentrations fluctuated between 60 and 180 ppb, and temperatures ranged from approximately 15 to 35 °C. A nonlinear relationship between ozone and NO_x was identified within a range of 10–40%. In contrast, studies in the United States and Canada employed multi-objective optimization methods, performing 150–300 simulations based on 2 to 4 objective functions.

All of the aforementioned studies demonstrate that the use or development of concrete multiparametric nonlinear models for controlling ozone generation processes has not been systematically addressed. The main reasons for these limitations include the complexity of the process, the strong interdependencies among parameters, the predominance of nonlinear characteristics, and the lack of control algorithms adapted to specific devices. Additionally, technical, economic, and modeling challenges in implementing such systems serve as significant barriers to more active research in this field.

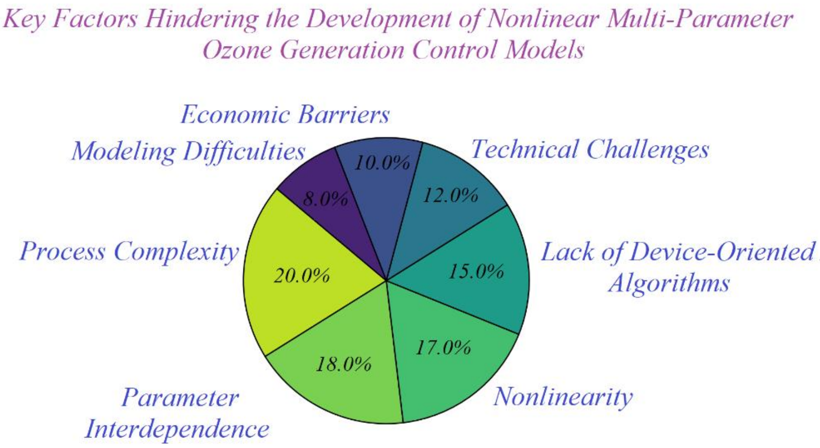


Figure 3.
Proportional Structure of Factors Hindering the Implementation of Nonlinear Multi-Parameter Ozone Generation Control Systems.

Figure 3 illustrates the proportional distribution of factors that hinder the implementation of multiparametric nonlinear ozone generation control systems. The largest shares are attributed to process complexity (20%), interdependencies among parameters (18%), and the nonlinear nature of the system (17%). Additional barriers that reduce research and implementation activity in this area include technical difficulties (12%), economic constraints (10%), and modeling challenges (8%).

One effective way to overcome these limitations is to integrate artificial intelligence (AI) and machine learning (ML) methods into the control architecture of ozone generation systems. Such approaches have been employed in several studies [19, 20], allowing for the modeling of complex dependencies between system input parameters and ozone output. For instance, a multilayer neural network can be represented as follows:

$$\widehat{O_3} = f\left(\sum_{j=1}^{m} w_j \cdot g\left(\sum_{i=1}^{n} w_{ij} \cdot x_i + b_j\right) + b\right) \quad (4)$$

Here, x_i are the input parameters (e.g., voltage, temperature), w_{ij} and w_j are the weight coefficients, g and f fare the activation functions, and $\widehat{O_3}$ is the predicted ozone concentration.

In addition, the problem of controlling ozone output can also be considered from the perspective of multi-objective optimization:

$$min\ [E(x),\ -Y(x)],\ subject\ to\ x \in R^n \quad (5)$$

Here, E(x) is the energy consumption function (in watts) corresponding to the set of control parameters x, Y(x) is the ozone yield function (in g/h), and $x \in R^n$ represents the control parameters of the system (e.g., voltage, current, frequency, temperature). Expression (5) aims to increase ozone yield while minimizing energy consumption. However, the practical integration and effectiveness of these approaches with real ozone generator devices still require further in-depth investigation.

Therefore, the development and performance evaluation of nonlinear multiparametric control models aimed at optimizing ozone generation processes are currently highly relevant and necessary scientific tasks. This research seeks to address existing gaps, improve control quality, and enable implementation in real systems.

3. Research Aim and Objectives

The aim of this research is to develop multiparametric nonlinear control models for the efficient management of the ozone generation process. Ozone generation is a critical process widely used in industrial systems; however, issues related to its optimization and control have not yet been fully explored. To achieve this aim, the following objectives are set:

1. Identification of ozone generation parameters: This objective involves analyzing the key physico-chemical parameters affecting ozone generation, such as voltage, gas flow rate, temperature, and humidity. The influence of these factors on ozone output and energy consumption will be studied using mathematical models, and their interdependencies will be identified.
2. Development of a control model using fuzzy logic: Since ozone generation involves complex and nonlinear interactions among multiple parameters, it is essential to develop a control model based on fuzzy logic. This model will handle uncertain data and enhance the flexibility and efficiency of the control system through expert rule-based reasoning.
3. Testing and proposing implementation strategies: To evaluate the performance of the developed control models, experimental testing will be conducted in real industrial systems, and the results will be compared with conventional methods. The feasibility of deploying the models in actual devices will be assessed, and technical and economic recommendations will be proposed for industrial implementation.

