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Scientific paper

Modelling and Multi-Objective Optimization of Continuous Indirect Electro-Oxidation Process for RTB21 Dye Wastewater Using ANN-GA Approach

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Abstract

A continuous indirect electro-oxidation (EO) process was developed using graphite electrode to investigate the treatability of reactive turquoise blue RTB21 dye wastewater under specific operating conditions of initial pH, current density, hydraulic retention time (HRT), and electrolyte (NaCl) concentration. The experiments were performed in accordance with the central composite design (CCD), and the findings were used to create a model utilizing artificial neural networks (ANNs). According to the predicted findings of the ANN model, the MSE values for colour and COD removal efficiencies were estimated to be 0.748 and 0.870, respectively, while the R^2 values were 0.9999 and 0.9998, respectively. The Multi-objective optimization using genetic algorithm (MOGA) over the ANN model maximizes the multiple responses: colour and COD removal efficiency (%). The MOGA generates a non-dominated Pareto front, which provides an insight into the process's optimum operating conditions.

Keywords: Multi-objective optimization, Artificial neural network, Genetic algorithm, wastewater, reactive turquoise blue 21

1. Introduction

Clean water and sanitation is one of the major agenda of the United Nation's sustainable development initiative. According to the UN's world water development report 2021, around 2 billion individuals live under water stress conditions, and by 2030, the world would face a water deficit of 40%.[1] The quantity of wastewater generated worldwide has increased exponentially due to the rise in population and rapid industrial and technological development over the last few decades. India generates approximately 64,000 tonnes of dyes annually, of which 7,040 tonnes are dumped directly into the environment. These dyestuffs are widely used by textiles, paper and pulp, leather, and many other industries, but unfortunately, their impact on health and the environment are poorly evaluated.[2] Despite numerous Physico-chemical techniques for dye wastewater treatment, most of these systems appear to be marred by low practical efficiency or an inadequate benefit-cost ratio. Several traditional, as well as novel strategies, have been proposed in the literature to treat dye wastewater. These include adsorption by activated carbon,[3] chemical coagulation,[4] photodegradation under UV light irradiation,[5] hydrodynamic cavitation,[6] sonochemical degradations,[7] ozonation,[8] electrocoagulation,[9] Fenton like processes,[10] membrane filtration,[11] electrochemical methods,[12–14] and many more.

A primary drawback with many of these dye removal techniques is that they cannot remove all types of dyes from the wastewater. Adsorption is a highly successful technique for treating dye-containing effluent, but adsorbent regeneration is an expensive process. Prolonged treatment time and post-treatment solid disposal are limitations of the adsorption process.[15] Chemical coagulation can bring high removal efficiency and a high quantity of wastewater but relatively high processing costs.[16] Fenton-like techniques generate a substantial amount of sludge and are thus impractical for completely degrading dye molecules. Almost all types of dyes may be separated from wastewater using the membrane process. There is no sludge development, and footprint requirement is also low. However, the cost of the membrane and associated equipment and the fouling issue during operation are drawbacks of the membrane process.[17] While biological treatment could be cost-competitive, it is less effective to deal with refractory organic wastes.[16] As a result, finding an effective and environmentally acceptable treatment technique with high removal efficiency and low cost is essential for completely removing dye molecules from industrial wastewater.

Electrochemical techniques, such as anodic oxidation or indirect electrochemical oxidation (EO), have garnered significant interest in industrial wastewater treatment.[18]Electrochemical techniques offer enormous promise for wastewater treatment due to their wide range of environmental compatibility, increased process efficiency, and cost-effectiveness. However, several process factors, such as initial pH, current density, electrolyte concentration, process time, etc., impact electrochemical processes. Thus, optimizing process parameters is crucial from a process performance, economic, and scale-up perspective.[19]

Typically, modelling and optimization of electrochemical processes have been described using the conventional one-variable-at-a-time approach (OVAT). However, OVAT ideas suffer from several drawbacks, including the inability to show the interactive effect of process factors, being time demanding, and economically costly.[20] Artificial intelligence (AI) has gained immense attention to overcome such limitations and emerged as an encouraging tool for modelling and process optimization. AI tools, such as ANN, GA, fuzzy logic, and machine learning have been widely considered for modeling and optimizing wastewater treatment processes.[21] ANN, inspired by biological neuron phenomena of the human brain, was a computational modelling technique used for non-linear problems and to predict the output values for given input parameters from their training values.[22] GA optimization tool can be used to more precisely optimized the ANN model. GA is a search heuristic algorithm inspired by Charles Darwin's principle of natural evolution on the concept of "survival of the fittest". The GA approach is used to search for a global optimum solution with the ANN model as a fitness function.[23]

Single-objective optimization of the electrochemical process using the ANN-GA approach has been fairly reported in the literature. However, optimization problems involve multiple objectives, which require simultaneously to optimize: maximize or minimize. Many attempts have so far been made for multi-objective optimization of the electrocoagulation process for wastewater. However, to the best of our knowledge, the literature has not reported ANN modeling accompanied by multi-objective optimization using GA of continuous EO process for dye wastewater. In this work, our primary objective of research is to develop two distinctive ANN models for the prediction of colour removal efficiency and COD removal efficiency for continuous EO process to degrade reactive turquoise blue 21 (RTB21) dye wastewater. Finally, ANN models are simultaneously optimized using the GA approach to maximize both the objectives: colour removal efficiency and COD removal efficiency.

2. Materials and Method

2. 1. Chemicals and Materials

M/s Snehal Dye Chem Ltd, Ankleshwar, Gujarat, India, supplied the model RTB21 dye. All other chemicals used during experiments were of analytical grade. Deionized water (DI) with 1 μS/cm conductivity was used to perform all experiments. Graphite electrode plates (10×10×0.2 cm) used in the EO process were procured from M/s Prime Industries, Maharashtra, India.

