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Prediction of Surface Area of Material (MnO_2) by Neuro-Fuzzy Techniques

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Abstract

The Neuro-Fuzzy Techniques in MATLAB software used ANFIS (Adaptive Neuro-Fuzzy Inference System) accuracy to predict the surface area of MnO2 through best parameter correlations. This paper uses data obtained from different recent research works in the analysis. He conducted data processing that involved factors analysis and elimination of redundant data through his data file. Prediction of surface area through experimental synthesis parameters was achieved by using ANFIS in MATLAB software. The data consisting of 30, ITwas split into training and testing sets where training occupied 70% and the remaining 30% served for testing. The material surface area prediction through MATLAB-operated ANFIS model relies on four synthesis parameters consisting of Reaction Time and Temperature and Material quantity and experimental surface Area during hydrothermal process. The ANFIS prediction model displays these characteristics: Epochs between 0 and 50 while initial MSE positioned at 28.09 then decreases before reaching a final MSE at 28.08 thereby enabling an accuracy rate of surface area prediction at 91% together with a 9% difference between predicted and actual values thus offering the possibility to optimize material surface area by adjusting predictors. The surface area measurement of MnO2 became possible for the first time through ANFIS prediction when researchers optimized the hydrothermal synthesis parameters.

Keywords: Neuro-Fuzzy Model, MATLAB, ANFIS, Prediction of Surface Area, MnO2

Introduction

The surface area of a material is a critical factor influencing performance and effectiveness in divers field(1). It plays a role in the adsorption of pollutants and contaminants, contributing to environmental remediation efforts(2). In the field of electronics, materials with optimized surface properties are essential for device performance and functionality(3,4). The surface area can be enhanced by tuning the hydrothermally synthesis parameter of material(5) . It is not easy to experimentally synthesis of material by changing parameters(6,7). Hence, the machine learning approach can be used for find the best parameter for higher surface area of the material(8). It serves as a comprehensive package encompassing various data structures and general algorithm . Understanding and manipulating surface area characteristics are fundamental in advancing materials science and technology across various industries. To find the surface area of material by experimental process we faces many problem like long time to complete synthesis process and how many hours we needs, how much compound we have to take to for material synthesis, how much degree temperature required for maximized the surface, to over come all these problems we have used machine learning approached.

Neuro-Fuzzy system

A Neuro-Fuzzy system is a smart model that mixes two things — Fuzzy Logic and Neural Networks. Fuzzy logic is a way to think like humans. For example, we say, “If the weather is very hot, then switch on the fan.” We don’t use exact numbers all the time — we use words like hot, cold, slow, or fast.

This is how fuzzy logic works — it deals with unclear or approximate values. But to create a fuzzy system, we usually need experts to write rules and define how much is “hot” or “cold.” This is not always easy.(9,10) On the other side, a neural network is a system that can learn from data. It works like the human brain — it looks at examples and understands patterns. But neural networks are hard to understand from the inside; they are often called black-box models, because we don’t clearly see how they make decisions.

Now, when we combine fuzzy logic with neural networks, we get a Neuro-Fuzzy system. It learns from data like a neural network, and it also explains things in human-like rules like a fuzzy system. So, we don’t have to write all the fuzzy rules ourselves — the system learns and adjusts them automatically by looking at real-world data. The most popular type is called ANFIS (Adaptive Neuro-Fuzzy Inference System).(11)

In ANFIS, we give the system some input values (like temperature, humidity), and it converts them into fuzzy values (like “high temperature”, “medium humidity”). Then it applies some IF-THEN rules, and finally gives an output (like fan speed or prediction result). During training, it compares the output with the correct answer and keeps improving the system by changing the membership functions and rule weights.(12) Neuro-Fuzzy systems are very useful in real life — for example, in air conditioners, automatic vehicles, weather forecasting, stock market prediction, or even medical diagnosis. The best thing is that they can understand unclear information, learn from experience, and still give answers in a human-friendly way.