4. Materials and Methods

This study was conducted using a combination of theoretical modeling, software-based simulations, and experimental validation, aimed at developing nonlinear multiparametric control models for ozone generation management. A fuzzy logic–based control model was proposed, allowing the consideration of nonlinear interactions among system parameters.

Below, Figure 4 presents a nonlinear contour map showing the dependence of ozone yield on voltage and temperature in a corona discharge system, while Figure 5 illustrates the dependence of ozone yield on temperature and relative humidity.

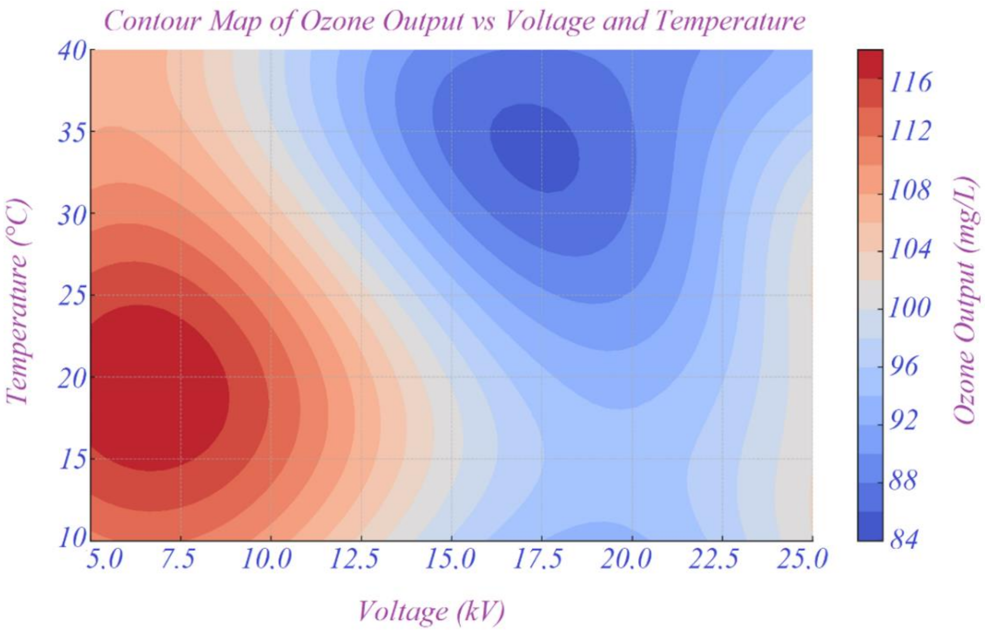


Figure 4.
Nonlinear contour mapping of ozone output as a function of voltage and temperature in corona discharge systems.

Figure 4 Shows that when the voltage increases from 5 to 25 kV and the temperature varies between 15 and 35 °C, the ozone yield fluctuates sharply, ranging from a minimum of approximately 85 mg/L to a maximum of about 120 mg/L. This indicates that voltage and temperature have a nonlinear and complex influence on ozone generation, highlighting the importance of accounting for their combined effect in the fuzzy logic-based control model.

