EEET ECOLOGICAL ENGINEERING & ENVIRONMENTAL TECHNOLOGY

Ecological Engineering & Environmental Technology, 2026, 27(10), 508–525
https://doi.org/10.12912/27197050/231186
ISSN 2719–7050, License CC-BY 4.0

Received: 2026.08.01
Accepted: 2026.09.03
Published: 2026.09.10

Solar-powered electrocoagulation unit with artificial neural network-based prediction for sustainable treatment of oily wastewater

Esraa R. Abbas[1], Eman S. A. Al-Sammarraie[1*], Saja A. Alattar[2], Akram H. Abed[3], Saja M. Alardhi[4], Thabit A. Ahmed[5], Alyaa H. Abdalsalam[4]

[1] Environmental Research Center, University of Technology-Iraq, Al-Sina'a Str., 10066 Baghdad, Iraq
[2] College of Chemical Engineering, University of Technology-Iraq, Al-Sina'a Str., 10066 Baghdad, Iraq
[3] Higher Institute of Artificial Intelligence, University of Technology-Iraq, Al-Sina'a Str., 10066 Baghdad, Iraq
[4] Institute of Nanotechnology and Advanced Materials Research for Postgraduate Studies, University of Technology-Iraq, Al-Sina'a Str,, 10066 Baghdad, Iraq
[5] Petroleum Research and Development Center, Ministry of Oil, Bub Al-Sham, Baghdad, Iraq
* Corresponding author's e-mail: eman.s.awad@yandex.com

ABSTRACT

Oily refinery effluent is still a major environmental concern, because it is so difficult to treat as well as the large amounts of energy used in treating it using traditional technology. This study evaluated a low-cost and renewable source of energy system known as a solar-powered electro-coagulation unit (SPEU), of treating refinery wastewater while providing an opportunity for energy savings. Real oily effluent collected from a refinery in Baghdad (Al-Daura Refinery, Iraq) has been treated to electrocoagulation using aluminum sacrificial electrodes with variable operating parameters. The impacts of electrical current density and time for electrolysis on removal efficiencies for turbidity, oil and grease, total suspended solid (TSS), sludge generation and energy consumption have also been examined. An artificial neural network (ANN) model was established for predicting the removal efficiency based upon the operational parameters that are considered the model input values. Experimental data were collected which illustrated how current impacts pollutant removal; the optimal operating conditions in terms of current and treatment time (i.e., 5A, 45 minutes) resulted in 87% turbidity removal, 97% suspended solids removal, and up to 88% oil removal using pre-treatment while consuming an average of 15 kW-h/m^3. In addition, the optimized ANN was capable of accurately predicting both the performance of the system and experimental data that had not been used during the development of the model by generating a minimum mean square error of 9.05×10^{-17} and a training correlation coefficient of R = 1. these results show a potential opportunity for electrochemical treatment systems driven by renewable energy to provide sustainable, intelligent alternatives to industrial wastewater management.

Keywords: artificial neural network, electrocoagulation, oily wastewater, photovoltaic energy, renewable energy, solar-powered.

INTRODUCTION

More than one-third of the world suffers an acute shortage of freshwater, driven by the huge amounts of industrial effluents produced every year (Boinpally et al., 2023). Effective wastewater remediation has become a crucial technique in order to balance availability with population demand. Conventional industrial effluent produced from different sources like factories, car-wash station and others include complicated combination of pollutants, such as heavy metals, pathogens, dyes together with some natural or inorganic particulates that will pollute the water source (Al-Sammarraie et al., 2025). Petroleum-based contaminants are a major among. This oil wastewater originating from petrochemicals, textiles, and pharmaceuticals introduces recalcitrant, harmful and frequently carcinogenic chemicals into the environment (Kausar et al., 2022). In absence of appropriate treatment, these oily materials pollute soil and water resources as well as emit volatile organic compounds (VOCs) into the atmosphere, constituting a multi-dimensional threat to aquatic biodiversity and population health. Thus, it follows that recycling refinery effluent meeting relevant internal reuse specifications like in cooling towers and boiler feed systems. Environmentally, it restricts the amount of toxic discharge into natural ecosystems and greatly reduces freshwater use in its operations. Therefore, efficient treatment of refinery wastewater has become one of the major environmental challenges being faced throughout the world (Khan et al., 2024). There have been several approaches used for remediation of oily wastewater pollution, including biological processes (Guo et al., 2024) and chemical destabilization techniques (Li et al., 2023), as well as physical methods involving gravity separation (Łukasiewicz, 2025), centrifugation-based oil–water emulsions treatment systems (Vinh et al., 2021) and membrane filtration based on various principal mechanisms (Ali et al., 2024). While they have been shown to be highly effective, such as adsorption (Virender et al., 2025) and coagulation-flocculation (Iber et al., 2023). Even with their canonical high efficiencies, these processes also suffer from disadvantages like longer treatment time, increased operational cost, use of supplemental hazardous chemicals and potentially generate additional secondary pollutants. The other approaches are typically hindered by high energy requirements and the necessity of secondary treatment stages. Thus, electrocoagulation (EC) has evolved into a potential alternative (Butler et al., 2011).

EC process is a good preliminary technique where treatment of oil-water mixture receives significant benefits such as low operational complexity, down with reagent requirement and minimal sludge production, it provides less environmental impacts compared to conventional remedial techniques (Kabdaşlı et al., 2012). EC is a novel process incorporating electrochemistry, coagulation and flotation combining them to a single reactor system. Through the use of a direct electrical current to sacrificial metal electrodes (generally iron or Aluminum) immersed in the effluent, this process facilitates anodic dissolution of the metal resulting in generation of highly reactive, in-situ coagulants (metal hydroxides) (Iber et al., 2023).

These electrochemically produced species are efficient in neutralizing the surface charge of colloidal particles and collectively agglomerate emulsified oils, adsorbed contaminants or dissolved pollutants to form larger flocks enhanced for further separation. At the same time, cathodic reduction of water produces microbubbles of hydrogen gas that adhere to the flocs formed and carry them upward using electroflotation (Butler et al., 2011). EC has significant advantages over traditional chemical coagulation methods, such as elimination of external chemical aids, lower sludge volume and toxicity generation, short retention time, as well as capacity for the removal of a wide variety of pollutants simultaneously (Kabdaşlı et al., 2012).

While these quantitative advantages justify the use of EC, its application for large scale industrial processing has historically been limited due to a reliance on constant electrical power supply, increasing operating costs considerably in locations with high energy tariffs or unstable grid infrastructure. With the goal of reducing the large energy cost associated with EC processes to a level which could better satisfy global sustainability requirements, utilization of renewable sources—the focus here being solar photovoltaic (PV) science—has been identified as a principal functionalization technology for these reactions (Çetinkaya, 2025). Solar-powered electro-coagulation (SPEC) systems utilize the large amount of solar radiation and convert it directly into direct current (DC), which is required to promote electrochemical reactions. By adopting this synergistic strategy not only can the wastewater treatment process be decoupled from fossil-fuel-driven power grids, but also allows for a substantial reduction of carbon footprint and long-term operating cost associated with effluent remediating (Nawarkar & Salkar, 2019).

With considering the nature of SPEC systems being decentralized, self-sufficient and environmentally friendly technologies, they are extremely appropriate for remote industrial processes or locations with high solar insolation. Furthermore, Iraq offers a unique and robust environment for SPEC technologies tailored for its geographical and economic context. Iraq, one of the largest oil producing countries in the world, has a large petroleum refining infrastructure which produces huge amounts of complex wastewater (Albrazanjy et al., 2024).

At the same time, this country lays in a region with an incredibly high potential for solar energy. The annual average of sunny hours in Iraq exceeds 3000, and the daily solar irradiance intensity is always 5.0 to 5.6 kWh/m² (Al-Kayiem & Mohammad, 2019). Such constant high intensity solar radiation, available in every season, is considered to be an ideal energy source for several processes related to industrial applications. Transitioning from fossil fuel-driven technologies to solar-driven ones is not just an environmental strategy in Iraq but both an economic necessity for energy diversification and a core approach to reducing domestic use of fossil fuels which should be less dependent on the local market (Ali & Athari, 2026).

RELATED WORKS

The electrocoagulation system powered by a solar photovoltaic array to discharge wastewater has been jointly assessed by many authors. AlJaberi et al. (2020) used central composite rotatable design to investigate the optimum conditions for the treatment of real oily saline wastewater discharged from drilling oil wells using electrocoagulation technique. They found that the obtained concentrations of TDS, TSS, HCO_3, Cl and Ca were 93555 ppm (17.50%), 11011 ppm (83.22%), 189 ppm (60.38%), 80000 ppm (22%) and 4200 ppm (25%) respectively under the optimum values of operational parameters (1.625 A and 40 min).

The investigators explored a sequential 3-step treatment approach that included chemical coagulation (CC) as the first stage, followed by solar-powered electrocoagulation (EC), and adsorption as the final step (Al-Qodah et al., 2024). During stage I, ferrorus sulfate performed the best with a TOC removal efficiency of 68%. In the second step (electrocoagulation, EC), a maximum increase of 47.1% in filth elimination effectiveness was reached for the final polishing stage, several inorganic adsorbents were screened and two of the top inorganic candidates exhibited high capacities (75% removal efficiency for Pigment Blue 15:4 and 69% for PB7) compared to commercial activated carbon (80%).

