Research article

Optimization of adaptive neuro–fuzzy inference system (ANFIS) parameters via Box-Behnken experimental design approach: The prediction of chromium adsorption

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ABSTRACT

Prediction of adsorption via Adaptive Neuro–Fuzzy Inference System (ANFIS) can save the cost and time in practical applications. Chromium (VI) adsorption data obtained at different temperature, activated carbon dosage and pH values were evaluated by using MATLAB ANFIS. In order to achieve prediction of adsorption via ANFIS with acceptable error values, optimum membership function (MF) and optimum number of MF were determined by using Box-Behnken experimental design (BBD) method. In order to determine the optimum number of MF for each input, all combinations given in BBD matrix were examined via ANFIS, then, regression models for each MFs were developed between the root mean square error (RMSE) and MF numbers of each input. The most used five membership functions (triangular, trapezoidal, generalized bell shaped, Gaussian, Gaussian 2) were investigated. According to the analysis of variance (ANOVA), regression models developed for the test data with triangular and trapezoidal membership functions were significant in the 95 % confidence level. Predictions were employed via ANFIS by using optimum MF numbers of each inputs (6, 6, 3 for triangular MF and 8, 8, 2 for trapezoidal MF). Consequently, the best Cr(VI) adsorption percentage prediction (RMSE = 1.9084 and R^2 = 0.992) was obtained by using triangular membership function with optimum MF numbers. Response surface plots, which gives the relationship between MF numbers and RMSE values for triangular MF were also evaluated. In this study, it was demonstrated that MF type and numbers, which are crucial for good prediction via ANFIS grid partition method, can be determined optimally by applying experimental design methodology.

1. Introduction

Adaptive Neuro-Fuzzy Inference System (ANFIS), an artificial neural network based on the Takagi-Sugano fuzzy inference system, is a MATLAB application to make estimations depending on functions prepared by training fuzzy logic with a given data set. ANFIS take data inputs and compute according to the membership function (MF) to estimate an outcome by combining the flexibility of fuzzy logic and the learning capability of neural networks. It is a powerful tool as a practical alternative to non-linear regression modeling especially for prediction complex processes. It has the ability to capture complex non-linear relationships and to adapt to the uncertainties in the data set. The computations are done by several layers inside the ANFIS structure. First-level MFs are used to

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determine which cluster is more suitable. Following this, IF-THEN rules are applied to the data. Rules are generated from crisp data fed to the system for training. Calculations are carried out according to MFs and the rules, and then an estimation of the system can be achieved [1]. ANFIS works by using fuzzy rules to model a system's input-output relationship. The fuzzy rules are defined by membership functions (MFs). The membership functions define how the input variable(s) are related to the output variable(s) [2].

ANFIS algorithm is divided into two main stages accordingly: the training stage and the testing stage. During the training stage, the ANFIS model is trained using chosen numbers of set of input and output data. These data sets could be taken from any experimental studies or various sources of process applications. The training data are used to optimize and make machines learn the parameters of the fuzzy rules and neural network. The training algorithm uses the backpropagation algorithm to adjust the parameters of the neural network. When the ANFIS model was trained, it was ready to be used to predict the output variable for new input data during the testing stage. Accordingly, the outputs taken from the ANFIS model whether model outputs and data set outputs meet with each other, hence, model accuracy is tested [3,4]. Grid partition, one of the most used method to generate FIS, uses different membership functions (MFs) to create an inference system. The most used membership functions are triangular (trimf), trapezoidal (trapmf), gaussian (gaussmf) and gaussian-2 membership function (gauss2mf). The user selects the membership functions for each inputs and outputs, and the number of MF for each inputs. This method is generally used in all studies because the model can be shaped by the user depending on the experimental data. The user must determine MF correctly to achieve realistic results [5]. Training carries on until the RMSE (root mean square error) value approaches a constant value. Finally, the resulted model is plotted against training, or testing data, hence, it is possible to determine which experimental data was correctly predicted. Different MFs and numerous MF numbers can be examined, and depending on the type and number of MF, different predictions with a variety of errors can be obtained.