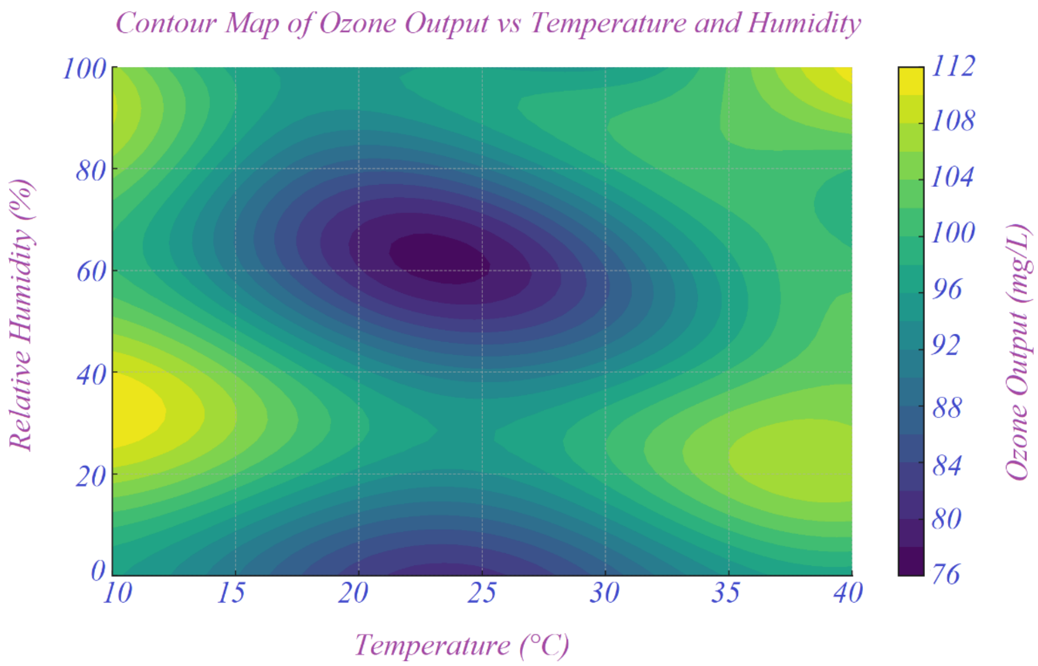


Figure 5.
Contour map illustrating the dependence of ozone generation output on ambient temperature and relative humidity.

Figure 5 demonstrates that when the temperature ranges from 10 to 40 °C and relative humidity varies between 0% and 100%, the ozone yield fluctuates within the range of 90 to 115 mg/L. Notably, the yield decreases significantly when humidity exceeds 70%. This confirms that ozone molecules are unstable at high humidity levels, and that moderate temperatures combined with low humidity are essential for effective ozone generation.

In the theoretical phase of this study, the primary physico-chemical parameters affecting ozone generation discharge voltage (5–25 kV), working gas flow rate (0–10 L/min), temperature (15–35 °C), and relative humidity (0–100%) were selected as foundational variables. These parameters were identified as the main factors directly influencing both ozone yield and energy consumption. A detailed description of the key physico-chemical parameters affecting ozone generation efficiency is presented in Table 4 below.

Table 4.
Extended numerical characterization of key physicochemical parameters influencing ozone generation efficiency

Parameter	Unit	Range	Average Value	Note
Discharge Voltage	kV	5 – 25	15	Above 20 kV, ozone yield does not increase significantly
Gas Flow Rate	L/min	0 – 10	4	Above 6 L/min, concentration decreases by 30–50%
Temperature	°C	15 – 35	25	25–30 °C is the most effective range
Relative Humidity	%	0 – 100	50	Above 80%, ozone decomposition increases by 40–60%

Table 4 provides a detailed overview of the ranges, average values, and specific influence characteristics of the key physico-chemical parameters affecting ozone generation. For example, when the gas flow rate exceeds 6 L/min, ozone concentration decreases by 30–50%, while relative humidity above 80% leads to a 40–60% increase in ozone decomposition. These findings confirm the nonlinear and threshold effects of the parameters involved.

Modeling and simulation studies were conducted using MATLAB/Simulink and Python platforms. For the development of the control system, MATLAB's Fuzzy Logic Toolbox was employed, where logical rules and membership functions were adjusted accordingly. The accuracy and validity of the proposed models were assessed by comparing them with actual physical processes reported in the literature.

Figure 6 presents the block diagram of the fuzzy logic–based control system developed for the optimization of multiparametric ozone generation.