2. 2. Electrochemical experiments

The continuous flow EO rector was constructed from an acrylic sheet with three sections, as shown in Fig.1, with

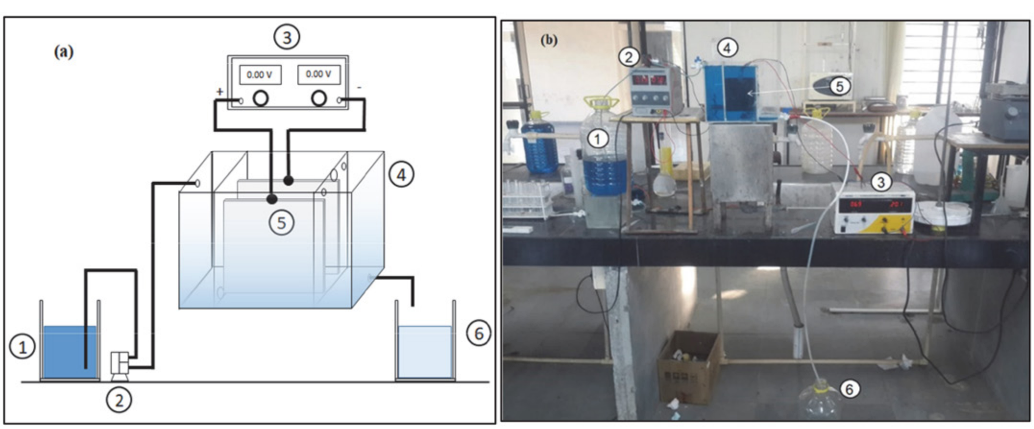

Fig. 1. (a) A conceptual schematic diagram of Continuous EO experimental setup, (b) Actual Experimental setup of continuous EO process: (1) RTB21 Wastewater Reservoir, (2) Peristaltic Pump, (3) DC Power Supply, (4) Electrochemical Cell, (5) Graphite Electrodes, and (6) Receiving cell

a working volume of 1.5 L. The two graphite electrode plates were connected vertically with a gap of 10 mm, connected in monopolar mode to a DC power supply (Make: SIGMA, 0–30 V 0-5 A). A mini peristaltic pump (GOSO Technology, Model: AB 11, 7.5 W) was used to pump the simulated wastewater into the top of the first section of the EO rector from the reservoir. The wastewater from the first section passed to the second section through holes provided at the bottom of the first section, flowed upward through the layers of the electrodes, and drained out at the third section from the top of the reactor. After experiencing the specified EO process time, the effluent samples of the continuous EO process were collected. To change the pH of the solution, dilute solutions of H_2SO_4 and NaOH were used. NaCl was added to the solution as an electrolyte to adjust the conductivity.

The colour removal efficiency of the sample collected at various time intervals was calculated using Eq. 1.[24]

$$\text{Colour removal efficiency (\%)} = (1 - \frac{A}{A_0}) \times 100 \quad (1)$$

Where A_0 and A are the light absorbance of a sample before and after the electrochemical process, respectively, measured using a UV/VIS spectrophotometer (Model CL 335).

$$\text{COD removal efficiency (\%)} = (1 - \frac{C}{C_0}) \times 100 \quad (2)$$

Where C_0 and C are the COD of a sample before and after the electrochemical process, respectively, measured using the open reflux method following standard methodologies (APHA. American Public Health Association 2005).

2. 3. Experimental design

Central composite design (CCD) was used for the design of experiments (DOE). Four process variables: initial pH (3-11), Current density (100-300 A/m^2), Hydraulic retention time (HRT) (50-150 min), Electrolyte NaCl concentration (1-3 g/L), with five levels used for the design of experiments as shown in Table 1.

Table 1. Experiment range and levels of Independent variable used as per CCD.

Variables	Levels −2(α)	−1	0	+1	+2(α)
Initial pH	3	5	7	9	11
CD (A/m^2)	100	150	200	250	300
HRT (min)	50	75	100	125	150
NaCl Conc. (g/L)	1	1.5	2	2.5	3

A total of 31 experiments as per Table 2 design were performed, and colour removal efficiency and COD removal efficiency were calculated. To avoid systemic bias, the runs were carried out in a randomized manner. Colour removal and COD removal efficiencies were considered to be response 1 and response 2, respectively. These were obtained for the experiments performed and are presented in Table 2.

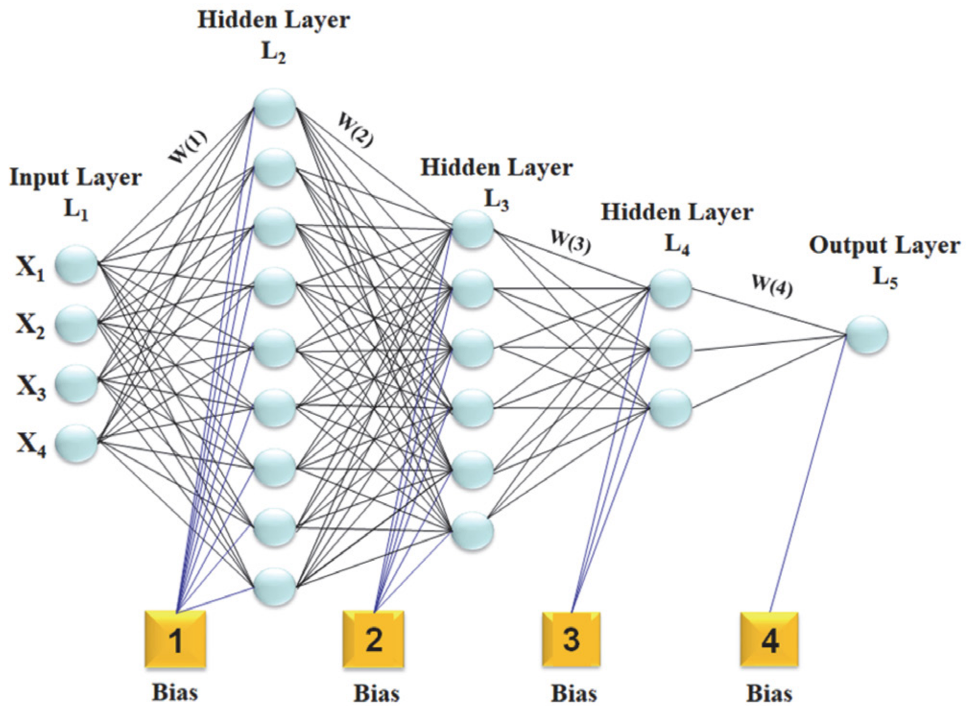

Fig. 2. Optimized architecture of ANN network for EO process.

Table 2. CCD design with observed and predicted responses.