The research conducted on solar electrochemical -SPEC treatment of low-concentration petrochemicals wastewater (Abuduaini et al., 2025). The aluminum plate is the anode of the electrochemical cell, while stainless-steel mesh (SSM 304) serves as the cathode to introduce life in pollutant removal. The maximum COD removal efficiency (52.9%) was achieved at optimized SPEC treatment conditions including 35 V applied voltage, 30 min operating time, 1.2 cm strip spacing and 249 rpm of agitation.

Bolivand & Delnavaz (2025) explored the economic and combinations of a practical solar-driven electrocoagulation process to treat real petroleum refinery wastewater with an initial chemical oxygen demand (COD) value of 406 mg/L, using perforated aluminium plates running as both anode and cathode powered directly by array of photovoltaic solar panels. with 70% of COD and 15.3% of TDS removal efficiencies, the system was performed competitively.

Nawarkar and Salkar (2019) investigated an electrocoagulation system in continuous-mode, powered by a battery-buffered solar photovoltaic array for municipal wastewater treatment. The system was successful in the large-scale utility of pollutant removal, with efficiencies of chemical oxygen demand, turbidity and total dissolved solids (TDS) achieved being 92.01%, 93.97% and 49.78% respectively.

Mohamad et al. (2025) investigated a solar-photovoltaic-powered electrocoagulation system tailored for the treatment of textile industrial effluent. Under the evaluated operating conditions, the configuration yielded competitive pollutant clearance, securing removal efficiencies of 55%, 82%, and 52% for total suspended matters (SS), turbidity (Tur), and chemical oxygen demand, respectively.

Although previous studies have demonstrated the feasibility of solar-powered electrocoagulation for oily wastewater treatment, limited attention has been given to integrating renewable-energy-driven electrocoagulation with intelligent predictive modelling in a unified framework. Furthermore, few studies have simultaneously evaluated treatment efficiency, energy consumption, sludge generation, and predictive performance using real refinery wastewater under practical operating conditions. To address these research gaps, the present study develops a solar-powered electrocoagulation unit (SPEU) powered by photovoltaic energy and integrates an Artificial Neural Network model to predict treatment performance. The proposed framework systematically evaluates pollutant removal efficiency, energy consumption, and environmental sustainability, providing an intelligent and sustainable solution for refinery wastewater treatment under Iraqi operating conditions.

Comparison with previous studies

Table 1 lists previous studies on wastewater treatment systems, optimization/prediction methods, key findings and the research gaps bridged by the present study. Table 1 shows that most of the recent studies have been related to the optimization of electrocoagulation operating conditions, using traditional statistical methods like response surface methodology (RSM) or factorial experimental design. While some investigations have presented good removal efficiencies of pollutants, only a few investigations have used Artificial Neural Networks for prediction of the system performance and no one has used ANN model with a solar powered electrocoagulation system for the treatment of oily wastewater. Thus, the present study has been conducted to incorporate renewable PV energy, the electrocoagulation technology and ANN based predictive modelling. This combined solution does not just improve the efficiency of the treatment system, but also helps to reduce dependence on grid electricity, operating costs and supports an environmentally friendly wastewater treatment.

Table 1. Comparison of previous studies on wastewater treatment, optimization techniques, and research gap

Reference	Wastewater type	Treatment system	Optimization/ prediction method	Main findings	Research gap compared with present study
Moneer et al. (2023)	Synthetic oily wastewater	Batch electrocoagulation (Al electrodes)	Response surface methodology (RSM)	Achieved about 97% turbidity removal and optimized operating conditions.	No renewable energy source and no ANN prediction model.
Jasim et al. (2023)	Real refinery oily wastewater	Continuous electrocoagulation reactor	Experimental evaluation	Reactor design significantly affected treatment efficiency and TDS removal.	Did not investigate solar energy integration or AI-based prediction.
El Jery et al. (2023)	Oil industry wastewater	Electrocoagulation	ANN + empirical correlations	ANN accurately predicted COD removal under different operating conditions.	Did not develop a solar-powered EC system or assess environmental sustainability.
Fotovat & Hosseini (2023)	Synthetic oily wastewater	Continuous electrocoagulation	RSM optimization	Simultaneously optimized oil removal efficiency and energy consumption.	Optimization relied on statistical methods without ANN or photovoltaic energy.
Nascimento et al. (2023)	Oil-in-water emulsion	Continuous EC with polarity switching	Factorial experimental design	Improved oil removal while evaluating aluminum release into the environment.	Focused on electrode polarity rather than intelligent prediction or solar operation.
Eksi et al. (2024)	Oil-water emulsions	Electrocoagulation / electropersulfate	Box–Behnken Design	COD removal reached about 97% with optimized operating conditions.	No ANN implementation and no renewable-energy-powered reactor.
Muvel et al. (2024)	Review of oily wastewater	Electrocoagulation	Comprehensive Review	Highlighted recent advances, optimization methods, and future needs for modeling and intelligent control.	Identified AI integration as a future research direction but did not present an ANN application.
Present study	Oily wastewater	Solar-powered electrocoagulation unit	Artificial neural network (ANN)	Combines photovoltaic-powered electrocoagulation with ANN-based prediction of oil/COD removal and energy consumption while evaluating environmental sustainability.	Novel integration of renewable energy, electrocoagulation, and artificial intelligence in a single framework.

MATERIALS AND METHODS

Characterization of oily wastewater samples

The actual oily wastewater which utilized in our experiments was sourced from a Midland Refineries Company, Daura Refinery, Baghdad, Iraq, before it enters the treating processes at the refinery. Table 2 provides the physicochemical characteristics of this oily wastewater.

A pre-treatment was performed for the source of oily wastewater, due to the high concentration of oil and grease in the source which could affect the efficiency of the treatment process. A separating funnel was used as a pre-treatment, where sample was left for an adequate period to allow the two phases to separate, and then the lower aqueous layer was carefully withdrawn. This procedure ensures more accurate representation of the characteristics of the treatable wastewater.

Table 2. Characteristics of oily wastewater

Parameters	Values
pH	7.64–7.79
Turbidity, NTU	86–148
Total suspended solid (TSS), mg/l	29–102
Total dissolved solid (TDS), mg/l	1341–1452
Oil and grease without pre- treatment, mg/l	249.6–283.2
Oil and grease with pre-treatment, mg/l	99.84–113.28

SPEC reactor configuration and experimental methodology

The experimental setup for SPEC reactor consists of photovoltaic panel coupled with a charge controller, energy storage unit, voltage/current regulator, Al plates (anode and cathode), acrylic cell, and digital multi-meter. The experimental setup was installed on the top of the main building of Environmental Research Center at the University of Technology-Iraq (latitude: 33.33°, longitude: 44.44°). The SPEU was powered by a 50 W polycrystalline PV panel oriented to face south for better solar radiation exposure, as shown in Figure 1. The charge controller acts as a power management hub, controlling the power coming from PV panel to safely charge the energy storage unit while simultaneously directing power to the SPEC reactor. A 50 Ah, 12 V battery acts as an energy storage unit, mitigating the power fluctuations from the PV panel and ensuring the SPEC reactor operates during periods of low solar radiation. An integrated electrical voltage / current regulator positioned between the energy storage unit and the SPEC reactor, which regulates and reads the voltage/current parameters supplied to SPEC reactor. The oily wastewater treatment was performed using an Al plates anode and cathode with a size of (10×5×0.172 cm). The two electrodes were placed vertically in a 5-liter acrylic glass reactor (length 20

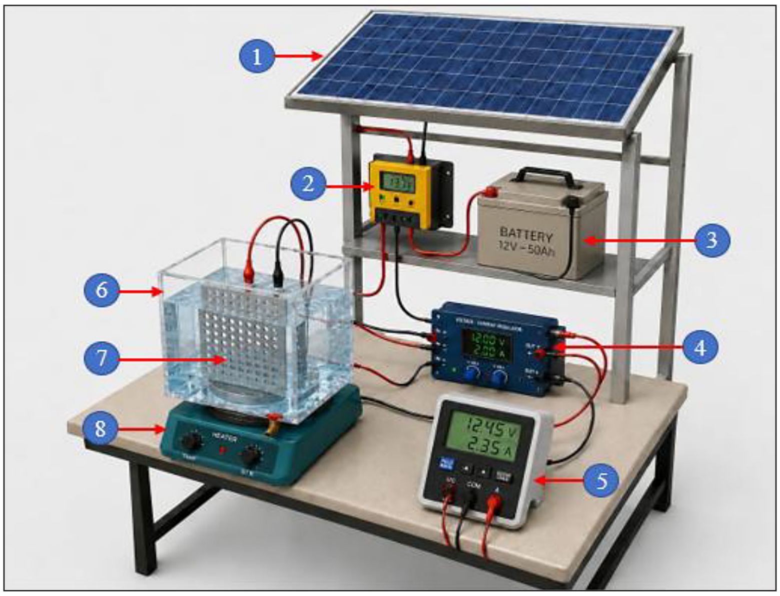

Figure 1. Schematic diagram of the experimental setup: 1 - PV panel, 2 - charge controller, 3 - energy storage unit, 4 - voltage/current regulator, 5 - digital multi-meter, 6 - acrylic cell, 7 - Al plate, 8 - digital scale

cm, width 14 cm, and height 16 cm) and were connected by a copper wire. Prior to each test, 3 L of oily wastewater was used in the SPEU at voltage of 12 Volts, current values of (2 A and 5 A) and time of (15, 30, 45, and 60 min). Upon completion of the treatment, a sample of the treated water was collected for subsequent analysis for TSS, turbidity, and oil and grease.