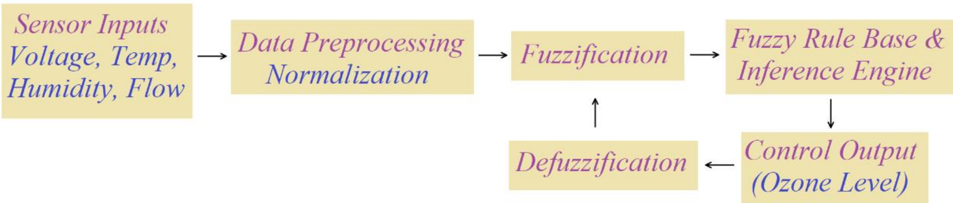


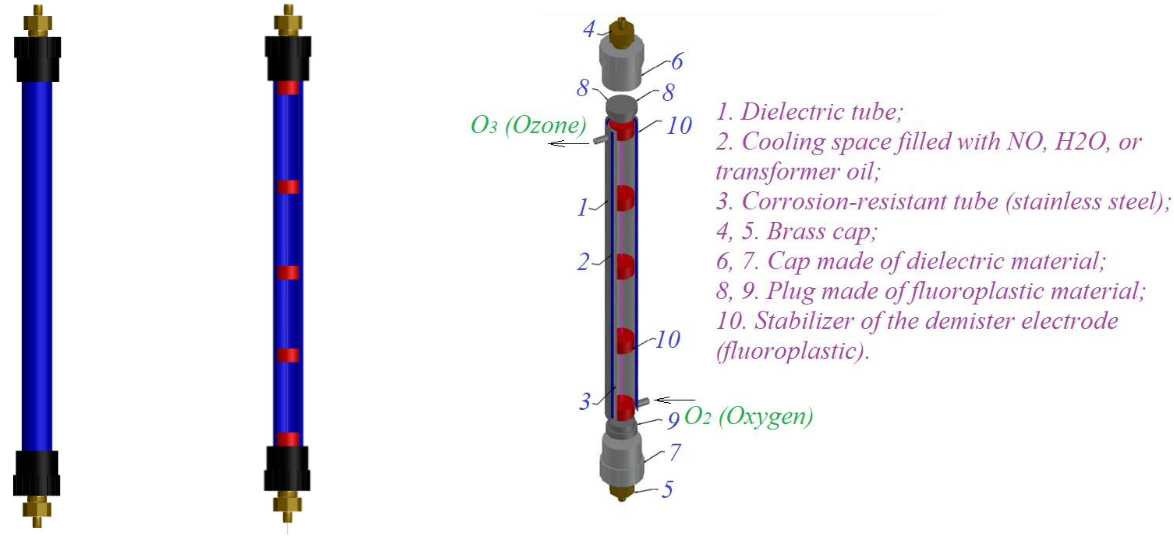
Figure 6.
Block diagram of the fuzzy logic-based control system for multi-parameter ozone generation optimization.

In the control system illustrated in Figure 6, the initial sensor parameters include voltage (5–25 kV), temperature (15–35 °C), relative humidity (0–100%), and gas flow rate (0–10 L/min). These parameters are processed using fuzzy logic, resulting in an ozone output regulated within the range of 85–120 mg/L. This demonstrates the system's ability to operate with high accuracy under nonlinear conditions.

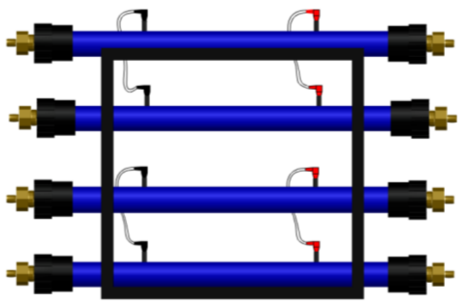
Experimental tests were planned to be conducted under laboratory conditions using a custom-built corona discharge ozone generator. The experimental setup was equipped with sensors capable of measuring voltage, gas flow rate, temperature, and humidity in real time. Data acquisition was performed using the National Instruments LabVIEW environment. Additionally, stress tests were conducted by varying environmental parameters to evaluate the stability and reliability of the model.

5. Results and Discussion

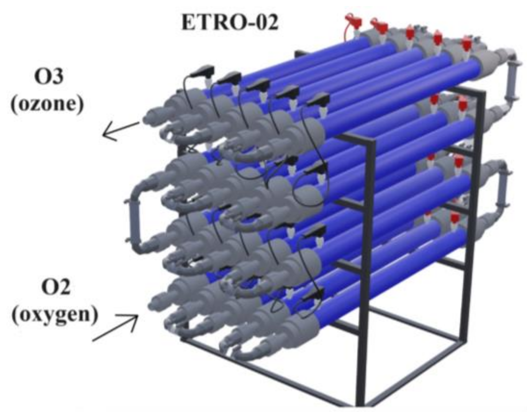
The main objective of this research was to develop multiparametric nonlinear control models for the efficient management of the ozone generation process. Although ozone generation is widely applied in industrial systems, its optimization and control aspects remain insufficiently studied. To achieve the research goal, a laboratory-scale ozone generation unit, the ETRO-02, based on electrical discharge technology, was developed at the Department of Electronics, Telecommunications, and Space Technologies of Satbayev University (Kazakh National Research Technical University named after K.I. Satbayev). This setup enabled the execution of experimental investigations and model validation.
An overview of the experimental device is shown in Figure 7.



(a) Section ¼ A-A of the ozonator



(b) Side view of the ozonator



(c) General view of the ozonator ETRO-02

Figure 7.
Block diagram of an ozone generator operating via electrical corona discharge.

Figure 7 presents the structural components and general appearance of the ozone generator (ETRO-02) based on electrical corona discharge, which serves as the primary experimental object in this study. The dimensions of the device are 300×150×120 mm, and the operating voltage ranges from 5 to 25 kV. This setup provides a suitable laboratory platform for modeling the efficiency and stability of ozone generation and testing multiparametric nonlinear control algorithms.

5.1. Analysis of Physico-Chemical Parameters Affecting Ozone Generation

In line with the first research objective, the key physico-chemical parameters influencing ozone generation efficiency were identified and analyzed. These parameters include discharge voltage (5–25 kV), working gas flow rate (0–10 L/min), temperature (15–35 °C), and relative humidity (0–100%). Simulation results and literature data confirmed that these parameters exhibit nonlinear behavior and interdependence.