Exp. Run	Parameters (Actual value)				Response 1 Colour removal (%)		Response 2 COD removal (%)	
	pH	Current density	HRT	NaCl Conc.	Expt.	ANN Predicted	Expt.	ANN Predicted
1	3	200	100	2.0	21.12	21.12	12.78	11.99
w`2	5	150	75	1.5	14.20	14.25334	9.60	9.69
3	5	150	75	2.5	45.02	45.02	21.21	21.53
4	5	150	125	1.5	33.89	33.89	25.55	26.33
5	5	150	125	2.5	65.32	65.31208	40.22	39.71
6	5	250	75	1.5	24.79	24.79	15.50	16.24
7	5	250	75	2.5	48.22	48.22	32.30	32.41
8	5	250	125	1.5	77.01	76.86996	44.50	44.24
9	5	250	125	2.5	99.20	99.2	60.12	61.95
10	7	100	100	2.0	44.32	44.32	21.30	20.75
11	7	200	50	2.0	8.26	8.26	6.40	5.75
12	7	200	100	1.0	43.43	43.43	32.23	31.58
13	7	200	100	2.0	96.11	95.64333	58.23	58.65
14	7	200	100	2.0	95.15	95.64333	59.03	58.65
15	7	200	100	2.0	96.28	95.64333	59.34	58.65
16	7	200	100	2.0	95.92	95.64333	58.51	58.65
17	7	200	100	2.0	95.10	95.64333	58.11	58.65
18	7	200	100	2.0	95.50	95.64333	59.20	58.65
19	7	200	100	2.0	95.00	95.64333	58.11	58.65
20	7	200	100	3.0	97.00	97	62.00	61.13
21	7	200	150	2.0	78.12	78.12	52.80	51.93
22	7	300	100	2.0	89.22	89.22	50.50	49.54
23	9	150	75	1.5	9.40	9.4	5.90	5.97
24	9	150	75	2.5	38.88	38.88	17.10	17.82
25	9	150	125	1.5	28.23	28.23	22.34	22.61
26	9	150	125	2.5	56.20	56.2	35.11	36.00
27	9	250	75	1.5	19.99	19.25079	12.12	12.52
28	9	250	75	2.5	40.87	40.64716	28.33	28.69
29	9	250	125	1.5	70.05	70.05	39.80	40.53
30	9	250	125	2.5	91.10	90.93601	58.70	58.23
31	11	200	100	2.0	8.10	8.1	5.30	4.57

2. 4. ANN Model

ANN models were created for both the responses to measure the performance of the EO reactor to treat the RTB21 model dye wastewater. The artificial neural network (ANN) is a soft computation tool inspired by biological neurons in the brain.[25] In recent years, the ANN has been employed as an efficient and versatile approach in various applications.[26] In ANN, there are three layers: the input layer, one or more hidden layers, and the output layer shown in Fig. 2.

An ANN's structure is made of processing components referred to as neurons (nodes). Weights and biases are used to connect each layer of neurons.[27] The weighted sum of each neuron's inputs are passed through the activation function to produce the output.[28] Feed-forward Levenberg-Marquardt Back-Propagation (LM-BP) algorithms were used for learning. ANN models were developed for both responses to evaluate the EO reactor's performance in treating the RTB21 model dye wastewater. The mean square error (MSE) was utilized for training the ANN. 70% of the data were used to train the neural network. After training, the remaining data were used in an equivalent proportion for validation and testing. More data were allocated for the training, which resulted in an improved model with a shorter processing time.

The testing offered an unbiased evaluation of the network's performance, whereas the validation evaluated the network's generalization, which was terminated when no further progress was detected.[29] The ANN models can be used as a fitness function for a GA used for multi-objective EO process optimization.

2. .5 GA Model

GA is a well-known robust AI technique for solving global search optimization problems.[30] The GA algorithm is based on Darwin's evolutionary theory. The 'gamultiobj' function in MATLAB (R2020b) was used to generate the Pareto front of colour removal efficiency and COD removal efficiency using GA and the direct search toolbox. The 'gamultiobj' function in MATLAB employs a controlled elitist GA, which is a variation of NSGA-II.[31]

Initially, a random population of individuals called chromosomes is randomly generated within the lower and upper limits of decision variables, and the optimization process starts. Three genetic algorithm rules are used to produce the populations of the future generation: selection, crossover, and mutation. To generate the next generation, the best population was chosen based on fitness level function. The fitness value indicates an individual's merits for evaluation.[28] Crossover, also known as recombination, is the process through which two populations' genetic information is combined to generate new offspring. Then, random changes in the individual population are performed during the mutation process to preserve and add diversity. When the fitness value of a population does not improve over subsequent generations, the population eventually achieves the optimal solution.[32]

2. 6. ANN-GA

Typically, when we deal with more than one objective, they are often conflicting with each other. Therefore, objectives are simultaneously optimized using a multi-objective optimization algorithm; mathematically equally good solutions known as non-dominated or Pareto frontier are selected as the optimum designs.[33] ANN-MOGA has been applied for predicting optimum conditions of colour removal efficiency and COD removal efficiency. The ANN models were used as a fitness function for MOGA. An ANN function named myANN1 and myANN2 was trained using the experimental data for Colour removal efficiency and COD removal efficiency, respectively. Then, using MATLAB (R2020b) and the myANN1 and myANN2 function, a multi-objective function code was developed. Finally, the MOGA program was run to generate Pareto optimal solutions by setting all input variables' upper and lower limits.

3. Results and Discussion

3. 1. Experimental Results

In a batch electrochemical cell, the indirect electrochemical oxidation method was carried out to treat the RTB21 wastewater. The experimental results obtained from the batch process were then used to build a continuous process, and colour removal efficiency and COD removal efficiency were measured. Based on the batch process results, the initial pH, current density, and NaCl concentration range were fixed for the continuous process. It was possible to determine the influence of hydraulic retention time (HRT) on the colour removal and COD removal efficiency by altering the HRT values from 25 to 200 min, as shown in Fig. 3.