Mechanism of oil removal via the SPEU

This research utilizes an effluent of industrial wastewater produced by the Al-Daura Refinery as a treatment medium for a solar-powered electrocoagulation unit. The SPEU contains aluminum electrodes which are used as both anode and cathode in the electrochemical treatment process. The SPEU uses solar power to produce electric current that will remove contaminants from the wastewater by combining three processes including charge neutralization, adsorption and flotation. At both electrodes, the overall process is a combination of electrochemical reactions that occur simultaneously. As the solar-powered current is generated at the anode, it oxidizes the aluminum electrode and produces Al^{3+}, which are released in the wastewater and destabilize colloidal contaminants such as oil droplets and other suspended colloids. This destabilizing action occurs due to the fact that Al^{3+} reduce the zeta-potential of colloidal impurities; thus, these colloids will undergo coagulation through charge neutralization. Simultaneously, at the cathode, water is reduced generating OH- ions and H_2 gas. The resulting hydrogen gas bubbles adhere to the large oil particle aggregates, thus allowing for greater buoyancy which aids in their separation by electro flotation. The liberated Al^{3+} ions combine with the hydroxyl (OH^-) ion to create an aluminum hydroxide precipitation. This precipitation will function as a sorbent, using both surface complexation and electrostatic interaction to remove pollutants. The primary reactions occurring within the SPEU are represented as follows:

- At anode, metal oxidation

$$Al(s) \rightarrow Al^{3+} + 3e^- \quad (1)$$

- At cathode, water reduction

$$2H_2O + 2e^- \rightarrow H_2 + 2OH^- \quad (2)$$

- Generation of absorbing agent

$$Al^{3+} + 3OH^- \rightarrow Al(OH)_3 \quad (3)$$

Analytical measurements

In this study, the samples analyses were measured and recorded before and after the SPEU treatment. After treating and 20 min settling period, a supernatant was taken for analyzing. Standard methods of analysis were used to determine the concentration of parameters. The measurements were determined by using: turbidimeter (Lovibond, Germany) with method (Nephelometric, 2130 B) for turbidity analysis, Filtration assembly by using procedures described in method (2540 C and D) for TDS and TSS analysis, and titration method (5520 B. Partition-Gravimetric) for oil and grease analysis. The calculation formula for the removal efficiency (R%) is given in Equation (4):

$$R\% = \frac{C_i - C_f}{C_i} \times 100 \quad (4)$$

where: C_i and C_f are the concentrations of parameters initial and final wastewater solutions, respectively.

Energy consumption analysis

Energy consumption is a method used to compare the efficiency of different sized systems. It takes into consideration both how much energy the system consumes and its ability to remove contaminates. Therefore, energy consumption measures overall performance efficiency. A formula to determine energy consumption of an electrochemical system follows Equation (5) (Yamazaki et al., 2026):

$$E\ consumption = U \times I \times t \quad (5)$$

where: U – cell voltage [V], I – current [A], and t – operating time [s]. Units of E consumption are typically expressed as kWh.

Specific energy consumed (SEC) is a process divided by its performance. Performance can be measured by V (volume of water processed). The units for SEC are typically reported as kWh/m³.

$$SEC = \frac{E\ consumption}{V} \quad (6)$$

Artificial neural network modelling

For the solar-powered EC system for oily wastewater treatment, an artificial neural network model was created for predicting the system's performance. The multilayer perceptron (MLP) model was used to design the ANN, which had an input layer, one hidden layer, and an output layer. The input variables selected were time min, current (amp), turbidity (TUR), total suspended solid (TSS) and oil & grease and the outputs were treatment performance indicators TUR, TSS and oil & grease R% removal efficiency.

Before training, all experimental data were normalized to facilitate the convergence of the model. The data set was randomly split into three sets – 70% training, 15% validation, and 15% testing. The Levenberg–Marquardt back-propagation algorithm was used to optimize the network weights, and the hyperbolic tangent sigmoid (tansig) function was adopted in the hidden layer, and the linear function in the output layer of the network.

Apart from comparison of predicted to experimental values, the statistical performance indicators like mean squared error (MSE) and relative error (RE) were used to assess the performance of the ANN models in this study:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(Y_i - P_i) \tag{7}$$

The relative error was calculated using the following Equation (8):

$$\%RE = \frac{Y_i - P_i}{Y_i} * 100 \tag{8}$$

To evaluate the predictive accuracy of the developed ANN model, the relative error was used along with the mean squared error. It should be noted that RE is independent of the correlation coefficient (R) that is used during the regression analysis.

RESULTS AND DISCUSSION

Impact of current intensity on turbidity removal

The performance of the solar-powered electrocoagulation unit for oily wastewater treatment was systematically evaluated by monitoring turbidity reduction and removal efficiency at different applied currents (2 A and 5 A) over a 60-minute electrolysis period. The current applied during the operation of an electrocoagulation is a key parameter within the EC process since it directly controls (i) the rate at which anode dissolution is occurring, (ii) the generated species of coagulants in accordance with Faraday's law (iii), and finally, (iv) rates of hydrogen gas evolution at cathode that jointly control oil droplet flotation/separation.

The effect of applied current (at 2 A, as shown in Figure 2a) on residual turbidity and removal efficiency. An improvement in treatment efficiency exhibited a gradual increase with prolonged electrolysis time. The removal efficiency started at around 76% after 15 min and steadily increased to achieve the maximum of 84% by the end of the cycle (60 min). Simultaneously, the remaining turbidity showed a stable decrease from about 21 NTU down to 14 NTU. That this level persists suggests that the metal hydroxides are not generating much at lower current, but it is a consistent trend. Using coagulants over a stepwise time period enables the efficient neutralization of these negatively charged oil-water emulsion droplets thus producing stable flocs. So, a flat curve here indicates a coagulation regime which prevents other secondary adverse reactions.

In contrast, Figure 2b shows the system response upon an applied current of 5 A and in this case a faster and more dynamic treatment profile (in terms of dosage area needed for reaching similar precursor level compared to that by the 3 A applied current case). The removal efficiency saw a high initial rise, reaching an optimal maximum of 90% at 45 minutes and a very large decrease in residual turbidity, its lowest value. This rapid kinetic reaction is a result of the accelerated rate of anodic dissolution, which leads to high concentrations of monomeric and polymeric metal hydroxide species in bulk solution that quickly initiates destabilization and agglomeration of oil droplets from site oxidation. In addition, the increased current density promotes the production of micro-bubbles (H_2 and O_2) at the electrodes, which is particularly beneficial for bolstering the electro-flotation mechanism inducing stronger flocs sweeping to surface.

The drop-off in removal efficiency (declining to 85%) with a rise in residual turbidity at longer times (60 minutes compared to 45) is due to charge reversal/re-stabilization of colloids. Figure 2b shows that after an initial rapid increase in turbidity reduction, this rate slows down significantly for the remaining 15 minutes. Prolonged electrolysis at a high current lead to an excessive accumulation of positively charged metal hydroxides, which can over-neutralize the oil droplets, causing them to repel each other and re-disperse into the aqueous phase. Additionally,

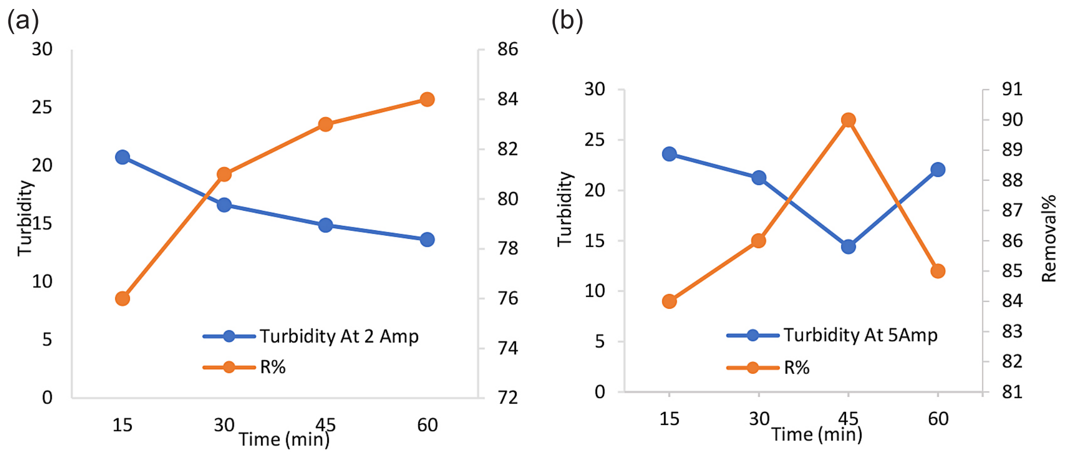

Figure 2. Influence of current (a) 2A, (b) 5A, on residua turbidity NTU and removal efficiency

the vigorous gas evolution at higher currents may induce excessive hydrodynamic shear forces, potentially breaking down the previously formed fragile flocs.

In accordance with a recent analysis by Al-Qodah et al. (2024), the pattern seen in the data collected for this project is similar. In their work they reported that when electrolysis is carried out at a high enough density of electrical current for long periods of time it may cause the flocculated particles to break apart into smaller pieces. As mentioned earlier Garcia-Segura & Brillas (2024) also identified that excessive amounts of metal ions may reverse the overall charge on the surface of the colloidal particles.

Impact of current intensity and time on oil removal

This study was investigated to remove oily wastewater generated directly from an oil refinery without first treating it through any previous steps. Oily wastewaters were evaluated based on their oil content (which ranged from 266.4).