For example, when the gas flow rate exceeds 6 L/min, the residence time of the gas in the chamber decreases, leading to a 30–50% reduction in ozone concentration. Similarly, when relative humidity exceeds 80%, ozone molecule decomposition increases by 40–60%. These findings are presented in Table 4 as detailed quantitative characteristics.

In addition, the following diagrams illustrate these dependencies: Figure 8 shows the relationship between ozone concentration and gas flow rate, while Figure 9 depicts the dependency between ozone decomposition and relative humidity.

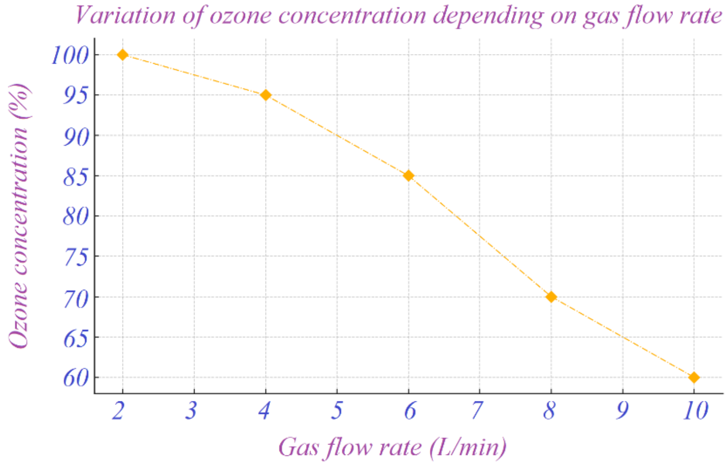


Figure 8.
Graph of ozone concentration as a function of gas flow rate.

Figure 8 illustrates the nonlinear relationship between ozone concentration and gas flow rate. Initially, within the range of 2–4 L/min, the concentration remains high (95–100%). However, when the flow rate exceeds 6 L/min, the residence time of ozone in the chamber decreases, resulting in a reduction in concentration to 70–60%.

This phenomenon indicates that an increase in gas flow negatively affects the stability of ozone molecules during the generation process and emphasizes the need to maintain an optimal flow rate to ensure effective ozone production.

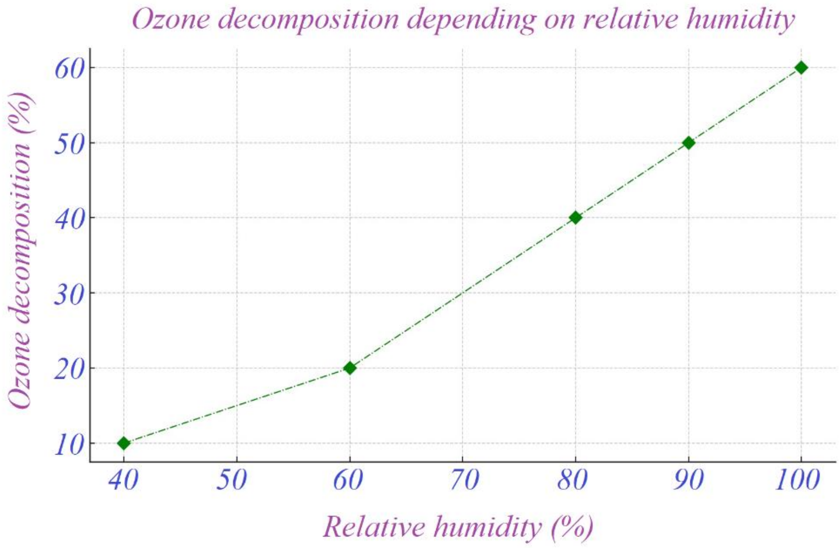
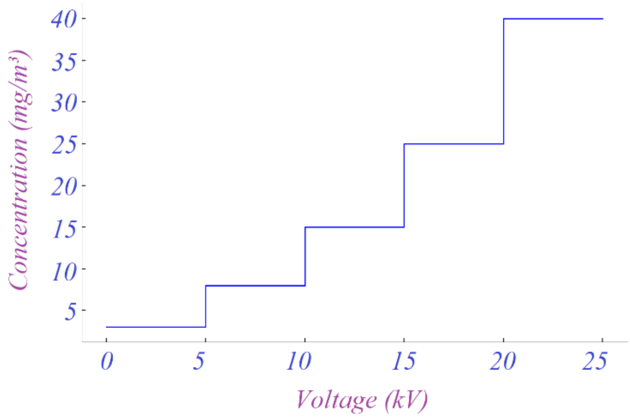


