

**PERFLUOROOCTANOIC ACIDS (PFOA) REMOVAL USING
ELECTROCHEMICAL OXIDATION: A MACHINE LEARNING
APPROACH**

BY

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Dedication

In the loving memory of my mother, whose unwavering belief in the power of education continues to inspire me every day. Your guidance, love, and sacrifices have shaped me into the person I am today. Though you are no longer with us, your spirit lives on in every achievement and milestone.

To my husband and daughter, whose endless support and encouragement sustained me through the challenges of this journey.

To my beloved family – my brothers, whose support has been a constant source of encouragement.

To my cherished friends, whose encouragement and understanding made the tough times bearable.

This thesis is dedicated to each of you, with heartfelt gratitude for your unwavering love, support, and belief in me. Thank you for being my guiding light.

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LIST OF ABBREVIATIONS

AAD: Average Absolute Deviation

Adj-R²: Adjusted coefficient of determination

ANFIS: Adaptive Neuro-Fuzzy Inference System

ANN: Artificial Neural Network

AOPs: Advanced Oxidation Processes

ARE: Absolute Relative Error

ARIMA: Autoregressive Integrated Moving Average

CC: Correlation Coefficient

COD: Chemical Oxygen Demand

DL: Deep Learning

DT: Decision Tree

EAOP: Electrochemical Advanced Oxidation Processes

EC: Electrocoagulation

EO: Electrochemical Oxidation

GBDT: Gradient Boosted Decision Tree

GA: Genetic Algorithm

KNN:K-Nearest Neighbors

LSTM: Long Short-Term Memory

MAE: Mean Absolute Error

MAPE: Mean Absolute Percentage Error

MRE: Mean Relative Error

MSE: Mean Squared Error

MSRE: Mean Squared Relative Error

MLP: Multilayer Perceptron

ML: Machine Learning

NN: Neural Network

PFCs: Perfluorinated compounds

PFAS: Per- and poly-fluoroalkyl substances

PFOA: Perfluorooctanoic Acid

PSO: Particle Swarm Optimization

R^2 : Coefficient of determination

RF: Random Forest

RMSE: Root Mean Square Error

RRMSE: Relative Root Mean Square Error

SEP: Standard Error of Prediction

SVR: Support Vector Regression

TDS: Total Dissolved Solids

ABSTRACT

Full Name : Sally Maen Alnaimat

Thesis Title : Perfluorooctanoic Acids (PFOA) Removal using Electrochemical Oxidation: A Machine Learning Approach

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The urgent need for effective methods to eliminate Perfluorooctanoic Acid (PFOA) has positioned electrooxidation (EO) as a leading solution for pollutant degradation. In this pursuit, machine learning (ML) models offer a powerful approach to accurately predict EO efficiency under diverse experimental conditions. This study rigorously evaluates multiple ML models, including K-Nearest Neighbors (KNN), Decision Tree (DT), Random Forest (RF), Gradient Boosted Decision Trees (GBDT), and Deep Learning (DL), to forecast PFOA removal efficiency. The results highlight the exceptional performance of DT and RF models, characterized by low error rates and high predictive accuracy. Specifically, the root mean square error (RMSE) values are 9.7 for DT and 7.9 for RF, with correlation coefficients between actual and predicted values of 0.94 and 0.97, respectively. These findings reveal the subtle performance differences between the models, with the RF model particularly noted for its robustness and consistency with real-world outcomes, corroborated by comprehensive metric evaluations. This study underscores the crucial role of selecting models that not only ensure high accuracy but also optimize computational efficiency. Moreover, it sheds

light on the significant influence of operational parameters, such as current density, pH, and electrode spacing, on the EO process. Utilizing Particle Swarm Optimization (PSO) for attribute weighting within the RF model, it was determined that factors like temperature, electrolyte concentration, and water matrix composition have a comparatively minor impact on EO efficiency. Overall, this study presents a robust ML framework for predicting EO efficiency in PFOA removal, offering a reliable tool for optimizing and advancing pollutant degradation technologies.

Keywords: Electrochemical oxidation, PFOA, Machine Learning, Random Forest, Decision Tree, Particle Swarm Optimization

ملخص الرسالة

الاسم الكامل: سالي معن النعيمات

عنوان الرسالة: إزالة الأحماض المشبعة بالفلور أوكتانويك (PFOA) باستخدام الأكسدة الكهروكيميائية: نهج التعلم

الآلي

التخصص: الهندسة المدنية

تاريخ الدرجة العلمية: صفر 1446

أدت الحاجة الملحة إلى طرق فعالة للقضاء على حمض البيروفلوروكتانويك (PFOA) إلى وضع الأكسدة الكهربائية (Electro oxidation) كحل رائد لتدهور الملوثات. في هذا المسعى، تقدم نماذج التعلم الآلي (Machine learning) نهجا قويا للتنبؤ بدقة بكفاءة الأكسدة الكهربائية في ظل ظروف تجريبية متنوعة. تقيم هذه الدراسة بدقة نماذج التعلم الآلي المتعددة ، بما في ذلك ك-أقرب جيران (K-Nearest Neighbors (KNN) ، وشجرة القرار (DT) ، والغابة العشوائية (RF) ، وأشجار القرار المعززة بالتدرج (GBDT) ، والتعلم العميق (DL) ، للتنبؤ بكفاءة إزالة PFOA. تسلط النتائج الضوء على الأداء الاستثنائي لنماذج DT و RF ، التي تتميز بمعدلات خطأ منخفضة ودقة تنبؤية عالية. على وجه التحديد ، قيم جذر متوسط مربع الخطأ (RMSE) هي 9.7 ل DT و 7.9 للترددات اللاسلكية ، مع معاملات ارتباط بين القيم الفعلية والمتوقعة تبلغ 0.94 و 0.97 ، على التوالي. تكشف هذه النتائج عن اختلافات الأداء الدقيقة بين النماذج ، مع ملاحظة نموذج RF بشكل خاص لمئاته واتساقه مع نتائج العالم الحقيقي ، والتي تؤكد تقييما المقاييس الشاملة. تؤكد هذه الدراسة على الدور الحاسم لاختيار النماذج التي لا تضمن الدقة العالية فحسب، بل تعمل أيضا على تحسين الكفاءة الحسابية. علاوة على ذلك، فإنه يلقي الضوء على التأثير الكبير للمعلمات التشغيلية، مثل كثافة التيار، ودرجة الحموضة، وتباعد الأقطاب الكهربائية، على عملية منظمة أصحاب العمل. باستخدام تحسين سرب الجسيمات (PSO) لترجيح السمات داخل نموذج التردد اللاسلكي، تم تحديد أن عوامل مثل درجة الحرارة وتركيز المنحل بالكهرباء وتكوين مصفوفة الماء لها تأثير طفيف نسبيا على كفاءة EO. بشكل عام، تقدم هذه الدراسة إطارا قويا للتعلم الآلي للتنبؤ بكفاءة EO في إزالة PFOA ، مما يوفر أداة موثوقة لتحسين وتطوير تقنيات تحليل الملوثات.

CHAPTER 1. INTRODUCTION

1.1 Introduction to Perfluorooctanoic Acid (PFOA)

Perfluorooctanoic Acid (PFOA) represents a distinctive subset of Per- and Polyfluoroalkyl Substances (PFAS) and belongs to the broader group of Perfluorinated Compounds (PFCs) (Ismail et al., 2023). These synthetic chemicals are renowned for their carbon-fluorine bonds, acknowledged as some of the most robust connections found in organic chemistry (Kuzukiran et al., 2022). The unique structure of PFCs, with fluorine atoms replacing hydrogen atoms on the carbon chain, imparts these compounds with remarkable stability and both hydrophobic and lipophobic properties (Pilli et al., 2021). The presence of functional groups, such as carboxylates, further endows PFOA with hydrophilicity and surfactant qualities, making it a valuable agent in various applications including firefighting foams, manufacturing processes in the electronics and textile industries, and military operations. Despite their utility, PFOA and other PFCs have raised significant environmental and health concerns due to their persistence and potential toxicological impacts. Accumulating evidence suggests associations between elevated PFOA levels in biological systems and various health issues, including thyroid disorders, increased uric acid levels, attention deficits in children, and weakened responses to vaccinations (Fenton et al., 2021; Knutsen et al., 2018). Given these concerns, PFOA has garnered attention from international regulatory bodies and has been listed under the Stockholm Convention for its potential global environmental impact (Wee and Aris, 2023).

1.2 Advanced Treatment Methods for PFOA Removal

Traditional methods for PFOA removal from the environment, such as adsorption, ion exchange, mechanical filtration, and biodegradation, often fall short in terms of efficiency (Yadav et al., 2022). In response, Advanced Oxidation Processes (AOPs) have emerged as more effective alternatives, leveraging the generation of reactive species under mild conditions to degrade PFOA into less harmful by-products. Electrochemical Oxidation (EO), in particular, has shown promise due to its ability to produce reactive radicals that facilitate the breakdown of PFOA into shorter-chain perfluorinated acids, which are less toxic (Song et al., 2023). The effectiveness of the EO process hinges on several crucial parameters, including the selection of anode and cathode materials—such as Boron-Doped Diamond (BDD), SnO_2 , TiO_2 , and PbO_2 for anodes, known for their superior oxygen evolution potential and electrochemical stability (Alkhadra et al., 2022). The spacing between electrodes, optimized to ensure efficient electric field distribution, and the characteristics of the electrolyte, often comprising sodium sulfate or sodium chloride at specific concentrations, play pivotal roles in the conductivity and generation of reactive species. The initial pH level of the solution, ambient temperature, and the PFOA concentration directly influence the reaction kinetics and degradation efficiency. Moreover, the current density and duration of electrolysis are adjusted to maximize PFOA degradation while considering energy efficiency and electrode longevity. The water matrix's characteristics can also impact the process by potentially leading to competing reactions and electrode fouling. Understanding and optimizing these parameters is essential for developing efficient, sustainable, and cost-effective EO systems for treating PFOA-contaminated water.

1.3 Role of Machine Learning in Enhancing PFOA Removal Efficiency

In the context of enhancing PFOA degradation through EO, Machine Learning (ML) stands out as a transformative approach for identifying the most crucial design parameters (Hosseinzadeh et al., 2022). By leveraging ML's advanced analytical capabilities, it becomes possible to sift through complex datasets generated from EO processes to pinpoint the parameters that significantly impact the removal efficiency of PFOA. This approach enables a more nuanced understanding of how variables such as electrode material selection, electrolyte composition, pH levels, and current density interconnect and influence the overall treatment outcome. ML algorithms can discern patterns and dependencies within the operational parameters, thereby guiding the optimization process to focus on the most impactful factors. This targeted optimization facilitated by ML not only promises to elevate the efficiency of PFOA degradation but also to streamline the design and operational strategies of EO systems, ensuring they are both effective and resource-efficient.

1.4 Objective of the Study

The main objectives of this thesis work are to:

- Perform a comparative analysis of Machine Learning (ML) algorithms: k-Nearest Neighbors (KNN), Decision Trees (DT), Random Forests (RF), Gradient Boosted Decision Trees (GBDT), and Deep Learning (DL) in modeling the removal of PFOA from contaminated water via EO process.
- Conduct a comprehensive assessment of independent variables including:
 - Type of anode and cathode utilized.

- Electrode spacing
 - Electrolyte diversity and concentration
 - Initial pH levels
 - Ambient temperature
 - PFOA's initial concentration
 - Current density
 - Electrolysis duration
 - Water matrix characteristics.
- Identify the most suitable ML methodologies for modeling PFOA removal via EO training ML algorithms on datasets derived from experimental EO processes and tuning models to accurately predict PFOA removal efficiency under varying conditions.
- Perform a comparative analysis of model performance based on predictive accuracy and precision of outputs.
- Carry out attribute weighing to evaluate the relative significance of independent variables in the EO process.

CHAPTER 2. LITERATURE REVIEW

1.5 Data Collection and Search Approach

The methodology adopted in this chapter commenced with the identification of relevant keywords based on predefined search parameters. Subsequently, a thorough search was conducted across multiple databases, with Scopus being the principal platform utilized. Scopus was chosen due to its extensive coverage of numerous scholarly journals and its provision of tools for information retrieval and bibliographic analysis, facilitating a robust assessment of research trends and performance within the field. Additionally, literature databases sourced from editorial and professional associations, such as Web of Science and Scopus, typically offer more reliable information due to their unique author identifier system, despite containing a smaller number of documents compared to systems like Google Scholar, which have broader coverage (Asadi et al., 2017; S. Adriaanse and Rensleigh, 2013). Two search queries were conducted: the first using the keyword "PFOA," resulting in 6266 retrieved documents, and the second employing both "PFOA" and "electrochemical oxidation," yielding 60 publications. The retrieved results were subjected to a bibliometric analysis.

1.6 Bibliometric Assessment

Using Scopus, a comprehensive bibliographic database, papers published within the specific topic were identified. The data provided by Scopus was utilized to analyze the number of published articles over time, as well as their affiliations and countries of origin.

Graphical representations were constructed to visualize the trends in publication counts over the years and to illustrate the distribution of publications among different countries.

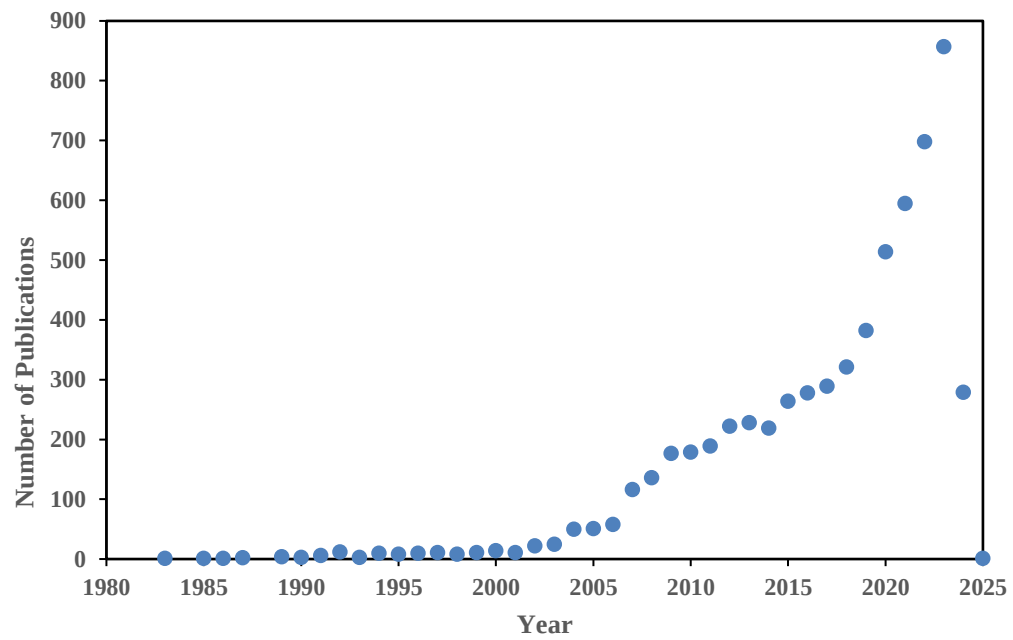
1.7 Bibliometric Analysis of Results

1.7.1 Trend Analysis of PFOA and Electrochemical Oxidation

The bibliometric analysis of published literature concerning the utilization of machine learning in water treatment research has unveiled a noticeable pattern. The number of documents has exhibited a consistent rise since 2018, with a particularly pronounced surge observed from 2020 onward (Figure 2-1a). The bulk of research activity in this domain has been concentrated between 2020 and 2024, encompassing a total of 2943 research publications out of 6266 articles published. The trend of publications in PFOA with electrochemical oxidation shows a gradual increase from 2011 to 2022 with 14 publications, with a peak in 2022 (Figure 2-1b)

This trend signifies a concerted effort by the scientific community to explore innovative solutions and strategies aimed at mitigating the impacts of PFOA contamination, thus emphasizing the urgency of advancing our understanding and technologies in this critical area.

(a)



(b)

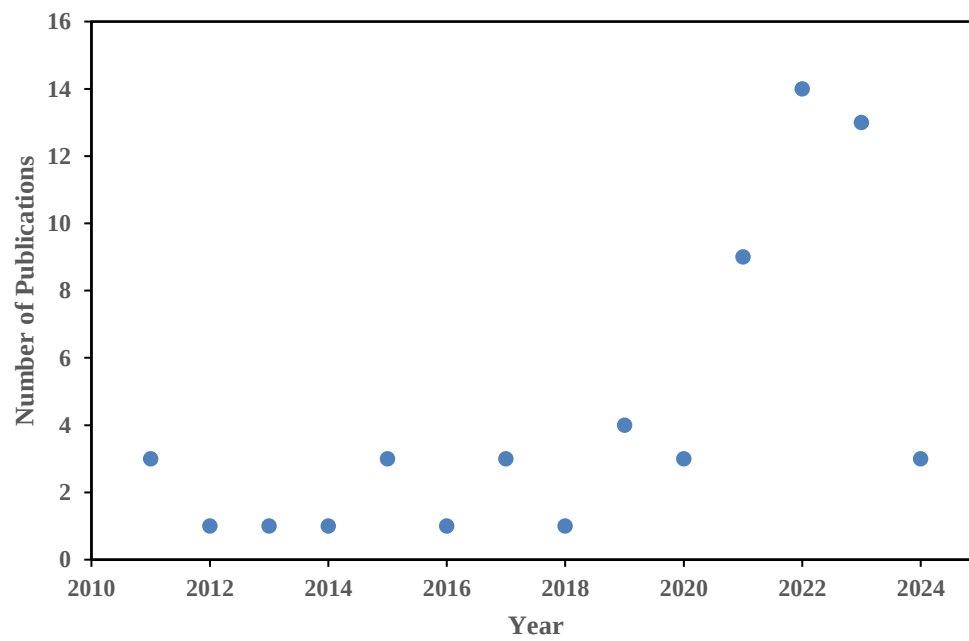


Figure 2-1: Yearly Number of Publications in (a) PFOA (B) PFOA and electrooxidation

1.7.2 Contributing Countries Analysis

Figure 2-2 illustrates the geographical distribution of published research on the application of electrochemical oxidation in PFOA treatment. China leads with 27 publications, followed by the United States with 21, and Australia with 7.