Chemical processes include many parameters, and finding relationships among those parameters can be challenging depending on the related system. Predicting the results depending on several parameters not only help optimize the process parameters for maximum efficiency but also it is a practical way for controlling product quality, ensuring safety and making real-time decision. ANFIS's fast, legitimate estimation and discovery of parameter relationships allows it to make faster progress with unknown systems. ANFIS has been applied in different estimation studies, such as production efficiency, battery life, drying of products, wastewater treatment etc. [6–11]. Sreekumar et al. (2020) applied adaptive neuro-fuzzy approach to predict cell pH for energy-efficient chlorate production. Gaussian with 3 MF numbers for each input (flow rates of brine, HCl, NaOH, cell electrolyte temperature) have been applied during ANFIS modelling in their study. ANFIS with statistical methods and hybrid learning model resulted with prediction accuracy of %88 [6]. Teimouri and Sohrabpoor (2013) studied application of adaptive neuro-fuzzy inference system and cuckoo optimization algorithm for analysing electrochemical machining process [9]. They informed that triangular membership function (MF) with 2-2-2-2 structure was the most precise model for material removal rate; on the other hand, gaussian model was the most precise for the prediction of surface roughness. Fan et al. (2018) applied ANFIS based model for the temperature prediction of lithium-ion power batteries [7]. They applied Gaussion MF type with 1,2 and 3 MF numbers for the inputs of ambient temperature, state of charge and current, respectively, and obtained predictions with 4.5 % mean error as a result of their study. Similarly, biosolid capture rate was modelled with respect to total solid, volatile solid content, and polymer dose via ANFIS by using Gaussian MF with 3-3-3 structure [8]. Dutta P. and Kumar A. (2018) studied on "Application of an ANFIS model to optimize the liquid flow rate of a process control system" [10]. Gaussian, triangular and generalized bell shape MF were modelled with 3-3-3, 3-3-3-3, 5-3-3-3 and 3-3-3-3-3 structures. They indicated that increasing MF number did not increase model performance, increasing epoch and training data increased model performance [10].

Studies showed that ANFIS is a practical tool to predict the results, however, ANFIS parameters have often been determined with trial-and-error method, which is non-systematic approach. There is a lack of understanding and explaining how to model ANFIS and how to determine the number of MF and MF type in the literature. Only Zhang et al. [12] stated a systematic optimization study to precise prediction of thermophysical properties of hybrid nanofluids by applying ANFIS with different types of clustering techniques, including grid partitioning, subtractive clustering, and fuzzy c-means. They indicated that the number of MFs for each input and the type of MF for each input are the structural parameters for grid partitioning ANFIS, and they tested all MFs but only with limited MF numbers (2 and 3) for each inputs [12]. There are some studies [13–17] related to the prediction of chromium adsorption via ANFIS, however, none of them focused on optimization of ANFIS parameters. Zafar et al. [13] employed Gaussian MF for each inputs (pH, adsorbent dosage, initial concentration) on Cr(VI) adsorption data. In the mentioned study [13], there is no examination about the MF type and number of MF for each input. Banza et al. [14] indicated that compared to ANN and RSM, ANFIS is the best prediction model for Cr(VI) adsorption onto cellulose nanocrystals–sodium alginate and, however, there is no information about the chosen MF type for inputs (time, dosage, pH and concentration) and output (adsorption capacity). Cr(VI) removal in textile wastewater using activated carbon was predicted with ANFIS in another study [15], as typical, without any systematic approach all MF types with one and two input numbers were examined. Yusuff et al. [16] predicted Cr(VI) adsorption onto activated eucalyptus biochar by applying ANFIS with generalized bell-shaped MF and 3 of MF numbers for each inputs (pH, concentration and time). In another study, Cr(VI) adsorption onto mesoporous Cerium Oxide was predicted by using ANFIS without giving the detail about ANFIS parameters like MF type and the numbers [17]. In the studies related to the chromium adsorption prediction, there is no systematic approach to determine optimum ANFIS parameters. Experimental data were modelled by using randomly determined ANFIS parameters, except the study by Kuyakhi and Boldaji [18] that they applied particle swarm optimization (PSO) algorithm with ANFIS in order to develop a predictive model for Cr(VI) removal on NiO nanoparticle.

In this study, we aimed to develop a systematic approach via experimental design methodology to obtain optimum ANFIS parameters (MF type and the numbers), hence to predict chromium adsorption percentage with high accuracy. In order to achieve the best prediction via ANFIS, optimum membership function (MF) type and optimum number of MF were determined by applying Box-Behnken experimental design (BBD) approach for the first time in this study.