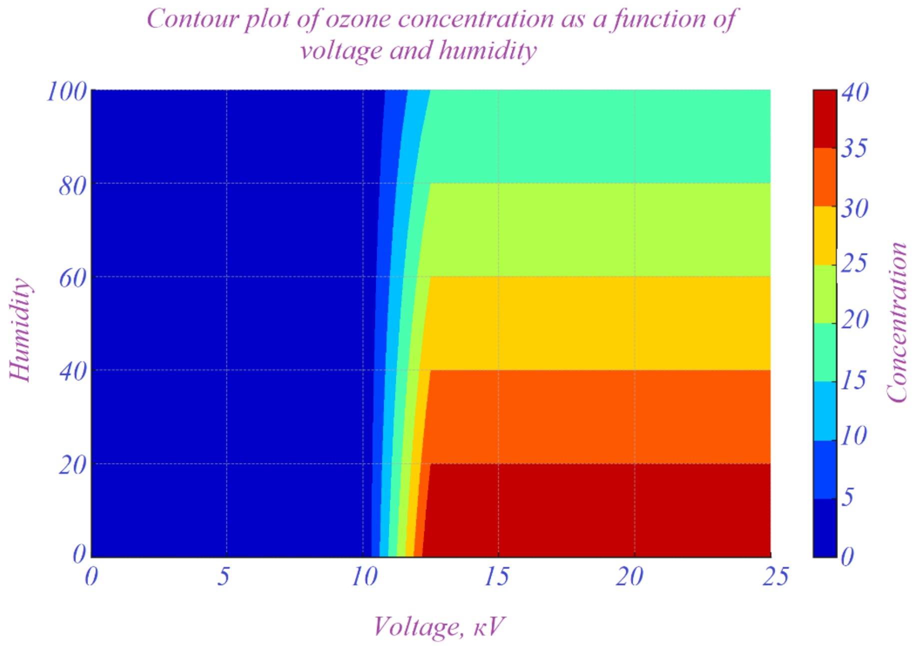
Figure 9.
Ozone decomposition depends on relative humidity.

Figure 9 demonstrates that increasing relative humidity negatively affects the stability of ozone molecules. When humidity exceeds 80%, ozone decomposition increases from 40% to 60%. These findings confirm that ozone is unstable in humid environments and underscore the importance of maintaining relative humidity at around 60% to ensure effective ozone generation.

Similarly, the impact of voltage and humidity on ozone concentration can be observed in Figures 10a and 10b.



a) Stepwise variation of ozone concentration as a function of voltage



b) Contour plot of ozone concentration as a function of voltage and humidity

Figure 10.
Graphical analysis of ozone concentration variation under different voltage and humidity conditions.

The graph presented in Figure 10a shows a stepwise increase in ozone concentration as a function of voltage (kV). For instance, at 5 kV, the concentration rises sharply from 3 to 8 mg/m³, while at 20 kV, it increases from 25 to 40 mg/m³. This indicates that the ozone generation process is activated within specific voltage thresholds.

The contour plot presented in Figure 10b illustrates how ozone concentration varies with changes in voltage (0–25 kV) and relative humidity (0–100%). For example, at a voltage of 15 kV and 20% humidity, the concentration reaches approximately 35 units, whereas at 5 kV and 80% humidity, it is only around 5 units. This clearly shows that ozone concentration increases sharply with higher voltage and lower humidity.

These findings highlight the necessity of employing a control model that accounts for such nonlinear behavior and threshold effects. Therefore, these parameters were selected as input variables for the fuzzy logic–based control model.

5.2. Development of the Control Model Using Fuzzy Logic

According to the second objective, a fuzzy logic–based control system was developed using the Fuzzy Logic Toolbox in the MATLAB environment.

