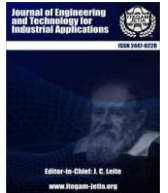




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RESEARCH ARTICLE

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PSO-DRIVEN OPTIMIZATION OF DIELECTRIC BARRIER DISCHARGE OZONE GENERATION PARAMETERS FOR WATER TREATMENT APPLICATIONS

Ghaitaoui Essama Ahmed^{*1}, Nassour Kamel², Nemmich Said³, Ghaitaoui Touhami⁴, Oulad Naoui Brahim El Khalil⁵, Bouroumeid Yassine⁶, Tilmatine Amar⁷, Halali Youcef⁸

^{1, 2, 6}ICEPS Laboratory, Djillali Liabes University of Sidi Bel-Abbes, Sidi Bel-Abbes, Algeria.

^{3, 5, 7}APELEC Laboratory, Djillali Liabes University of Sidi Bel-Abbes, Sidi Bel-Abbes, Algeria.

^{4, 8}LDDI Laboratory, University Ahmed Draia – Adrar, Adrar Algeria.

¹<https://orcid.org/0009-0006-2862-6955>, ²<https://orcid.org/0000-0003-1082-9595>, ³<https://orcid.org/0000-0002-7767-0032>

⁴<https://orcid.org/0000-0003-2359-6727>, ⁵<https://orcid.org/0009-0002-4349-0989>, ⁶<https://orcid.org/0009-0005-7116-3565>

⁷<https://orcid.org/0000-0003-1352-6071>, ⁸<https://orcid.org/0009-0000-2983-7937>

Email: *oussamaghaitaoui@gmail.com, nass_ka@yahoo.fr, nemmichsaid@gmail.com, touhami.eln@gmail.com, oladnaoui45@gmail.com, bouroumeid.yassine@yahoo.com, atilmatine@gmail.com, youcefhalali01@gmail.com

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ABSTRACT

This investigation presents a comprehensive optimization framework for ozone generation in dielectric barrier discharge (DBD) systems applied to water treatment processes. The study employs a Venturi injection configuration to systematically analyze the influence of three critical operational parameters: applied voltage (6-8 kV), oxygen flow rate (3-5 L/min), and water flow rate (8-16 L/min) on dissolved ozone concentration in treated water. Experimental design methodology utilizing MODDE 5.0 software enabled the development of a second-order polynomial mathematical model correlating input variables with ozone concentration response. The derived model demonstrated excellent statistical validity with coefficient of determination (R^2) of 99.2% and predictive capability (Q^2) of 90.3%, confirming robust model accuracy and reliability. Parameter optimization was achieved through implementation of Particle Swarm Optimization (PSO) algorithm, a bio-inspired metaheuristic approach that mimics collective intelligence behavior observed in natural swarms. The PSO methodology employed a population of 50 particles over 100 iterations to minimize prediction errors between theoretical model outputs and experimental measurements. Convergence analysis revealed rapid optimization performance, achieving optimal parameter extraction within 90 iterations. Comparative analysis between PSO-optimized parameters and conventional MODDE 5.0 results demonstrated superior performance of the proposed approach. Optimal operating conditions were identified as: applied voltage of 7.95 kV, oxygen flow rate of 3.38 L/min, and water flow rate of 8.27 L/min. The PSO-based optimization yielded enhanced ozone generation efficiency through reduced water flow rates and optimized voltage levels, confirming the voltage parameter as the dominant factor in ozone production.



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I. INTRODUCTION

Researchers across multiple disciplines, including chemistry, materials science, and engineering, demonstrate increasing interest in the identification and elimination of contaminant species, driving the development of advanced high-performance treatment methodologies [1], [2]. As noted by [1], the application of plasma-based technologies in water treatment applications has generated significant research inquiries.