The data shown in Figure 3a represent the effect of applying a current flow rate of 2 A, where removal of oils and effectiveness are illustrated. Removal efficiencies improved steadily throughout the process; however, there was some variation. Oil concentrations decreased from the starting point of 266.4 mg/L and reached their low points at 45 min (95.2 mg/L), and removal efficiencies were maximized and peaked at approximately 63%, respectively. Efficiency percentages for removing oil concentration rose dramatically during the first 30 min and reached a maximum percentage of approximately 62% by 45 min and then slightly declined to 57 % by 60 min. The minor decline in percent removal efficiency for oils from 62% at 45 min to 57% at 60 min as illustrated in Figure 3 can likely be attributed to several possible causes including: the saturation of the flocculants, or potential re-emulsification of some oil droplets if the flocs become unstable over extended periods at this lower current density. This phenomenon, often termed ‘floc breakage’ or ‘re-stabilization,’ suggests that while the initial coagulation is effective, prolonged exposure to the electrochemical environment at lower current densities might lead to a partial breakdown of the formed aggregates.

Conversely, Figure 3b, illustrates the behaviour of the system when treated with a higher current of 5 A, as opposed to that illustrated in Figure 3 (a), with the latter being subjected to a lower applied current of 1 A. The dynamic behaviour observed for the system subjected to the 5 A current represents a much faster and more efficient treatment profile than that observed for the system treated with 1A. When the current was elevated to 5amps, the amount of residual oil present in the water was reduced by approximately 79.7%, i.e., the residual oil content decreased from 266.4mg/L to 54.67 mg/L after 45 minutes of treatment time. Additionally, the oil removal efficiency exhibited a very high initial rate and achieved its maximum value (i.e., 81%) at 45 minutes into the treatment cycle. This extremely rapid rate of removal is directly related to the increased anodic dissolution rate associated with the higher current densities used during the treatment process; therefore, as a result of this increased dissolution rate, there are more monomeric and polymeric metal hydroxides formed in the bulk solution, these species

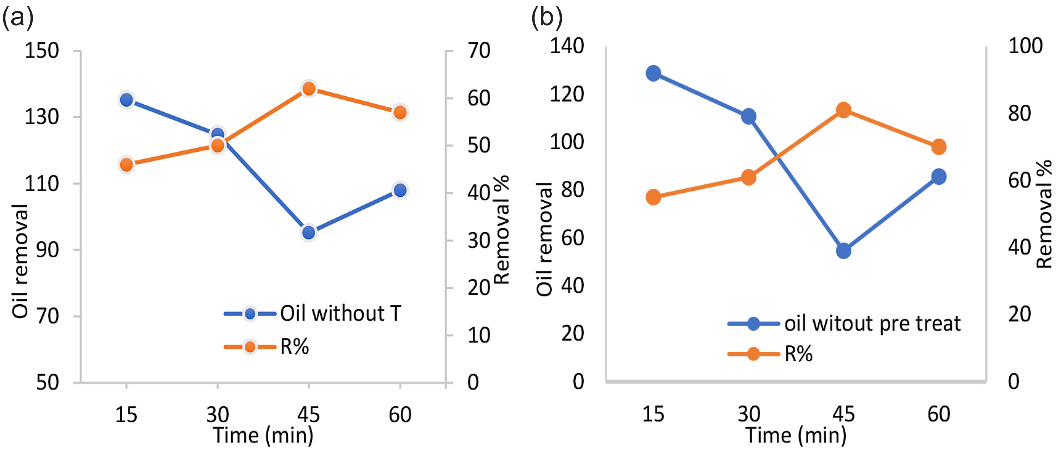

Figure 3. Influence of current (a) 2 A, (b) 5 A, on oil removal and removal efficiency (R%)

then cause a rapid destabilization and agglomeration of oil particles. Moreover, the increased current density enhances the formation of microbubbles (H_2 and O_2) on both electrode surfaces, which significantly enhance the effectiveness of the electro-flotation mechanism; thus, they facilitate the effective movement of the formed flocs to the surface where they can be removed.

The differences seen when comparing Figures 2 and 3 demonstrate that the major factor in the electrocoagulation process is current intensity. At a starting concentration of 266.4 mg/L for oil and using the solar-powered unit with a constant current of 5A for a time duration of 45 minutes would provide a reasonable trade-off between environmental impact and technical efficacy (i.e., energy used to achieve treatment).

Impact of pre-treatment on oil content and removal efficiency

To improve both treatment effectiveness and to lower the initial contaminant load, a preliminary step using skimming as a pretreatment method was applied. This skimming process reduced the initial oil content in the water from an average of 266 mg/L to 106.56 mg/L.

The subsequent electrocoagulation treatment was then evaluated under the identical electrical operating parameters (i.e., 2 A and 5 A), with the exception being the water had previously undergone skimming.

The performance of the EC treatment unit utilizing a current of 2 A was examined again for its ability to remove oil. As depicted in Figure 4(a), the oil treatment / removal efficiency is shown at a current of 2A post-pre-treatment. It can be observed that the amount of oil removed improved from 105.56 mg/L to 23.8 mg/L after 45 minutes of treatment time. Additionally, the removal efficiency R%, also improved to approximately 63% after 45 minutes of treatment.

There are major improvements in residual oil concentration and in removal efficiencies as compared to prior test results (no pretreatment). Pretreatment resulted in an increase in the removal percentage from 62% to 76%, when evaluated after 45 min. Also, there was a corresponding decrease in the final residual oil concentration at 45 minutes; i.e., from 95.2 mg/L to 23.8 mg/L. Therefore, the application of pre-treatment significantly improves the total pollutant loading for the EC treatment system resulting in improved removal percentages.

The Figure 4b, at 5 A current illustrates that there is a significant increase in the removal of oil and the efficiency of removal as compared to the 2A current. With pre-treatment of the water prior to passing through the electrocoagulation system; an additional significant increase in the removal efficiency occurred. At a total time of 45 min., the removal efficiency of EC was approximately 88%. This represents a substantial increase from the 81% efficiency demonstrated by EC when no pre-treatment was used. The amount of oil remaining in the treated water at the end of 45 min. was very small (i.e. 13.6675 mg/L). This indicates that the treatment was highly effective. The removal efficiency decreased slightly at 60 min. (from 83%), which may be attributed to the restabilization phenomenon previously described. However, this reduction in removal efficiency does not detract from the fact that pre-treatment had a positive effect on reducing the initial oil

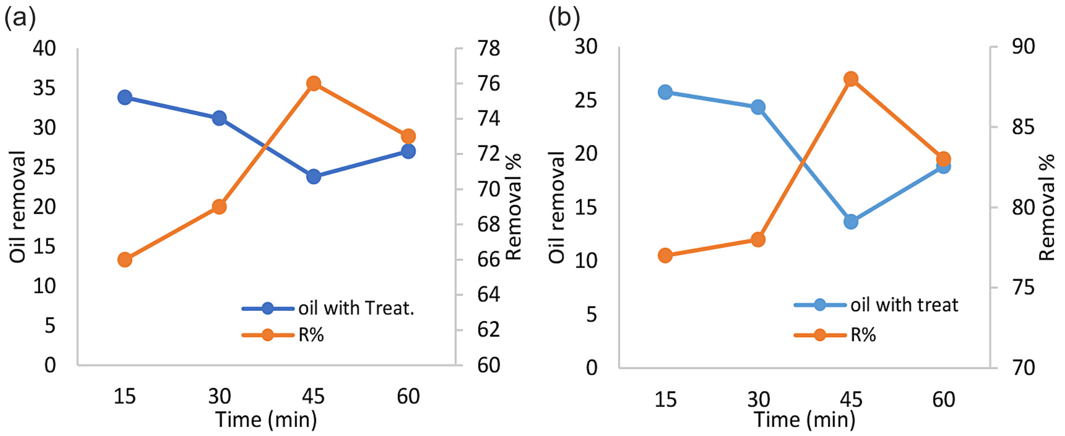

Figure 4. Secondary treatment of oil removal vs time at (a) 2 A, (b) 5 A

load thereby improving the kinetic and final effluent quality of EC.

Removal of total suspended solids through SPEU

One of the primary indicators of the success of an electrocoagulation treatment process for oil-rich wastewater is the decrease in the concentration of total suspended solids. The TSS removals were evaluated as a function of two different current intensities; 2A and 5A, over four-time intervals during electrolysis; 15, 30, 45 and 60 minutes. The range of initial TSS concentrations was from 29 mg/L to 102 mg/L.

At 2A, the TSS decreased from 13.33mg/L at 15 minutes to 2.67 mg/L at 60 minutes. Therefore, TSS removal efficiencies were determined to be 54%, 70%, 84% and 91% at the corresponding time periods; 15, 30, 45 and 60 minutes, respectively. The greatest amount of TSS removal efficiency was found to be 91% after 60 minutes. This suggests that longer electrolysis times can enhance TSS removal rates when utilizing low current densities. Similar trends have been observed by others in published reports, as increased electrolysis time will provide sufficient time for the formation of metal hydroxide flocs. Metal hydroxide flocs are known to promote both coagulation and sedimentation of suspended particle matter.