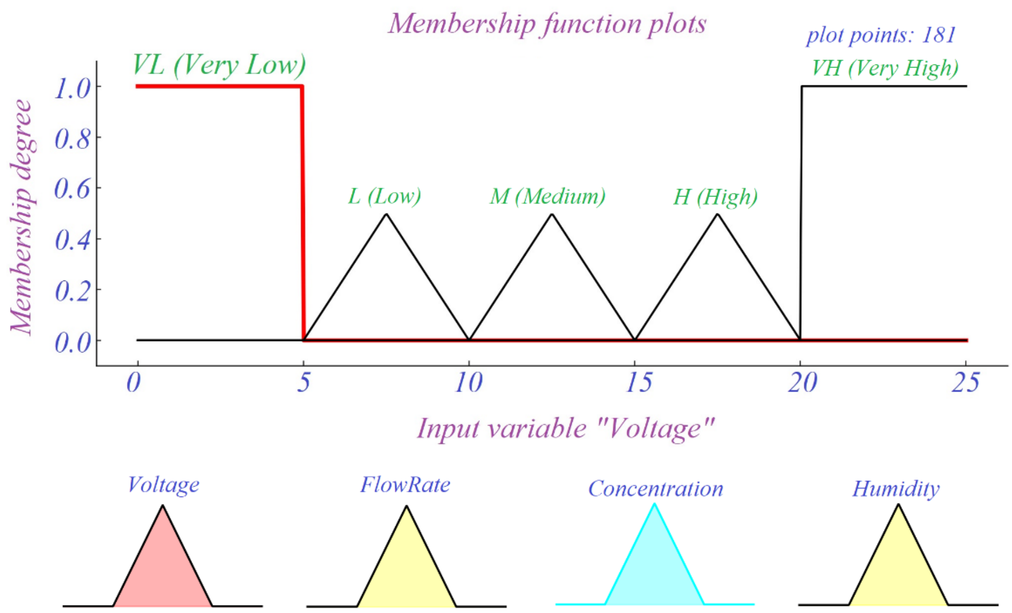


Figure 11.
Membership Function Plot of the Input Variable 'Voltage' in a Fuzzy Inference System.

Figure 11 illustrates the fuzzy membership functions of the input variable "Voltage," where the voltage range of 0–25 kV is divided into the linguistic values: VL (Very Low), L (Low), M (Medium), H (High), and VH (Very High). For example, the "VL" membership function reaches a full degree within the range of 0–5 kV, while the "M" value peaks between 10 and 15 kV. This enables an accurate representation of voltage significance within the fuzzy logic framework.

Similarly, Figure 12 presents the structural diagram of the fuzzy logic control system for ozone generation.

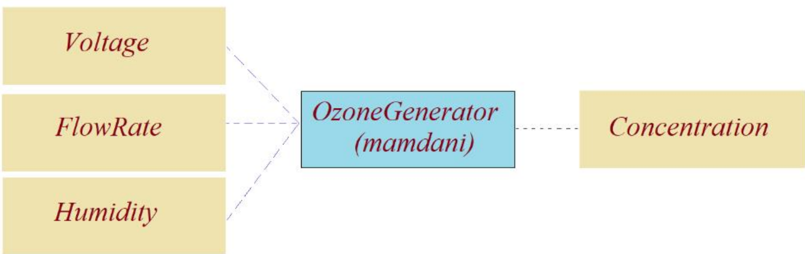


Figure 12.
Structural Diagram of the Fuzzy Logic Control System for Ozone Generation.

In Figure 12, three input variables, voltage (Voltage), flow rate (FlowRate), and relative humidity (Humidity) are provided to the ozone generation system. These inputs are processed using fuzzy logic (Mamdani method), and the output is defined as ozone concentration (Concentration). Specifically, the voltage ranges from 0 to 25 kV, the flow rate from 0 to 10 L/min, and the humidity from 0% to 100%. The output concentration is calculated within the range of 0 to 1 using fuzzy membership functions.

Membership functions were defined for each input parameter and adjusted based on expert knowledge and empirical data. The system architecture consists of four main stages: fuzzification, rule base, inference engine, and defuzzification. The complete block diagram of this architecture was presented earlier in Figure 6.

Modeling conducted in MATLAB/Simulink and Python platforms demonstrated that the proposed control system is capable of effectively managing the nonlinear dynamics of ozone generation. For example, under varying voltage and flow rate conditions, the model maintained ozone concentration within the stable range of 85–120 mg/L. This confirms that the fuzzy logic approach significantly improves control accuracy in uncertain and dynamic environments.

5.3. Model Testing and Industrial Recommendations

In accordance with the third objective, experimental tests were conducted on a laboratory-scale corona discharge ozone generator. The experimental setup was equipped with sensors for real-time measurement of voltage, temperature, humidity, and gas flow rate, with data acquisition carried out using the National Instruments LabVIEW platform. The system was tested under various operating conditions.

The results of the scientific investigation are summarized in Table 5 below.

Table 5.
Experimental Parameters of a Corona Discharge Ozone Generator under Various Operating Conditions.

Test No	Voltage (kV)	Temperature (°C)	Humidity (%)	Gas Flow Rate (L/min)	Logging Platform
1	5	22	30	2	LabVIEW
2	10	24	40	4	
3	15	26	50	6	
4	20	28	60	8	
5	25	30	70	10	

Table 5 presents the key parameters for five different operating modes of the corona discharge–based ozone generator. During these tests, the voltage ranged from 5 to 25 kV, the temperature varied between 22 and 30 °C, and the relative humidity was adjusted within the range of 30% to 70%. The gas flow rate was varied between 2 and 10 L/min. All experimental data were recorded in real time using the LabVIEW platform.

The results of the stress tests confirmed the flexibility and stability of the model, as it successfully adapted to changes in external environmental conditions while maintaining a consistent level of ozone output. The effectiveness of the model was evaluated in comparison with conventional PID control systems, demonstrating clear advantages in terms of energy efficiency and ozone concentration stability.