The other parameters, such as pH, current density, and NaCl concentration, were kept constant at 7, 200 A/m^{2}, and 2 g/L, respectively. HRT was found to have a beneficial influence on the EO process by increasing the response time. As per the DOE set, continuous EO process experiments were performed, and colour removal efficiency and COD removal efficiency were calculated, as shown in Table 2. By raising the HRT, adequate time for process reaction could be provided; hence, the colour removal efficiency (%) and the COD removal efficiency (%) improved. The synergistic effect of increased HRT can be attributed

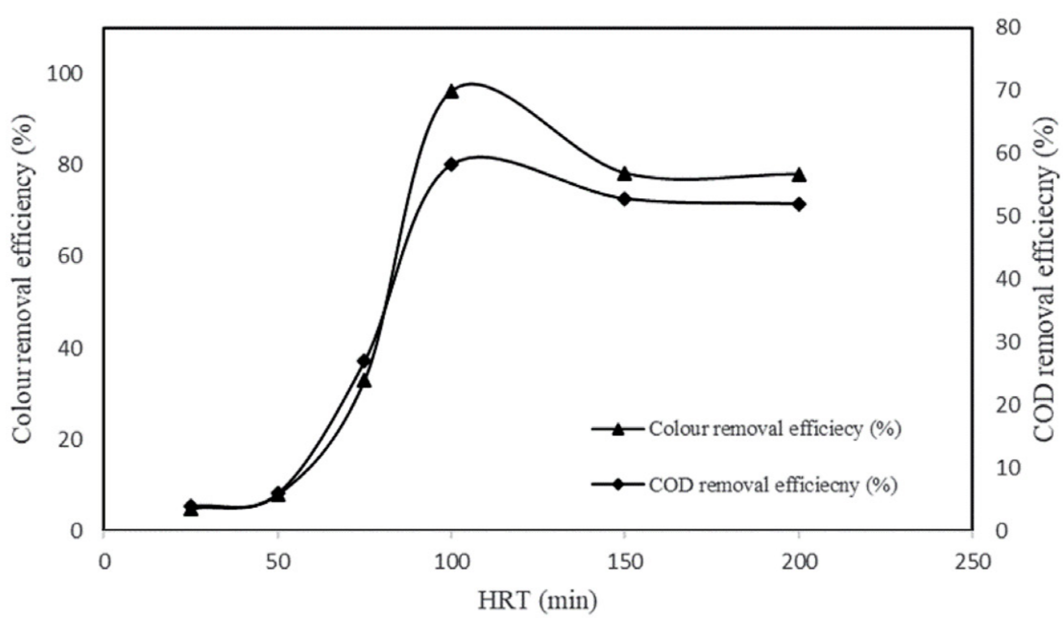

Fig. 3. Effect of HRT (min) on Colour removal efficiency (%) and COD removal efficiency (%) at 7 pH, 200 A/m^2CD, and 2 g/L NaCl concentration.

to the generation of more oxidants for pollutant degradation.[34] With the enhancement of HRT more than 100 min, degradation efficiency declines because of unsuitable side reactions.[35] The highest colour removal efficiency (%) and COD removal efficiency (%) achieved were 96.11% and 58.23% at 100 HRT (min), pH of 7, 200 A/m^2, and 2 g/L NaCl concentration.

3. 2. Prediction with ANN

The primary objective of the ANN is to predict the colour removal efficiency and COD removal efficiency for DOE data sets. The present research used a feed-forward LM-BP ANN with a tangent sigmoid transfer function (tansig) at a hidden layer. At each iteration, the ANN learns by testing and validating the predictability against the remaining data and deciding its absolute accuracy based on the overall correlation coefficient. It is always critical to pick a sufficient number of neurons in the hidden layer to properly well train the network. However, the larger the hidden layer's number of neurons, the longer it takes to process the data and learn the noise.[36] Therefore, a solid network is required to determine an accurate ANN architecture to obtain accurate predictions, and this step was developed through trial and error.[37] This was done to achieve the minimum possible deviation between predic-

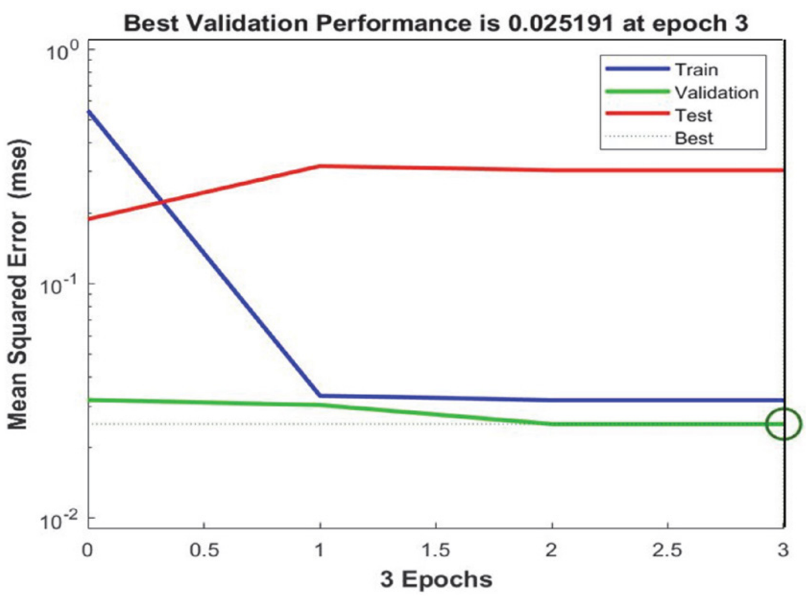

Fig. 4. Performance of ANN for colour removal efficiency

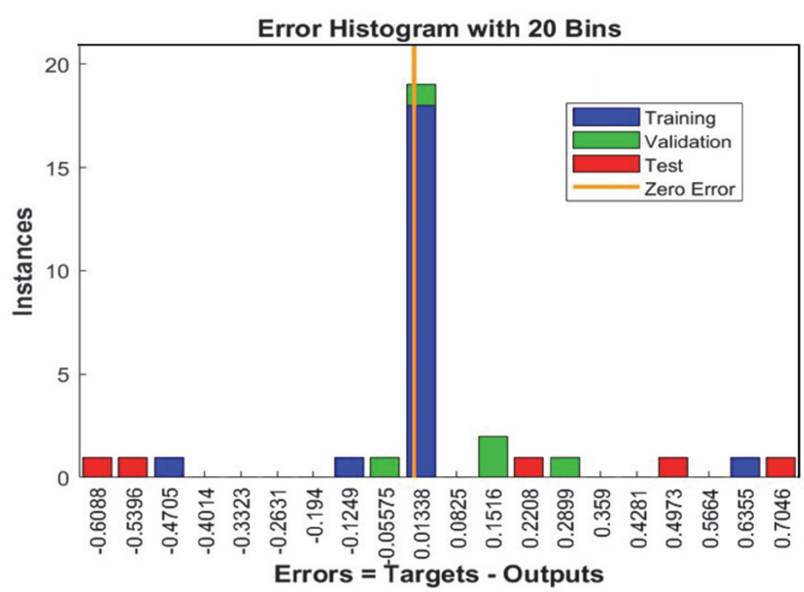

Fig. 5. Error histogram with 20 bins for the training, validation, and testing of ANN for colour removal efficiency prediction.