At 5 A the TSS concentrations in the solution reduced as time increased from 9.43 mg/L at 15 minutes down to 3.33 mg/L at 45 minutes. The TSS removal efficiency was 91% at 15 min., 94% at 30 min. and 97% at 45 min. However, there is an interesting trend that occurred after 45 minutes, where there was a small increase in TSS concentration of 11.51 mg/L (or removal efficiency of 89%) at 60 minutes. It is believed that the increase could have been caused by the settling of previously formed floccules being resuspended into the water due to excessive turbulence produced by large numbers of bubbles created when high current density is used. The highest TSS removal efficiency of 97% was found at a time period of 45 min. using an electric current of 5A. When evaluating the two current intensities, the use of 5 A demonstrated superior TSS elimination efficiency compared to using 2 A for most of the testing intervals (15 & 30 min). This could be attributed to Faradays law, where an increase in current will result in a larger rate of anodic degradation, thus increasing the number of coagulant ions available for pollutant removal. In addition, the relatively small reduction in efficiency observed at 60 minutes when operated at a maximum current of 5A suggests that it is critical to find an optimal balance between the intensity of applied currents and the duration of electrochemical treatment to ensure efficient use of electrical energy and minimize unnecessary electrical energy expenditure for inefficient processes.

The solar-powered electrocoagulation system demonstrated satisfactory removal of Total Suspended Solids in all testing conditions with efficiencies varying over a range from approximately 54% to about 97%.

The coagulated suspended solids referring to the sludge were weighed alongside with all coagulation processes. The sludge results is a crucial factor that directly indicates the effectiveness of the coagulation process as well as the operating expenses related to sludge

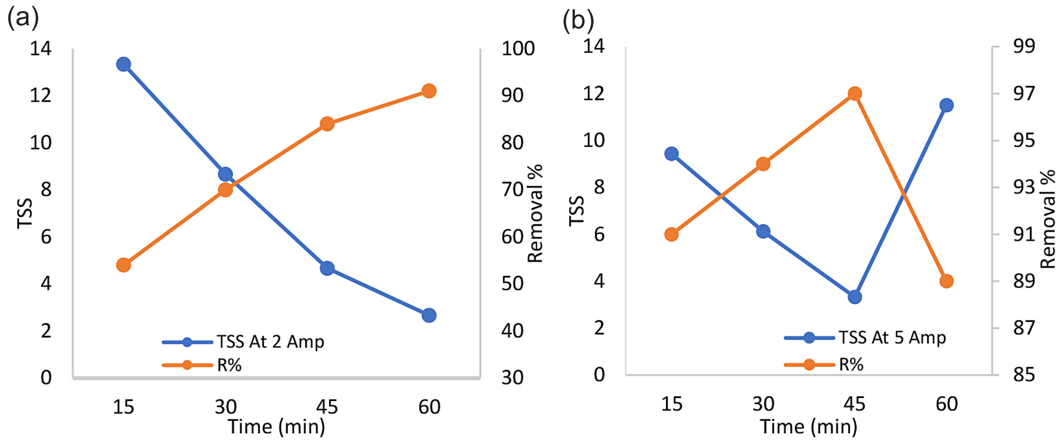

Figure 5. TSS removal vs time (a) at 2 A, (b) at 5 A

management and disposal is the amount of sludge produced during electrocoagulation. The sludge weight was measured at four electrolysis time intervals (15, 30, 45, and 60 minutes) under two current intensities, 2 A and 5 A (Figure 6). Sludge weight significantly increased at 2 A, rising from 0.4395 g after 15 minutes to 0.9842 g at 30 minutes, or 123.9%. This quick increase is in line with the first stage of anodic dissolution, when iron or aluminium ions are produced quickly and combine with hydroxide ions to create metal hydroxide flocs, which are the main solid phase of the subsequent sludge (Ofverstrom et al., 2010). At 45 minutes, the sludge weight decreased to 0.9184 g (-6.7%) due to floc compaction and partial settling within the reactor. However, the sludge weight climbed to a maximum of 1.0531 g by 60 minutes. The total sludge formed at 2 A throughout all runs was 3.395 g, with a mean of 0.849 ± 0.241 g. Compared to the two current intensities, the 5 A setting produced roughly 5.4% more total sludge than the 2 A setting over the whole testing period. This is consistent with previously published findings in the literature, where higher current densities typically provide bigger sludge volumes due to improved metal ion solubility and quicker floc formation (Moussa et al., 2017). The non-monotonic trends observed at both current intensities, particularly the mid-experiment decreases at 45 minutes, suggest that sludge accumulation in batch EC systems is not a simple linear function of time, but is influenced by dynamic interactions between floc formation, growth, breakage, and resuspension (Yang et al., 2025). These findings highlight the necessity of adjusting electrolysis time and current intensity in solar-powered EC systems to balance treatment efficiency with sludge management needs.

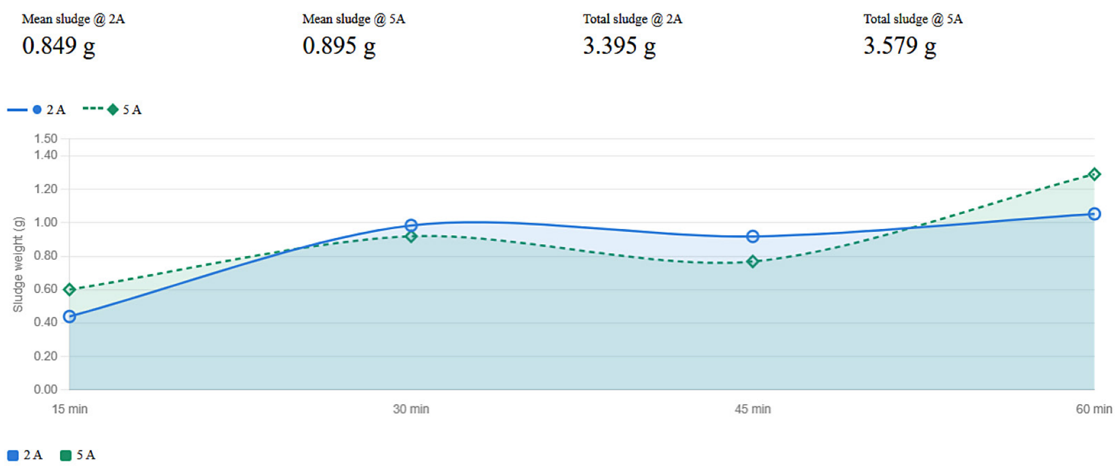

Figure 6. The sludge weight at four electrolysis time (15, 30, 45, and 60 minutes) under two current intensities, 2 A and 5 A

Management of sludge generated from coagulation processes in oil refineries

Oil refineries generate significant quantities of oily wastewater through processes like desalting, cooling and cleaning of equipment and therefore are among the most water intensive industrial operations (Diya'uddeen et al., 2011). Coagulation and electrocoagulation have received a lot of attention because they can remove a variety of contaminants found in refinery wastewater including suspended solids, dispersed oils and other pollutants. (Ofverstrom et al., 2010). While many of the above-mentioned processes have been successful to date in treating oil refinery effluent through various chemical and physical methods, one major issue that has developed from all of them is the amount of sludge generated during the treatment of the effluents. Sludge produced by oil refinery wastewater treatments through the use of coagulants creates serious environmental, operational, and regulatory problems.

The sludge produced from coagulation can be described as a complex mixture of water, petroleum-based compounds (hydrocarbons), inorganic particulates (such as iron and aluminium hydroxide) and metal ions (heavies) based upon the type of coagulant used in the process (Guangji Hu 2013). Various aspects affect how much sludge is created by wastewater treatment plants, such as how many contaminants are in the water and at what concentrations, which type and amount of coagulant is added to the wastewater prior to coagulation, what the pH of the wastewater is during the time that it is being treated by coagulation, and how long and/or intense the coagulation process was (Belone et al., 2025). The sludge generation rate for electrocoagulation processes can also be described with a basic application of Faradays Law. The total number of metal ions released from the sacrificial anode will determine the amount of flocculent formed; therefore, the amount of sludge generated will depend on the total number of metal ions released from the sacrificial anode (Kobya et al., 2010).

The EPA classifies petroleum industry refinery-generated coagulated sludge as a hazardous waste, which results in many countries having very strict regulations regarding its generation and handling (Hu et al., 2013). The majority of this classification comes from both the high hydrocarbon composition within the sludge and from the toxicity levels of the heavy metal contaminants found in the sludge. However, when these wastes are improperly disposed of they pose a great risk for surface and groundwater contamination that can harm not only aquatic life but also human health (Guangji Hu 2013). As such, managing refinery sludges properly has been identified as an essential component of operating any petroleum industry wastewater treatment process.

The current methods used in refinery waste management involve numerous different practices that can be broadly categorized into four main categories: volume reduction, treatment, recycling and ultimate disposal. All of these various practices focus on reducing the amount of sludge that is available to require additional treatment or disposal. Volume reduction practices are primarily based on limiting the total quantity of solids contained in the sludge by utilizing processes such as: gravity thickening; mechanical dewatering using either a centrifuge or press; and thermal drying. These three primary volume reduction techniques have been shown to reduce the overall mass and volume of sludge to facilitate easier treatment or disposal (Fakhru'l-Razi et al., 2009).

Diverse approaches such as biological degradation, solvent extraction, and thermal treatment are being evaluated to recover residual hydrocarbons and stabilize hazardous elements in the sludge matrix (da Silva et al., 2012). Newer technologies such as pyrolysis, ultrasonic treatment, and freeze/thaw conditioning are also being investigated as a means of enhancing the dewatering ability of the sludge and ultimately creating a source for material recycling (Belone et al., 2025).