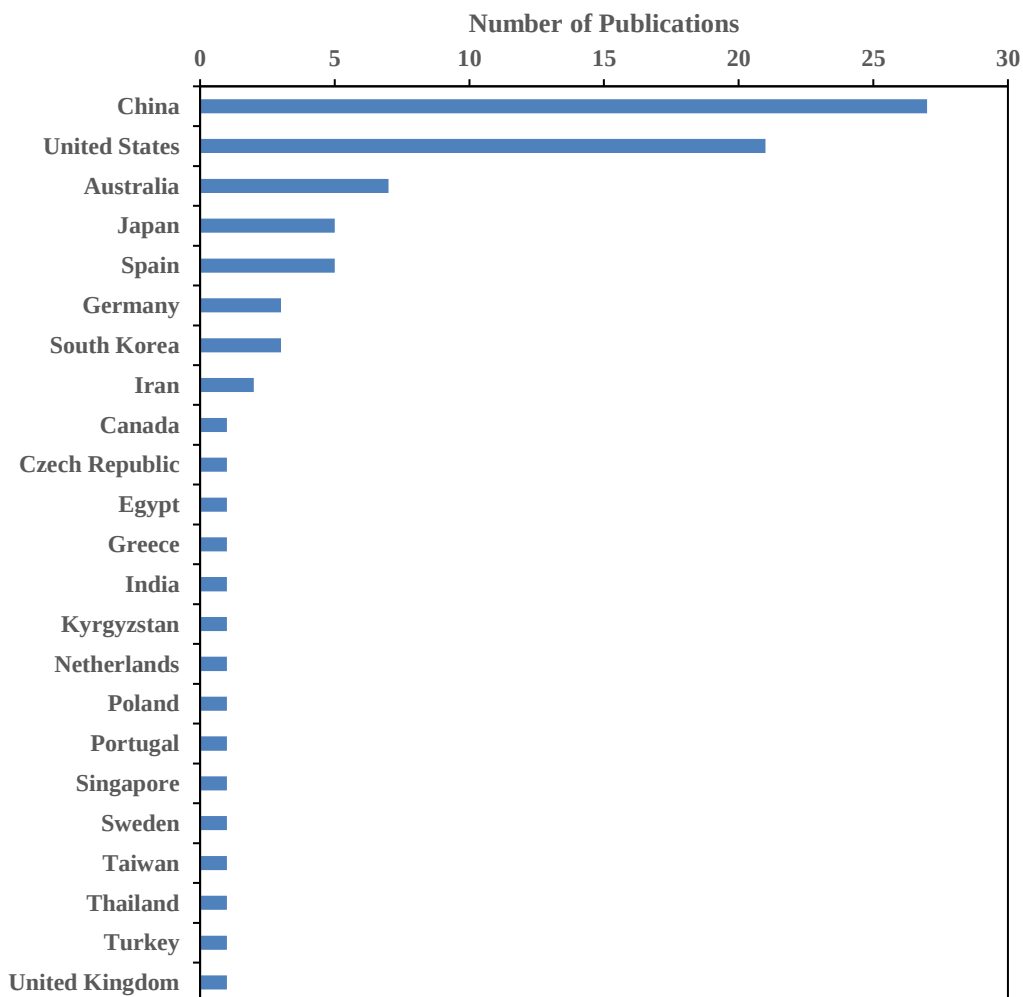


Figure 2-2: Distribution of Publications in PFOA and Electrochemical Oxidation Across Countries.

1.8 Application of Machine Learning in Water Treatment through Electrochemical Processes

In the realm of electrochemical treatment processes for pollutant removal, a diverse array of machine-learning models has been employed, as evidenced by recent studies. (Nabizadeh Chianeh et al., 2024) explored the application of artificial neural networks (ANN) and long short-term memory networks (LSTM) in electrooxidation processes for the removal of acid red 33 dye, reactive orange 7, acid yellow 3, and malachite green from industrial wastewater. The models exhibited strong predictive capabilities, with statistical indices such as MAE, RMSE, and CC demonstrating high accuracy. Similarly, (Khan et al., 2022) utilized ANN for anodic oxidation to eliminate navy blue dye, achieving remarkable results with indicators such as MSRE, SEP, MSE, AAD, MAE, and an adjusted R^2 close to 1. Electrocoagulation processes were also investigated, with (El Jery et al., 2023) employing ANN for the removal of chemical oxygen demand (COD) from wastewater in the oil industry. Meanwhile, SVR models were implemented by (Curteanu et al., 2014) in electrooxidation processes for the removal of COD, electric conductivity, total dissolved solids (TDS), total coli, and fecal coli from activated sludge of sewage. Other studies delved into novel combinations, such as (Zhu et al., 2021) integrating LSTM with ARIMA for electrocoagulation to remove heavy metal ions, and (Picos-Benítez et al., 2020) utilizing ANN-GA for electrooxidation to enhance the discoloration efficiency of Bromophenol blue dye. These endeavors showcase the effectiveness of machine learning models in predicting and optimizing electrochemical processes for pollutant removal across various water. For a comprehensive overview, the remaining studies from the literature are summarized in Table 2-1 below.

**Table 2-1: Summary of Machine Learning Studies Applied in Water Treatment
through Electrochemical Processes**

Process	Model	Response	Statistical indices	water matrix	Data	Ref.
EC	ANN	Acid red 33 dye removal	MAE=4.32, RMSE=5.72, RRMSE=0.36 CC=0.93	Industrial wastewater	31	(Nabizadeh Chianeh et al., 2024)
EC	LSTM_50	Reactive orange 7 removal	MAE=0.7, RMSE=0.95 RRMSE=0.16 CC=0.99	Industrial wastewater	31	(Nabizadeh Chianeh et al., 2024)
EC	LSTM_50	Acid yellow 3 removal	MAE=5.47 RMSE=7.45 RRMSE=0.41 CC=0.91	Industrial wastewater	31	(Nabizadeh Chianeh et al., 2024)
EC	LSTM_200	Malachite green removal	MAE=4.68 RMSE=6.41 RRMSE=0.35 CC=0.94	Industrial wastewater	31	(Nabizadeh Chianeh et al., 2024)
Anodic oxidation	ANN	Navy blue dye removal	MSRE=0.0002 2 SEP=0.014 MSE=0.62 AAD=0.009 MAE=0.448 Adj-R ² =0.999	Industrial wastewater	27	(Khan et al., 2022)
EC	ANN	Chemical oxygen demand(COD) removal	R ² =0.99 MAE=1.12%	wastewater from oil industry	299	(El Jery et al., 2023)

EO	SVR	COD removal	MSE=0.039 R ² =0.977	Activated sludge of sewage	100	(Curteanu et al., 2014)
EO	SVR	Electric conductivity increase	MSE=0.09 R ² =0.99	Activated sludge of sewage	100	(Curteanu et al., 2014)
EO	SVR	Total dissolved solids (TDS)	MSE=0.012 R ² =0.988	Activated sludge of sewage	100	(Curteanu et al., 2014)
EO	SVR	Total coli	MSE=0.2 R ² =0.92	Activated sludge of sewage	100	(Curteanu et al., 2014)
EO	SVR	Fecal coli	MSE=0.03 R ² =0.932	Activated sludge of sewage	100	(Curteanu et al., 2014)
EC	Combined LSTM with ARIMA	Removal rate of heavy metal ions	MSE=0.0000528 MAE=0.0057 MRE=0.6138 RMSE=0.007 R ² =0.948	industrial data collected from a wastewater treatment plant.	3938	(Zhu et al., 2021)
EC	ANN	final COD after treatment	CC=0.9560	raw sewage from a dairy industry	275	(Valente et al., 2014)
EO	ANN-GA	the discoloration of Bromophenol blue dye	RMSE=10.73 % MAPE =8.81 %	Sulfate wastewaters with Bromophenol blue dye	51	(Picos-Benítez et al., 2020)
EO	feed-forward NN (MLP)	final COD Concentration	ARE =7.98 % CC=0.9992	Industrial wastes with phenols	420	(Piuleac et al., 2010)
EC	feed-forward backpropagation network	Cr(VI) final concentration	CC = 0.976	Cr(VI) solution	212	(Aber et al., 2009)
EO	ANFIS	psychoactive pharmaceutical caffeine removal	R ² = 0.993 RMSE = 2.694	Municipal wastewater effluent, synthetic solution	40	(Gholami Shirkoochi et al., 2022)

EO	ANN-GA	Dissolved organic carbon (DOC)	MSE =0.0021 MAE =0.0345 R ² = 0.9914	urine	199	(Nascimen to et al., 2021)
Electrochemical reduction	ANN	nitrate removal	MSE=0.0448 R ² = 0.9020	simulated wastewater	85	(Meng et al., 2022)
EAOPs	ANN-GA	COD removal	R ² 0.946 RMSE = 0.022	simulated wastewater	25	(Yang et al., 2022)
EAOPs	ANN-GA	TN removal	R ² = 0.874 RMSE =0.028	simulated wastewater	25	(Yang et al., 2022)

EC – Electrocoagulation, EO - Electrochemical Oxidation, EAOPs - Electrochemical Advanced Oxidation Processes, ANN - Artificial Neural Network, LSTM - Long Short-Term Memory, SVR - Support Vector Regression, ARIMA - Autoregressive Integrated Moving Average, GA - Genetic Algorithm, NN - Neural Network, MLP - Multilayer Perceptron, ANFIS - Adaptive Neuro-Fuzzy Inference System, MAE - Mean Absolute Error, RMSE - Root Mean Square Error, RRMSE - Relative Root Mean Square Error, CC - Correlation Coefficient, MSRE - Mean Squared Relative Error, SEP - Standard Error of Prediction, MSE - Mean Squared Error, AAD - Average Absolute Deviation, Adj-R² - Adjusted coefficient of determination, R² – coefficient of determination, MAPE - Mean Absolute Percentage Error, ARE - Absolute Relative Error, MRE - Mean Relative Error.

1.9 Machine Learning Application for PFAS Removal in Water Treatment

Several studies have investigated the removal of PFAS, specifically PFOA and Perfluorooctanesulfonic Acid (PFOS), employing diverse treatment methods and machine learning models to deepen understanding and optimize processes. (Navidpour et al., 2022) explored photocatalysis for PFOA removal in contaminated water, employing Adaptive Boosting (AdaBoost), Gradient Boosting Machine (GBM), and Random Forest (RF) models. Their analysis, based on 1343 data points, utilized the Permutation Variable

Importance (PVI) technique to assess the significance of various parameters, including light irradiation time, type and dosage of catalyst, solution pH, irradiation intensity, initial PFOA concentration, oxidizing agents, irradiation wavelength, and solution temperature. Similarly, (Hosseinzadeh et al., 2022) focused on PFOS-contaminated effluent treated with nanofiltration. They applied RF, GBM, and AdaBoost models to 289 data points and used PVI to identify crucial parameters such as membrane type, temperature, PFOS concentration, pH, pressure, divalent cations, monovalent cations, and trivalent cations. In a broader context encompassing 234 PFASs, including PFOS and PFOA, (Karbassiyazdi et al., 2022) employed the XGBoost model for adsorption studies. Their analysis using the SHapley Additive exPlanations (SHAP) method revealed the importance of factors like temperature, pH, carbon chain number, initial concentration of PFAS, initial concentration of adsorbents, particle size, and types of adsorbents in the adsorption process. These studies collectively highlight the versatility of machine learning models in elucidating and optimizing the removal of PFAS from different matrices, providing valuable insights into the crucial parameters influencing treatment efficacy. matrices and pollutant types.

CHAPTER 3. Methodology

The methodology adopted in this study consists of two main phases (Figure 3-1). The first phase involves data integration and preprocessing, and the second phase is the ML model selection and development. The outcome of the first phase is the tidy dataset that feeds into the second phase.

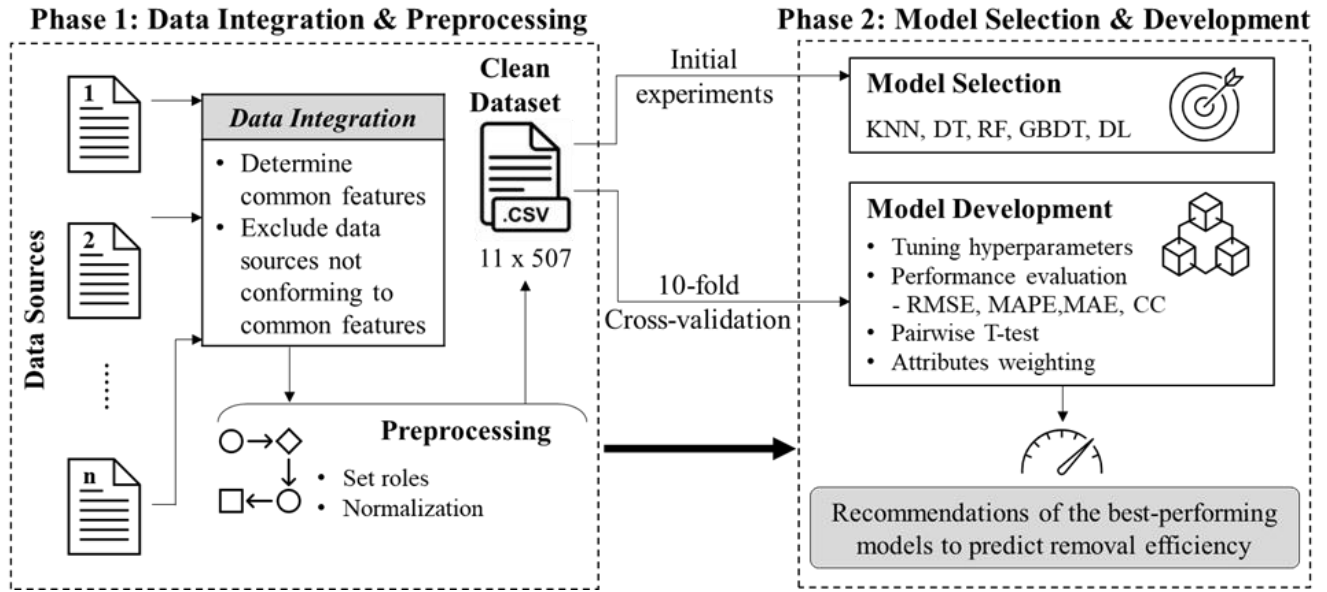


Figure 3-1: Research Methodology.

3.1 Data Integration and Preprocessing

This research aims to develop robust models for assessing the efficiency of the EO process in treating PFOA. A comprehensive review of existing literature was conducted to extract empirical data pertinent to the study. The synthesis of experimental outcomes from various sources informed the creation of the dataset (Asadi Zeidabadi et al. 2023; Barisci and Suri 2020; Li et al. 2022; Lin et al. 2012, 2018; Teng et al. 2024; Xu et al. 2017; Zhuo et al. 2012). The resultant dataset comprises 11 standard attributes and one target attribute, encapsulating 507 individual records (Table A1, Supplementary Material). The standard attributes include the type of anode and cathode

used, electrode spacing, electrolyte type and concentration, initial pH level, ambient temperature, initial PFOA concentration, current density, duration of electrolysis, and the type of water matrix. A summary of the experimental conditions for these standard attributes is presented in Figure 3-2, while Table 3-1 provides descriptive statistics for the numeric attributes. The primary focus for prediction within the dataset is the efficiency of PFOA removal, defined as the target attribute.

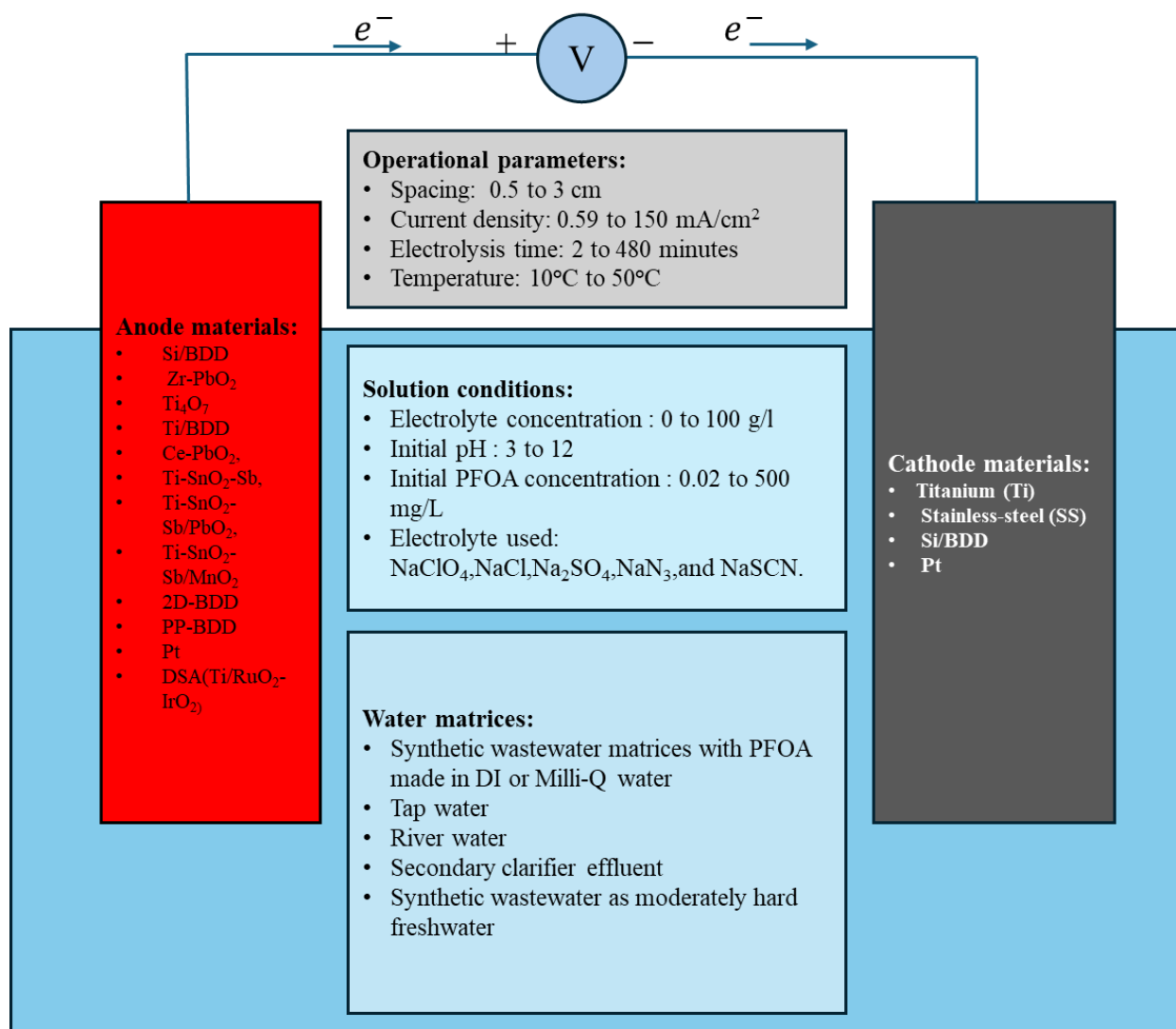


Figure 3-2: Summary of the Experimental Conditions of the 11 Standard Attributes Used in this Study.

Table 3-1: Descriptive Statistics of Numeric and Categorical Attributes Used in the Study.

Attributes	Median	Mean	Std.	Min.	Max.
Spacing (cm)	1	1.299	0.68	0.5	3
Electrolyte Concentration	2.5	4.327	13.50	0	100
Initial pH	5	5.499	1.82	3	12
Temperature (°C)	25	25.65	4.06	10	50
Initial Concentration (mg/L)	50	60.79	71.06	0.02	500
Current Density (mA/cm ²)	10	31.2	38.06	0	150
Electrolysis Time (minutes)	50	100.3	124.66	2	480

To ensure the uniformity of the data, and to avoid one attribute with a large scale from outweighing other variables with smaller scales, all the values of numeric attribute values in the dataset are changed to a common scale. This can be accomplished by normalizing each data point, x_i , using Equation (1). By performing normalization, all variables (i.e., attributes) are brought to the same scale in the range between zero and 1.

$$\text{Normalized value of } (x_i) = \frac{x_i - x_{\min}}{x_{\max} - x_{\min}} \quad (1)$$

Where $x_{\min}$ is the minimum value of the attribute data, and $x_{\max}$ is the maximum value of the attribute data.