tions and experimental results and limit the potential of over-fitting the model to the data. Numerous topologies were tested to obtain the optimal ANNs network based on the most miniature Mean Square Error (MSE) and largest Correlation coefficient (R) values. The best ANN network was a back-propagation with 4-9-6-3-1 neurons. The inputs consist of pH, CD, HRT, NaCl concentration, and output consists of colour removal efficiency and COD removal efficiency.

MSE is a statistic that represents the average of the squares of the errors, the magnitude by which the value indicated by the model varies from the quantity to be observed; when MSE reaches zero, it indicates that our model's error reduces. The R is calculated by dividing the coefficient of determination (R^2) by its square root function, which determines the relationship between outputs and targets. The R-value of 0 and 1 indicates a random relationship and close relationship, respectively.

For the colour removal efficiency, the optimum network performance was reached at an epoch of 3. Fig. 4 shows the performance of the ANN for colour removal efficiency prediction during training, validation, and testing and the mean squared error (MSE) of the network.

As shown in Fig. 4, the error started at a high value during training, validation, and testing but gradually reduced as the number of epochs increased. The training was terminated at epoch 3 to prevent overfitting the data sets, and the best validation performance was achieved at epoch 3, with a mean square error of 0.025191.

As the error histogram of the colour removal efficiency (Fig. 5) shows, most of the errors fall between –0.6066 and 0.7046. The zero error is in a vertical line parallel to the ordinate with 19 instances during training.

The values of regression coefficient of correlation between the experimentally obtained colour removal and the ANN predicted colour removal during training, validation, and testing are 0.99998, 1, and 0.999993 (Fig. 6 (a,b,c)), respectively. The regression coefficient of the network (training, testing, and validation) was 0.99996 (Fig. 6 (d)).

For the COD removal efficiency, the optimum network performance was reached at an epoch of 2. Fig. 7 shows the performance of the ANN for COD removal efficiency prediction during training, validation, and testing and the mean squared error (MSE) of the network. As Fig. 7 shows, the best validation performance occurred at epoch 2, with a 0.01971 MSE value.