2. Materials and methods

2.1. Dataset

Batch adsorption data (Tables S–1) obtained at different pH, carbon dosage and temperature were taken from our previous study [19]. Batch Cr(VI) adsorption onto biomass (peach stone) based steam activated carbon was studied at isothermal and constant pH conditions. Chromium(VI) adsorption experiments were carried out by agitating 2–60 mg of activated carbon with 50 mL of Cr(VI) solution of 30 mg/L at pH from 2 to 8 at different temperature of 295–318 K in an orbital shaker until equilibrium. Equilibrium Cr(VI) concentrations were determined at 540 nm wavelength by using UV Spectrophotometer after complexing with diphenylcarbazide at acidic medium [20]. Equilibrium adsorption percentages were determined by using Eq. 1

$$Adsorption\ (\%) = \left(\frac{C_0 - C_e}{C_0}\right) \times 100 \tag{1}$$

where C_0 and C_e are the Cr(VI) initial and equilibrium concentrations (mg/L), respectively.

Table S-1 shows the adsorption data, with 82 % utilized for training and 18 % for testing in ANFIS. This study employed adsorption temperature, carbon amount, and pH as inputs, with adsorption percentage serving as the output variable.

2.2. ANFIS application

Adsorption training data (No:1–40 in Tables S–1) were loaded to Matlab (2022b) ANFIS application. Grid Partition method was applied with different MF types and numbers in order to generate FIS output. Training was carried on until the error value approached a constant RMSE (root mean square error) value. During this training process, ANFIS iteratively updates its parameters using optimization algorithms with the goal of minimizing the difference between the predicted and actual outputs. Then, ANFIS model, predicted outputs and train RMSE values were produced by the software. After training, ANFIS model was ready for testing. Subsequently, the software was run with the test data (No:41–49 in Tables S–1) for validation of the developed ANFIS model, then, predicted outputs and the test RMSE value were obtained. Definition equation of RMSE is given in Eq. 2

$$RMSE = \sqrt{\frac{\Sigma_{i=1}^{n}(\widehat{y}_i - y_i)^2}{n}} \tag{2}$$

where, $\widehat{y}_i$ and y_i are the predicted and experimental values, respectively, n is the total data number.

In order to determine the effect of MF number, different MFs were applied for both inputs (pH, carbon dosage, and temperature). Constant type MF function was used for the output (adsorption percentage). There are numerous possibilities for the number of input MF. In order to limit these possibilities, firstly, for each parameter, the same number of MF was chosen for each input as 5-5-5, 10-10-10 and 15-15-15, which also represents the center points in the BBD matrix. For each case, the RMSE values of the training and testing data sets were recorded. Then, by examining the RMSE values, center points were chosen for the further experimental design evaluations.

2.3. Box-Behnken experimental design (BBD) approach

Adsorption data set has three inputs, accordingly, for each input, the number of MF has to be determined. A typical three-parameter BBD matrix given in Tables S–2 was applied in order to determine the effect of MF numbers for each input. MF1, MF2 and MF3 represent the coded level of MF numbers of input 1, 2 and 3, respectively. The levels, 2, 5 and 8 correspond the codded values as −1, 0 and 1, as seen in Tables S–3. In order to determine the optimum number of MF for each input, all combinations achieved from BBD were examined via ANFIS, and the RMSE values of training and testing data sets were recorded. RMSE values taken from ANFIS were transferred into the Design Expert 13.0 Software (academic version), and regression models, which give the relationship between the MF numbers and the RMSE values for training and testing data, were developed and evaluated by using ANOVA.

2.4. Optimization of MF numbers and 3D response surface plots

Optimization module in Design Expert Software was employed in order to obtain optimum MF numbers for each input (MF1, MF2 and MF3), which gave the minimum RMSE (R1 and R2) for both train and test data. The relationship between RMSE values for train and test data and MF numbers were also evaluated by using 3D response surface plots obtained from Design Expert Software. Block flow diagram of the ANFIS parameters optimization and prediction process is given in Fig.S-1. As seen in the diagram, after obtaining optimum ANFIS parameters via experimental design approach, ANFIS was run with the optimum MF type and MF numbers, hence, optimum ANFIS model was developed.

3. Results and discussion

3.1. Effect of MF numbers on prediction

By using the same number of MF for three inputs and the most used five MF types, train adsorption data and test data were examined via ANFIS and then, RMSE values were obtained as given in Table 1. As the number of MF was increased, RMSE value for train data reduced but test error increased. It was evaluated that MF number of five could be the center point for the further experimental design investigations.