Once the data from different sources are integrated and combined, the common features are determined, the missing values are replaced, and all numerical values are normalized, we obtain the cleaned dataset that will feed into the second phase for model development and performance measuring. This cleaned dataset is often referred to as “tidy data” in which “each variable forms a column; each observation forms a row; and each type of observational unit forms a table” (Wickham, 2014).

3.2 Model Selection and Development

All models, which are described in the subsequent section, are trained and validated using a 10-fold cross-validation approach (Wang et al., 2021). Specifically, we propose the utilization of a 10-fold cross-validation method as a robust and effective training and validation method. In this technique, the dataset is split into 10 subsets. Each iteration involves using 9 subsets as the training set and 1 subset as the testing set for the developed models. The k-fold cross-validation approach ensures a robust validation procedure where all available data is used to measure model performance using input data that was not used for training the model.

The model selection and development phase involved the application of default parameters across a spectrum of ML algorithms. Specifically, we opted to experiment with KNN, DT, RF, GBDT, and DL, utilizing the RapidMiner® software platform. Following this, a rigorous pre-screening protocol was implemented to evaluate the performance of these models. The selection of the most appropriate model was grounded in a comprehensive analysis of performance metrics (Botchkarev, 2019), including the root mean square error (RMSE) – Equation (2), the mean absolute error (MAE) – Equation (3), the mean absolute percentage error (MAPE) – Equation (4), and the correlation coefficient (CC) – Equation (5).

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (a_i - p_i)^2} \quad (2)$$

$$MAE = \frac{1}{n} \sum_{i=1}^n |a_i - p_i| \quad (3)$$

$$MAPE = \frac{100}{n} \sum_{i=1}^n \left| \frac{a_i - p_i}{a_i} \right| \quad (4)$$

$$CC = \frac{n \sum a_i p_i - \sum a_i \sum p_i}{\sqrt{n \sum a_i^2 - (\sum a_i)^2} \sqrt{n \sum p_i^2 - (\sum p_i)^2}} \quad (5)$$

Where a_i is the actual removal efficiency of record i , p_i is the predicted removal efficiency of record i , and n is the total number of records in the dataset.

Beyond the evaluation of model performance through the aforementioned metrics, the study incorporated a paired t-test which is a robust statistical method employed to determine the significance of performance disparities across the ML models under consideration. This test is particularly suitable for comparing two related samples, such as the performance metrics of different ML models evaluated on the same dataset. The null hypothesis (H_0) posits that there is no significant difference in the performance of the models, while the alternative hypothesis (H_1) suggests a significant difference exists. Mathematically, the paired t-test is expressed as per Equation (6).

$$t = \frac{\bar{d}}{s_d / \sqrt{n}} \quad (6)$$

where: $\bar{d}$ is the mean of the differences between the performance metrics of the models, s_d is the standard deviation of the differences, and n is the number of paired performance measurements. The difference for each pair is calculated as $d_i = x_i - y_i$, where x_i and y_i are the performance metrics (e.g., accuracy, RMSE) of the two models for the i -th observation. The mean of the differences $\bar{d}$ is given by Equation (7) and the standard deviation is given by Equation (8).

$$\bar{d} = \frac{1}{n} \sum_{i=1}^n d_i \quad (7)$$

$$s_d = \sqrt{\frac{1}{n-1} \sum_{i=1}^n (d_i - \bar{d})^2} \quad (8)$$

The resulting t-value is then compared against the critical value from the t-distribution with $n-1$ degrees of freedom to determine the significance. A t-value greater than the critical value indicates that the null hypothesis can be rejected, thereby confirming that the performance differences between the models are statistically significant. This rigorous approach ensures that any observed performance disparities are not due to random chance but reflect genuine differences in model efficacy.

3.2.1 K-Nearest Neighbors (KNN)

KNN stands out as a non-parametric method that excels in identifying local patterns and potential outliers based on input similarities (Saleem et al. 2024). KNN is a straightforward yet powerful algorithm that operates by locating the 'k' closest data points in the feature space to a given input and then predicting the output based on these neighbors. In the context of regression, KNN predicts the output value by computing the arithmetic mean of the output values associated with the 'k' nearest neighbors. This approach leverages the assumption that similar input features are likely to yield similar output values, making it particularly effective in scenarios where the relationship between input and output variables is complex or non-linear. The non-parametric nature of KNN means that it does not make any assumptions about the underlying data distribution. This characteristic is advantageous in the context of PFOA removal via EO, where the data may exhibit intricate patterns due to varying experimental conditions such as current density, pH, electrode

spacing, and electrolyte concentration. By relying on the proximity of data points, KNN can adapt to the local structure of the data, providing robust predictions even in the presence of outliers and noise.

3.2.2 Decision Tree (DT)

A DT is a versatile and interpretable hierarchical ML algorithm. DTs make decisions based on input features, facilitating the understanding of the crucial factors influencing the considered output variable. This non-parametric algorithm organizes a population into branch-like segments, forming an inverted tree structure with a root node, internal nodes, and leaf nodes. In the construction of a DT model, pivotal steps include splitting, stopping, and pruning. The splitting process entails selecting optimal variables and corresponding thresholds to effectively divide the dataset at each internal node, enhancing the separation of classes or improving predictive accuracy. Stopping criteria are crucial determinants that govern when the growth of the tree should cease, preventing overfitting by imposing conditions such as reaching a specified depth, having too few samples in a node, or achieving a defined level of homogeneity within a node. Stopping ensures the tree's complexity remains controlled, promoting generalizability to new, unseen data. Post-growth, pruning comes into play, refining the tree structure by selectively removing branches or subtrees. This fine-tuning process enhances the model's overall performance on validation or test data, mitigating overfitting and facilitating improved generalization to novel observations (Berry 2000; Hastie et al. 2009; Patel and Upadhyay 2012). Collectively, these steps contribute to the creation of an effective DT model that strikes a balance between complexity and predictive accuracy.

3.2.3 Random Forest (RF)

RF, an ensemble method built upon DT, is applied to enhance the predictive accuracy and robustness of the PFOA removal model. An RF comprises N individual DTs, each grown on a unique training dataset derived from the original training dataset through a process known as bagging. Bagging involves generating bootstrap samples and providing a distinct set of training data for each tree. This mechanism is crucial for RF as it helps prevent overfitting by introducing diversity in the training sets used for each tree (Schorr et al. 2020). In each node of a tree within the RF, only a subset of all available variables is considered for splitting the node. The selection of the variable for node splitting is based on minimizing errors, such as the mean squared error. The process continues recursively until the number of remaining samples falls below a predefined threshold. After growing each of the M trees using bootstrap samples, the RF predicts the output variable (y_m) for a given input data (x_{new}). The final prediction (y_{new}) of the model is obtained by averaging all individual predictions (y_n) from each tree as shown in Equation (9) (Wu et al. 2017). This ensemble approach enhances predictive accuracy and robustness by combining the strengths of multiple DTs.

$$y_{new}(x_{new}) = \frac{1}{M} \sum_{m=1}^M y_m(x_{new}) \quad (9)$$

3.2.4 Gradient Boosted Decision Trees (GBDT)

Gradient Boosting is utilized to sequentially build an ensemble of DTs, each correcting the errors of its predecessor. This algorithm enhances predictive performance, capturing subtle relationships in the data. GBDT method operates as a numerical optimization algorithm with the objective of discovering an additive model that minimizes the designated loss function. Essentially, the

algorithm incrementally incorporates a new DT, often termed a "weak learner," at each iteration to effectively diminish the overall loss function. In the context of regression, the algorithm initiates the model with an initial guess, commonly a DT that maximally reduces the loss function, usually the mean squared error. Subsequently, at each step, a new DT is fitted to the current residual and added to the existing model, updating the residual. This iterative process continues until a user-defined maximum number of iterations is reached. This sequential approach, known as stage-wise, ensures that DTs added in prior steps remain unaltered. By fitting DTs to the residuals, the model is refined in regions where it exhibits suboptimal performance. The methodology optimally combines weak learners to progressively enhance the model's accuracy, making it a potent tool in predictive modeling (Touzani et al. 2018).

3.2.5 Deep Learning (DL)

In contrast to conventional ML techniques, DL algorithms leverage a series of interconnected layers comprising straightforward yet nonlinear modules. This architecture facilitates a gradual transformation of data patterns into higher-dimensional and increasingly abstract features. As a result, DL models exhibit enhanced nonlinear fitting capabilities compared to traditional methods (Hwangbo et al. 2021). DL algorithms possess the capability of conducting end-to-end training, where a single model can seamlessly handle the entire process from raw data to the final output. This eliminates the intricate collaboration and interdependence among multiple models that is characteristic of traditional ML methods (LeCun et al. 2015).

3.3 Feature weighting using Particle Swarm Optimization

In this study, PSO is employed to optimize the attribute weights of the RF model predicting the efficiency of PFOA removal via EO. PSO is a population-based stochastic optimization technique

inspired by the social behavior of birds flocking or fish schooling. It is particularly well-suited for optimizing complex, multidimensional problems, making it an ideal choice for attribute weighting in ML. PSO operates by initializing a swarm of particles, where each particle represents a potential solution in the search space. These particles explore the space by updating their positions and velocities based on their own experience and the experience of their neighbors (Farzin et al. 2024). The position of each particle is influenced by three components: inertia (reflecting the particle's tendency to continue moving in its current direction), the cognitive component (drawing the particle towards its personal best-known position), and the social component (pulling the particle towards the swarm's global best-known position).

For this study, the PSO parameters were carefully selected to ensure a thorough exploration of the attribute weight space while maintaining computational efficiency. The population size was set to 75 particles, ensuring a diverse representation of potential solutions. The algorithm was allowed to run for a maximum of 30 generations, providing ample opportunity for the particles to converge towards an optimal set of attribute weights. Uniform weights of 1 were assigned to the inertia, local best, and global best components, reflecting a balanced consideration of exploration and exploitation in the search process. The position and velocity updates for each particle are governed by Equations (10) and (11), respectively.

$$x_{t+1_{id}} = x_{t_{id}} + v_{t+1_{id}} \quad (10)$$

$$v_{t+1_{id}} = w \cdot v_{t_{id}} + c_1 \cdot r_1 (p_{id} - x_{t_{id}}) + c_2 \cdot r_2 (p_{gd} - x_{t_{id}}) \quad (11)$$

Where $x_{t+1_{id}}$ and $v_{t+1_{id}}$ are the updated position and velocity of particle (id) at time (t+1), $x_{t_{id}}$ and $v_{t_{id}}$ are the current position and velocity of particle (id) at time (t), w is the inertia weight controlling the impact of the previous velocity, c_1 and c_2 are constants representing the cognitive

and social components, respectively, r_1 and r_2 are random values between 0 and 1, p_{id} is the personal best-known position of particle (id), and p_{gd} is the globally best-known position in the entire swarm.

The primary focus of using PSO in this context is to optimize the attribute weights for the RF model. Attribute weighting is crucial as it adjusts the significance of different features in the model, thereby enhancing predictive accuracy. Each particle in the PSO algorithm represents a potential set of weights for the attributes. The optimization process ensures that the weights are adjusted to improve the model's predictive accuracy, allowing the model to focus on the most relevant features.

CHAPTER 4. Results and Discussion

4.1 Performance Analysis and Model Selection

The selection of the optimal model is guided by specific priorities, such as accuracy, interpretability, and computational efficiency. The hyperparameters of the chosen models have been carefully tuned to optimize their performance. For instance, the DT model utilizes the least squares criterion with a maximum depth of 10. Similarly, the RF model employs the least squares criterion, with a maximum depth of 10, 200 trees, and a subset ratio of 0.8. The GBDT model is configured with a maximum depth of 10, 200 trees, a sample rate of 1.00, and a learning rate of 0.01. The DL model employs the Maxout activation function, with 200 epochs, and 2 hidden layers, each consisting of 50 neurons. For the KNN model, the parameter k is set to 5, utilizing a weighted vote based on Euclidean distance.

The evaluation of various ML models using different performance metrics, as presented in Table 4-1, provides significant insights. Lower RMSE and MAE values generally indicate smaller prediction errors. In this context, the DT and RF models demonstrate the best predictive accuracy, exhibiting the lowest RMSE and MAE. Additionally, the MAPE offers an assessment of the average percentage error, where the DT, RF, and DL models display relatively lower MAPE values. The CC is most favorable in the RF model, reflecting a strong correlation between predictions and actual outcomes. In terms of execution time, the DT model demonstrates the fastest processing, while GBDT and DL took the longest time. In this study, DT and RF emerge as strong performers across various metrics, with RF particularly standing out for its high correlation and relatively lower execution time. It should be noted that the execution time here refers to the time

taken to train and test the model (10-fold CV) using a standard laptop computer with a 64-bit processor, Intel i7 CPU at 2.50 GHz clock speed, and 16 GB of RAM.

Table 4-1: Model Performance Measures

	Performance Metrics				
Model	RMSE	MAE	MAPE	CC	Avg. Execution Time (ms)
KNN	17.4	13.1	128.1%	0.80	88
DT	9.7	7.1	31.9%	0.94	42
RF	7.9	5.8	76.9%	0.97	2297
GBDT	12.9	9.9	226.0%	0.91	5675
DL	11.8	7.9	113.2%	0.92	33725

The outcomes of the paired t-test, as presented in Table 4-2, reveal statistically significant disparities among various ML models. Notably, significant differences were identified between models such as KNN versus DT, RF, GBDT, and DL, as well as between DT and RF, and RF and GBDT. These findings align with the interpretation of performance measures presented herein, where models exhibiting RMSE, MAE, and MAPE, along with higher Correlation CC, were considered to outperform others. In particular, DT and RF models consistently demonstrated superior performance across these metrics compared to other models. Conversely, the absence of statistical difference between DL and GBDT supports our observation that these two models demonstrate similar performance. Therefore, the combined analysis of performance measures and

paired t-test results reinforces the robustness of our conclusions regarding the relative efficacy of ML models in predicting PFOA removal efficiency.

Table 4-2: Significance matrix of the paired t-test (significance level, $\alpha=0.05$)*

	KNN	DT	RF	GBDT	DL
KNN	-	0.000	0.000	0.000	0.000
DT		-	0.005	0.002	0.064
RF			-	0.000	0.001
GBDT				-	0.379
DL					-

**Values smaller than $\alpha = 0.05$ indicate probably a significant difference between the actual mean values of model outputs. This means that the difference between the model outputs is not due to random sampling, but rather due to actual performance.*

In Figure 4-1a, the box plot showcases the performance of the 10-fold cross-validation for the various models in predicting PFOA removal efficiency, measured by RMSE. RF stands out with the lowest median RMSE, indicating superior overall performance. DT and GBDT show moderate performance, while DL demonstrates slightly higher RMSE and notable variability. Conversely, kNN exhibits the highest median RMSE, highlighting the lower average performance with significant variability. Moving to Figure 4-1b, MAE trends mirror those observed in RMSE, with RF excelling in performance and kNN displaying the highest median MAE. This consistency underscores the reliability of the algorithms, emphasizing the importance of considering both central tendencies and spread. Figure 4-1c illustrates MAPE percentages, emphasizing GBDT with the highest variability and spread. DT stands out with a lower median MAPE, while RF shows moderate MAPE with an outlier of about 376%. DL and kNN exhibit comparable performance. Figure 4.1d reveals the correlation coefficients, where RF demonstrates the highest correlation,

followed by DT and GBDT in terms of medians and spread. In contrast, kNN exhibits the lowest correlation, indicating comparatively weaker predictive performance. Based on this analysis, RF emerges as a promising candidate for deep modeling and weight optimization. Its superior performance, consistent trends across metrics, and strong correlation coefficients position it as a favorable choice for further refinement and exploration in modeling PFOA removal via EO.