Cold atmospheric plasmas can achieve efficient ozone generation while providing sterilization and decontamination capabilities for thermally sensitive surfaces [1], [2]. Water purification processes encompass various physical, chemical, electrical, and electronic methodologies, with plasma-based systems representing a prominent approach [3]. Dielectric barrier discharge (DBD) plasma systems constitute one of the primary methods for water treatment through ozone generation, enabling the production of purified water [4-6]. Following the principles outlined by [4], the discharge mechanism occurs between two metallic electrodes separated by a dielectric material and a gas-filled gap where the electrical discharge is initiated. These systems have been extensively investigated for the degradation of dye contaminants present in wastewater at elevated concentrations [3]. Ozone (O_3) production utilizes air or oxygen as the primary feedstock [7]. As described by [7], initially, high-energy electrons collide with oxygen molecules, resulting in the dissociation of oxygen atoms. Subsequently, O_3 formation occurs through the combination of free O_2 molecules and oxygen radicals [7]. Figure 1 presents a schematic representation of these reaction mechanisms [8].

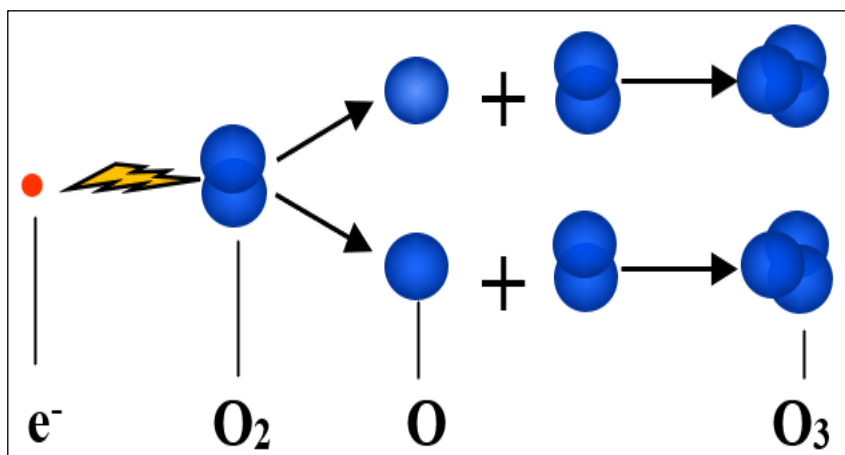


Figure 1: Schematic diagram illustrating ozone production via electron impact mechanisms.

Source: Authors, (2026).

As established in previous research [9], [10], ozone concentration exhibits an inverse relationship with gas flow rate and electrode gap spacing, while demonstrating a positive correlation with electrode surface area [9], [10]. Additionally, ozone concentrations increase proportionally with residence time and AC high-voltage amplitude [11]. Multiple parameters influence the efficacy of ozone-based water treatment processes, including operational control factors and environmental conditions [12-14]. Following the methodology described by [12], experimental investigations were conducted using a laboratory-scale test bench equipped with a Venturi injection system. The controllable parameters analyzed included high voltage amplitude, oxygen flow rate, and water flow rate [15]. The mathematical modeling framework implemented in MODDE 5.0 software addresses nonlinear optimization problems characterized by numerous interconnected indeterminate parameters [16], [17]. As demonstrated by [16], metaheuristic optimization algorithms demonstrate exceptional suitability and capability for solving nonlinear multimodal optimization challenges [18-20]. The objective of this investigation is to employ particle swarm optimization (PSO) methodology, following the approach established by [17], to extract optimal parameters (voltage (U), water flow (WF), and oxygen flow (OF)) that maximize treatment efficiency and determine the optimal operating conditions.