3.2. Experimental design approach and regression models

RMSE values of train and test data obtained with different MF types and MF numbers (Tables S–2) can be seen in Table 2. There are variety of RMSE values depending on MF types and numbers for each input. As seen in Table 2 that depending on the chosen MF number and type, adsorption percentage can be estimated with the range of 2.9 and 162.8 of RMSE values. This range is too much and unacceptable for the prediction studies. It can be clearly seen that determination of optimum MF number and MF types for each input is crucial for the prediction studies. For this purpose, obtained RMSE values (Table 2) were transferred into Design Expert 13.0 (academic version) in order to develop regression models between the RMSE values and MF number for each MF type.

In order to statistically analyse the developed models for each MF type, ANOVA was employed via Design Expert Software. The method of the least squares is typically used to estimate the regression coefficients. P-value is used to identify process parameters, which has statistically significant effect on each response. P-values less than 0.05 indicate that parameters are significant in 95 % confidence interval. As can be seen in Table 3, developed regression models for the train RMSE (R1) are mostly significant in 95 % confidence interval with the high R^2 values. However, developed regression models for test RMSE (R2) are significant only for triangular and trapezoidal membership functions in 95 % confidence level. Accordingly developed quadratic models for trimf and trapmf are given in Table 4. R1 and R2 show the RMSE value obtained with train data and test data, respectively, and the subscripts indicate the MF type. As can be seen from Table 4 that depending on MF type, the MF numbers of each input has different coefficient, which means different effect on RMSE. It can be concluded that, the optimum numbers of MF for each input should be determined depending on the used MF type.

3.3. 3D response surface plots

3D response surface plots, which give the relationship between RMSE values for train and test data and MF numbers for each inputs can be seen in Fig. 1. As seen in Fig. 1a–c, as MF2 increases, the train RMSE reach the lowest value at all MF1 and MF3 numbers whereas the test RMSE has the highest value (Fig. 1 d,f). It is clear that the optimum MF2 numbers should be determined in order to obtain the lowest RMSE for both test and train data. MF3 and MF1 numbers slightly affect on train RMSE, on the other hand, low MF3 number and middle MF1 numbers give the lowest RMSE value (Fig. 1 b,e). It was concluded that MF numbers for each inputs can affect the predictions in different ranges, and depending on the variety and data type optimum MF number could be different. In the literature, the researchers tend to use the same MF numbers for each input [6–11,13–16]. As we observed that in order to make good predictions these MF numbers should be optimized for each input and for each different dataset.

3.4. Optimization of MF numbers for the best prediction

Optimum MF numbers (after rounding to the nearest integer) were determined for triangular and trapezoidal membership functions as 6-6-3 and 8-8-2 for input1, 2 and 3, respectively. Objective function was RMSE value for both train and test data and the goal was to obtain the lowest RMSE. As can be seen in Fig. 2, different optimum MF numbers were obtained for trimf and trapmf. ANFIS prediction was also examined by using obtained optimum MF numbers, then, RMSE values obtained via ANFIS and regression model were compared (Fig. 2). It is clearly seen that trimf is the most fitting regression model matches with ANFIS very well. Prediction with trimf type with the optimum MF numbers of 6, 6 and 3 for input 1,2 and 3 (temperature, carbon dosage and pH) resulted in good

Table 1
RMSE values for train and test data obtained at different MF numbers.

MF Type	Number of MF (Input 1- Input 2- Input 3)					
	5-5-5		10-10-10		15-15-15	
	RMSE		RMSE		RMSE	
	Train	**Test**	**Train**	**Test**	**Train**	**Test**
Trimf	0.83764	3.68980	0.03964	39.07820	0.00011	48.79680
Trapmf	3.07220	35.43130	0.03544	47.45490	0.00011	48.72450
Gbellmf	0.72650	4.08420	0.00444	55.54230	0.00013	47.31220
Gaussmf	0.24849	3.46980	0.03465	41.47770	0.00012	48.30940
Gauss2mf	0.51320	5.00120	0.02616	43.20830	0.00012	48.52450

Table 2

RMSE values obtained from ANFIS via BBD approach.