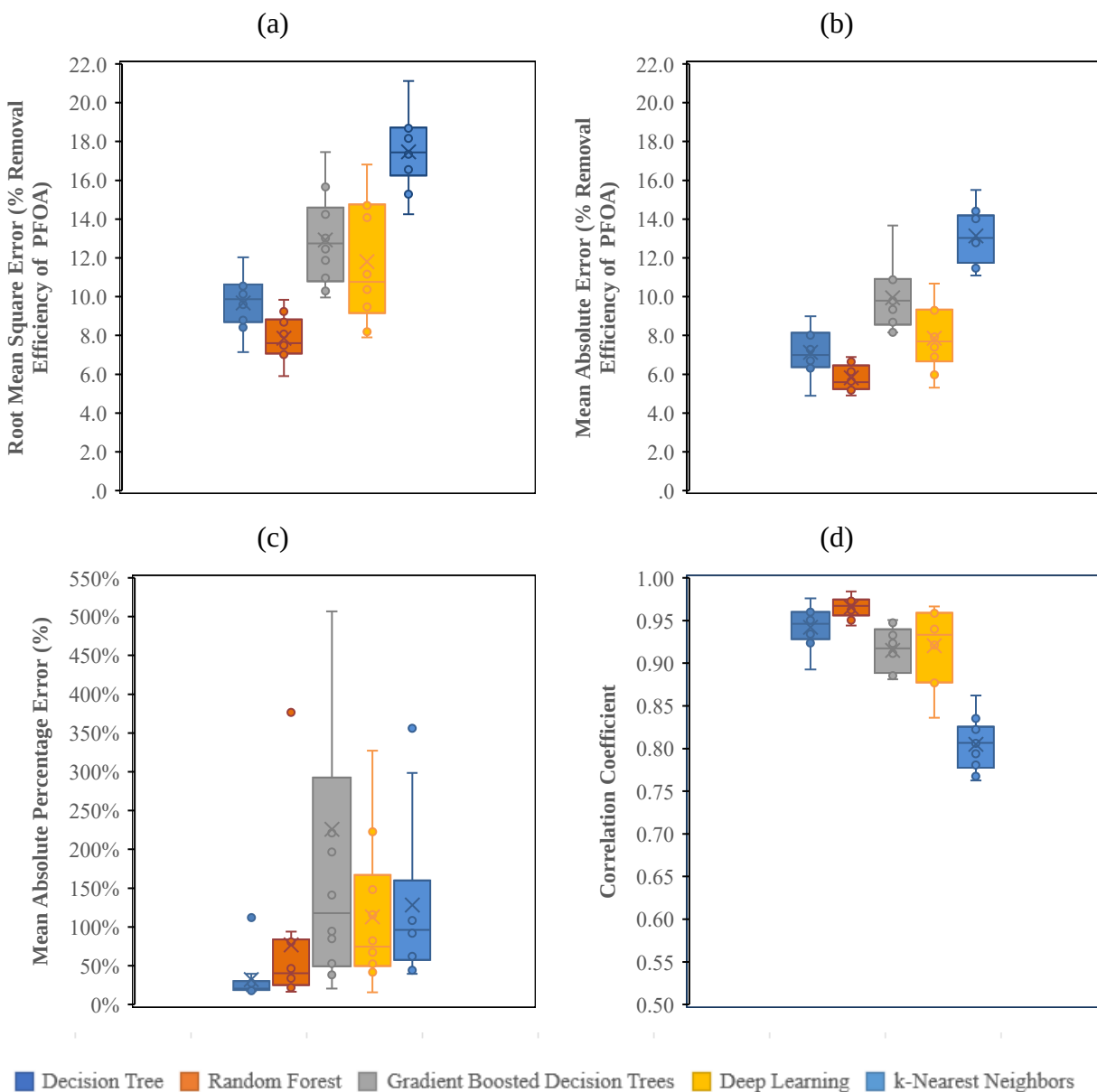
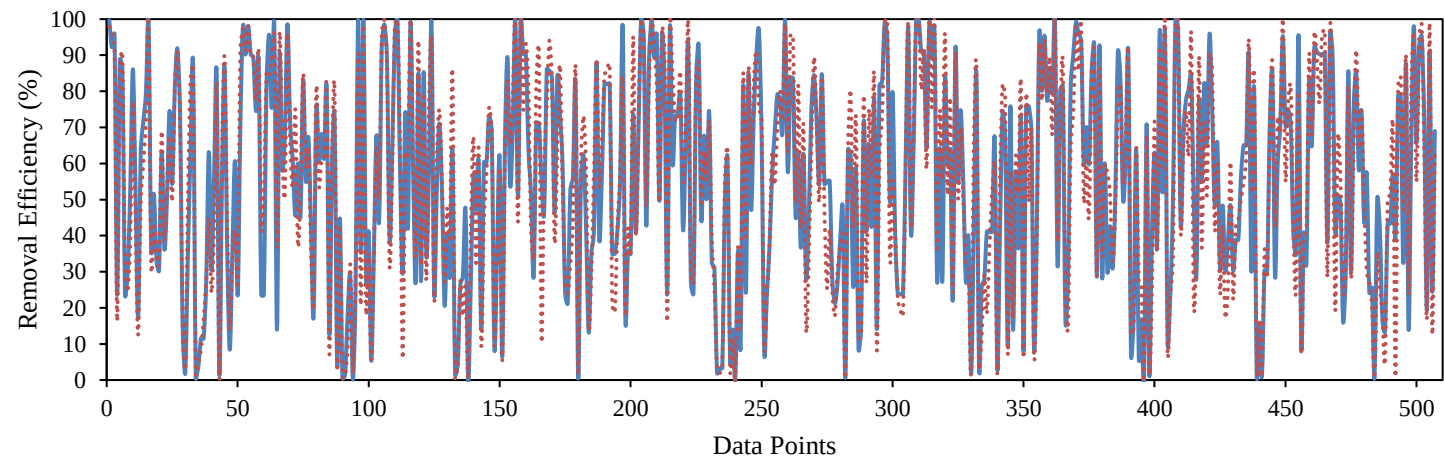


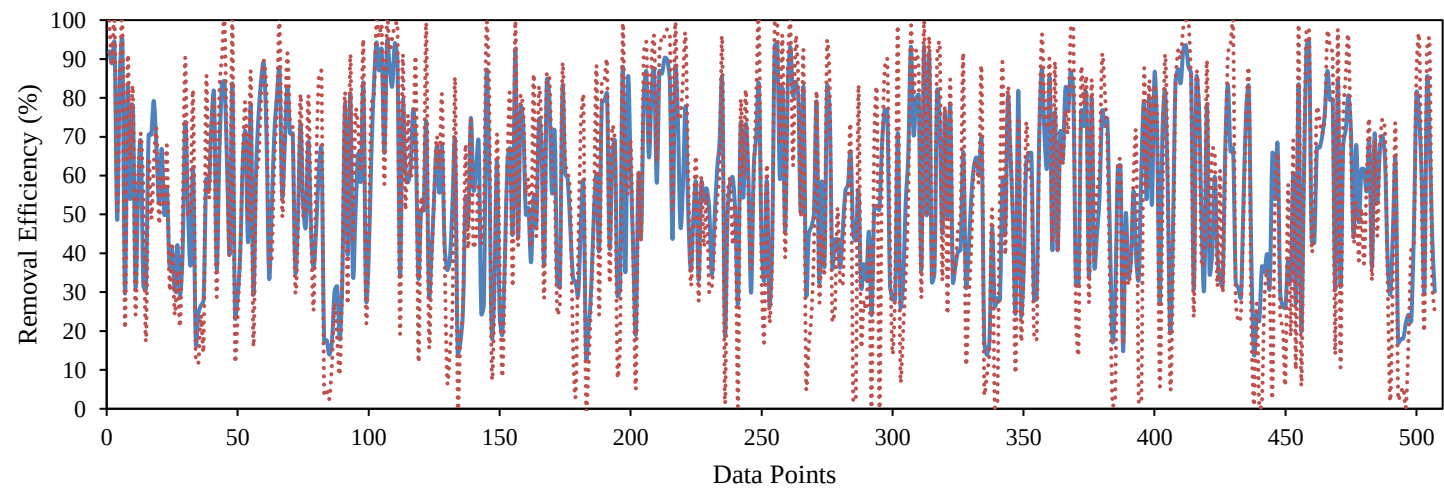
Figure 4-1: Performance Comparison of Supervised Learning Algorithms for PFOA Removal.

The actual vs predicted values for removal efficiency using the DT and GBDT models indicate a varying level of accuracy as depicted in Figures 4-2a and 4-2b. While some predictions closely align with the actual values, there are instances of notable deviations. In contrast, the RF model exhibits remarkable predictive capabilities, precisely capturing removal efficiency as illustrated in Figure 4-2c. This observation aligns with the findings discussed in the performance measures and the results of the paired t-test.

(a)



(b)



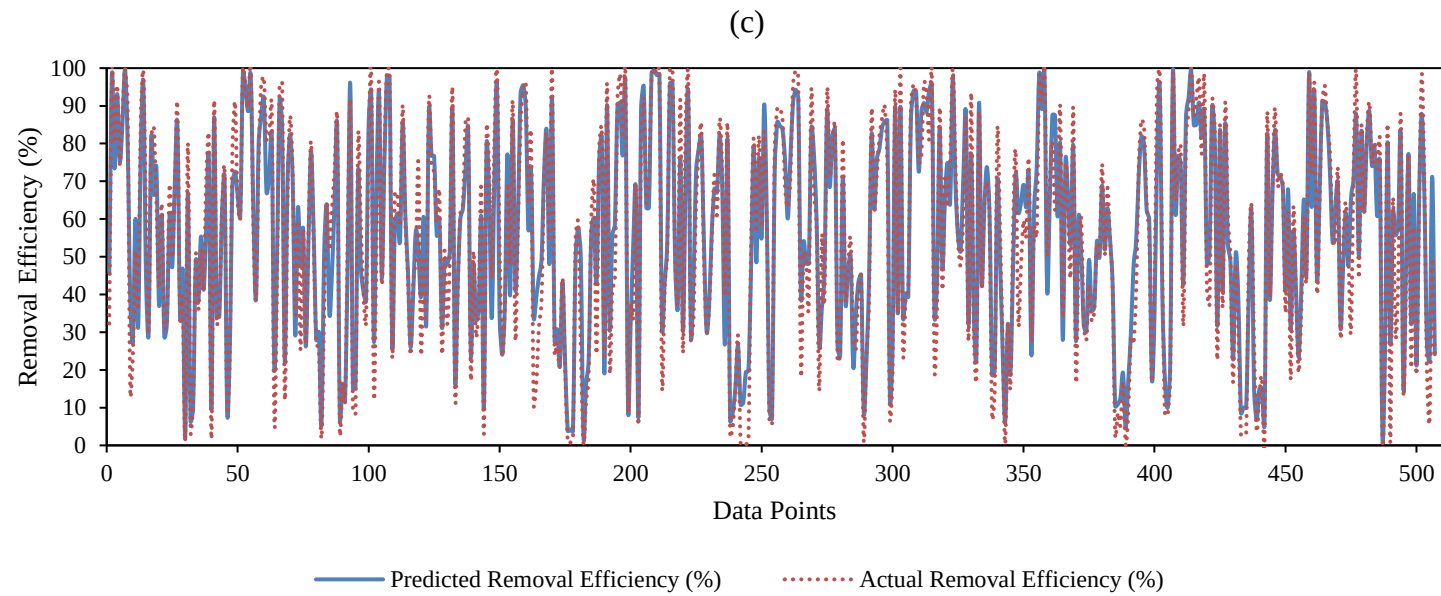


Figure 4-2: Comparison of Actual vs. Predicted Removal Efficiency of PFOA using Machine Learning Models:
(a) Decision Trees (DTs), (b) Gradient Boosted Decision Trees (GBDT), and (c) Random Forest (RF).

4.2 Attribute weighting in RF via PSO

The parameter settings for the PSO algorithm, as discussed in Section 3.3, have been carefully selected to optimize its convergence and exploratory efficacy. This optimization process has led to significant enhancements in the performance indicators of the RF model. Specifically, the model achieved an RMSE of 7.038 (± 0.900), an MAE of 5.178 (± 0.730), and a CC of 0.972 (± 0.008). These metrics underscore the robustness and accuracy of the model in predicting the efficiency of PFOA removal via EO. The resultant attribute weights, derived from the optimized PSO-RF model configuration, are presented in Figure 4-3. These weights reflect the relative importance of each attribute in the predictive model. The following discussion will delve into the significance of each attribute weight as determined by the PSO, providing insights into their impact on the model's predictive capabilities and the overall process of PFOA removal efficiency.

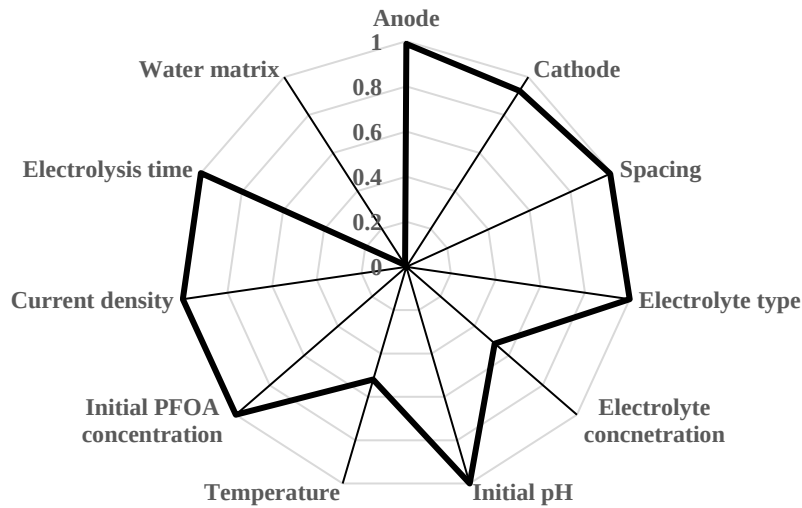


Figure 4-3: Weight Attribution in Particle Swarm Optimization (PSO)- Random Forest (RF) Model.

4.2.1 Anode

The mechanisms of direct electron transfer at the anode surface and the mediation of degradation through electro-generated active species, including hydroxyl radicals ($\text{OH}^\bullet$), chlorine radicals ($\text{Cl}^\bullet$), hydrogen peroxide (H_2O_2), and ozone (O_3), are of paramount importance (McBeath et al. 2019). Despite the apparent inefficacy of $\text{OH}^\bullet$, $\text{Cl}^\bullet$, H_2O_2 , and O_3 in the degradation of PFOA, the phenomenon predominantly hinges on the direct oxidation process, wherein electrons are transferred from PFOA molecules to the anode, thereby facilitating the pollutant's breakdown (Zhuo et al. 2012).

Further investigations into the efficacy of specific anode materials have revealed significant variations in their ability to reduce PFOA concentrations. Lin et al. (2012) documented a substantial decrease in PFOA levels—90.3%, 91.1%, and 31.7%—using $\text{Ti}/\text{SnO}_2\text{-Sb}$, $\text{Ti}/\text{SnO}_2\text{-Sb}/\text{PbO}_2$, and $\text{Ti}/\text{SnO}_2\text{-Sb}/\text{MnO}_2$ anodes, respectively, under a regime of a constant current density of $10 \text{ mA}/\text{cm}^2$, with a $10 \text{ mmol}/\text{L}$ NaClO_4 supporting electrolyte, over a duration of 90 minutes at an initial PFOA concentration of $100 \text{ mg}/\text{L}$ (Lin et al. 2012).

Distinctive outcomes were observed in another study where a Polypropylene-Boron-Doped Diamond (PP-BDD) anode accomplished a complete 100% decomposition of PFOA within 150 minutes, contrasting with a Two-Dimensional-BDD anode that managed a 67% decomposition efficiency over 180 minutes (Li et al. 2022). This variation in anodic efficiency underscores the critical role of anode material in the electrochemical degradation process of PFOA, a factor that has been quantitatively validated by its substantial weighting

of 0.988 within the PSO-RF model, affirming the material's pivotal influence on the degradation efficacy.

4.2.2 Cathode

Serving as the pivotal site for reduction reactions within an electrochemical system, the cathode completes the circuit by accepting electrons from the external circuit, a process that marks the consummation of the electrochemical reaction initiated at the anode (Medel et al. 2020). In the specific context of PFOA degradation, when employing a BDD anode coupled with various cathodic materials including reduced graphene oxide (rGA), Iron(III) oxide-reduced graphene oxide (Fe_3O_4 -rGA), Copper-reduced graphene oxide (Cu-rGA), graphite electrode (GE), and Titanium (Ti), the degradation efficiency exhibited a distinct hierarchy. Within the initial 240 minutes, the degradation rates of PFOA were sequenced as follows: Fe_3O_4 -rGA (91.21%) > Cu-rGA (87.64%) > rGA (83.26%) > GE (72.62%) > Ti (57.20%), showcasing the significant impact of cathode material choice on PFOA degradation rates (Li et al. 2023).

In a separate investigation by Teng et al. (2024), the use of a salt bridge to segregate anodic from cathodic reactions revealed a disparate outcome (Teng et al. 2024). Here, PFOA degradation was quantified at 56.3% within the anodic compartment utilizing NaCl as the electrolyte medium, while the cathodic compartment showed no detectable degradation over an 8-hour period (Teng et al. 2024). This stark contrast underscores the critical role of the electrochemical environment and the configuration of the electrochemical cell in dictating the efficiency and locus of PFOA degradation, thereby highlighting the complex interplay between anodic and cathodic reactions in the overall degradation process.

4.2.3 Inter-electrodes Spacing

The influence of electrode spacing on the EO process of PFOA, particularly concerning the voltage across the electrodes and the mass transfer rate of PFAS, has been underscored as pivotal. Degradation ratios of 95.9%, 90.3%, 78.0%, and 68.9%, corresponding to electrode distances of 0.5, 1.0, 1.5, and 2.0 cm, respectively, were reported by Lin et al. (2012) (Lin et al. 2012). In a similar vein, Xu et al. (2017) documented degradation ratios of 93.2%, 88.7%, 80.5%, and 62.5% for electrode distances of 0.5, 1.0, 1.5, and 2.0 cm, respectively (Xu et al. 2017). These findings were corroborated by Barisci and Suri (2021), who also supported the observed trends (Barisci and Suri 2021). It was noted that an increased gap between electrodes was linked with a longer diffusion distance for the analyte, necessitating prolonged electrolysis durations. This highlights the complex interplay between electrode distance and the efficacy of PFOA degradation within electrochemical treatments. The significance of this factor was further validated within the PSO-RF model, where it was attributed a weight of 1.

4.2.4 Current Density

Model analyses conducted in this study highlight the crucial influence of current density on enhancing PFOA degradation, giving it considerable emphasis in predictive models, aligning with widespread findings in this field. The efficacies of degradation and defluorination of PFOA in aqueous solutions are fundamentally associated with the electron transfer capabilities and the generation of $\text{OH}^\bullet$. The latter, particularly the proficiency in hydroxyl radical formation, is highly dependent on the applied current density. The positive impact of elevated current density on PFOA removal has been

consistently observed across various studies, each examining a range of current densities. Early research indicates minimal PFOA breakdown at lower densities (below 0.12 mA/cm²) yet marks significant advancements—reaching up to 97.48%—at 0.59 mA/cm² (Zhuo et al. 2012). Subsequent studies further confirm that PFOA decay rates surge with higher current densities, surpassing 90% efficiency at levels above 15 mA/cm², attributed to improved electron transfer and radical formation at these intensified densities (Xu et al. 2017). PFOA degradation in water was also shown to increase with current density, achieving up to a 98.8% reduction at 40 mA/cm² after 90 minutes (Lin et al. 2012). At lower densities, such as 2.5 mA/cm², degradation was under 50%, but efficiencies exceeded 90% at 25 mA/cm² (Barisci and Suri 2020). This trend, suggesting enhanced electron transfer and radical generation at higher densities, was supported by Asadi Zeidabadi et al. (2023) (Asadi Zeidabadi et al. 2023). Furthermore, Barisci and Suri (2021) observed PFOA concentration drops between 22% and 94% at varying densities from 5 to 100 mA/cm² within an hour (Barisci and Suri 2021). These findings underscore current density's crucial role in PFOA degradation, as reflected in model optimizations where the RF model, improved via PSO, assigned current density a significant weight.

4.2.5 Electrolysis Time

Increasing the electrolysis time in EO processes can significantly impact the degradation of PFOA. As time increases, more molecules of PFOA come into contact with the electrodes, where oxidation and reduction reactions occur. This prolonged exposure allows for a greater extent of chemical transformations, ultimately leading to enhanced degradation of PFOA. Barisci and Suri (2020) noted that the electrolysis time utilized in their study was considerably shorter, lasting only 1 hour (Barisci and Suri 2020), compared

to the longer durations reported in existing literature, typically ranging from 3 to 6 hours in studies conducted by others (Liang et al. 2018; Urtiaga et al. 2015). Therefore, extending the electrolysis time could potentially result in higher PFOA degradation, as observed in these referenced studies.

Research conducted by Asadi Zeidabadi et al. (2023) revealed a relationship between time and the concentrations of the generated by-products (Asadi Zeidabadi et al. 2023). It was observed that these concentrations followed a time-dependent trend, initially increasing, reaching a peak, and then declining. This trend suggested a process where the by-products were formed and subsequently degraded over time (Asadi Zeidabadi et al. 2023). Thus, assigning a substantial weight to electrolysis time in the PSO-RF model is supported by its significant impact on PFOA degradation, as highlighted by the findings of the studies above.