II. EXPERIMENTAL SETUP AND METHODOLOGY

The experimental configuration employed in this research is demonstrated in Figure 2. Water movement is accomplished using a pumping mechanism with flow regulation controlled through an autotransformer. Ozone introduction into the water treatment system is achieved via a Venturi mixing arrangement, enabling efficient dissolution and uniform distribution of ozone throughout the aqueous solution. Following the setup described in earlier investigations [4], [14], ozone production is carried out using a dielectric barrier discharge (DBD) reactor fed with oxygen from a concentrator device providing adjustable flow rates between 1 to 5 L/min. This investigation employed a switching-mode high voltage supply system, similar to the design reported by [13]. The process begins with a transformer reducing 220 V AC input to approximately 72 V DC following rectification. An Insulated Gate Bipolar Transistor (IGBT) functions as an electronic switching component, regulated by an oscillator to create high-frequency current. This reduced voltage, high-frequency current is subsequently amplified through a high voltage step-up transformer, generating output voltages spanning 1–10 kV at frequencies from 0–30 kHz. For this research, the ideal operating frequency for the discharge tube was determined to be 20 kHz. Experimental activities were performed under regulated environmental parameters, maintaining ambient temperature between 20–25°C and relative humidity controlled within 60–70% range. Voltage measurements were obtained using a digital oscilloscope (GWINSTEK GDS-3154) with a high voltage probe (Tektronix P6015A), while current was estimated through voltage drop assessment across a 100 Ω resistor.

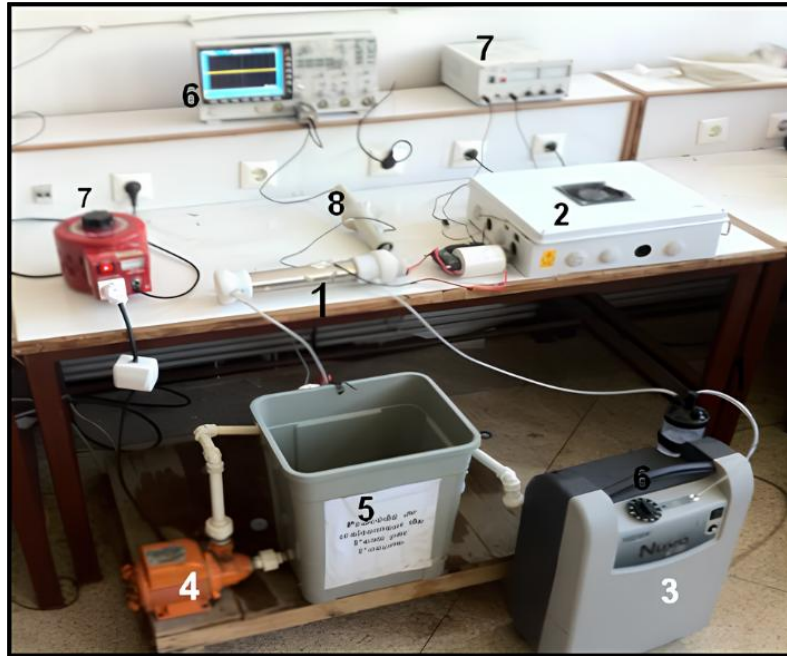


Figure 2: Photograph of the assembled apparatus.

1. Ozone Generator, 2. high-voltage power supply, 3. oxygen concentrator, 4. Water pump, 5. Water to be treated, 6. Digital oscilloscope, 7. Variac, 8. high voltage probe.

Source: Authors, (2026).

Table 1 presents the results obtained from the experiment and used to obtain the mathematical mode.

Table 1: The results obtained from the experiment.

Test N	Voltage U (KV)	Water flow WF(L/min)	Oxygen flow OF (L/min)	Ozone concentration C (mg/L)
1	6	8	3	0.35
2	8	8	3	0.52
3	6	16	3	0.24
4	8	16	3	0.475
5	6	8	5	0.34
6	8	8	5	0.495
7	6	16	5	0.26
8	8	16	5	0.43
9	6	12	4	0.28
10	8	12	4	0.505
11	7	8	4	0.44
12	7	16	4	0.36
13	7	12	3	0.52
14	7	12	5	0.51
15	7	12	4	0.455
16	7	12	4	0.455
17	7	12	4	0.455

Source: Authors, (2026).