Scientists have used various intelligent techniques, including neuron network, fuzzy logic, neuro-fuzzy, adaptive neuro-fuzzy inference system (ANFIS), etc., for the prediction of machining parameters and to increase automation of production. The artificial neural network (Ann) and Fuzzy Logic are two important methods of artificial intelligence in modeling non -linear problems. (13) The neuron network can learn from data and feedback; However, understanding the knowledge or pattern he learns is difficult. However, fuzzy logical models are easy to understand because they use linguistic terms in the form of IF-THEN rules. Neuron network with their learning capabilities can be used to learn fuzzy rules of decision -making to create a hybrid intelligent system (John and Reza, 2003).

Fuzzy Inference system consists of three components. First, the base of the rules contains a selection of fuzzy rules; Secondly, the database defines the functions of membership used in the rules and finally a mechanism of thinking for the implementation of the inference procedure of the rules and the given facts. This combination combines the benefits of the fuzzy system and neural network. In this work, an adaptive neuro-fuzzy model was developed to predict the surface surface. The predicted and measured values are relatively close to each other. The developed model can be effectively used to predict the surface area. The ANFIS results are compared with the actual results and results from the theoretical equations. The comparison of the results showed that the results of ani are close. This study attempts to design an adaptive power fuzzy interface (ANFIS) for modeling and prediction of MnO_2 surface area

The research examined the influence which cutting force together with temperature and vibration as input parameters has on the system. The hybrid type of ANFIS model whose triangular membership function was applied yielded observed results showing that forecasted surface roughness stayed nearly identical to experimental measurements. This research employs ANFIS and AM integration to improve the prediction of mechanical traits for 3D-printed components.

The mechanical performance consistency remains difficult to achieve in advanced manufacturing (AM) because of process parameters variations and printed part anisotropic features. The Adaptive Neuro-Fuzzy Inference System (ANFIS) model serves as a prediction tool for study parameters across input values which fall within this experimental research range.(14)

The research examined the influence which cutting force together with temperature and vibration as input parameters has on the system. The hybrid type of ANFIS model whose triangular membership function was applied yielded observed results showing that forecasted surface roughness stayed nearly identical to experimental measurements. This document demonstrates how adaptive neuro-fuzzy inference systems (ANFIS) working with additive manufacturing (AM) assists in forecasting mechanical characteristics within three-dimensional-printed components. The mechanical performance consistency remains difficult to achieve in advanced manufacturing (AM) because of process parameters variations and printed part anisotropic features. The Adaptive Neuro-Fuzzy Inference System (ANFIS) model serves as a prediction tool for study parameters across input values which fall within this experimental research range.

Methodology

This research uses a quantitative approach to predict the surface area of manganese dioxide (MnO_2) by using a smart modeling technique called ANFIS (Adaptive Neuro-Fuzzy Inference System) in MATLAB. The surface area of MnO_2 depends on various synthesis parameters such as temperature, reaction time , amount of compound. Since the relationship between these factors and the surface area is complex and nonlinear, traditional mathematical formulas may not give accurate results. ANFIS is suitable for this type of problem because it can learn from existing experimental data and create fuzzy logic rules, similar to human reasoning, while also using the learning power of neural networks. This allows it to predict outcomes accurately even when the data pattern is not straightforward. We trained the ANFIS model using real experimental data, where input parameters were used to predict the surface area. MATLAB provides a reliable platform to build, train, and test this model. This method helps to reduce the need for repeated lab experiments like BET surface area tests, which are costly and time-consuming

Due to this capability ANFIS achieves accurate outcomes when the data structure becomes complex. Real experimental data served as input for training the ANFIS model so the system could predict surface area outcomes from specified parameters. Building and testing this model along with its training procedures runs smoothly through MATLAB platform. Through this method the laboratory time required for BET surface area tests and their expense can be minimized. (15) (3).