4.2.6 Temperature

Raising the temperature from 10 to 22 °C resulted in a notable enhancement of PFOA degradation, ranging from 83.3% to 90.7%. However, subsequent increments in temperature within the broader range of 22–50 °C only marginally influenced oxidation, leading to a modest increase in degradation efficiency from 90.7% to 94.6%. This suggests a slight positive effect of temperature on PFOA degradation (Asadi Zeidabadi et al. 2023). Consequently, the assignment of a weight of 0.520 to temperature in the PSO-RF model aligns with the observation that its impact on PFOA degradation is relatively modest.

4.2.7 Electrolyte Type

The employment of sodium sulfate (Na_2SO_4) as an electrolyte in the electrochemical degradation of PFOA has been observed to yield superior degradation outcomes compared to sodium chloride (NaCl), a phenomenon that Barisci & Suri (2020) attribute to the diminished conductivity of the PFOA solution in the presence of Na_2SO_4 (Barisci and Suri 2020). This reduction in conductivity leads to an elevated average voltage (26.7 V for Na_2SO_4 versus 22.6 V for NaCl), thereby facilitating a more efficient electron transport from the anode to the cathode. The decreased solution resistance associated with Na_2SO_4 amplifies the potential difference across the electrodes, thereby enhancing the degradation of PFOA through a more spontaneous electron flow toward the cathode.

In contrast, the utilization of sodium perchlorate (NaClO_4) as a supporting electrolyte has been shown to detrimentally affect the PFOA degradation rate, as elucidated by Lin et al. (2018) (Lin et al. 2018). This decrement is ascribed to the competitive interference of the chlorine evolution reaction at the anode surface, which detracts from the efficacy of PFOA degradation. Additionally, in scenarios where sodium nitrate (NaNO_3) is used as the electrolyte, the decomposition efficiency of PFOA on a PP-BDD anode was reported to reach 71.1% following 180 minutes of electrolysis by Li et al. (2022) (Li et al. 2022). Remarkably, under analogous conditions, the utilization of Na_2SO_4 as the electrolyte facilitated complete PFOA removal, thus underscoring the superior degradation performance of Na_2SO_4 electrolytes in comparison to NaNO_3 . These empirical findings align with the insights derived from the PSO-RF model, which ascribes a significant weight of 1 to the choice of electrolyte, thereby affirming the pivotal role of the electrolyte type in influencing the electrochemical degradation efficiency of PFOA.

4.2.8 Electrolyte Concentration

As for the impact of electrolyte concentration, Asadi Zeidabadi et al. (2023) observed its dependency on the initial concentration of PFOA (Asadi Zeidabadi et al. 2023). In low PFOA concentrations, increasing Na_2SO_4 concentration from 0.1% to 10% significantly raised the PFOA reaction rate. In contrast, at high PFOA concentrations, the reaction rate slightly decreased with increasing sulfate concentration (Asadi Zeidabadi et al. 2023). Similarly, Urtiaga et al. (2015) observed a marginal improvement in PFOA degradation kinetics at lower NaClO_4 concentrations (1.4 g/L) compared to higher concentrations (8.4 g/L) (Urtiaga et al. 2015). Although the enhancement was notable, achieving over 90% removal of PFOA required the utilization of BDD electrodes at a current density of 200 mA/cm^2 . This finding underscores the moderate influence of electrolyte concentration on the overall degradation efficiency (Urtiaga et al. 2015). The PSO-RF model, acknowledging the collective insights from these studies, assigns a weight of 0.519 to electrolyte concentration. This weight reflects the moderate yet discernible influence of electrolyte concentration within the broader spectrum of factors affecting PFOA degradation.

4.2.9 Initial pH

This investigation reveals the nuanced role of pH in the degradation of PFOA, showcasing how varying acidity levels can either enhance or impede the breakdown process. In one study, PFOA degradation rates were influenced by pH, with higher efficiency in acidic conditions (Zhuo et al. 2012). Degradation decreased at high pH due to reduced hydroxyl radical generation, and extreme acidity also hindered efficiency. Acidic to neutral pH levels

showed better PFOA removal compared to alkaline conditions, where hydroxyl anion adsorption at the anode reduced efficiency (Barisci and Suri 2021). Electrolysis effects and electrolyte concentration also affected PFOA degradation, with no significant pH impact noted in some studies (Teng et al. 2024). It was also found that degradation improved from 76.8% to 96.5% as pH decreased from 9 to 3, supporting pH's importance in PFOA removal models (Lin et al. 2012). The PSO-RF model assigns a weight of 1 to this factor, which aligns with the consistent findings across these studies, emphasizing the significant role of pH in driving PFOA degradation.

4.2.10 PFOA Initial Concentration

The impact of initial PFOA concentration on EO efficiency is underscored by a series of studies, revealing nuanced dynamics in removal rates. Ma et al. (2015) found that PFOA removal efficiency decreased from 90.9% at an initial concentration of 10 mg/L to 83.9% with an increase to 200 mg/L, highlighting the concentration's significant influence on EO effectiveness (Ma et al. 2015). This observation aligns with Barisci & Suri (2021), who reported a marked decline in degradation efficiency from 94% at 100 µg/L to 43% at 10 mg/L, attributing the reduced removal rates at higher concentrations to the generation of short-chain intermediates, which intensify competition for degradation pathways (Barisci and Suri 2021). Building on this, Lin et al. (2018) documented an enhanced decay rate at lower initial concentrations, ranging from 0.5 mmol/L to 2.0 µmol/L, suggesting a more pronounced electro-sorption effect at diminished substrate levels (Lin et al. 2018). Lin et al. (2012) conducted a comprehensive analysis across initial concentrations from 5 to 500 mg/L. Their findings revealed degradation ratios ranging between 85.4% and 94.8% after 90 minutes of electrolysis (Lin et al. 2012).

Xu et al. (2017) and Zhuo et al. (2012) presented findings that further complexify the relationship between initial PFOA concentration and removal efficiency. Xu et al. (2017) observed increased removal ratios of 91.3%, 88.7%, 85.5%, and 81.1% for concentrations of 200, 100, 50, and 20 mg/L, respectively, after 90 minutes, suggesting higher initial concentrations facilitate more effective PFOA decarboxylation due to increased interaction with the Si/ BDD surface (Xu et al. 2017). Similarly, Zhuo et al. (2012) reported removal efficiencies of 79.33%, 70.99%, and 68.54% for concentrations of 50, 30, and 20 mg/L, respectively, post 30 minutes of electrolysis. These collective insights underscore the critical role and complex interplay of initial PFOA concentration in determining the efficiency of EO processes, a fact that is mirrored in its significant weighting within the PSO-RF model (Figure 5), reflecting its pivotal impact on treatment outcomes.

4.2.11 Water Matrix

The inclusion of the study by Teng et al. (2024) in our dataset provided valuable insights into the suitability of the EO-Sodium Chloride (EO-NaCl) system across various water matrices (Teng et al. 2024). Notably, the study assessed four distinct water matrices: tap water (TW), secondary clarifier effluent (SCE), river water (RW), and synthetic wastewater (SW). The degradation of PFOA exhibited enhancement in SW and SCE, attributed to the higher concentration of Cl^- in these matrices. However, RW and TW showed no significant effect on PFOA degradation. Despite these variations, the differences in removal efficiency among the four water matrices were marginal, with removal efficiencies ranging from 83% to 91% after 480 minutes of treatment (Teng et al. 2024). Furthermore, it's noteworthy that most of the studies incorporated in our analysis utilized synthetic SW, consisting of Milli-Q or deionized water spiked with various compounds and concentrations of PFAS. As a

result, the influence of the water matrix on the degradation process could be considered negligible. This conclusion is supported by the PSO-RF model, which assigned a weight of zero to this feature.

CHAPTER 5. Conclusion

5.1. Summary of Key Findings

In conclusion, a thorough assessment of various ML models for forecasting the efficiency of PFOA removal by the EO process elucidated subtle distinctions in their performance, with DT and RF models displaying notably higher accuracy, as indicated by their lower RMSE, MAE, and MAPE scores. The RF model, in particular, distinguished itself through robust predictive capabilities and strong correlation with actual outcomes, further validated by correlation coefficient analysis and its superior performance across multiple metrics. The analysis also highlighted a balance between accuracy and computational speed, where DT models were the quickest. The statistical relevance of these performance differences was confirmed by paired t-test results, reinforcing the consistent superiority of DT and RF over other models, while DL and GBDT models showed similar efficacy. Additionally, an in-depth examination within the RF framework using PSO for attribute weighting revealed key factors such as applied current density, initial pH, and electrode spacing as pivotal in PFOA removal through EO. The investigation into individual parameters further underscored their specific impacts on removal efficiency, enhancing the understanding of the EO process's complexity. This integrated analysis of ML models alongside experimental observations offers valuable insights for advancing predictive modeling in treatment applications and provides practical guidance for optimizing EO processes for effective PFOA removal, positioning the RF model as an instrumental tool for future research and application in this domain.

5.2. Practical Implications

The findings from this study hold significant practical implications for the field of electrochemical water treatment, particularly in the context of removing PFOA from contaminated water sources. By identifying the machine learning models that exhibit superior performance in forecasting PFOA removal efficiency through EO, namely DT and RF models, this research provides valuable guidance for practitioners and researchers alike.

Firstly, the emphasis on DT and RF models underscores the importance of leveraging robust predictive capabilities and a strong correlation with actual outcomes when developing forecasting tools for PFOA removal. Incorporating these models into the design and optimization of EO treatment systems can enhance decision-making processes and improve overall treatment efficacy.

Moreover, the identification of key factors such as applied current density, initial pH, and electrode spacing as pivotal in PFOA removal through EO offers practical insights for optimizing treatment parameters. By focusing efforts on controlling and manipulating these influential variables, practitioners can tailor EO processes to maximize PFOA removal efficiency while minimizing resource consumption and operational costs.

Furthermore, the demonstrated balance between accuracy and computational speed, with DT models being the quickest, highlights the importance of considering both performance metrics when selecting a modeling approach. Depending on specific application requirements and computational resources available, practitioners can make informed decisions regarding the most suitable model for their predictive modeling needs.

5.3. Study Limitations and Future Research Directions

While this study provides valuable insights into the predictive modeling of PFOA removal efficiency through EO processes using ML models, several limitations need to be acknowledged.

One significant limitation lies in the availability and completeness of data. Some papers lacked essential information about the attributes used in their experiments, which might have impacted the comprehensiveness of the analysis. Moreover, the reliance on synthetic water matrices in most studies limited the diversity of the dataset, potentially leading to biases in model performance evaluation.

A notable limitation of this study lies in the source material itself. The data used for analysis were primarily derived from experimental studies conducted on a laboratory scale, rather than on a pilot or full-scale basis. This limitation restricts the extrapolation of findings to real-world applications.

Building upon the insights gained from this study, several avenues for future research can be identified:

Data Augmentation and Diversity: Addressing the limitations associated with synthetic water matrices by incorporating real-world datasets with diverse water compositions and contaminant profiles would enhance the robustness and applicability of predictive models.

Practical Implementation and Validation: Translating research findings into practical applications requires rigorous validation under real-world conditions. Collaborating with industry partners and stakeholders to implement and validate ML-based predictive models

in operational EO treatment systems would facilitate technology transfer and accelerate the adoption of innovative approaches for addressing water contamination challenges.

By addressing these limitations and pursuing future research directions, the field can continue to advance towards more effective and sustainable water treatment solutions, leveraging the promising potential of ML and electrochemical technologies for environmental remediation.

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Supplementary Information

Anode used	Cathode used	spacing(cm)	Electrolyte used	electrolyte concentration (g/L)	initial pH	Temperature	initial con. mg/L	current density (mA/cm ²)	electrolysis time (minutes)	water matrix	Removal efficiency %
A	M	3	NaClO ₄	1.4	3	32	50	0.12	10	SW - single PFAS -PFOA	0
A	M	3	NaClO ₄	1.4	3	32	50	0.12	20	SW - single PFAS -PFOA	0
A	M	3	NaClO ₄	1.4	3	32	50	0.12	30	SW - single PFAS -PFOA	0
A	M	3	NaClO ₄	1.4	3	32	50	0.12	45	SW - single PFAS -PFOA	0
A	M	3	NaClO ₄	1.4	3	32	50	0.12	60	SW - single PFAS -PFOA	0
A	M	3	NaClO ₄	1.4	3	32	50	0.12	90	SW - single PFAS -PFOA	0
A	M	3	NaClO ₄	1.4	3	32	50	0.12	120	SW - single PFAS -PFOA	0
A	M	3	NaClO ₄	1.4	3	32	50	0.59	10	SW - single PFAS -PFOA	32.28
A	M	3	NaClO ₄	1.4	3	32	50	0.59	20	SW - single PFAS -PFOA	54.08
A	M	3	NaClO ₄	1.4	3	32	50	0.59	30	SW - single PFAS -PFOA	69.38
A	M	3	NaClO ₄	1.4	3	32	50	0.59	45	SW - single PFAS -PFOA	83.03
A	M	3	NaClO ₄	1.4	3	32	50	0.59	60	SW - single PFAS -PFOA	92.18
A	M	3	NaClO ₄	1.4	3	32	50	0.59	90	SW - single PFAS -PFOA	97.5
A	M	3	NaClO ₄	1.4	3	32	50	0.59	120	SW - single PFAS -PFOA	97.84
A	M	3	NaClO ₄	1.4	3	32	50	5.88	10	SW - single PFAS -PFOA	41.43
A	M	3	NaClO ₄	1.4	3	32	50	5.88	20	SW - single PFAS -PFOA	65.22
A	M	3	NaClO ₄	1.4	3	32	50	5.88	30	SW - single PFAS -PFOA	78.54
A	M	3	NaClO ₄	1.4	3	32	50	5.88	45	SW - single PFAS -PFOA	90.18

Anode used	Cathode used	spacing(cm)	Electrolyte used	electrolyte concentration (g/L)	initial pH	Temperature	initial con. mg/L	current density (mA/cm ²)	electrolysis time (minutes)	water matrix	Removal efficiency %
A	M	3	NaClO ₄	1.4	3	32	50	5.88	60	SW - single PFAS -PFOA	96.34
A	M	3	NaClO ₄	1.4	3	32	50	5.88	90	SW - single PFAS -PFOA	99.17
A	M	3	NaClO ₄	1.4	3	32	50	5.88	120	SW - single PFAS -PFOA	99.67
A	M	3	NaClO ₄	1.4	3	32	50	17.64	10	SW - single PFAS -PFOA	43.76
A	M	3	NaClO ₄	1.4	3	32	50	17.64	20	SW - single PFAS -PFOA	64.39
A	M	3	NaClO ₄	1.4	3	32	50	17.64	30	SW - single PFAS -PFOA	77.37
A	M	3	NaClO ₄	1.4	3	32	50	17.64	45	SW - single PFAS -PFOA	91.18
A	M	3	NaClO ₄	1.4	3	32	50	17.64	60	SW - single PFAS -PFOA	94.34
A	M	3	NaClO ₄	1.4	3	32	50	17.64	90	SW - single PFAS -PFOA	98.17
A	M	3	NaClO ₄	1.4	3	32	50	17.64	120	SW - single PFAS -PFOA	99.83
A	M	3	NaClO ₄	1.4	3	32	50	23.24	10	SW - single PFAS -PFOA	50.76
A	M	3	NaClO ₄	1.4	3	32	50	23.24	20	SW - single PFAS -PFOA	67.8
A	M	3	NaClO ₄	1.4	3	32	50	23.24	30	SW - single PFAS -PFOA	80.11
A	M	3	NaClO ₄	1.4	3	32	50	23.24	45	SW - single PFAS -PFOA	89.58
A	M	3	NaClO ₄	1.4	3	32	50	23.24	60	SW - single PFAS -PFOA	95.45
A	M	3	NaClO ₄	1.4	3	32	50	23.24	90	SW - single PFAS -PFOA	98.11
A	M	3	NaClO ₄	1.4	3	32	50	23.24	120	SW - single PFAS -PFOA	100
A	M	3	NaClO ₄	1.4	3	32	50	23.24	10	SW - single PFAS -PFOA	48.13
A	M	3	NaClO ₄	1.4	3	32	50	23.24	20	SW - single PFAS -PFOA	72.2
A	M	3	NaClO ₄	1.4	3	32	50	23.24	30	SW - single PFAS -PFOA	79.56
A	M	3	NaClO ₄	1.4	3	32	50	23.24	45	SW - single PFAS -PFOA	89.45
A	M	3	NaClO ₄	1.4	3	32	50	23.24	60	SW - single PFAS -PFOA	95.71
A	M	3	NaClO ₄	1.4	3	32	50	23.24	90	SW - single PFAS -PFOA	99.89
A	M	3	NaClO ₄	1.4	9	32	50	23.24	10	SW - single PFAS -PFOA	42.75

Anode used	Cathode used	spacing(cm)	Electrolyte used	electrolyte concentration (g/L)	initial pH	Temperature	initial con. mg/L	current density (mA/cm2)	electrolysis time (minutes)	water matrix	Removal efficiency %
A	M	3	NaClO4	1.4	9	32	50	23.24	20	SW - single PFAS -PFOA	68.57
A	M	3	NaClO4	1.4	9	32	50	23.24	30	SW - single PFAS -PFOA	77.47
A	M	3	NaClO4	1.4	9	32	50	23.24	45	SW - single PFAS -PFOA	89.34
A	M	3	NaClO4	1.4	9	32	50	23.24	60	SW - single PFAS -PFOA	95.71
A	M	3	NaClO4	1.4	12	32	50	23.24	90	SW - single PFAS -PFOA	99.78
A	M	3	NaClO4	1.4	12	32	50	23.24	10	SW - single PFAS -PFOA	40.88
A	M	3	NaClO4	1.4	12	32	50	23.24	20	SW - single PFAS -PFOA	63.52
A	M	3	NaClO4	1.4	12	32	50	23.24	30	SW - single PFAS -PFOA	74.51
A	M	3	NaClO4	1.4	12	32	50	23.24	45	SW - single PFAS -PFOA	86.59
A	M	3	NaClO4	1.4	12	32	50	23.24	60	SW - single PFAS -PFOA	92.31
A	M	3	NaClO4	1.4	12	32	50	23.24	90	SW - single PFAS -PFOA	98.57
A	M	3	NaClO4	1.4	3	32	20	23.24	10	SW - single PFAS -PFOA	31.63
A	M	3	NaClO4	1.4	3	32	20	23.24	20	SW - single PFAS -PFOA	57.77
A	M	3	NaClO4	1.4	3	32	20	23.24	30	SW - single PFAS -PFOA	67.99
A	M	3	NaClO4	1.4	3	32	20	23.24	45	SW - single PFAS -PFOA	81.44
A	M	3	NaClO4	1.4	3	32	20	23.24	60	SW - single PFAS -PFOA	88.45
A	M	3	NaClO4	1.4	3	32	20	23.24	90	SW - single PFAS -PFOA	99.81
A	M	3	NaClO4	1.4	3	32	20	23.24	120	SW - single PFAS -PFOA	100
A	M	3	NaClO4	1.4	3	32	30	23.24	10	SW - single PFAS -PFOA	38.83
A	M	3	NaClO4	1.4	3	32	30	23.24	20	SW - single PFAS -PFOA	63.07
A	M	3	NaClO4	1.4	3	32	30	23.24	30	SW - single PFAS -PFOA	70.83
A	M	3	NaClO4	1.4	3	32	30	23.24	45	SW - single PFAS -PFOA	87.69
A	M	3	NaClO4	1.4	3	32	30	23.24	60	SW - single PFAS -PFOA	90.91
A	M	3	NaClO4	1.4	3	32	30	23.24	90	SW - single PFAS -PFOA	100