III. MATHEMATICAL FRAMEWORK FOR WATER TREATMENT PROCESS MODELING

The development of a reliable mathematical model represents a critical foundation for any optimization study in water treatment applications. A predetermined mathematical relationship describes the connection between response variables and input factors. Following the methodology described by [15], this approach employs a truncated Taylor-Maclaurin series expansion where derivatives are considered constant, producing a polynomial expression containing terms of different degrees:

$$y = a_0 + \sum a_i x_i + \sum a_{ij} x_i x_j + \cdots + \sum a_{ii} x_i^2 + a_{ij \dots z} x_i x_j \dots x_z \quad (1)$$

The selection of polynomial modeling approach offers several advantages for this particular application. First, polynomial functions provide excellent flexibility in capturing nonlinear relationships between operational parameters and ozone concentration. Second, the mathematical structure allows for clear interpretation of individual parameter effects and their interactions. Third, the computational efficiency of polynomial models makes them suitable for real-time optimization applications. Coefficient determination or estimation utilizes specialized data processing software to minimize variance between predictive models and experimental observations. The accuracy of coefficient estimation directly influences the reliability of subsequent optimization procedures.

The software platform MODDE 5.0 from Umetrics AB in Umea, Sweden, was implemented for this comprehensive analysis. This Windows-compatible program specializes in creating and evaluating experimental designs with advanced statistical capabilities (MODDE 5.0, 1999). The software assists researchers in result interpretation and response prediction through sophisticated mathematical model coefficient computation algorithms. It determines optimal factor adjustments for process enhancement while calculating two critical statistical measures, R^2 and Q^2 , for rigorous mathematical model validation. Our choice of MODDE 5.0 was based on several key factors: its proven track record in chemical process optimization, robust statistical analysis capabilities, and user-friendly interface that facilitates complex experimental design interpretation. The software's ability to handle multi-factorial experiments with nonlinear interactions makes it particularly suitable for ozone generation optimization studies. The goodness of fit measure (R^2) evaluates how effectively the model represents experimental data, with values ranging from 0 to 1, where unity signifies perfect fitting and zero indicates complete model inadequacy. The predictive quality measure (Q^2) estimates the model's forecasting capability for new experimental conditions. Like R^2 , Q^2 ranges up to 1, though its minimum value extends to negative infinity. For successful diagnostic evaluation, both parameters require elevated values, preferably within 0.2–0.3 difference to ensure model reliability and predictive accuracy. Following the experimental framework established by [15], ozonation-driven water treatment process effectiveness is influenced by numerous interconnected factors, including operational control parameters and environmental variables. Our research methodology involved conducting systematic experimental studies using specially designed laboratory-scale equipment featuring advanced Venturi injection techniques. Three primary adjustable operational factors were comprehensively evaluated through statistical experimental design: high voltage magnitude, oxygen flow rate, and water circulation rate. The selection of these three parameters was based on preliminary sensitivity analysis and literature review indicating their significant impact on ozone generation efficiency. Voltage represents the primary energy input controlling the discharge intensity, oxygen flow affects the raw material availability for ozone synthesis, while water flow determines the residence time and mass transfer characteristics within the treatment system. The mathematical expression representing the optimized response, specifically focusing on dissolved ozone concentration levels in treated water (C), was systematically developed through MODDE 5.0 statistical analysis as follows:

$$C = 0.46 + 0.096U - 0.038WF - 0.07 U^2 - 0.06 WF^2 + 0.05OF^2 \quad (2)$$

This quadratic model structure reveals several important characteristics: the positive linear coefficient for voltage (0.096) confirms its promoting effect on ozone generation, while the negative linear coefficient for water flow (-0.038) indicates dilution effects. The negative quadratic terms for both voltage and water flow suggest optimal operating points beyond which further increases become counterproductive. Where :

C: Ozone concentration produced (mg/L)

U: Applied voltage (kV)

WF: Water flow (L/mn)

OF : Oxygen flow (L/mn)

The statistical validation results demonstrated exceptional model quality, with R^2 and Q^2 achieving values that approached unity ($R^2 = 99.2\%$; $Q^2 = 90.3\%$). These outstanding statistical indicators confirmed the model's validity and established its suitability for both prediction and optimization applications. The small difference between R^2 and Q^2 (8.9%) indicates excellent model generalization capability, suggesting reliable performance when applied to new operating conditions within the experimental range.