A quantitative comparison of the performance metrics of the fuzzy logic and PID control systems is presented in Table 6 below.

Table 6.
Quantitative Comparison of Performance Metrics between Fuzzy Logic and PID Control Systems.

Metric	Fuzzy Logic Model	PID Control System
Adaptability to Environmental Changes	High	Limited
Ozone Output Stability (%)	95	75
Energy Consumption (W)	120	150
Overall Efficiency (%)	88	72

Table 6 provides a quantitative comparison between the performance of fuzzy logic and traditional PID control systems. The fuzzy model maintained ozone output stability at 95%, while the PID system achieved only 75%. Furthermore, the energy consumption of the fuzzy model was 120 W, compared to 150 W for the PID system. As a result, the overall efficiency of the fuzzy system reached 88%, while the PID system achieved 72%, confirming the superior performance of the fuzzy approach. Based on these results, technical and economic recommendations were developed for potential industrial-scale implementation. This study confirms that the fuzzy logic–based control system represents an effective and applicable solution for integration into industrial ozone generation units.

All research objectives were systematically fulfilled, and the outcomes validate the practical applicability of the proposed model.

6. Discussion of Research Findings

The results obtained in this study confirm the effectiveness of the proposed nonlinear multiparametric fuzzy logic control model for ozone generation systems. This conclusion is supported by the experimental data in Table 5, which show that the system maintained a stable ozone output (85–120 mg/L) under varying operating conditions (voltage: 5–25 kV, humidity: 30–70%, temperature: 22–30 °C, flow rate: 2–10 L/min). Additionally, the contour plots in Figures 4 and 5 visually illustrate the nonlinear relationships among these parameters. Figure 6 shows the block diagram that describes how the fuzzy logic system processes the input parameters to regulate ozone output.

Unlike traditional PID controllers, the proposed method effectively handles nonlinear dynamics and complex inter-parameter interactions. This distinction is clearly demonstrated in Table 6, where the fuzzy logic model outperforms the PID system in terms of ozone output stability (95% vs. 75%), energy consumption (120 W vs. 150 W), and overall efficiency (88% vs. 72%).

Although prior studies (e.g., Poznyak, et al. [16], Alsmadi, et al. [17] and Mintz, et al. [18]) proposed various control approaches, most of them did not incorporate parameter integration or were based on predictive models. Therefore, the model developed in this study represents a significant step toward solving real-world control challenges.

However, some limitations should be noted. The model was validated only within a limited range of parameters (e.g., temperature 15–35 °C, voltage up to 25 kV) and tested in a laboratory environment. Its performance under long-term industrial operating conditions remains unverified. Additionally, the fuzzy system relies on sensor accuracy, which may not always be guaranteed in real-world conditions.

Another limitation lies in the manual tuning of the rule base and membership functions, which were configured based on expert knowledge and may introduce subjectivity. In the future, this issue could be addressed by incorporating machine learning algorithms that optimize fuzzy system parameters based on historical data.

Further development of this research should focus on expanding the parameter space, increasing the generalizability of the model, and conducting full-scale industrial testing. The integration of AI-based optimization methods (as described in

Equation 5) would enhance the flexibility and robustness of the control system. However, challenges such as increased computational load, complexity of hardware integration, and ensuring real-time system responsiveness must be considered.

In conclusion, the proposed fuzzy logic–based model presents an effective alternative to traditional control methods in ozone generation processes. With further refinement and broader testing, the model has strong potential for industrial application.

7. Conclusion

The scientific objectives set for developing nonlinear multiparametric control models for efficient ozone generation have been fully achieved and substantiated by quantitative results.

First, the key physico-chemical parameters influencing ozone generation were identified. As demonstrated in Figures 8 and 9 and Table 4, ozone concentration decreased by 40% when the gas flow rate exceeded 6 L/min, and ozone decomposition increased by 40–60% when relative humidity rose above 80%. These findings confirm the complex nonlinear interactions among system parameters.

Second, a fuzzy logic–based control model was developed in MATLAB. As illustrated in Figures 11 and 12, the model used voltage (0–25 kV), flow rate (0–10 L/min), and humidity (0–100%) as input variables and accurately regulated ozone concentration (0–1 units) as output. The model maintained ozone yield in the 85–120 mg/L range, demonstrating higher accuracy than traditional PID control.

Third, experimental tests conducted using the LabVIEW platform under laboratory conditions showed that the fuzzy system maintained 95% stability even under varying environmental parameters. The fuzzy model consumed 120 W of energy, compared to 150 W for the PID system, indicating a 20% improvement in energy efficiency. Additionally, the overall efficiency reached 88% for the fuzzy system and 72% for the PID system Table 6.

Thus, the fuzzy logic–based model demonstrated high efficiency and is proposed as a promising and industrially applicable solution for controlling ozone generation processes.

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