No	MF 1-MF2-MF3	Trimf		Trapmf		Gbellmf		Gaussmf		Gauss2mf	
		RMSE		RMSE		RMSE		RMSE		RMSE	
		Train	Test	Train	Test	Train	Test	Train	Test	Train	Test
1	2-5-2	2.328	4.334	1.902	5.344	1.880	4.922	2.012	4.584	1.929	4.546
2	2-5-8	2.140	5.044	3.235	35.555	1.626	6.694	1.184	11.531	0.869	5.933
3	2-8-5	1.416	13.919	1.078	32.211	0.529	162.792	0.903	113.202	0.755	24.319
4	5-2-8	5.021	7.469	6.159	7.507	15.505	9.332	5.498	7.567	5.058	7.887
5	5-8-2	1.256	3.503	1.764	5.221	0.499	14.395	1.140	2.922	0.887	3.459
6	5-5-5	0.838	3.690	3.072	35.431	0.727	4.084	0.248	3.470	0.513	5.001
7	8-5-2	1.501	3.805	1.800	4.947	1.401	3.704	1.435	3.665	1.349	3.598
8	5-2-2	5.056	7.690	6.201	7.878	15.844	9.885	5.507	7.757	5.100	8.130
9	8-8-5	0.566	12.474	0.332	35.161	0.015	32.964	0.414	15.212	0.040	17.115
10	5-5-5	0.838	3.690	3.072	35.431	0.727	4.084	0.248	3.470	0.513	5.001
11	8-5-8	0.838	3.691	3.072	35.431	0.727	4.096	0.248	3.471	0.513	5.003
12	8-2-5	5.021	7.469	6.159	7.507	15.505	9.332	5.479	7.556	5.051	7.889
13	2-2-5	5.389	7.750	6.252	7.753	15.829	9.429	5.538	7.845	5.083	8.165
14	5-5-5	0.838	3.690	3.072	35.431	0.727	4.084	0.248	3.470	0.513	5.001
15	5-8-8	0.566	12.492	0.332	35.163	0.0156	33.049	0.415	14.927	0.054	16.338

MF1, MF2, MF3: membership function number for input1, 2 and 3, respectively.

Table 3

ANOVA results for developed models.

MF Type		Sum of Squares	df	Mean Square	F-value	p-value	R^2	Significance
trimf	Train	48.88	9	5.43	247.70	<0.0001	0.9978	Significant
	Test	163.57	8	20.45	5.61	0.0249	0.882	Significant
trapmf	Train	60.36	9	6.71	15.31	0.0039	0.9650	Significant
	Test	2812.98	9	312.55	7.29	0.0207	0.9292	Significant
gbellmf	Train	651.78	9	72.42	9528.88	<0.0001	0.9999	Significant
	Test	17993.87	7	2570.55	3.69	0.0533	0.7867	Not Significant
gaussmf	Train	69.03	9	7.6	116.63	<0.0001	0.9953	Significant
	Test	8195.05	7	1170.72	3.18	0.0749	0.7608	Not Significant
gauss2mf	Train	58.40	9	6.49	237.83	<0.0001	0.9977	Significant
	Test	433.14	9	48.13	3.24	0.1045	0.8535	Not Significant

Table 4

Developed regression models.

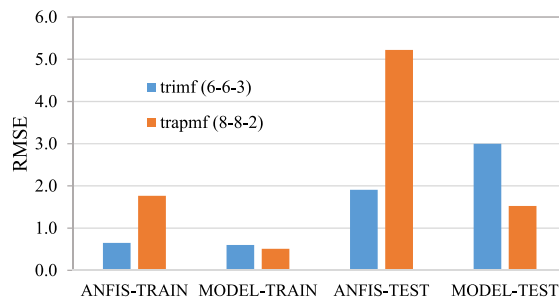| MF Type	Regression models
Trimf	$R1_{Trimf} = 11.5272 - 0.5553 \bullet MF1 - 2.5001 \bullet MF2 - 0.3202 \bullet MF3 - 0.0134 \bullet MF1 \bullet MF2 - 0.0132 \bullet MF1 \bullet MF3 - 0.0182 \bullet MF2 \bullet MF3 + 0.0549 \bullet MF1^2 + 0.1963 \bullet MF2^2 + 0.0411 \bullet MF3^2$
	$R2_{Trimf} = 21.3268 - 1.7351 \bullet MF1 - 6.3298 \bullet MF2 + 0.2698 \bullet MF3 - 0.0323 \bullet MF1 \bullet MF2 + 0.2558 \bullet MF2 \bullet MF3 + 0.1746 \bullet MF1^2 + 0.5712 \bullet MF2^2 - 0.1159 \bullet MF3^2$
Trapmf	$R1_{Trapmf} = 6.5275 + 0.4579 \bullet MF1 - 1.4326 \bullet MF2 + 0.4775 \bullet MF3 - 0.0182 \bullet MF1 \bullet MF2 - 0.0017 \bullet MF1 \bullet MF3 - 0.0386 \bullet MF2 \bullet MF3 - 0.0405 \bullet MF1^2 + 0.0831 \bullet MF2^2 - 0.0229 \bullet MF3^2$
	$R2_{Trapmf} = -47.7858 + 4.2734 \bullet MF1 + 10.3085 \bullet MF2 + 11.6398 \bullet MF3 + 0.0888 \bullet MF1 \bullet MF2 + 0.0076 \bullet MF1 \bullet MF3 + 0.8420 \bullet MF2 \bullet MF3 - 0.4665 \bullet MF1^2 - 1.1750 \bullet MF2^2 - 1.2127 \bullet MF3^2$