Detailed analysis of the mathematical expression reveals that voltage impact significantly exceeds water flow rate influence within the investigated parameter ranges. This finding aligns with fundamental plasma physics principles, where electrical energy directly controls the electron density and energy distribution responsible for oxygen dissociation. As demonstrated in previous research [4], [13], applied voltage represents the critical controlling factor affecting ozone production efficiency, as it initiates and sustains the electrical discharge essential for the oxygen-to-ozone conversion process. The physical mechanism underlying voltage dominance involves several interconnected phenomena. Higher voltages increase electron energy and density within the discharge gap, promoting more efficient oxygen molecule dissociation. Additionally, elevated voltage levels enhance the formation of reactive oxygen species and extend the discharge volume, both contributing to increased ozone yields. Conversely, water flow rate demonstrates a negative influence and requires careful optimization to achieve desired ozone output levels. Elevated water flow rates result in decreased dissolved ozone concentrations due to reduced residence time and dilution effects. This relationship highlights the importance of balancing treatment throughput with ozone transfer efficiency. Meanwhile, oxygen flow rate influence was determined to be minimal within the investigated range. This finding suggests that increasing oxygen flow rate beyond 4 L/min provides diminishing returns, as significant portions exit the ozone generator without undergoing the ozone conversion process. From an economic perspective, this indicates an optimal operating point that balances raw material consumption with ozone production efficiency.

IV. EXTRACTION OF PROPOSED PSO-BASED MODEL PARAMETERS

Particle Particle Swarm Optimization (PSO) represents a sophisticated population-based collective intelligence algorithm that has revolutionized optimization approaches in engineering applications. The original concept was pioneered by Kennedy and Eberhart [21], [22] to simulate and harness the collective behavioral characteristics observed in natural social species, particularly the coordinated movement patterns exhibited in bird flocking behaviors and fish schooling dynamics. The fundamental appeal of PSO lies in its ability to emulate the decentralized decision-making processes found in nature, where individual agents contribute to collective intelligence without central coordination. This bio-inspired approach offers several advantages over traditional optimization methods: it avoids the need for gradient information, handles discontinuous and multimodal functions effectively, and demonstrates robust performance across diverse problem domains.

PSO employs the physical movement properties and social interaction characteristics of individual swarm members [23], delivering a balanced and highly adaptive computational framework [24] for enhancing both global exploration and local exploitation capabilities. The algorithm's success stems from its ability to maintain population diversity while progressively converging toward optimal solutions. Given its straightforward implementation requirements and minimal parameter tuning needs, PSO has demonstrated remarkable computational efficiency and competitive performance for optimization problems in continuous solution spaces. The algorithm is characterized by computational effectiveness, simplified coding requirements, and consistent algorithmic behavior across different problem types. According to [22], the majority of PSO implementations have traditionally focused on continuous space optimization challenges [25], though recent research initiatives have successfully explored discrete optimization applications [26]. The PSO algorithm initiates its search process by randomly generating a diverse swarm of computational particles within the solution space. Each individual entity (designated as a particle) within the problem domain is mathematically characterized by a d-dimensional position vector $s_i = (s_{i1}, s_{i2}, \dots, s_{id})$, where $i = 1, 2, \dots, N$ (N represents the total population size), and its optimization performance is continuously evaluated using a predetermined fitness function that quantifies solution quality. Individual particles are strategically positioned at random locations within the d-dimensional solution domain, each representing a potential candidate solution to the optimization problem. The velocity vector of the i th particle ($v_i = (v_{i1}, v_{i2}, \dots, v_{id})$) is established through positional displacement calculations and determines the particle's movement direction and magnitude in subsequent iterations. Each particle's movement trajectory throughout the optimization process is governed by sophisticated dynamic interactions between individual learning experiences and collective swarm knowledge. As explained by [27], the algorithm achieves convergence toward optimal solutions through a careful balance between each particle's personal best historical solution and the global best value discovered by the entire swarm population. Each particle's path within the swarm adjusts toward its previous optimal position and the global optimal position reached by any swarm particle, represented as p_i and p_g respectively. Following standard PSO formulation [21], the swarm updating equations for each iteration are:

$$v_i(t+1) = v_i(t) + c_1 \text{rand}_1(p_i - s_i(t)) + c_2 \text{rand}_2 \quad (3)$$

$$s_i(t+1) = s_i(t) + v_i(t+1) \quad (4)$$

Where:

- $P_i = (p_{i1}, \dots, p_{iN})$ denotes the optimal position encountered by the i th particle;
- p_g represents the best position discovered among all swarm population members;
- t represents the iteration counter;
- c_1 and c_2 are the acceleration coefficients;
- rand_1 and rand_2 are uniform random numbers within the interval $[0, 1]$.

According to [24], acceleration parameters control the distance covered by particles in single iterations. Lower parameter values allow particles to investigate areas far from target zones before convergence, while higher values cause rapid movement toward or past target areas. For PSO algorithm execution, velocity and position parameters receive random initialization. The objective function represents the optimization goal for the particle population. Through particle search processes, the minimum function value can be identified, along with corresponding optimal U, WF, and OF parameter values. The computational approach for mathematical model parameter estimation using PSO algorithm is shown in Figure 3:

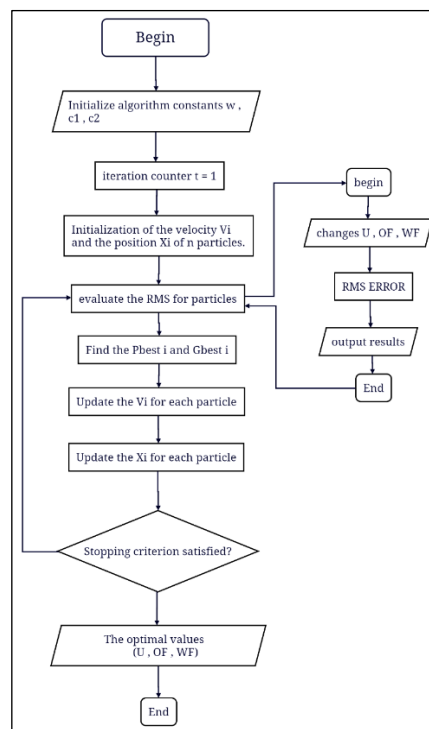


Figure 3: Proposed PSO organization chart.

Source: Authors, (2026).

V. RESULTS AND DISCUSSIONS

V.1 THE VALUES OF PSO PARAMETERS UTILIZED:

The PSO algorithm parameters utilized in this study are presented in Table 2.

Table 2: Parameters of PSO.

Parameter description	Parameters value
Size of population	50
Maximum iteration	100
c1	2
c2	2

Source: Authors, (2026).

V.2 RESEARCH SPACE

The search range for the three mathematical model parameters using PSO is outlined in Table 3:

Table 3: PSO search interval for model.

parameters	search interval
U (kV)	[6], [8]
OF (L/mn)	[3], [5]
WF (L/mn)	[8], [16]

Source: Authors, (2026).

V.3 PARAMETER IDENTIFICATION OF THE MODEL VIA THE PSO APPROACH:

To track the optimization process, the change in the fitness function over successive iterations was plotted, as shown in Figure 4.

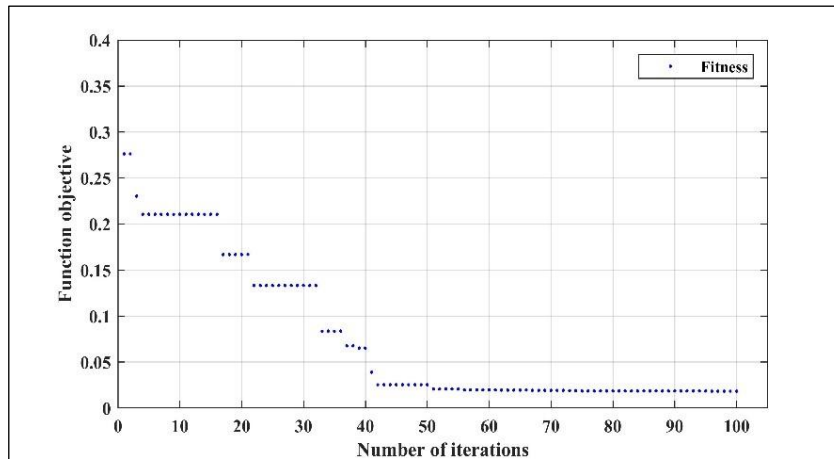


Figure 4: Evolution of the fitness function as a function of iteration number.