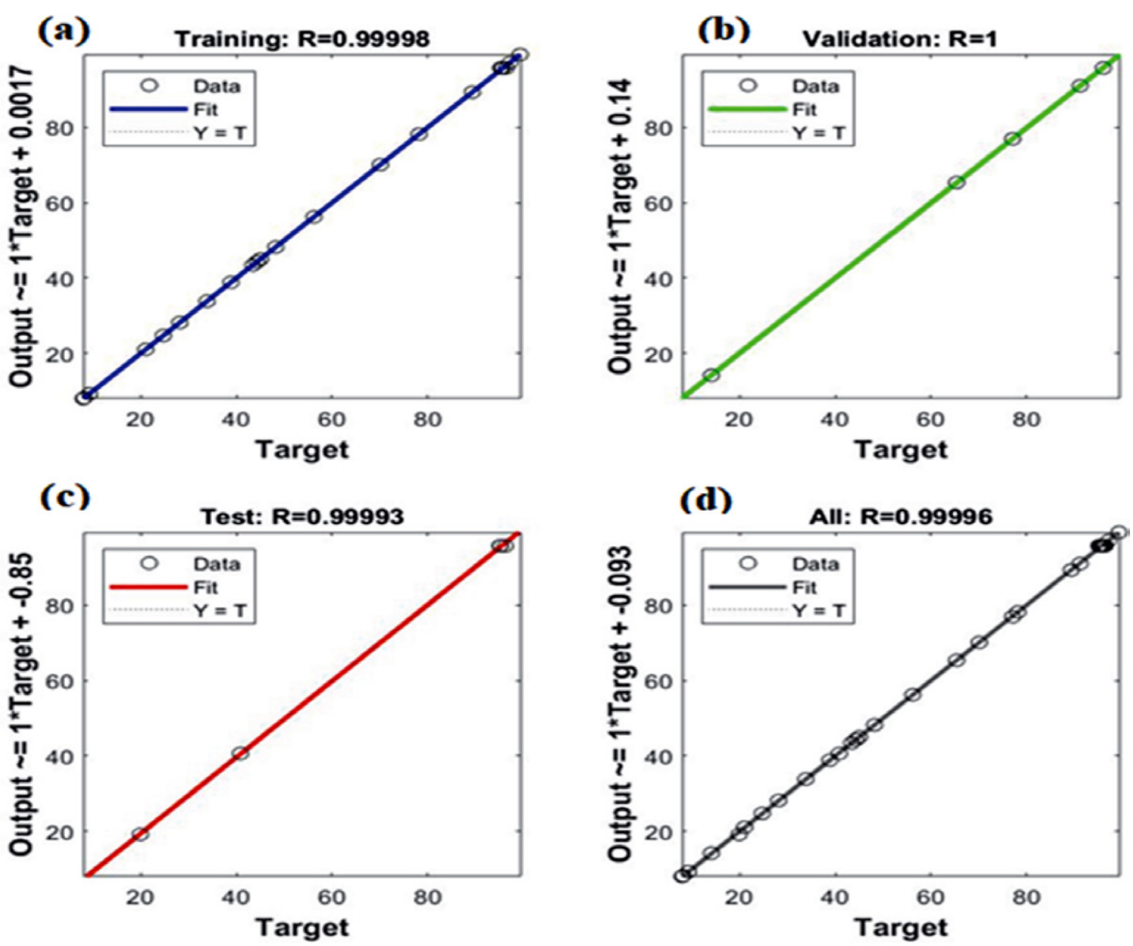

Fig. 6. ANN predictions of colour removal efficiency versus experimental data

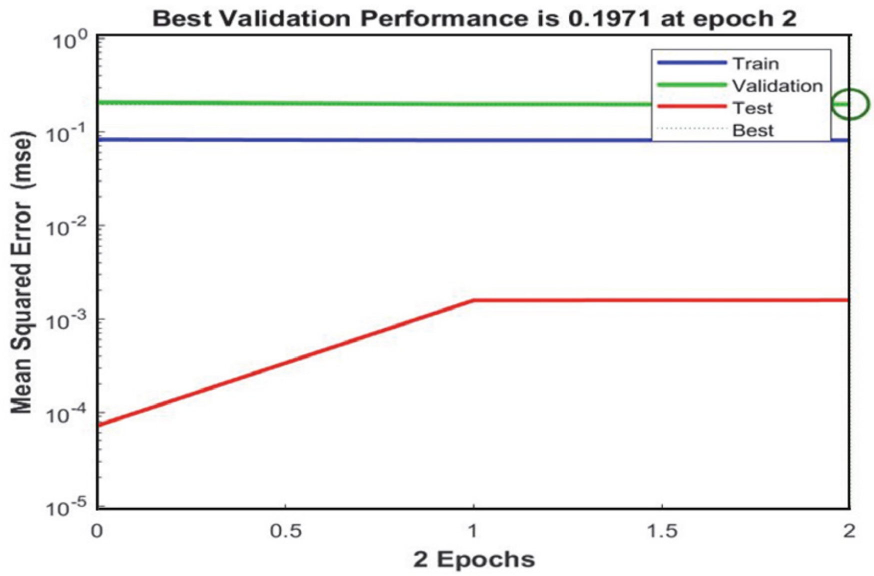

Fig. 7. Performance of ANN for COD removal efficiency.

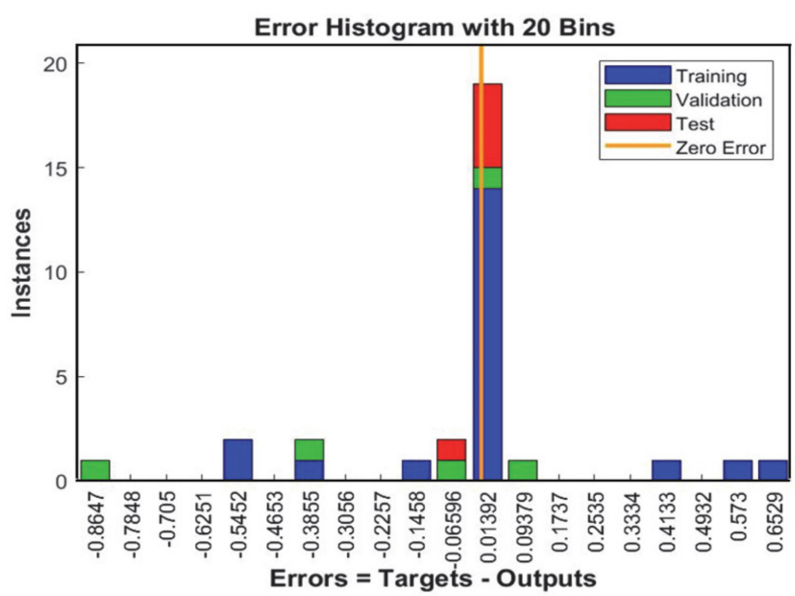

Fig. 8. Error histogram with 20 bins for the training, validation, and testing of ANN for COD removal efficiency prediction.

Fig. 8 shows the error histogram of the ANN for COD removal efficiency. As the error histogram shows, most of the errors fall between -0.8647 and 0.6529. The zero error is in a vertical line parallel to the ordinate with 19 instances during training.

The regression coefficient of correlation between the experimentally obtained COD removal efficiency and the ANN predicted COD removal efficiency during training, validation, and testing is shown in Fig. 9 (a,b,c) with values of 0.9999, 0.99987, and 1, respectively. The regression coefficient of the network (training, testing, and validation) was 0.99989, as shown in Fig. 9 (d).

3. 3. ANN-GA Process Result

The well-trained ANNs MATLAB functions were used as the fitness function, and the MOGA function is used to optimize all responses simultaneously using the "gamultiobj" algorithm. Fig. 10 depicts the conceptual model of the technique designed for multi-objective optimization of a continuous EO process for RTB21 dye wastewater treatment using ANN and MOGA.

The upper and lower bounds are set in accordance with DOE data. To generate the Pareto front, the population size, and scattered crossover rate was set to 50 and