prediction with the low RMSE values (0.64882 and 1.9084 for train and test, respectively) as seen in Fig. 3. Adsorption percentage predicted by ANFIS with optimum MF numbers of trimf are in good agreement ($R^2 = 0.992$) with the experimental data (Fig. 4). Tubular data belong these points are also given in Tables S–4.

Comparison of Cr(VI) adsorption prediction studies are given in Table 5. As seen that ANFIS configurations vary significantly among the studies, with differences in the number and type of membership functions for different input variables. Among the predictive Cr(VI) adsorption studies, Banza et al. [14] and Dubey et al. [17] performed the best ANFIS prediction with the lowest RMSE (0.007 and 0.038) and high R^2 (0997 and 0.99) values, however, there is no information about the used membership function and number in their studies. The adsorption data used in the study was obtained by applying response surface methodology [14]. This approach may positively affect the prediction accuracy. In the later study [17], compared to others, high numbers of experimental data (total 320) employed in ANFIS modelling could be responsible for this high accuracy. As expected, Kuyakhi and Boldaji [18] obtained higher accuracy prediction by applying particle swarm optimization (PSO) algorithm with ANFIS.

Compared to the others, developed ANFIS model in this study performed better than the studies [13,15,16] in terms of RMSE and/or R^2, indicating better predictive accuracy. In addition, our study performed well in terms of R^2 and is comparable with the
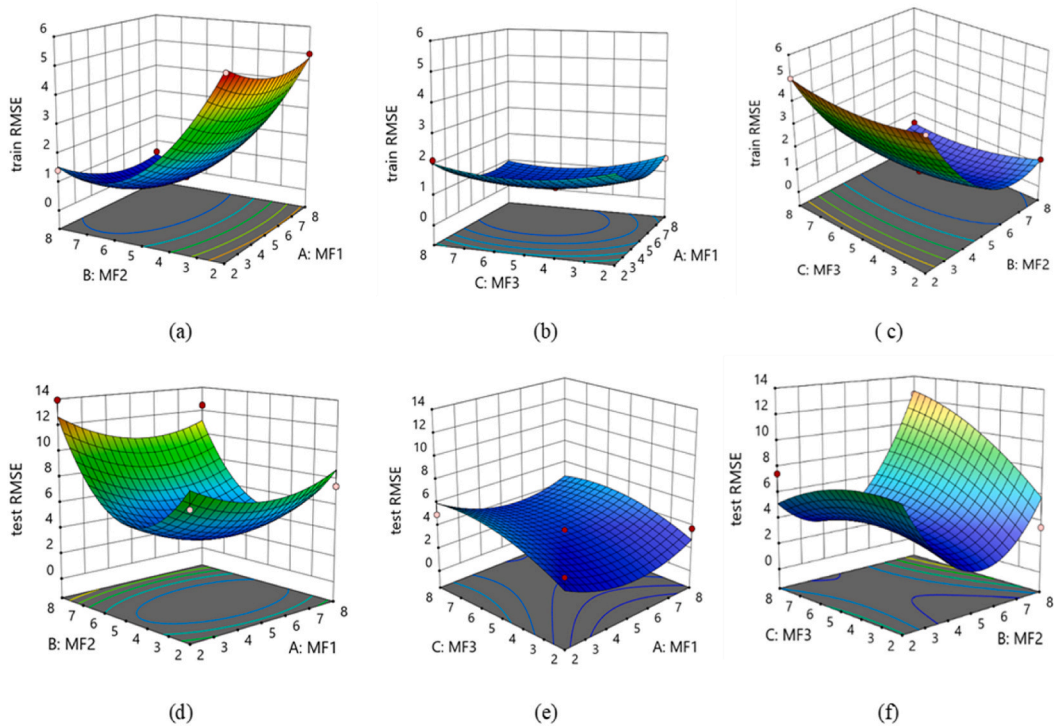
Fig. 1. Response surface plots for triangular MF a) relationship between MF1 and MF2 with train RMSE b) relationship between MF1 and MF3 with train RMSE c) relationship between MF2 and MF3 with train RMSE d) relationship between MF1 and MF2 with test RMSE e) relationship between MF1 and MF3 with test RMSE, f) relationship between MF2 and MF3 with test RMSE.