Anode used	Cathode used	spacing(cm)	Electrolyte used	electrolyte concentration (g/L)	initial pH	Temperature	initial con. mg/L	current density (mA/cm2)	electrolysis time (minutes)	water matrix	Removal efficiency %
A	M	3	NaClO ₄	1.4	3	32	30	23.24	120	SW - single PFAS -PFOA	100
B	M	1	NaClO ₄	1.224	4.8	25	100	10	5	SW - single PFAS -PFOA	16.31
B	M	1	NaClO ₄	1.224	4.8	25	100	10	10	SW - single PFAS -PFOA	23.56
B	M	1	NaClO ₄	1.224	4.8	25	100	10	20	SW - single PFAS -PFOA	42.15
B	M	1	NaClO ₄	1.224	4.8	25	100	10	30	SW - single PFAS -PFOA	51.21
B	M	1	NaClO ₄	1.224	4.8	25	100	10	60	SW - single PFAS -PFOA	74.92
B	M	1	NaClO ₄	1.224	4.8	25	100	10	90	SW - single PFAS -PFOA	87.46
B	M	1	NaClO ₄	1.224	4.8	25	100	5	90	SW - single PFAS -PFOA	76.7
B	M	1	NaClO ₄	1.224	4.8	25	100	15	90	SW - single PFAS -PFOA	92.1
B	M	1	NaClO ₄	1.224	4.8	25	100	20	90	SW - single PFAS -PFOA	96.1
B	M	1	NaClO ₄	1.224	4.8	25	100	30	90	SW - single PFAS -PFOA	97
B	M	0.5	NaClO ₄	1.224	4.8	25	100	10	90	SW - single PFAS -PFOA	93.2
B	M	1.5	NaClO ₄	1.224	4.8	25	100	10	90	SW - single PFAS -PFOA	80.5
B	M	2	NaClO ₄	1.224	4.8	25	100	10	90	SW - single PFAS -PFOA	62.5
B	M	1	NaClO ₄	1.224	4.8	25	5	10	90	SW - single PFAS -PFOA	95.4
B	M	1	NaClO ₄	1.224	4.8	25	10	10	90	SW - single PFAS -PFOA	95.6
B	M	1	NaClO ₄	1.224	4.8	25	20	10	90	SW - single PFAS -PFOA	81.1
B	M	1	NaClO ₄	1.224	4.8	25	50	10	90	SW - single PFAS -PFOA	85.5
B	M	1	NaClO ₄	1.224	4.8	25	200	10	90	SW - single PFAS -PFOA	91.3
C	N	1.5	NaClO ₄	2.449	5	25	207	5	10	SW - single PFAS -PFOA	28.49
C	N	1.5	NaClO ₄	2.449	5	25	207	5	30	SW - single PFAS -PFOA	58.46
C	N	1.5	NaClO ₄	2.449	5	25	207	5	60	SW - single PFAS -PFOA	84.57
C	N	1.5	NaClO ₄	2.449	5	25	207	5	90	SW - single PFAS -PFOA	95.7
C	N	1.5	NaClO ₄	2.449	5	25	207	5	120	SW - single PFAS -PFOA	98.52

Anode used	Cathode used	spacing(cm)	Electrolyte used	electrolyte concentration (g/L)	initial pH	Temperature	initial con. mg/L	current density (mA/cm2)	electrolysis time (minutes)	water matrix	Removal efficiency %
C	N	1.5	NaClO4	2.449	5	25	207	5	150	SW - single PFAS -PFOA	99.7
C	N	1.5	NaClO4	2.449	5	25	207	5	180	SW - single PFAS -PFOA	99.85
D	N	1.5	NaClO4	2.449	5	25	207	5	10	SW - single PFAS -PFOA	20.62
D	N	1.5	NaClO4	2.449	5	25	207	5	30	SW - single PFAS -PFOA	49.41
D	N	1.5	NaClO4	2.449	5	25	207	5	60	SW - single PFAS -PFOA	75.37
D	N	1.5	NaClO4	2.449	5	25	207	5	90	SW - single PFAS -PFOA	90.06
D	N	1.5	NaClO4	2.449	5	25	207	5	120	SW - single PFAS -PFOA	95.7
D	N	1.5	NaClO4	2.449	5	25	207	5	150	SW - single PFAS -PFOA	97.63
D	N	1.5	NaClO4	2.449	5	25	207	5	180	SW - single PFAS -PFOA	99.41
E	N	1.5	NaClO4	2.449	5	25	207	5	10	SW - single PFAS -PFOA	13.95
E	N	1.5	NaClO4	2.449	5	25	207	5	30	SW - single PFAS -PFOA	36.65
E	N	1.5	NaClO4	2.449	5	25	207	5	60	SW - single PFAS -PFOA	64.09
E	N	1.5	NaClO4	2.449	5	25	207	5	90	SW - single PFAS -PFOA	81.01
E	N	1.5	NaClO4	2.449	5	25	207	5	120	SW - single PFAS -PFOA	89.61
E	N	1.5	NaClO4	2.449	5	25	207	5	150	SW - single PFAS -PFOA	95.99
E	N	1.5	NaClO4	2.449	5	25	207	5	180	SW - single PFAS -PFOA	97.63
C	N	1.5	NaClO4	2.449	5	25	103.5175	5	15	SW - single PFAS -PFOA	38.08
C	N	1.5	NaClO4	2.449	5	25	103.5175	5	30	SW - single PFAS -PFOA	64.14
C	N	1.5	NaClO4	2.449	5	25	103.5175	5	40	SW - single PFAS -PFOA	77.45
C	N	1.5	NaClO4	2.449	5	25	103.5175	5	60	SW - single PFAS -PFOA	89.65
C	N	1.5	NaCl	1.169	5	25	103.5175	5	15	SW - single PFAS -PFOA	19.22
C	N	1.5	NaCl	1.169	5	25	103.5175	5	30	SW - single PFAS -PFOA	41.4
C	N	1.5	NaCl	1.169	5	25	103.5175	5	40	SW - single PFAS -PFOA	51.2
C	N	1.5	NaCl	1.169	5	25	103.5175	5	60	SW - single PFAS -PFOA	67.1

Anode used	Cathode used	spacing(cm)	Electrolyte used	electrolyte concentration (g/L)	initial pH	Temperature	initial con. mg/L	current density (mA/cm2)	electrolysis time (minutes)	water matrix	Removal efficiency %
F	M	1	NaClO ₄	1.224	5	25	100	10	15	SW - single PFAS -PFOA	34.02
F	M	1	NaClO ₄	1.224	5	25	100	10	30	SW - single PFAS -PFOA	49.35
F	M	1	NaClO ₄	1.224	5	25	100	10	45	SW - single PFAS -PFOA	66.19
F	M	1	NaClO ₄	1.224	5	25	100	10	60	SW - single PFAS -PFOA	81.75
F	M	1	NaClO ₄	1.224	5	25	100	10	90	SW - single PFAS -PFOA	90.8
G	M	1	NaClO ₄	1.224	5	25	100	10	15	SW - single PFAS -PFOA	36.81
G	M	1	NaClO ₄	1.224	5	25	100	10	30	SW - single PFAS -PFOA	55.62
G	M	1	NaClO ₄	1.224	5	25	100	10	45	SW - single PFAS -PFOA	71.18
G	M	1	NaClO ₄	1.224	5	25	100	10	60	SW - single PFAS -PFOA	82.21
G	M	1	NaClO ₄	1.224	5	25	100	10	90	SW - single PFAS -PFOA	91.73
H	M	1	NaClO ₄	1.224	5	25	100	10	15	SW - single PFAS -PFOA	5.92
H	M	1	NaClO ₄	1.224	5	25	100	10	30	SW - single PFAS -PFOA	10.8
H	M	1	NaClO ₄	1.224	5	25	100	10	45	SW - single PFAS -PFOA	16.14
H	M	1	NaClO ₄	1.224	5	25	100	10	60	SW - single PFAS -PFOA	23.8
H	M	1	NaClO ₄	1.224	5	25	100	10	90	SW - single PFAS -PFOA	31.47
F	M	1	NaClO ₄	1.224	5	25	100	5	15	SW - single PFAS -PFOA	24.47
F	M	1	NaClO ₄	1.224	5	25	100	5	30	SW - single PFAS -PFOA	38.33
F	M	1	NaClO ₄	1.224	5	25	100	5	45	SW - single PFAS -PFOA	51.34
F	M	1	NaClO ₄	1.224	5	25	100	5	60	SW - single PFAS -PFOA	63.22
F	M	1	NaClO ₄	1.224	5	25	100	5	90	SW - single PFAS -PFOA	77.23
F	M	1	NaClO ₄	1.224	5	25	100	20	15	SW - single PFAS -PFOA	36.63
F	M	1	NaClO ₄	1.224	5	25	100	20	30	SW - single PFAS -PFOA	58.98
F	M	1	NaClO ₄	1.224	5	25	100	20	45	SW - single PFAS -PFOA	73.97
F	M	1	NaClO ₄	1.224	5	25	100	20	60	SW - single PFAS -PFOA	90.24

Anode used	Cathode used	spacing(cm)	Electrolyte used	electrolyte concentration (g/L)	initial pH	Temperature	initial con. mg/L	current density (mA/cm ²)	electrolysis time (minutes)	water matrix	Removal efficiency %
F	M	1	NaClO ₄	1.224	5	25	100	20	90	SW - single PFAS -PFOA	97.74
F	M	1	NaClO ₄	1.224	5	25	100	30	15	SW - single PFAS -PFOA	42.15
F	M	1	NaClO ₄	1.224	5	25	100	30	30	SW - single PFAS -PFOA	75.53
F	M	1	NaClO ₄	1.224	5	25	100	30	45	SW - single PFAS -PFOA	85.71
F	M	1	NaClO ₄	1.224	5	25	100	30	60	SW - single PFAS -PFOA	95.9
F	M	1	NaClO ₄	1.224	5	25	100	30	90	SW - single PFAS -PFOA	99.15
F	M	1	NaClO ₄	1.224	5	25	100	40	15	SW - single PFAS -PFOA	61.39
F	M	1	NaClO ₄	1.224	5	25	100	40	30	SW - single PFAS -PFOA	86.14
F	M	1	NaClO ₄	1.224	5	25	100	40	45	SW - single PFAS -PFOA	94.06
F	M	1	NaClO ₄	1.224	5	25	100	40	60	SW - single PFAS -PFOA	98.59
F	M	1	NaClO ₄	1.224	5	25	100	40	90	SW - single PFAS -PFOA	99.86
F	M	1	NaClO ₄	1.224	3	25	100	10	15	SW - single PFAS -PFOA	29.9
F	M	1	NaClO ₄	1.224	3	25	100	10	30	SW - single PFAS -PFOA	41.72
F	M	1	NaClO ₄	1.224	3	25	100	10	45	SW - single PFAS -PFOA	59.67
F	M	1	NaClO ₄	1.224	3	25	100	10	60	SW - single PFAS -PFOA	66.76
F	M	1	NaClO ₄	1.224	3	25	100	10	90	SW - single PFAS -PFOA	81.64
F	M	1	NaClO ₄	1.224	7	25	100	10	15	SW - single PFAS -PFOA	28.23
F	M	1	NaClO ₄	1.224	7	25	100	10	30	SW - single PFAS -PFOA	44.37
F	M	1	NaClO ₄	1.224	7	25	100	10	45	SW - single PFAS -PFOA	58.55
F	M	1	NaClO ₄	1.224	7	25	100	10	60	SW - single PFAS -PFOA	70.79
F	M	1	NaClO ₄	1.224	7	25	100	10	90	SW - single PFAS -PFOA	82.48
F	M	1	NaClO ₄	1.224	9	25	100	10	15	SW - single PFAS -PFOA	23.92
F	M	1	NaClO ₄	1.224	9	25	100	10	30	SW - single PFAS -PFOA	42.84
F	M	1	NaClO ₄	1.224	9	25	100	10	45	SW - single PFAS -PFOA	49.93

Anode used	Cathode used	spacing(cm)	Electrolyte used	electrolyte concentration (g/L)	initial pH	Temperature	initial con. mg/L	current density (mA/cm2)	electrolysis time (minutes)	water matrix	Removal efficiency %
F	M	1	NaClO ₄	1.224	9	25	100	10	60	SW - single PFAS -PFOA	60.92
F	M	1	NaClO ₄	1.224	9	25	100	10	90	SW - single PFAS -PFOA	74.69
F	M	1	NaClO ₄	1.224	11	25	100	10	15	SW - single PFAS -PFOA	14.46
F	M	1	NaClO ₄	1.224	11	25	100	10	30	SW - single PFAS -PFOA	33.1
F	M	1	NaClO ₄	1.224	11	25	100	10	45	SW - single PFAS -PFOA	45.06
F	M	1	NaClO ₄	1.224	11	25	100	10	60	SW - single PFAS -PFOA	53.27
F	M	1	NaClO ₄	1.224	11	25	100	10	90	SW - single PFAS -PFOA	64.26
F	M	0.5	NaClO ₄	1.224	5	25	100	10	15	SW - single PFAS -PFOA	55.73
F	M	0.5	NaClO ₄	1.224	5	25	100	10	30	SW - single PFAS -PFOA	74.86
F	M	0.5	NaClO ₄	1.224	5	25	100	10	45	SW - single PFAS -PFOA	84.5
F	M	0.5	NaClO ₄	1.224	5	25	100	10	60	SW - single PFAS -PFOA	89.39
F	M	0.5	NaClO ₄	1.224	5	25	100	10	90	SW - single PFAS -PFOA	96.09
F	M	1.5	NaClO ₄	1.224	5	25	100	10	15	SW - single PFAS -PFOA	17.32
F	M	1.5	NaClO ₄	1.224	5	25	100	10	30	SW - single PFAS -PFOA	38.13
F	M	1.5	NaClO ₄	1.224	5	25	100	10	45	SW - single PFAS -PFOA	51.54
F	M	1.5	NaClO ₄	1.224	5	25	100	10	60	SW - single PFAS -PFOA	63.83
F	M	1.5	NaClO ₄	1.224	5	25	100	10	90	SW - single PFAS -PFOA	77.93
F	M	2	NaClO ₄	1.224	5	25	100	10	15	SW - single PFAS -PFOA	12.43
F	M	2	NaClO ₄	1.224	5	25	100	10	30	SW - single PFAS -PFOA	24.3
F	M	2	NaClO ₄	1.224	5	25	100	10	45	SW - single PFAS -PFOA	37.43
F	M	2	NaClO ₄	1.224	5	25	100	10	60	SW - single PFAS -PFOA	48.88
F	M	2	NaClO ₄	1.224	5	25	100	10	90	SW - single PFAS -PFOA	62.99
F	M	1	NaClO ₄	1.224	5	25	5	10	15	SW - single PFAS -PFOA	35
F	M	1	NaClO ₄	1.224	5	25	5	10	30	SW - single PFAS -PFOA	60.45

Anode used	Cathode used	spacing(cm)	Electrolyte used	electrolyte concentration (g/L)	initial pH	Temperature	initial con. mg/L	current density (mA/cm2)	electrolysis time (minutes)	water matrix	Removal efficiency %
F	M	1	NaClO4	1.224	5	25	5	10	45	SW - single PFAS -PFOA	73.18
F	M	1	NaClO4	1.224	5	25	5	10	60	SW - single PFAS -PFOA	87.27
F	M	1	NaClO4	1.224	5	25	5	10	90	SW - single PFAS -PFOA	94.09
F	M	1	NaClO4	1.224	5	25	10	10	15	SW - single PFAS -PFOA	31.82
F	M	1	NaClO4	1.224	5	25	10	10	30	SW - single PFAS -PFOA	54.32
F	M	1	NaClO4	1.224	5	25	10	10	45	SW - single PFAS -PFOA	72.27
F	M	1	NaClO4	1.224	5	25	10	10	60	SW - single PFAS -PFOA	84.77
F	M	1	NaClO4	1.224	5	25	10	10	90	SW - single PFAS -PFOA	91.36
F	M	1	NaClO4	1.224	5	25	20	10	15	SW - single PFAS -PFOA	28.52
F	M	1	NaClO4	1.224	5	25	20	10	30	SW - single PFAS -PFOA	49.32
F	M	1	NaClO4	1.224	5	25	20	10	45	SW - single PFAS -PFOA	71.82
F	M	1	NaClO4	1.224	5	25	20	10	60	SW - single PFAS -PFOA	83.98
F	M	1	NaClO4	1.224	5	25	20	10	90	SW - single PFAS -PFOA	91.48
F	M	1	NaClO4	1.224	5	25	50	10	15	SW - single PFAS -PFOA	22.64
F	M	1	NaClO4	1.224	5	25	50	10	30	SW - single PFAS -PFOA	47.67
F	M	1	NaClO4	1.224	5	25	50	10	45	SW - single PFAS -PFOA	60.18
F	M	1	NaClO4	1.224	5	25	50	10	60	SW - single PFAS -PFOA	78.38
F	M	1	NaClO4	1.224	5	25	50	10	90	SW - single PFAS -PFOA	86.35
F	M	1	NaClO4	1.224	5	25	200	10	15	SW - single PFAS -PFOA	34.58
F	M	1	NaClO4	1.224	5	25	200	10	30	SW - single PFAS -PFOA	53.07
F	M	1	NaClO4	1.224	5	25	200	10	45	SW - single PFAS -PFOA	64.45
F	M	1	NaClO4	1.224	5	25	200	10	60	SW - single PFAS -PFOA	74.4
F	M	1	NaClO4	1.224	5	25	200	10	90	SW - single PFAS -PFOA	85.21
F	M	1	NaClO4	1.224	5	25	500	10	15	SW - single PFAS -PFOA	27.65