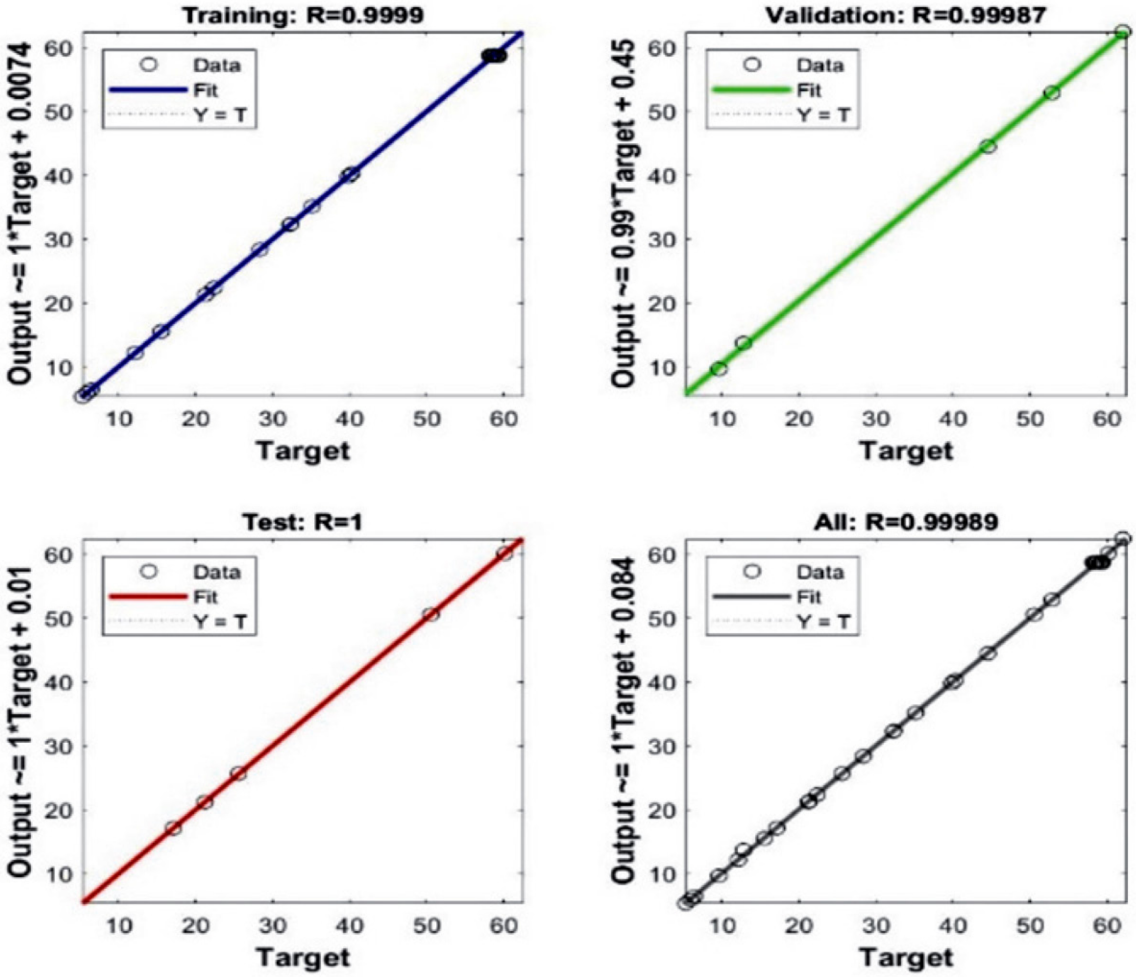

Fig. 9. ANN predictions of colour removal efficiency versus experimental data.

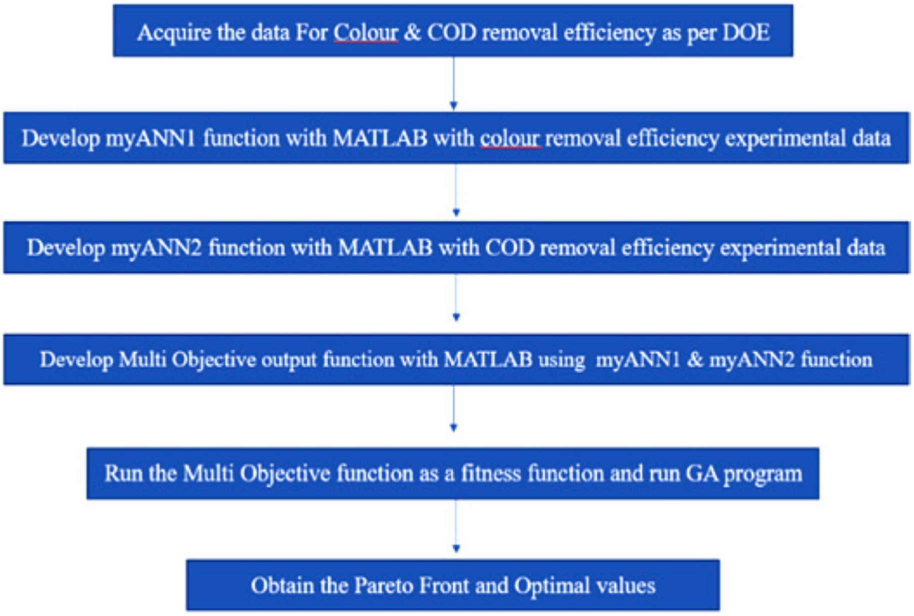

Fig. 10. Conceptual model of ANN-MOGA.

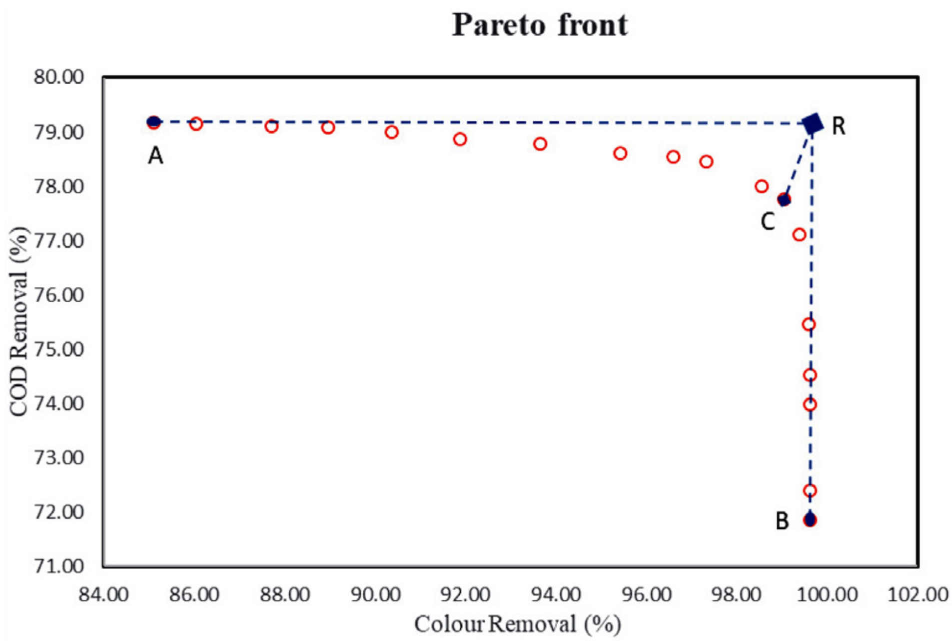

Fig. 11. Pareto front of solutions obtained from multi-objective optimization of colour removal efficiency and COD removal efficiency.

Table 3. Pareto front results.