Fig. 2. RMSE values obtained via Regression model and ANFIS prediction at optimum conditions.

studies [14,17,18]. In conclusion, the optimization of membership function numbers in this study contributed to the accuracy of prediction model, and resulted in good predictive performance of Cr(VI) adsorption.

4. Conclusion

ANFIS is a great tool to predict Cr(VI) adsorption percentage, however, ANFIS prediction can be obtained over a very wide error range depending on MF type and MF number chosen. For different MF types, optimum MF number for each input could be different. In order to predict the results with high accuracy, determining optimum MF type and the number of MF are crucial steps. It was demonstrated first time that optimum MF and MF number can be determined effectively by applying Box-Behnken experimental design method in this study. According to the developed approach in this study, Cr(VI) adsorption was predicted very well with very low RMSE of 1.9084 and high R^2 of 0.9922 via ANFIS with triangular MF type and the optimum MF numbers of 6, 6 and 3 for temperature, carbon dosage and pH inputs, respectively. Compared to the most studies in the literature, developed optimum ANFIS model in this study performed better predictive accuracy.

The optimization of membership function numbers contributed to the accuracy of prediction model, and resulted in good predictive performance of Cr(VI) adsorption. Consequently, developed optimization approach in this study can be applied to the any ANFIS
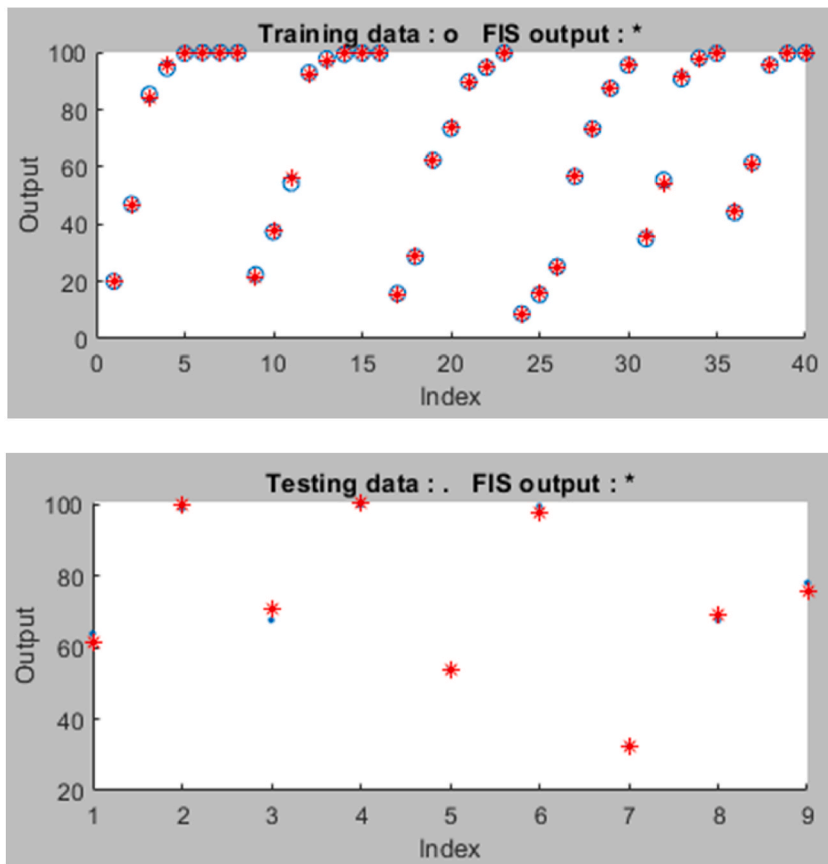
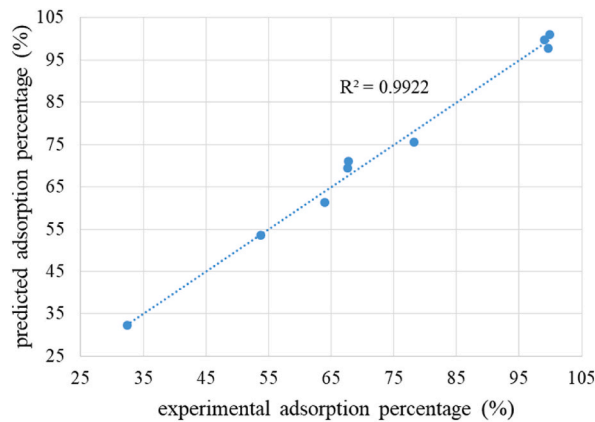**Fig. 3.** Train and test data vs FIS output obtained with optimum ANFIS model (trimf 6-6-3).