From an environmental perspective, management of refinery sludge has moved from merely treating it as waste toward treating it as a potential resource for which value can be realized. The three major areas for realizing that value are; using a combination of solvents and heat to recover residual oil from the sludge, use of the dried (dewatered) sludge cake as a supplemental fuel in cement kiln operations and/or as a source of raw materials used in construction activities, and bio-treatment of the sludge to produce biogas through anaerobic digestion (da Silva et al., 2012; Guangji Hu 2013).

The methods for the removal of sludges described above are also consistent with those of the circular economy. They can help reduce disposal costs, recover embedded energy and material as well. Despite developments in sludge treatment (ST) technologies and sludge valorization (SV), it is still difficult to manage coagulated sludge from an economic point of view, and also from a technical viewpoint. Some of the primary barriers to achieving effective sludge treatment include the unpredictable nature of sludge composition, stringent governmental regulations that control how it can be disposed of and the substantial capital and operating expenses required to develop sophisticated technologies to treat sludge (Belone et al., 2025). Thus, developing affordable, eco-friendly and viable sludge treatment solutions will continue to be a significant area of focus in industrial wastewater treatment.

Neural network performance

The entire experimental data set (100 data points) was split into two independent sets to assess the ANN predictive capability in an unbiased manner. The first subset (70 experimental records) for network training and model development. In this stage, the ANN was trained to learn the nonlinear relationship between the operational parameters: time min, current (amp), TUR, TSS oil & grease and; and the outputs were the treatment performances indicator: TUR, TSS and oil & grease R% removal efficiency.

The rest of the 30 experimental records (30% of the experimental records) were completely removed from the training process and used to perform model testing independently. This testing data was not used in the network for weight adjustment, parameter optimization and architecture selection. Hence, the results of the tests will give a realistic picture about the prediction ability and generalization value of the created ANN model when it is presented with unseen data.

Training algorithm (TRAINR, TRAINLM and TRAINRP), transfer functions (LOGSIG, TANSIG and PURELN), and hidden layer architectures were explored. It was found that the feedforward neural network with five inputs, 30 hidden nodes, three outputs and trained by the algorithm TRAINLM is the optimum structure. The MSE and R of this architecture were the minimum (9.0533e-17) and maximum (1), respectively, in the training phase, which showed that the experimental and predicted outputs were well fitted (Figure 7a).

The regression performance of the developed model for the training, validation, testing, and overall data sets is shown in Figure 7b. As shown in the figures, the regression lines are very close to ideal reference line (Y = T), which means that the predicted outputs and the target values are very close to each other (almost perfect correlation). Regression equations have slopes around 1 with very small intercepts, indicating that there are no systematic prediction errors. Moreover, all the data points are concentrated around the regression line showing that the predictive accuracy and generalization performance is very high for the proposed model.

In order to further test the predictive performance of the optimized ANN model, the independently tested data set with 30 experimental records never used during training was used. In Figure 7c, the prediction results with this external testing subset are shown. Figure X shows how the measured values compare to the predicted values for the three water quality parameters (turbidity, total suspended solids and oil). The developed regression model is shown to be able to predict correctly all the parameters, but the prediction performance is different. For TUR, the regression equation (y = 0.9997x) suggests a nearly perfect fit between the predicted and actual values, as the slope is very close to 1, which means there is a high prediction accuracy and very little systematic error. The model showed a good correlation between observed and model values with R^2 value of 0.9265 for TSS, indicating that the model accounts about 92.65% of the variance in the observed values. The regression slope is 0.8427, which means that higher values tend to be slightly underestimated. Similarly, the Oil parameter exhibited good predictive performance with an R^2 value of 0.8955, indicating that about 89.55% of the variation in the actual measurements is captured by the model. However, the regression slope of 0.7153 suggests a greater degree of underestimation compared with TUR and TSS, particularly at higher concentrations. Overall, the regression results confirm that the proposed model is capable of predicting the investigated water quality parameters with high accuracy, while TUR achieved the best performance among the three parameters.

There are many factors that affect the trained network, such as: training function, number of layers and neurons, and transfer function. In this study, different training function were used

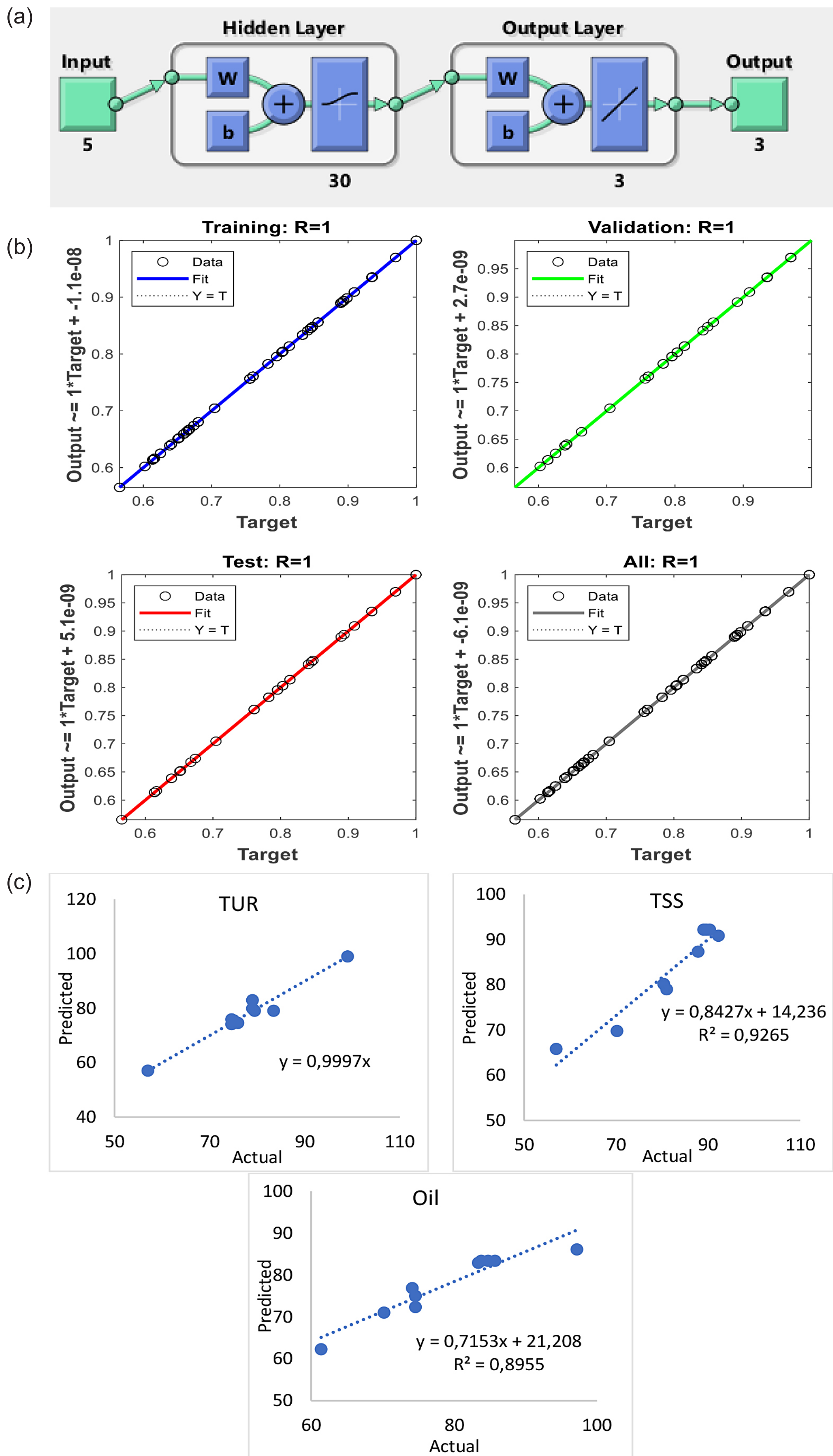

Figure 7. (a) Optimized ANN architecture (5–30–3–3), (b) regression analysis for training, validation, testing, and overall datasets during ANN development, and (c) prediction performance of the trained ANN model on the independent testing dataset (30 unseen records).

Table 3. Different factors effect on training of ANN

Training function	No. of layers	Layers	No. of neurons	Transfer function	MSE	R
TRAINR	2	layer 1	10	LOGSIG	0.0053971	0.80418
		layer 2	2	PURELN		
TRAINLM	2	layer 1	15	LOGSIG	0.0004554	0.98597
		layer 2	2	PURELN		
TRAINRP	2	layer 1	20	LOGSIG	0.0004612	0.98406
		layer 3	2	PURELN		
TRAINLM	2	layer 1	30	TANSIG	9.0533e-17	1
		layer 2	3	PURELN		

(TRAINR, TRAINLM and TRAINRP) as mentioned in Table 3. with different transfer function (TANSIG, LOGSIG and PURELN). Furthermore, two and three layers including (10,15,20 and 30) of experimental neurons.

Increasing the number of hidden neurons and hidden layers improves the learning ability of trained neural networks, but it can also increase the likelihood of overfitting, especially when dealing with limited data. In this study, increasing the correlation coefficient (R), which coincided with a decrease in the mean squared error (MSE), did not lead to instability between training, testing, and validation performance. This indicates that the improved network design was excellent and met the required specifications (Tabaraki & Khodabakhshi, 2020).