Anode used	Cathode used	spacing(cm)	Electrolyte used	electrolyte concentration (g/L)	initial pH	Temperature	initial con. mg/L	current density (mA/cm2)	electrolysis time (minutes)	water matrix	Removal efficiency %
F	M	1	NaClO ₄	1.224	5	25	500	10	30	SW - single PFAS -PFOA	50.63
F	M	1	NaClO ₄	1.224	5	25	500	10	45	SW - single PFAS -PFOA	59.61
F	M	1	NaClO ₄	1.224	5	25	500	10	60	SW - single PFAS -PFOA	72.35
F	M	1	NaClO ₄	1.224	5	25	500	10	90	SW - single PFAS -PFOA	84.98
I	N	1	Na ₂ SO ₄	7.102	7	25	207	20	30	SW - single PFAS -PFOA	25.32
I	N	1	Na ₂ SO ₄	7.102	7	25	207	20	60	SW - single PFAS -PFOA	41.69
I	N	1	Na ₂ SO ₄	7.102	7	25	207	20	90	SW - single PFAS -PFOA	55.12
I	N	1	Na ₂ SO ₄	7.102	7	25	207	20	120	SW - single PFAS -PFOA	59.08
I	N	1	Na ₂ SO ₄	7.102	7	25	207	20	150	SW - single PFAS -PFOA	64.07
I	N	1	Na ₂ SO ₄	7.102	7	25	207	20	180	SW - single PFAS -PFOA	67.26
J	N	1	Na ₂ SO ₄	7.102	7	25	207	20	30	SW - single PFAS -PFOA	30.05
J	N	1	Na ₂ SO ₄	7.102	7	25	207	20	60	SW - single PFAS -PFOA	57.29
J	N	1	Na ₂ SO ₄	7.102	7	25	207	20	90	SW - single PFAS -PFOA	73.91
J	N	1	Na ₂ SO ₄	7.102	7	25	207	20	120	SW - single PFAS -PFOA	93.48
J	N	1	Na ₂ SO ₄	7.102	7	25	207	20	150	SW - single PFAS -PFOA	98.98
J	N	1	Na ₂ SO ₄	7.102	7	25	207	20	180	SW - single PFAS -PFOA	99.62
A	A	1	Na ₂ SO ₄	0.4	7	25	0.2	2.5	10	SW - single PFAS -PFOA	24.27
A	A	1	Na ₂ SO ₄	0.4	7	25	0.2	2.5	20	SW - single PFAS -PFOA	27.95
A	A	1	Na ₂ SO ₄	0.4	7	25	0.2	2.5	30	SW - single PFAS -PFOA	30.94
A	A	1	Na ₂ SO ₄	0.4	7	25	0.2	2.5	40	SW - single PFAS -PFOA	36.5
A	A	1	Na ₂ SO ₄	0.4	7	25	0.2	2.5	50	SW - single PFAS -PFOA	42.65
A	A	1	Na ₂ SO ₄	0.4	7	25	0.2	2.5	60	SW - single PFAS -PFOA	51.62
A	A	1	NaCl	0.4	7	25	0.2	2.5	10	SW - single PFAS -PFOA	22.31
A	A	1	NaCl	0.4	7	25	0.2	2.5	20	SW - single PFAS -PFOA	24.19

Anode used	Cathode used	spacing(cm)	Electrolyte used	electrolyte concentration (g/L)	initial pH	Temperature	initial con. mg/L	current density (mA/cm2)	electrolysis time (minutes)	water matrix	Removal efficiency %
A	A	1	NaCl	0.4	7	25	0.2	2.5	30	SW - single PFAS -PFOA	27.26
A	A	1	NaCl	0.4	7	25	0.2	2.5	40	SW - single PFAS -PFOA	30.94
A	A	1	NaCl	0.4	7	25	0.2	2.5	50	SW - single PFAS -PFOA	32.99
A	A	1	NaCl	0.4	7	25	0.2	2.5	60	SW - single PFAS -PFOA	35.56
A	A	1	NO	0	7	25	0.2	2.5	10	SW - single PFAS -PFOA	17.78
A	A	1	NO	0	7	25	0.2	2.5	20	SW - single PFAS -PFOA	21.28
A	A	1	NO	0	7	25	0.2	2.5	30	SW - single PFAS -PFOA	24.02
A	A	1	NO	0	7	25	0.2	2.5	40	SW - single PFAS -PFOA	26.84
A	A	1	NO	0	7	25	0.2	2.5	50	SW - single PFAS -PFOA	30.43
A	A	1	NO	0	7	25	0.2	2.5	60	SW - single PFAS -PFOA	31.88
A	A	1	Na2SO4	0.4	5	25	10	25	10	SW - single PFAS -PFOA	32.18
A	A	1	Na2SO4	0.4	5	25	10	25	20	SW - single PFAS -PFOA	44.41
A	A	1	Na2SO4	0.4	5	25	10	25	30	SW - single PFAS -PFOA	69.03
A	A	1	Na2SO4	0.4	5	25	10	25	40	SW - single PFAS -PFOA	80.97
A	A	1	Na2SO4	0.4	5	25	10	25	50	SW - single PFAS -PFOA	84.74
A	A	1	Na2SO4	0.4	5	25	10	25	60	SW - single PFAS -PFOA	88.22
A	A	1	Na2SO4	0.4	7	25	0.2	6	10	SW - single PFAS -PFOA	36.4
A	A	1	Na2SO4	0.4	7	25	0.2	6	20	SW - single PFAS -PFOA	38.87
A	A	1	Na2SO4	0.4	7	25	0.2	6	30	SW - single PFAS -PFOA	42.17
A	A	1	Na2SO4	0.4	7	25	0.2	6	40	SW - single PFAS -PFOA	44.37
A	A	1	Na2SO4	0.4	7	25	0.2	6	50	SW - single PFAS -PFOA	49.73
A	A	1	Na2SO4	0.4	7	25	0.2	6	60	SW - single PFAS -PFOA	53.43
A	A	1	Na2SO4	0.4	7	25	0.2	12	10	SW - single PFAS -PFOA	46.29
A	A	1	Na2SO4	0.4	7	25	0.2	12	20	SW - single PFAS -PFOA	50

Anode used	Cathode used	spacing(cm)	Electrolyte used	electrolyte concentration (g/L)	initial pH	Temperature	initial con. mg/L	current density (mA/cm2)	electrolysis time (minutes)	water matrix	Removal efficiency %
A	A	1	Na2SO4	0.4	7	25	0.2	12	30	SW - single PFAS -PFOA	54.81
A	A	1	Na2SO4	0.4	7	25	0.2	12	40	SW - single PFAS -PFOA	63.32
A	A	1	Na2SO4	0.4	7	25	0.2	12	50	SW - single PFAS -PFOA	67.72
A	A	1	Na2SO4	0.4	7	25	0.2	12	60	SW - single PFAS -PFOA	74.59
A	A	1	Na2SO4	0.4	7	25	0.2	25	10	SW - single PFAS -PFOA	49.59
A	A	1	Na2SO4	0.4	7	25	0.2	25	20	SW - single PFAS -PFOA	55.36
A	A	1	Na2SO4	0.4	7	25	0.2	25	30	SW - single PFAS -PFOA	61.54
A	A	1	Na2SO4	0.4	7	25	0.2	25	40	SW - single PFAS -PFOA	71.7
A	A	1	Na2SO4	0.4	7	25	0.2	25	50	SW - single PFAS -PFOA	80.63
A	A	1	Na2SO4	0.4	7	25	0.2	25	60	SW - single PFAS -PFOA	90.66
A	A	1	Na2SO4	0.4	3	25	0.2	25	10	SW - single PFAS -PFOA	50.52
A	A	1	Na2SO4	0.4	3	25	0.2	25	20	SW - single PFAS -PFOA	54.01
A	A	1	Na2SO4	0.4	3	25	0.2	25	30	SW - single PFAS -PFOA	61.24
A	A	1	Na2SO4	0.4	3	25	0.2	25	40	SW - single PFAS -PFOA	70.03
A	A	1	Na2SO4	0.4	3	25	0.2	25	50	SW - single PFAS -PFOA	81.78
A	A	1	Na2SO4	0.4	3	25	0.2	25	60	SW - single PFAS -PFOA	90.96
A	A	1	Na2SO4	0.4	5	25	0.2	25	10	SW - single PFAS -PFOA	54.65
A	A	1	Na2SO4	0.4	5	25	0.2	25	20	SW - single PFAS -PFOA	60.85
A	A	1	Na2SO4	0.4	5	25	0.2	25	30	SW - single PFAS -PFOA	68.22
A	A	1	Na2SO4	0.4	5	25	0.2	25	40	SW - single PFAS -PFOA	74.94
A	A	1	Na2SO4	0.4	5	25	0.2	25	50	SW - single PFAS -PFOA	86.56
A	A	1	Na2SO4	0.4	5	25	0.2	25	60	SW - single PFAS -PFOA	94.44
A	A	1	Na2SO4	0.4	7	25	0.2	25	10	SW - single PFAS -PFOA	49.74
A	A	1	Na2SO4	0.4	7	25	0.2	25	20	SW - single PFAS -PFOA	55.04

Anode used	Cathode used	spacing(cm)	Electrolyte used	electrolyte concentration (g/L)	initial pH	Temperature	initial con. mg/L	current density (mA/cm ²)	electrolysis time (minutes)	water matrix	Removal efficiency %
A	A	1	Na ₂ SO ₄	0.4	7	25	0.2	25	30	SW - single PFAS -PFOA	61.89
A	A	1	Na ₂ SO ₄	0.4	7	25	0.2	25	40	SW - single PFAS -PFOA	71.58
A	A	1	Na ₂ SO ₄	0.4	7	25	0.2	25	50	SW - single PFAS -PFOA	80.62
A	A	1	Na ₂ SO ₄	0.4	7	25	0.2	25	60	SW - single PFAS -PFOA	90.44
A	A	1	Na ₂ SO ₄	0.4	9	25	0.2	25	10	SW - single PFAS -PFOA	12.79
A	A	1	Na ₂ SO ₄	0.4	9	25	0.2	25	20	SW - single PFAS -PFOA	16.67
A	A	1	Na ₂ SO ₄	0.4	9	25	0.2	25	30	SW - single PFAS -PFOA	27.13
A	A	1	Na ₂ SO ₄	0.4	9	25	0.2	25	40	SW - single PFAS -PFOA	32.56
A	A	1	Na ₂ SO ₄	0.4	9	25	0.2	25	50	SW - single PFAS -PFOA	39.53
A	A	1	Na ₂ SO ₄	0.4	9	25	0.2	25	60	SW - single PFAS -PFOA	47.67
A	A	1	Na ₂ SO ₄	0.4	11	25	0.2	25	10	SW - single PFAS -PFOA	7.24
A	A	1	Na ₂ SO ₄	0.4	11	25	0.2	25	20	SW - single PFAS -PFOA	14.47
A	A	1	Na ₂ SO ₄	0.4	11	25	0.2	25	30	SW - single PFAS -PFOA	20.67
A	A	1	Na ₂ SO ₄	0.4	11	25	0.2	25	40	SW - single PFAS -PFOA	25.58
A	A	1	Na ₂ SO ₄	0.4	11	25	0.2	25	50	SW - single PFAS -PFOA	31.14
A	A	1	Na ₂ SO ₄	0.4	11	25	0.2	25	60	SW - single PFAS -PFOA	40.31
K	K	1	Na ₂ SO ₄	7.102	4.6	25	50	100	60	SW - single PFAS -PFOA	0.76
K	K	1	Na ₂ SO ₄	7.102	4.6	25	50	100	120	SW - single PFAS -PFOA	0.76
K	K	1	Na ₂ SO ₄	7.102	4.6	25	50	100	180	SW - single PFAS -PFOA	1.78
K	K	1	Na ₂ SO ₄	7.102	4.6	25	50	100	240	SW - single PFAS -PFOA	1.91
K	K	1	Na ₂ SO ₄	7.102	4.6	25	50	100	300	SW - single PFAS -PFOA	2.93
K	K	1	Na ₂ SO ₄	7.102	4.6	25	50	100	360	SW - single PFAS -PFOA	1.91
K	K	1	Na ₂ SO ₄	7.102	4.6	25	50	100	420	SW - single PFAS -PFOA	3.31
K	K	1	Na ₂ SO ₄	7.102	4.6	25	50	100	480	SW - single PFAS -PFOA	3.06

Anode used	Cathode used	spacing(cm)	Electrolyte used	electrolyte concentration (g/L)	initial pH	Temperature	initial con. mg/L	current density (mA/cm ²)	electrolysis time (minutes)	water matrix	Removal efficiency %
K	K	1	NaN ₃	3.2505	4.6	25	50	100	60	SW - single PFAS -PFOA	34.52
K	K	1	NaN ₃	3.2505	4.6	25	50	100	120	SW - single PFAS -PFOA	49.81
K	K	1	NaN ₃	3.2505	4.6	25	50	100	180	SW - single PFAS -PFOA	54.9
K	K	1	NaN ₃	3.2505	4.6	25	50	100	240	SW - single PFAS -PFOA	59.49
K	K	1	NaN ₃	3.2505	4.6	25	50	100	300	SW - single PFAS -PFOA	61.27
K	K	1	NaN ₃	3.2505	4.6	25	50	100	360	SW - single PFAS -PFOA	63.82
K	K	1	NaN ₃	3.2505	4.6	25	50	100	420	SW - single PFAS -PFOA	63.82
K	K	1	NaN ₃	3.2505	4.6	25	50	100	480	SW - single PFAS -PFOA	64.2
K	K	1	NaCl	2.922	4.6	25	50	100	60	SW - single PFAS -PFOA	27.13
K	K	1	NaCl	2.922	4.6	25	50	100	120	SW - single PFAS -PFOA	39.75
K	K	1	NaCl	2.922	4.6	25	50	100	180	SW - single PFAS -PFOA	51.72
K	K	1	NaCl	2.922	4.6	25	50	100	240	SW - single PFAS -PFOA	62.93
K	K	1	NaCl	2.922	4.6	25	50	100	300	SW - single PFAS -PFOA	73.25
K	K	1	NaCl	2.922	4.6	25	50	100	360	SW - single PFAS -PFOA	80.13
K	K	1	NaCl	2.922	4.6	25	50	100	420	SW - single PFAS -PFOA	83.31
K	K	1	NaCl	2.922	4.6	25	50	100	480	SW - single PFAS -PFOA	85.73
K	K	1	NaSCN	4.0535	4.6	25	50	100	60	SW - single PFAS -PFOA	25.73
K	K	1	NaSCN	4.0535	4.6	25	50	100	120	SW - single PFAS -PFOA	42.17
K	K	1	NaSCN	4.0535	4.6	25	50	100	180	SW - single PFAS -PFOA	58.6
K	K	1	NaSCN	4.0535	4.6	25	50	100	240	SW - single PFAS -PFOA	72.99
K	K	1	NaSCN	4.0535	4.6	25	50	100	300	SW - single PFAS -PFOA	81.15
K	K	1	NaSCN	4.0535	4.6	25	50	100	360	SW - single PFAS -PFOA	85.1
K	K	1	NaSCN	4.0535	4.6	25	50	100	420	SW - single PFAS -PFOA	86.88
K	K	1	NaSCN	4.0535	4.6	25	50	100	480	SW - single PFAS -PFOA	87.01

Anode used	Cathode used	spacing(cm)	Electrolyte used	electrolyte concentration (g/L)	initial pH	Temperature	initial con. mg/L	current density (mA/cm ²)	electrolysis time (minutes)	water matrix	Removal efficiency %
K	K	1	NO	0	4.6	25	50	100	60	SW - single PFAS -PFOA	0.65
K	K	1	NO	0	4.6	25	50	100	120	SW - single PFAS -PFOA	1.57
K	K	1	NO	0	4.6	25	50	100	180	SW - single PFAS -PFOA	2.35
K	K	1	NO	0	4.6	25	50	100	300	SW - single PFAS -PFOA	3.92
K	K	1	NO	0	4.6	25	50	100	360	SW - single PFAS -PFOA	3.92
K	K	1	NO	0	4.6	25	50	100	420	SW - single PFAS -PFOA	3.79
K	K	1	NO	0	4.6	25	50	100	480	SW - single PFAS -PFOA	4.7
K	K	1	NaCl	0.2922	4.6	25	50	100	60	SW - single PFAS -PFOA	2.61
K	K	1	NaCl	0.2922	4.6	25	50	100	120	SW - single PFAS -PFOA	8.62
K	K	1	NaCl	0.2922	4.6	25	50	100	180	SW - single PFAS -PFOA	11.62
K	K	1	NaCl	0.2922	4.6	25	50	100	300	SW - single PFAS -PFOA	13.19
K	K	1	NaCl	0.2922	4.6	25	50	100	360	SW - single PFAS -PFOA	14.88
K	K	1	NaCl	0.2922	4.6	25	50	100	420	SW - single PFAS -PFOA	16.71
K	K	1	NaCl	0.2922	4.6	25	50	100	480	SW - single PFAS -PFOA	17.89
K	K	1	NaCl	0.5844	4.6	25	50	100	60	SW - single PFAS -PFOA	5.35
K	K	1	NaCl	0.5844	4.6	25	50	100	120	SW - single PFAS -PFOA	11.49
K	K	1	NaCl	0.5844	4.6	25	50	100	180	SW - single PFAS -PFOA	16.84
K	K	1	NaCl	0.5844	4.6	25	50	100	300	SW - single PFAS -PFOA	26.24
K	K	1	NaCl	0.5844	4.6	25	50	100	360	SW - single PFAS -PFOA	27.28
K	K	1	NaCl	0.5844	4.6	25	50	100	420	SW - single PFAS -PFOA	27.81
K	K	1	NaCl	0.5844	4.6	25	50	100	480	SW - single PFAS -PFOA	28.98
K	K	1	NaCl	1.461	4.6	25	50	100	60	SW - single PFAS -PFOA	11.62
K	K	1	NaCl	1.461	4.6	25	50	100	120	SW - single PFAS -PFOA	17.75
K	K	1	NaCl	1.461	4.6	25	50	100	180	SW - single PFAS -PFOA	25.59

Anode used	Cathode used	spacing(cm)	Electrolyte used	electrolyte concentration (g/L)	initial pH	Temperature	initial con. mg/L	current density (mA/cm2)	electrolysis time (minutes)	water matrix	Removal efficiency %
K	K	1	NaCl	1.461	4.6	25	50	100	300	SW - single PFAS -PFOA	41.91
K	K	1	NaCl	1.461	4.6	25	50	100	360	SW - single PFAS -PFOA	44.78
K	K	1	NaCl	1.461	4.6	25	50	100	420	SW - single PFAS -PFOA	50.39
K	K	1	NaCl	1.461	4.6	25	50	100	480	SW - single PFAS -PFOA	51.31
K	K	1	NaCl	2.922	4.6	25	50	0	60	SW - single PFAS -PFOA	0
K	K	1	NaCl	2.922	4.6	25	50	0	120	SW - single PFAS -PFOA	0.13
K	K	1	NaCl	2.922	4.6	25	50	0	180	SW - single PFAS -PFOA	0.38
K	K	1	NaCl	2.922	4.6	25	50	0	300	SW - single PFAS -PFOA	0.51
K	K	1	NaCl	2.922	4.6	25	50	0	360	SW - single PFAS -PFOA	0.63
K	K	1	NaCl	2.922	4.6	25	50	0	420	SW - single PFAS -PFOA	1.01
K	K	1	NaCl	2.922	4.6	25	50	0	480	SW - single PFAS -PFOA	1.26
K	K	1	NaCl	2.922	4.6	25	50	25	60	SW - single PFAS -PFOA	9.36
K	K	1	NaCl	2.922	4.6	25	50	25	120	SW - single PFAS -PFOA	18.46
K	K	1	NaCl	2.922	4.6	25	50	25	180	SW - single PFAS -PFOA	24.15
K	K	1	NaCl	2.922	4.6	25	50	25	300	SW - single PFAS -PFOA	28.82
K	K	1	NaCl	2.922	4.6	25	50	25	360	SW - single PFAS -PFOA	31.98
K	K	1	NaCl	2.922	4.6	25	50	25	420	SW - single PFAS -PFOA	35.9
K	K	1	NaCl	2.922	4.6	25	50	25	480	SW - single PFAS -PFOA	36.79
K	K	1	NaCl	2.922	4.6	25	50	50	60	SW - single PFAS -PFOA	15.3
K	K	1	NaCl	2.922	4.6	25	50	50	120	SW - single PFAS -PFOA	28.82
K	K	1	NaCl	2.922	4.6	25	50	50	180	SW - single PFAS -PFOA	36.92
K	K	1	NaCl	2.922	4.6	25	50	50	300	SW - single PFAS -PFOA	51.96
K	K	1	NaCl	2.922	4.6	25	50	50	360	SW - single PFAS -PFOA	59.8
K	K	1	NaCl	2.922	4.6	25	50	50	420	SW - single PFAS -PFOA	67.89