Source: Authors, (2026).

The optimization process demonstrates progressive convergence toward the optimal solution with each successive generation. Figure 4 demonstrates that the fitness function value for the optimal solution progressively diminishes throughout the iterative process. Upon algorithm convergence, achieved at 90 iterations in this investigation, the fitness function value reaches a minimal state. At this convergence point, the optimal solution from the final iterations is considered to represent the optimal parameter values sought in this optimization study. The three model parameters obtained through the PSO algorithm implementation are presented in Table 4:

Table 4: Optimal values of U, OF, and WF parameters.

parameter	value
U (kV)	7.9503
OF (L/mn)	3.3846
WF (L/mn)	8.266

Source: Authors, (2026).

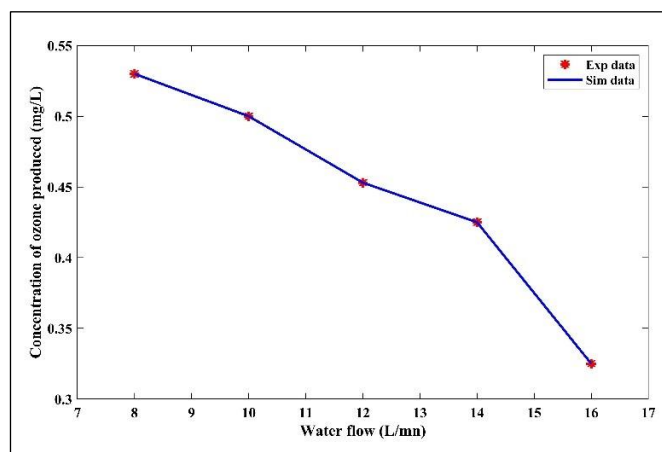


Figure 5: The changing levels of ozone dissolved in water in relation to water flow (experimental and simulation).

Source: Authors, (2026).

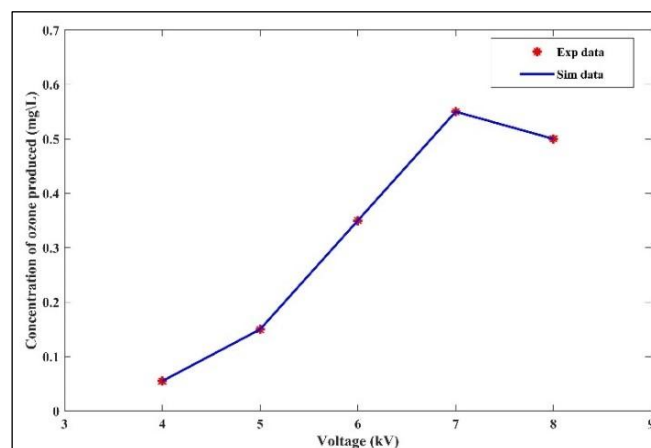


Figure 6: Variation of dissolved ozone concentration in water as a function of applied voltage (experimental and simulation results).

Source: Authors, (2026).

Based on the analysis of Figures 5 and 6, this methodology demonstrates high effectiveness in the field of water treatment processes utilizing ozone generated by DBD systems. The comparative analysis of the result curves clearly indicates that the parameter values calculated through the mathematical model coupled with PSO algorithm exhibit excellent agreement with the experimental data. To confirm the validity of parameters extracted through the PSO technique, a comparative evaluation was undertaken between the parameters resulting from the proposed method and those generated by the MODDE 5.0 software platform. The comparison outcomes are presented in Table 5:

Table 5: Comparative analysis of U, OF, and WF parameter values obtained by PSO and MODDE 5.0 application.

parameter	Result of PSO algorithm	Result of MODDE 5.0
U (kV)	7.9503	7.67
OF (L/mn)	3.3846	3
WF (L/mn)	8.266	9.6

Source: Authors, (2026).