The close agreement between the experimental and predicted values, together with the tight clustering of the data points around the ideal regression line, indicates that the trained neural network did not merely memorize the training data. It, however, was able to learn the underlying nonlinear relations between turbidity (TUR), total suspended solids (TSS) and oil and grease and thus had good predictive accuracy and generalization performance. This is in line with previous studies that found that models with similar performances on training, validation and testing sets, are less prone to overfitting and show better generalization ability (Dishar & Muhammed, 2023; Pandey & Kumar, 2023).

The TRAINLM algorithm with 30 hidden neurons gave the best training performance as shown in the lowest MSE (9.0533×10^{-17}) and highest correlation coefficient (R = 1.0) showing excellent agreement between the predicted and target values in the training dataset.

Energy consumption analysis of the SPEC process

The specific energy consumption (SEC) of the proposed SPEU unit was determined based upon the optimal operational parameters (i.e., 12 V, 5 A, 45 minutes of operation, and a treated wastewater volume of 3 Liters). The total energy consumption utilized by the SPEU unit during the treatment process was 0.045 kWh, which corresponding to a specific energy consumption value of 15 kWh/m^{-3}.

The SEC value obtained in this research is within the range that has been previously reported for other electrocoagulation-based processes used for wastewater treatment. Elkacmi et al. (Elkacmi et al., 2020) noted a specific energy Consumption of 9.86 kWh/m^{-3} when treating olive mill wastewater with an external loop airlift reactor via photovoltaic electrocoagulation. A similar value was also reported by Gök and Gülyaşar(Gök & Gülyaşar, 2025) who observed an approximate SEC of 20 kWh/m^{-3} during electro-coagulation of real metal plating wastewaters under optimal operation. Also, Sameh, et al. (Sameh et al., 2020) reported an average SEC value of approximately 33.33 kWh/m^{-3} for the electrocoagulation treatment of tannery wastewater.

The variations in SEC data from the referenced research are due to the variability in characteristics of wastewater; reactor designs; types of electrodes used; the current densities applied; length of time for electrolysis; and objectives of treatment. Also, since all components of the proposed SPEU were powered by a photovoltaic energy system (PVES), which is comprised of solar panels, an electrical charge controller and battery storage unit, this allows for full disconnection from conventional electric grids and increases environmental sustainability of the treatment process.

CONCLUSIONS

This study clearly showed that it is possible to use photovoltaic energy in combination with electrocoagulation technology for treating real oily refinery wastewater using a newly developed solar-powered electrocoagulation unit as well as used this new SPEU to remove several types of contaminants from the wastewater such as turbidity, total suspended solids and oil & grease, which would reduce the need to rely upon traditional sources of electric power. Experimental evaluation confirmed that treatment performance was strongly dependent on applied current and electrolysis time. Operating at 5 A and treatment duration of 45 minutes resulted in a good balance among pollutant removal efficiency, generation of sludge and energy consumption. Under these operating conditions SPEU achieved high removal efficiency and competitive specific energy consumption and this shows viability technically and environmentally for treating refinery wastewater.

In this research, it was shown that the combination of ANN with Solar ECO could be an accurate prediction model for treating oily wastewater. The optimized ANN architecture (5–30-3–3) trained by TRAINLM algorithm had the lowest MSE and the highest correlation coefficient. The high correlation between the prediction and experimental results gives confidence to the model to learn the underlying nonlinearities of the treatment process. Hence, the developed ANN model has the potential to be used as a decision support system to optimize the process and also to design energy efficient and sustainable wastewater treatment systems.

REFERENCES

1. Abuduaini, R., Achagri, G., He, Y.-L., Chen, Z., Aini, D., Halik, Ü., Parkash, A., Ismail, R., Ma, P.-C., & Kadier, A. (2025). Treatment of wastewater from the petrochemical industry by a solar-powered electrocoagulation process: optimization of crucial operating parameters using response surface methodology. *Environmental Science: Water Research & Technology*, *11*(7), 1704-1719. https://doi.org/10.1039/d5ew00037h
2. Al-Kayiem, H. H., & Mohammad, S. T. (2019). Potential of renewable energy resources with an emphasis on solar power in Iraq: An outlook. *Resources*, *8*(1), 42. https://doi.org/10.1016/S0960-1481(98)00107-4
3. Al-Qodah, Z., Al-Shannag, M., Hudaib, B., & Bani-Salameh, W. (2024). Enhancement of dairy wastewater treatment efficiency in batch chemical-assisted solar-powered electrocoagulation-adsorption system. *Case Studies in Chemical and Environmental Engineering*, *9*, 100760. https://doi.org/10.1016/j.cscee.2024.100760
4. Al-Sammarraie, E. S., Al-Ghezi, B. S., Al-Ithawi, W. K., Nikonov, I. L., Kovalev, I. S., Altobee, A. M., Sabirova, T. M., Zyryanov, G. V., Awad, M., & Meskher, H. (2025). Investigating performance properties of three new types of UF membranes for carwash sector applications. *Journal of Applied Polymer Science*, *142*(36), e57407. https://doi.org/10.1002/app.57407
5. Albrazanjy, M. G., Hasan, M. M., Al-Jadir, T., Kadhim, W. A., Rahim, M. H. A., & Al-Rubaiey, N. A. (2024). Efficient and Sustainable Remediation of Refinery Wastewater Using Electrocoagulation and Advanced Oxidation Techniques. *Ecological Engineering & Environmental Technology*, *25*. https://doi.org/10.12912/27197050/178335
6. Ali, S., Wang, R., Huang, H., Yin, S., & Feng, X. (2024). Per-and polyfluoroalkyl substance separation by NF and RO membranes: a critical evaluation of advances and future perspectives. *Environmental Science: Water Research & Technology*, *10*(9), 1994-2012. https://doi.org/10.1039/d4ew00066h
7. Ali, Z., & Athari, H. (2026). Beyond Barrels and Generators: Solar Power Economics and Market Potential in Iraq. *NTU Journal of Renewable Energy*, *10*(1), 31-38. https://doi.org/10.56286/nkp6b206
8. AlJaberi, F. Y., Ahmed, S. A., & Makki, H. F. (2020). Electrocoagulation treatment of high saline oily wastewater: evaluation and optimization. *Heliyon*, *6*(6). https://doi.org/10.1016/j.heliyon.2020.e03988
9. Belone, M. C. L., Yli-Rantala, E., Sarlin, E., & Kokko, M. (2025). Microplastics in an anaerobic digester treating sewage sludge: Occurrence and factors affecting their identification with Raman spectroscopy. *Journal of hazardous materials*, *491*, 138015. https://doi.org/10.1016/j.jhazmat.2025.138015
10. Boinpally, S., Kolla, A., Kainthola, J., Kodali, R., & Vemuri, J. (2023). A state-of-the-art review of the electrocoagulation technology for wastewater treatment. *Water Cycle*, *4*, 26-36. https://doi.org/10.1016/j.watcyc.2023.01.001
11. Bolivand, N., & Delnavaz, M. (2025). Oil Wastewater Treatment by Electrocoagulation Process Using Scrap Aluminum as Electrodes: Optimization and Economic Evaluation. *Journal of Water and Wastewater; Ab va Fazilab (in persian)*, *36*(4), 1-17. https://doi.org/10.22093/wwj.2026.560644.3532
12. Butler, E., Hung, Y.-T., Yeh, R. Y.-L., & Suleiman Al Ahmad, M. (2011). Electrocoagulation in wastewater treatment. *Water*, *3*(2), 495-525. https://doi.