Sr No.	pH	CD	HRT	NaCl Conc.	Colour removal efficiency	COD removal efficiency
1	8.787827	299.5076	138.5276	2.996047	99.61891	73.9798
2	6.363786	298.0398	140.3197	2.081875	85.10173	79.17201
3	6.449391	298.1739	140.1821	2.235604	91.86767	78.88044
4	6.974005	299.1398	138.9455	2.56925	99.39556	77.10913
5	9.185247	299.9831	138.2816	2.999956	99.62148	71.86423
6	6.363786	298.0085	140.3197	2.107265	86.02775	79.16041
7	6.428636	299.3274	140.3134	2.171365	88.94894	79.08443
8	6.711324	298.9897	139.8307	2.345993	96.60149	78.53708
9	7.927858	298.8051	138.4173	2.989545	99.61496	74.53391
10	8.10627	299.6478	139.1243	2.908942	99.60828	75.46253
11	6.847544	298.2432	140.1611	2.494421	99.04663	77.75342
12	6.579091	298.9179	139.9584	2.312797	95.42957	78.61332
13	6.45257	298.1872	140.203	2.146821	87.71312	79.09912
14	6.79187	298.932	139.2222	2.43517	98.55288	77.99996
15	6.92752	298.8918	139.8317	2.372651	97.32729	78.46639
16	6.593751	298.7015	140.2943	2.202841	90.35593	79.00198
17	9.091421	299.5083	138.4265	2.996635	99.62033	72.40382
18	6.534363	298.0117	140.3169	2.274754	93.64972	78.79096

0.8, respectively. The Pareto front, as a result of MOO, is depicted in Fig. 11. Table 3 contains the input values for both responses in accordance with Pareto solutions.

The multi-objective optimization solution of colour removal efficiency and COD removal efficiency has no unique solution but a mathematically equally good solution known as non-dominated or Pareto optimal solutions. As can be observed colour removal efficiency increases from 85.10% to 99.62% at the cost of decreasing COD removal efficiency from 79.17% to 72.40%. As shown from this Fig. 10, the Pareto front provides all possible Colour removal efficiency and COD removal efficiency choices. The utopia point C (99.05, 77.75) is selected such that it has the minimum Euclidean distance from the reference point R. The reference point is a point corresponding to maximum values of colour removal efficiency point B (99.62, 72.40) and COD removal efficiency point A (85.10, 79.17).

Table 4. Statistical Parameters of well-trained ANN models for colour removal efficiency and COD removal efficiency.

Statistical Parameters	MSE	RMSE	MAE	MPE (%)	Chi Square statistics (χ^2)	R^2
Colour removal efficiency	0.0748	0.2735	0.1462	0.2737	0.0478	0.9999
COD removal efficiency	0.0870	0.2949	0.1569	0.1398	0.0919	0.9998

3. 4. Confirmatory Experiments

The results of the well-trained ANNs model were checked with their predicted capability in terms of standard statistical performance parameters such as mean square error (MSE), root mean square error (RMSE), mean absolute error (MAE), model predictive error (MPE) (%), Chi-Square statistics (χ^2), and R^2. A chi-square test is a statistical test used to compare experimental results with predicted results. The value of χ^2 is close to zero, and the R^2 value close to one displays the well-trained ANN models. Statistical parameters of well-trained ANN models for color and COD removal efficiencies are presented in Table 4.

Optimized parameters (pH: 6.85, CD: 298.24 A/m^2, HRT: 140.16 min, NaCl concentration: 2.49 g/L) generated by the ANN-MOGA model for achieving maximizing Colour removal efficiency (%) and COD removal efficiency (%) simultaneously were validated by performing confirmatory experiments. The confirmatory experiment was carried out at the predicted optimal condition for model validation in triplicate, and average values are shown in Table 5.

Table 5. Comparative results of optimized and confirmatory experiments for model validation.

Process Parameters	ANN-MOGA Optimized Value	ANN-MOGA Experimental Value
pH	6.85	6.9
CD	298.24	299
HRT	140.16	141
NaCl Conc.	2.49	2.5
Colour removal efficiency (%)	99.05	98.82
COD removal efficiency (%)	77.75	77.60

A perusal of Table 5 indicates close agreements between optimized and experimental values. The percentage variation between experimental and simulated results was determined in the ~±1% error range. This suggested that the models' prediction capacity was satisfactory. Hence, the adequacy of ANN-MOGA models on predicting the Colour removal efficiency (%) and COD removal efficiency (%) was validated.

4. Conclusion

The ANN approach was successfully used to forecast all responses for continuous EO processes in accordance with an input parameter such as pH, current density, hydraulic retention time, and NaCl concentration. To build ANN models, the feed-forward LM-BP training algorithm was used. The well-trained ANN models had three hidden layers with 9-6-3 neurons in the hidden layers. For colour removal efficiency and COD removal efficiency, the MSE values were 0.748, 0.870, and the R^2 values were 0.9999, 0.9998, respectively. The ANN modelling technique could offer several advantages, including speed, dependability, fault tolerance, resilience, universal application, and usability, making it an intriguing choice for modelling complicated systems such as wastewater treatment.

The use of a genetic algorithm to perform multi-objective optimization of the ANN model resulted in a set of Pareto optimum points. The solutions to the Pareto front points could be utilised as a guideline for designing a continuous EO for the RTB21 dye wastewater process. The ANN-MOGA approach was utilised to estimate the best process variable values for maximum colour removal efficiency and COD removal efficiency, which resulted in the generation of the Convex nature Pareto front. The utopia point (99.05, 77.75) was selected such that it had the minimum euclidean distance from the reference point R. In essence, data obtained in the present study could be useful for possible scale-up of the electro-oxidation process for similar types of reactive dyes.

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Povzetek

Razvili smo kontinuirni posredni proces elektrooksidacije (EO) z uporabo grafitne electrode, s katerim smo preučili možnosti odstranjevanja barvila turkizno modro RTB21 in odpadnih voda: Pri tem smo optimirali začeno pH vrednost, gostoto električnega toka, zadrževalni čas (HRT) in koncentracijo elektrolita (NaCl). Poskusi so bili izvedeni v skladu s središčnim sestavljenim **načrtom** (ang. CCD), rezultati pa so bili uporabljeni za učenje modela na osnovi umetnih nevronskih mrež (ang. ANN). Glede na predvidene ugotovitve modela ANN so bile MSE vrednosti za učinkovitost odstranjevanja barve in KPK ocenjene na 0.748 oziroma 0.870, vrednosti R2 pa na 0.9999 oziroma 0.9998. Večkriterijska optimizacija z genetskimi algoritmi (MOGA) uporabljena po ANN modelu je odatno optimizirala učinkovitost odstranjevanja barvo in zmanjševanja KPK. MOGA poda nedominantno (Pareto) fronto, ki omogočajo vpogled v optimalne pogoje delovanja procesa.