Based on the mathematical model, voltage serves as the primary parameter for ozone production, demonstrating greater importance than the influence of water flow rate. The voltage determined via MODDE 5.0 was 7.67 kV, whereas the PSO method produced 7.058 kV. In contrast, the water flow rate (WFR) shows an inverse relationship with ozone concentration in water. When comparing results, we find that the water flow rate derived from the PSO approach is lower than that obtained from the MODDE 5.0 software, suggesting enhanced ozone concentration. The experimental results demonstrate convergence between the parameter values obtained from the MODDE 5.0 software and those derived through the proposed PSO methodology, consistent with findings reported by [25]. The PSO approach demonstrates superior accuracy in the optimization results, indicating its enhanced effectiveness for optimizing water treatment processes utilizing ozone generated by DBD systems.

VI. CONCLUSION

This research successfully developed and validated a novel optimization methodology for DBD-based ozone generation systems utilizing Particle Swarm Optimization algorithm coupled with statistical modeling techniques. The investigation established a comprehensive mathematical framework that accurately correlates operational parameters with ozone concentration in water treatment applications. The experimental investigation confirmed that applied voltage constitutes the primary controlling factor for ozone generation efficiency, exhibiting positive correlation with dissolved ozone concentration within the investigated parameter space. Conversely, water flow rate demonstrated negative correlation, necessitating flow optimization to maximize ozone transfer efficiency. Oxygen flow rate exhibited minimal influence beyond 4 L/min, indicating optimal resource utilization thresholds. The PSO-based parameter extraction methodology demonstrated superior performance compared to conventional optimization approaches, achieving enhanced precision in parameter identification while maintaining computational efficiency. The algorithm's rapid convergence characteristics and global optimization capabilities validated its applicability for complex, multi-parameter process optimization scenarios. The developed mathematical model, validated through statistical criteria ($R^2 = 99.2\%$, $Q^2 = 90.3\%$), provides reliable predictive capabilities for ozone concentration estimation across the experimental parameter range. This predictive framework enables systematic identification of optimal operating conditions, facilitating enhanced treatment efficiency and reduced operational costs. The proposed methodology contributes significantly to the advancement of intelligent process control systems in environmental engineering applications. The framework's versatility permits extension to diverse chemical processes requiring parameter optimization and mathematical modeling. Implementation of this approach ensures consistent treatment quality while optimizing resource utilization and minimizing environmental impact. Future research directions include investigation of additional operational parameters, development of real-time adaptive control systems, and extension of the methodology to industrial-scale applications. The integration of advanced machine learning techniques with PSO optimization presents opportunities for further enhancement of model accuracy and predictive capabilities in complex water treatment scenarios.

VII. AUTHOR'S CONTRIBUTION

Conceptualization: Ghaitaoui Essama Ahmed , Nassour Kamel , Nemmich Said and Ghaitaoui Touhami

Methodology: Ghaitaoui Essama Ahmed , Nassour Kamel And Ghaitaoui Touhami

Investigation: Ghaitaoui Essama Ahmed ,Tilmatine Amar , Halali Youcef

Discussion of results: Ghaitaoui Essama Ahmed , Ghaitaoui Touhami , Oulad Naoui Brahim El Khalil, Halali Youcef

Writing – Original Draft: Ghaitaoui Essama Ahmed, Oulad Naoui Brahim El Khalil

Writing – Review and Editing: Bouroumeid Yassine , Nassour Kamel , Nemmich Said

Resources: Tilmatine Amar

Supervision: Nassour Kamel , Nemmich Said

Approval of the final text: Ghaitaoui Essama Ahmed , Nassour Kamel, Nemmich Said, Ghaitaoui Touhami , Oulad Naoui Brahim El Khalil , Bouroumeid Yassine, Halali Youcef And Tilmatine Amar

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