org/10.3390/w3020495

13. Çetinkaya, A. Y. (2025). Integration of electrocoagulation and solar energy for sustainable wastewater treatment: a thermodynamic and life cycle assessment study. *Environmental Monitoring and Assessment*, *197*(2), 224. https://doi.org/10.1007/s10661-025-13662-x
14. da Silva, L. J., Alves, F. C., & de França, F. P. (2012). A review of the technological solutions for the treatment of oily sludges from petroleum refineries. *Waste Management & Research*, *30*(10), 1016-1030. https://doi.org/10.1177/0734242X12448517
15. Dishar, H. K., & Muhammed, L. A. (2023). A review of the overfitting problem in convolution neural network and remedy approaches. *Journal of Al-Qadisiyah for Computer Science and Mathematics*, *15*(2), Page 155–165-Page 155–165. https://doi.org/10.29304/jqcm.2023.15.2.1240
16. Diya'uddeen, B. H., Daud, W. M. A. W., & Aziz, A. A. (2011). Treatment technologies for petroleum refinery effluents: A review. *Process Safety and Environmental Protection*, *89*(2), 95-105. https://doi.org/10.1016/j.psep.2010.11.003
17. Eksi, H. S., Kazak, O., & Akkaya, G. K. (2024). Separation of oil–water emulsions by electrocoagulation and electro-persulfate with sonication pretreatment: Determination of economical electrode configuration, optimization, and comparison. *Separation and Purification Technology*, *343*, 127071. https://doi.org/10.1016/j.seppur.2024.127071
18. El Jery, A., Salman, H. M., Al-Ansari, N., Sammen, S. S., Maktoof, M. A. J., & Al-Bonsrulah, H. A. (2023). Optimization of oil industry wastewater treatment system and proposing empirical correlations for chemical oxygen demand removal using electrocoagulation and predicting the system's performance by artificial neural network. *PeerJ*, *11*, e15852. https://doi.org/10.7717/peerj.15852
19. Elkacmi, R., Boudouch, O., Hasib, A., Bouzaid, M., & Bennajah, M. (2020). Photovoltaic electrocoagulation treatment of olive mill wastewater using an external-loop airlift reactor. *Sustainable Chemistry and Pharmacy*, *17*, 100274. https://doi.org/10.1016/j.scp.2020.100274
20. Fakhru'l-Razi, A., Pendashteh, A., Abdullah, L. C., Biak, D. R. A., Madaeni, S. S., & Abidin, Z. Z. (2009). Review of technologies for oil and gas produced water treatment. *Journal of Hazardous Materials*, *170*(2-3), 530-551. https://doi.org/10.1016/j.jhazmat.2009.05.044
21. Fotovat, F., & Hosseini, M. (2023). Treatment of oily wastewater by electrocoagulation: Simultaneous optimization of oil removal efficiency and specific energy consumption. *Journal of Water Process Engineering*, *55*, 104221. https://doi.org/10.1016/j.jwpe.2023.104221
22. Garcia-Segura, S., & Brillas, E. (2024). Redesigning electrochemical-based Fenton processes: An updated review exploring advances and innovative strategies using phenol degradation as key performance indicator. *Applied Catalysis O: Open*, *194*, 206980. https://doi.org/10.1016/j.apcato.2024.206980
23. Gök, Z., & Gülyaşar, H. C. (2025). Preliminary laboratory assessment of the removal of heavy metals from metal plating wastewater by electrocoagulation. *Water, Air, & Soil Pollution*, *236*(6), 327. https://doi.org/10.1007/s11270-025-07979-z
24. Guangji Hu , J. L., Guangming Zeng (2013). Recent development in the treatment of oily sludge from petroleum industry: A review. *Journal of Hazardous Materials,* , *261*, 470-490. https://doi.org/10.1016/j.jhazmat.2013.07.069
25. Guo, H., Qin, Q., Hu, M., Chang, J.-S., & Lee, D.-J. (2024). Treatment of refinery wastewater: current status and prospects. *Journal of Environmental Chemical Engineering*, *12*(2), 112508. https://doi.org/10.1016/j.jece.2024.112508
26. Hu, G., Li, J., & Zeng, G. (2013). Recent development in the treatment of oily sludge from petroleum industry: a review. *Journal of Hazardous Materials*, *261*, 470-490. https://doi.org/10.1016/j.jhazmat.2013.07.069
27. Iber, B. T., Torsabo, D., Chik, C. E. N. C. E., Wahab, F., Sheikh Abdullah, S. R., Abu Hassan, H., & Kasan, N. A. (2023). Response surface methodology (RSM) approach to optimization of coagulation-flocculation of aquaculture wastewater treatment using chitosan from carapace of giant freshwater prawn Macrobrachium rosenbergii. *Polymers*, *15*(4), 1058. https://doi.org/10.3390/polym15041058
28. Jasim, M. A., AlJaberi, F. Y., Salman, A. D., Alardhi, S. M., Le, P.-C., Kulcsár, G., & Jakab, M. (2023). Studying the effect of reactor design on the electrocoagulation treatment performance of oily wastewater. *Heliyon*, *9*(7). https://doi.org/10.1016/j.heliyon.2023.e17794
29. Kabdaşlı, I., Arslan-Alaton, I., Ölmez-Hancı, T., & Tünay, O. (2012). Electrocoagulation applications for industrial wastewaters: a critical review. *Environmental Technology Reviews*, *1*(1), 2-45. https://doi.org/10.1080/21622515.2012.715390
30. Kausar, F., Bagheri, A. R., Rasheed, T., Bilal, M., Rizwan, K., Nguyen, T. A., & Iqbal, H. M. (2022). Nanomaterials for removal of heavy metals from wastewater. *Nano-biosorbents for decontamination of water, air, and soil pollution*, 135-161. https://doi.org/10.1080/21622515.2012.715390
31. Khan, R., Haram, Z., Ahmad, W., Sohni, S., Xu, J., & Ilyas, M. (2024). Removal of hydrocarbon pollutants from refinery wastewater using N-hexadecylchitosan as an efficient adsorptive platform. *Scientific Reports*, *14*(1), 17236. https://doi.org/10.1038/

s41598-024-66429-8

32. Kobya, M., Demirbas, E., Dedeli, A., & Sensoy, M. (2010). Treatment of rinse water from zinc phosphate coating by batch and continuous electrocoagulation processes. *Journal of Hazardous Materials*, *173*(1-3), 326-334. https://doi.org/10.1016/j.jhazmat.2009.08.092
33. Li, R., Isowamwen, O. F., Ross, K. C., Holsen, T. M., & Thagard, S. M. (2023). PFAS–CTAB complexation and its role on the removal of PFAS from a lab-prepared water and a reverse osmosis reject water using a plasma reactor. *Environmental Science & Technology*, *57*(34), 12901-12910. https://doi.org/10.1021/acs.est.3c03679
34. Łukasiewicz, E. (2025). Coagulation–Sedimentation in Water and Wastewater Treatment: Removal of Pesticides, Pharmaceuticals, PFAS, Microplastics, and Natural Organic Matter. *Water*, *17*(21), 3048. https://doi.org/10.3390/w17213048
35. Mohamad, H. A. E. D., Hemdan, M., Bastawissi, A. A. E., Bastawissi, A. E. M., Panchal, H., & Sadasivuni, K. K. (2025). Industrial wastewater treatment by electrocoagulation powered by a solar photovoltaic system. *Energy Sources, Part A: Recovery, Utilization, and Environmental Effects*, *47*(1), 9479-9489. https://doi.org/10.1080/15567036.2021.1950870
36. Moneer, A., Thabet, W., Khedawy, M., El-Sadaawy, M., & Shaaban, N. A. (2023). Electrocoagulation process for oily wastewater treatment and optimization using response surface methodology. *International Journal of Environmental Science and Technology*, *20*(12), 13859-13872. https://doi.org/10.1007/s13762-023-05003-7
37. Moussa, D. T., El-Naas, M. H., Nasser, M., & Al-Marri, M. J. (2017). A comprehensive review of electrocoagulation for water treatment: Potentials and challenges. *Journal of Environmental Management*, *186*, 24-41. https://doi.org/10.1016/j.jenvman.2016.10.032
38. Muvel, H., Jindal, M. K., Tewari, P. K., & Anand, V. (2024). Advancements in electrocoagulation for oily wastewater treatment: Mechanisms, efficiency, and applications. *Journal of Water Process Engineering*, *68*, 106291. https://doi.org/10.1016/j.jwpe.2024.106291
39. Nascimento, B. Z., Muniz, E. P., Cotta, A. J. B., Oliveira, F. D. C., & da Silva Porto, P. S. (2023). Oily wastewater treatment by a continuous flow electrocoagulation reactor with polarity switch: Assessment of the relation between process variables and the aluminum released to the environment. *Journal of Environmental Management*, *347*, 119072. https://doi.org/10.1016/j.jenvman.2023.119072
40. Nawarkar, C., & Salkar, V. (2019). Solar powered electrocoagulation system for municipal wastewater treatment. *Fuel*, *237*, 222-226. https://doi.org/10.1016/j.fuel.2018.09.140
41. Ofverstrom, S., Sapkaite, I., & Dauknys, R. (2010). An investigation of impact of iron and aluminium addition on the anaerobic digestion process. *Linnaeus Eco-Tech*, 558-563. https://doi.org/10.15626/Eco-Tech.2010.059
42. Pandey, E., & Kumar, S. (2023). Gaps in Generalization Theory of Neural Networks. Recent Developments in Electronics and Communication Systems: Proceedings of the First International Conference on Recent Developments in Electronics and Communication Systems (RDECS-2022), https://doi:10.3233/ATDE221272,
43. Sameh, J., Wali, A., Buonerba, A., Zarra, T., Belgiorno, V., Naddeo, V., & Ksibi, M. (2020). Efficient and sustainable treatment of tannery wastewater by a sequential electrocoagulation-UV photolytic process. *arXiv preprint arXiv:2010.03285*. https://doi.org/10.1016/j.jwpe.2020.101642
44. Tabaraki, R., & Khodabakhshi, M. (2020). Performance comparison of wavelet neural network and adaptive neuro-fuzzy inference system with small data sets. *Journal of Molecular Graphics and Modelling*, *100*, 107698. https://doi.org/10.1016/j.jmgm.2020.107698
45. Vinh, D., Zinurov, V., Dmitrieva, O., & Kharkov, V. (2021). Separation of oil-water emulsion in laboratory setup with u-shaped elements. MATEC Web of Conferences, https://doi.org/10.1051/matecconf/202134603077
46. Virender, V., Pandey, V., Kumar, A., Raghav, N., Bhatia, P., Pombeiro, A. J., Singh, G., & Mohan, B. (2025). Tactical metal–organic frameworks (MOFs) adsorbent advantages in removal applications. *Environmental Science and Pollution Research*, *32*(11), 6380-6404. https://doi.org/10.1007/s11356-025-36153-5
47. Yamazaki, E. R., Yuan, Y., He, X., Verma, A., Jang, G. G., Giammar, D., Chellam, S., Jassby, D., Tsouris, C., & Hatzell, M. C. (2026). Electrocoagulation in Water Treatment: Targeted Contaminant Removal and Laboratory Best Practices. *ACS ES&T Water*, *6*(6), 3255-3282. https://doi.org/10.1021/acsestwater.5c01550
48. Yang, B., Sun, Y., Liu, Q., Wang, X., & Zhang, X. (2025). Wastewater sludge dewatering enhancement by flocculant selection and electrochemical pretreatment. *Separations*, *12*(10), 264. https://doi.org/10.3390/separations12100264