Anode used	Cathode used	spacing(cm)	Electrolyte used	electrolyte concentration (g/L)	initial pH	Temperature	initial con. mg/L	current density (mA/cm ²)	electrolysis time (minutes)	water matrix	Removal efficiency %
K	K	1	NaCl	2.922	4.6	25	50	50	480	SW - single PFAS -PFOA	69.79
K	K	1	NaCl	2.922	4.6	25	50	150	60	SW - single PFAS -PFOA	41.34
K	K	1	NaCl	2.922	4.6	25	50	150	120	SW - single PFAS -PFOA	57.02
K	K	1	NaCl	2.922	4.6	25	50	150	180	SW - single PFAS -PFOA	70.54
K	K	1	NaCl	2.922	4.6	25	50	150	300	SW - single PFAS -PFOA	81.67
K	K	1	NaCl	2.922	4.6	25	50	150	360	SW - single PFAS -PFOA	84.96
K	K	1	NaCl	2.922	4.6	25	50	150	420	SW - single PFAS -PFOA	87.99
K	K	1	NaCl	2.922	4.6	25	50	150	480	SW - single PFAS -PFOA	89
L	K	1	NaCl	2.922	4.6	25	50	100	60	SW - single PFAS -PFOA	0.85
L	K	1	NaCl	2.922	4.6	25	50	100	120	SW - single PFAS -PFOA	0
L	K	1	NaCl	2.922	4.6	25	50	100	180	SW - single PFAS -PFOA	1.71
L	K	1	NaCl	2.922	4.6	25	50	100	300	SW - single PFAS -PFOA	0.14
L	K	1	NaCl	2.922	4.6	25	50	100	360	SW - single PFAS -PFOA	0
L	K	1	NaCl	2.922	4.6	25	50	100	420	SW - single PFAS -PFOA	1.56
L	K	1	NaCl	2.922	4.6	25	50	100	480	SW - single PFAS -PFOA	2.99
K	K	1	NaCl	2.922	7.47	25	50	100	60	River water	24.17
K	K	1	NaCl	2.922	7.47	25	50	100	120	River water	39.58
K	K	1	NaCl	2.922	7.47	25	50	100	180	River water	54.25
K	K	1	NaCl	2.922	7.47	25	50	100	240	River water	63.01
K	K	1	NaCl	2.922	7.47	25	50	100	300	River water	71.64
K	K	1	NaCl	2.922	7.47	25	50	100	360	River water	78.91
K	K	1	NaCl	2.922	7.47	25	50	100	420	River water	81.5
K	K	1	NaCl	2.922	7.47	25	50	100	480	River water	83.97
K	K	1	NaCl	2.922	6.95	25	50	100	60	Tap water	26.88

Anode used	Cathode used	spacing(cm)	Electrolyte used	electrolyte concentration (g/L)	initial pH	Temperature	initial con. mg/L	current density (mA/cm2)	electrolysis time (minutes)	water matrix	Removal efficiency %
K	K	1	NaCl	2.922	6.95	25	50	100	120	Tap water	41.18
K	K	1	NaCl	2.922	6.95	25	50	100	180	Tap water	55.36
K	K	1	NaCl	2.922	6.95	25	50	100	240	Tap water	65.35
K	K	1	NaCl	2.922	6.95	25	50	100	300	Tap water	74.35
K	K	1	NaCl	2.922	6.95	25	50	100	360	Tap water	82
K	K	1	NaCl	2.922	6.95	25	50	100	420	Tap water	84.09
K	K	1	NaCl	2.922	6.95	25	50	100	480	Tap water	86.31
K	K	1	NaCl	2.922	7.27	25	50	100	60	Secondary clarifier effluent	28.73
K	K	1	NaCl	2.922	7.27	25	50	100	120	Secondary clarifier effluent	42.54
K	K	1	NaCl	2.922	7.27	25	50	100	180	Secondary clarifier effluent	56.47
K	K	1	NaCl	2.922	7.27	25	50	100	240	Secondary clarifier effluent	67.32
K	K	1	NaCl	2.922	7.27	25	50	100	300	Secondary clarifier effluent	77.93
K	K	1	NaCl	2.922	7.27	25	50	100	360	Secondary clarifier effluent	84.46
K	K	1	NaCl	2.922	7.27	25	50	100	420	Secondary clarifier effluent	86.68
K	K	1	NaCl	2.922	7.27	25	50	100	480	Secondary clarifier effluent	89.52
K	K	1	NaCl	2.922	7.82	25	50	100	60	SW as a moderately hard FW	32.43
K	K	1	NaCl	2.922	7.82	25	50	100	120	SW as a moderately hard FW	47.23
K	K	1	NaCl	2.922	7.82	25	50	100	180	SW as a moderately hard FW	59.56
K	K	1	NaCl	2.922	7.82	25	50	100	240	SW as a moderately hard FW	72.75
K	K	1	NaCl	2.922	7.82	25	50	100	300	SW as a moderately hard FW	82.12
K	K	1	NaCl	2.922	7.82	25	50	100	360	SW as a moderately hard FW	87.67
K	K	1	NaCl	2.922	7.82	25	50	100	420	SW as a moderately hard FW	89.89
K	K	1	NaCl	2.922	7.82	25	50	100	480	SW as a moderately hard FW	91.12
A	N	1	Na2SO4	1	3	22	0.2	10	2	SW - single PFAS -PFOA	23.61

Anode used	Cathode used	spacing(cm)	Electrolyte used	electrolyte concentration (g/L)	initial pH	Temperature	initial con. mg/L	current density (mA/cm ²)	electrolysis time (minutes)	water matrix	Removal efficiency %
A	N	1	Na ₂ SO ₄	1	3	22	0.2	10	5	SW - single PFAS -PFOA	44.37
A	N	1	Na ₂ SO ₄	1	3	22	0.2	10	10	SW - single PFAS -PFOA	64.18
A	N	1	Na ₂ SO ₄	1	3	22	0.2	10	15	SW - single PFAS -PFOA	81
A	N	1	Na ₂ SO ₄	1	3	22	0.2	10	30	SW - single PFAS -PFOA	96.07
A	N	1	Na ₂ SO ₄	1	5.5	22	0.2	10	2	SW - single PFAS -PFOA	14.11
A	N	1	Na ₂ SO ₄	1	5.5	22	0.2	10	5	SW - single PFAS -PFOA	32.29
A	N	1	Na ₂ SO ₄	1	5.5	22	0.2	10	10	SW - single PFAS -PFOA	54.95
A	N	1	Na ₂ SO ₄	1	5.5	22	0.2	10	15	SW - single PFAS -PFOA	68.79
A	N	1	Na ₂ SO ₄	1	5.5	22	0.2	10	30	SW - single PFAS -PFOA	90.64
A	N	1	Na ₂ SO ₄	1	5.5	22	0.2	10	60	SW - single PFAS -PFOA	100
A	N	1	Na ₂ SO ₄	1	7	22	0.2	10	2	SW - single PFAS -PFOA	9.5
A	N	1	Na ₂ SO ₄	1	7	22	0.2	10	5	SW - single PFAS -PFOA	20.9
A	N	1	Na ₂ SO ₄	1	7	22	0.2	10	10	SW - single PFAS -PFOA	41.52
A	N	1	Na ₂ SO ₄	1	7	22	0.2	10	15	SW - single PFAS -PFOA	55.36
A	N	1	Na ₂ SO ₄	1	7	22	0.2	10	30	SW - single PFAS -PFOA	75.03
A	N	1	Na ₂ SO ₄	1	9	22	0.2	10	2	SW - single PFAS -PFOA	7.19
A	N	1	Na ₂ SO ₄	1	9	22	0.2	10	5	SW - single PFAS -PFOA	18.72
A	N	1	Na ₂ SO ₄	1	9	22	0.2	10	10	SW - single PFAS -PFOA	42.88
A	N	1	Na ₂ SO ₄	1	9	22	0.2	10	15	SW - single PFAS -PFOA	57.67
A	N	1	Na ₂ SO ₄	1	9	22	0.2	10	30	SW - single PFAS -PFOA	76.8
A	N	1	Na ₂ SO ₄	1	5.5	10	0.2	10	2	SW - single PFAS -PFOA	8.4
A	N	1	Na ₂ SO ₄	1	5.5	10	0.2	10	5	SW - single PFAS -PFOA	20.73
A	N	1	Na ₂ SO ₄	1	5.5	10	0.2	10	10	SW - single PFAS -PFOA	43.77
A	N	1	Na ₂ SO ₄	1	5.5	10	0.2	10	15	SW - single PFAS -PFOA	57.99

Anode used	Cathode used	spacing(cm)	Electrolyte used	electrolyte concentration (g/L)	initial pH	Temperature	initial con. mg/L	current density (mA/cm ²)	electrolysis time (minutes)	water matrix	Removal efficiency %
A	N	1	Na ₂ SO ₄	1	5.5	10	0.2	10	30	SW -4 PFAS compounds	83.33
A	N	1	Na ₂ SO ₄	1	5.5	35	0.2	10	2	SW -4 PFAS compounds	17.07
A	N	1	Na ₂ SO ₄	1	5.5	35	0.2	10	5	SW -4 PFAS compounds	35.91
A	N	1	Na ₂ SO ₄	1	5.5	35	0.2	10	10	SW -4 PFAS compounds	57.72
A	N	1	Na ₂ SO ₄	1	5.5	35	0.2	10	15	SW -4 PFAS compounds	72.36
A	N	1	Na ₂ SO ₄	1	5.5	35	0.2	10	30	SW -4 PFAS compounds	92.14
A	N	1	Na ₂ SO ₄	1	5.5	50	0.2	10	2	SW -4 PFAS compounds	18.7
A	N	1	Na ₂ SO ₄	1	5.5	50	0.2	10	5	SW -4 PFAS compounds	42.28
A	N	1	Na ₂ SO ₄	1	5.5	50	0.2	10	10	SW -4 PFAS compounds	61.52
A	N	1	Na ₂ SO ₄	1	5.5	50	0.2	10	15	SW -4 PFAS compounds	75.61
A	N	1	Na ₂ SO ₄	1	5.5	50	0.2	10	30	SW -4 PFAS compounds	94.31
A	N	1	Na ₂ SO ₄	10	5.5	22	0.2	10	5	SW -4 PFAS compounds	35.02
A	N	1	Na ₂ SO ₄	10	5.5	22	0.2	10	10	SW -4 PFAS compounds	61.94
A	N	1	Na ₂ SO ₄	10	5.5	22	0.2	10	15	SW -4 PFAS compounds	81.62
A	N	1	Na ₂ SO ₄	10	5.5	22	0.2	10	30	SW -4 PFAS compounds	98.41
A	N	1	Na ₂ SO ₄	50	5.5	22	0.2	10	5	SW -4 PFAS compounds	51.95
A	N	1	Na ₂ SO ₄	50	5.5	22	0.2	10	10	SW -4 PFAS compounds	72.94
A	N	1	Na ₂ SO ₄	50	5.5	22	0.2	10	15	SW -4 PFAS compounds	95.22
A	N	1	Na ₂ SO ₄	50	5.5	22	0.2	10	30	SW -4 PFAS compounds	99.28
A	N	1	Na ₂ SO ₄	100	5.5	22	0.2	10	5	SW -4 PFAS compounds	59.04
A	N	1	Na ₂ SO ₄	100	5.5	22	0.2	10	10	SW -4 PFAS compounds	82.49
A	N	1	Na ₂ SO ₄	100	5.5	22	0.2	10	15	SW -4 PFAS compounds	98.41
A	N	1	Na ₂ SO ₄	100	5.5	22	0.2	10	30	SW -4 PFAS compounds	100
A	N	1	Na ₂ SO ₄	1	5.5	22	20	10	5	SW -4 PFAS compounds	9.48

Anode used	Cathode used	spacing(cm)	Electrolyte used	electrolyte concentration (g/L)	initial pH	Temperature	initial con. mg/L	current density (mA/cm ²)	electrolysis time (minutes)	water matrix	Removal efficiency %
A	N	1	Na ₂ SO ₄	1	5.5	22	20	10	15	SW - single PFAS -PFOA	23.9
A	N	1	Na ₂ SO ₄	1	5.5	22	20	10	30	SW - single PFAS -PFOA	40.52
A	N	1	Na ₂ SO ₄	1	5.5	22	20	10	60	SW - single PFAS -PFOA	69.09
A	N	1	Na ₂ SO ₄	10	5.5	22	20	10	5	SW - single PFAS -PFOA	10.44
A	N	1	Na ₂ SO ₄	10	5.5	22	20	10	15	SW - single PFAS -PFOA	27.75
A	N	1	Na ₂ SO ₄	10	5.5	22	20	10	30	SW - single PFAS -PFOA	44.23
A	N	1	Na ₂ SO ₄	10	5.5	22	20	10	60	SW - single PFAS -PFOA	70.6
A	N	1	Na ₂ SO ₄	50	5.5	22	20	10	5	SW - single PFAS -PFOA	7.97
A	N	1	Na ₂ SO ₄	50	5.5	22	20	10	15	SW - single PFAS -PFOA	19.37
A	N	1	Na ₂ SO ₄	50	5.5	22	20	10	30	SW - single PFAS -PFOA	35.16
A	N	1	Na ₂ SO ₄	50	5.5	22	20	10	60	SW - single PFAS -PFOA	61.68
A	N	1	Na ₂ SO ₄	100	5.5	22	20	10	5	SW - single PFAS -PFOA	6.04
A	N	1	Na ₂ SO ₄	100	5.5	22	20	10	15	SW - single PFAS -PFOA	17.45
A	N	1	Na ₂ SO ₄	100	5.5	22	20	10	30	SW - single PFAS -PFOA	32.69
A	N	1	Na ₂ SO ₄	100	5.5	22	20	10	60	SW - single PFAS -PFOA	58.1
A	N	1	Na ₂ SO ₄	1	5.5	22	0.02	10	5	SW - single PFAS -PFOA	37.65
A	N	1	Na ₂ SO ₄	1	5.5	22	0.02	10	10	SW - single PFAS -PFOA	62.88
A	N	1	Na ₂ SO ₄	1	5.5	22	0.02	10	15	SW - single PFAS -PFOA	78.5
A	N	1	Na ₂ SO ₄	1	5.5	22	0.02	10	30	SW - single PFAS -PFOA	100
A	N	1	Na ₂ SO ₄	1	5.5	22	1	10	5	SW - single PFAS -PFOA	24.7
A	N	1	Na ₂ SO ₄	1	5.5	22	1	10	15	SW - single PFAS -PFOA	49.4
A	N	1	Na ₂ SO ₄	1	5.5	22	1	10	30	SW - single PFAS -PFOA	79.84
A	N	1	Na ₂ SO ₄	1	5.5	22	1	10	60	SW - single PFAS -PFOA	98.93
A	N	1	Na ₂ SO ₄	1	5.5	22	5	10	5	SW - single PFAS -PFOA	13.08

Anode used	Cathode used	spacing(cm)	Electrolyte used	electrolyte concentration (g/L)	initial pH	Temperature	initial con. mg/L	current density (mA/cm ²)	electrolysis time (minutes)	water matrix	Removal efficiency %
A	N	1	Na ₂ SO ₄	1	5.5	22	5	10	15	SW - single PFAS -PFOA	33.51
A	N	1	Na ₂ SO ₄	1	5.5	22	5	10	30	SW - single PFAS -PFOA	55.27
A	N	1	Na ₂ SO ₄	1	5.5	22	5	10	60	SW - single PFAS -PFOA	91.05
A	N	1	Na ₂ SO ₄	1	5.5	22	20	10	5	SW - single PFAS -PFOA	8.14
A	N	1	Na ₂ SO ₄	1	5.5	22	20	10	15	SW - single PFAS -PFOA	23.9
A	N	1	Na ₂ SO ₄	1	5.5	22	20	10	30	SW - single PFAS -PFOA	40.85
A	N	1	Na ₂ SO ₄	1	5.5	22	20	10	60	SW - single PFAS -PFOA	68.89
A	N	1	Na ₂ SO ₄	1	5.5	22	50	10	5	SW - single PFAS -PFOA	6.41
A	N	1	Na ₂ SO ₄	1	5.5	22	50	10	15	SW - single PFAS -PFOA	22.43
A	N	1	Na ₂ SO ₄	1	5.5	22	50	10	30	SW - single PFAS -PFOA	38.72
A	N	1	Na ₂ SO ₄	1	5.5	22	50	10	60	SW - single PFAS -PFOA	64.22
A	N	1	Na ₂ SO ₄	1	5.5	22	100	10	5	SW - single PFAS -PFOA	5.34
A	N	1	Na ₂ SO ₄	1	5.5	22	100	10	15	SW - single PFAS -PFOA	19.36
A	N	1	Na ₂ SO ₄	1	5.5	22	100	10	30	SW - single PFAS -PFOA	34.85
A	N	1	Na ₂ SO ₄	1	5.5	22	100	10	60	SW - single PFAS -PFOA	60.48
A	N	1	Na ₂ SO ₄	1	5.5	22	200	10	5	SW - single PFAS -PFOA	5.61
A	N	1	Na ₂ SO ₄	1	5.5	22	200	10	15	SW - single PFAS -PFOA	17.76
A	N	1	Na ₂ SO ₄	1	5.5	22	200	10	30	SW - single PFAS -PFOA	36.58
A	N	1	Na ₂ SO ₄	1	5.5	22	200	10	60	SW - single PFAS -PFOA	60.21

Table A1: Data Points

In this study, various combinations of anodes and cathodes were employed to investigate the efficiency of the electrooxidation (EO) process for Perfluorooctanoic Acid (PFOA) removal. The anodes included Si/BDD (A), Zr-PbO₂ (B), Ti₄O₇ porous ceramic anode (C), Ti/BDD (D), Ce-PbO₂ (E), Ti/SnO₂-Sb (F), Ti/SnO₂-Sb/PbO₂ (G), Ti/SnO₂-Sb/MnO₂ (H), 2D-BDD (I), PP-BDD (J), Pt (K), and DSA (L). On the cathode side, Si/BDD (A), Pt (K), Ti (M), and Stainless steel (N) were employed. For the water matrices considered, SW stands for synthetic water and FW stands for fresh water.

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