Fig. 4. Predicted data obtained with optimum ANFIS model vs. experimental data.

prediction study, hence, depending on data set, optimum ANFIS model can be developed in order to obtain high accuracy prediction via ANFIS Grid Partition method. Furthermore, as a practical application, with the adaptation of this prediction model to the real adsorption processes, the process parameters can be optimized for maximum efficiency as well as real-time decision can be made depending on the inlet conditions of the process.

Data availability statement

Data included in article/supp. Material/referenced in article.

Table 5
The comparison of other ANFIS modeling studies on Cr(VI) adsorption.

WORK/PREDICTION MODEL	INPUTS	OUTPUT	MF TYPE (INPUT)	MF TYPE (OUTPUT)	INPUT MF NUMBER	Test RMSE – R^2	REF.
Cr(VI) removal onto modified maghemite nanoparticles/ANFIS	- pH - Adsorbent (g) - Cr(VI) conc. (mg/L)	Cr(VI) removal efficiency (%)	Gaussmf	n.a.	10-10-10	6.23 - n.a.	[13]
Cr(VI) adsorption onto cellulose nanocrystals–sodium alginate/ANFIS	- Time (min) - Adsorbent (g) - pH - Cr(VI) conc. (mg/L)	Cr(VI) adsorption capacity (mg/g)	n.a.	n.a.	3-3-3-3	0.007–0.997	[14]
Cr(VI) removal from textile wastewater using activated carbon/ANFIS	- Time - pH - Adsorbent (g)	Cr(VI) adsorption percentage (%)	Psigmf	Linear	3-3-3	n.a. - 0.3916	[15]
Cr(VI) adsorption onto activated eucalyptus biochar/ANFIS	- Cr(VI) conc. (mg/L) - Sorbent (g/L) - pH	Cr(VI) removal percentage (%)	Gbellmf	Constant	3-3-3	5.5090–0.920	[16]
Cr(VI) removal by NiO nanoparticles/ANFIS-PSO (Particle swarm optimization)	- Contact time - Cr(VI) conc.(mg/L) - Adsorbent (g) - pH	Cr(VI) removal percentage (%)	Gaussmf	Linear	–	0.0182–0.999	[18]
Cr(VI) adsorption onto mesoporous Cerium Oxide/ANFIS	- pH - Initial concentration - Contact time - Adsorbent dosage - Stirring rate	Cr(VI) adsorption percentage (%)	n.a.	n.a.	n.a.	0.038–0.99	[17]
Cr(VI) adsorption onto biomass based activated carbon/ANFIS	- Temperature (°C) - Carbon (mg) - pH	Cr(VI) adsorption percentage (%)	Trimf	Constant	6-6-3	1.9084–0.9922	This Work

CRediT authorship contribution statement

Dilek Duranoğlu: Writing – review & editing, Writing – original draft, Validation, Supervision, Software, Methodology, Investigation, Data curation, Conceptualization. **Esat Sinan Altın:** Writing – original draft, Visualization, Validation, Methodology, Investigation, Data curation. **İlknur Küçük:** Validation, Methodology, Investigation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.heliyon.2024.e25813.

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