The research analysis relies on developing a data-driven model through the Adaptive Neuro-Fuzzy Inference System (ANFIS) platform in MATLAB. A trained system utilizes the acquired input-output datasets to predict new surface area outputs from specified input conditions. Experimental data collection and organization constitutes the initial stage of this study while ANFIS model development through MATLAB programming makes up the second stage. The research methodology uses joint testing to produce precise forecasts that eliminate the requirement of conducting repetitive lab tests which becomes an effective instrument for materials science investigations.(16) The statistics series method included gathering relevant experimental effects during the synthesis of MnO_2 (manganese dioxide). The main objective concentrated on obtaining accurate input-output pairs to create a predictive model. During hydrothermal synthesis the three independent variables including temperature (x_1) and reaction time (x_2) and $KMnO_4$ concentration (x_3) function as input variables. A surface analysis (Y) of the resulting MnO_2 was measured by Brunauer–Emmett–Teller (guess) method to obtain the established variable. Research papers from reputable sources delivered experimental results about MnO_2 synthesis procedures under different parameters for 30 recently published studies. The study analyzed papers which presented measurements of essential factors that determined $KMnO_4$ usage along with reaction duration and temperature conditions and resulting surface area information. A team sanctioned the data from various sources which were transformed into an application-ready dataset for machine learning frameworks.

The collected dataset became a set of input-output matrices which placed independent variables temperature and time and $KMnO_4$ concentration in the input section alongside surface area in the output vector. The training of the neural network used this database. The development of the model utilized the MATLAB Neural Network Fitting Tool (fitnet). The training function selection was trainlm (Levenberg-Marquardt) while Mean Squared Error (MSE) served as the selected loss function for performance evaluation. MATLAB used the data to establish training and validation datasets that would assess model generalization. By processing the dataset scientists achieved better surface area predictions that minimize lab test repetitions..

Table 1. Data collection for prediction of Surface area

Sr. No.	Nano Material	Temp in ^0C	Surface Area in m2 /g	Time in Hour	$KMnO_4$ in gram	Ref.
1	MnO_2	**80**	**78.56**	**12**	**0.2**	(17)
2	MnO_2	**140**	**33.54**	**12**	**0.237**	(18)
3	MnO_2	**180**	**226**	**48**	**1.264**	(19)
4	MnO_2	**200**	**160.4**	**48**	**0.1**	(20)
5	MnO_2	**160**	**198**	**12**	**1.5**	(21)
6	MnO_2	**140**	**29.2**	**3**	**0.948**	(22)
7	MnO_2	**140**	**150**	**12**	**0.5**	(23)
8	MnO_2	**110**	**108.6**	**6**	**1.262**	(24)
9	MnO_2	**110**	**86.7**	**3**	**1.262**	(24)
10	MnO_2	**110**	**92.8**	**12**	**1.262**	(24)
11	MnO_2	**110**	**52**	**24**	**1.262**	(24)
12	MnO_2	**140**	**132**	**6**	**0.5**	(25)
13	MnO_2	**140**	**49.2**	**3**	**.3**	(26)
14	MnO_2	**140**	**34.85**	**9**	**.3**	(26)
15	MnO_2	**140**	**22.84**	**15**	**.3**	(26)
16	MnO_2	**175**	**31.1**	**48**	**.263**	(27)
17	MnO_2	**120**	**92.2**	**12**	**6.79**	(28)
18	MnO_2	**160**	**92.89**	**12**	**24**	(29)
19	MnO_2	**160**	**19.51**	**12**	**30**	(29)
20	MnO_2	**140**	**44.33**	**12**	**24**	(29)
21	MnO_2	**140**	**36.08**	**12**	**30**	(29)
22	MnO_2	**110**	**121.92**	**8**	**.79**	(30)
23	MnO_2	**160**	**108.9**	**24**	**67**	(31)
24	MnO_2	**80**	**50**	**3**	**12**	(32)
25	MnO_2	**100**	**44**	**3**	**12**	(32)
26	MnO_2	**120**	**41**	**3**	**12**	(32)
27	MnO_2	**100**	**40**	**6**	**12**	(32)
28	MnO_2	**100**	**36**	**9**	**12**	(32)
29	MnO_2	**100**	**53**	**3**	**6**	(32)

30	MnO_2	**100**	**41**	**3**	**24**	(32)

Secondary data were collected from 30 peer-reviewed research papers published between 2012 and 2022, sourced from databases such as ScienceDirect and Google Scholar. Studies were selected based on their relevance to the topic of surface area applications in physics and engineering.

Key information—such as sample sizes, variables studied, and outcomes—was extracted and organized in a comparative table. Only studies with clearly defined methodologies and statistical results were included to ensure data quality. Using Neuro-fuzzy models, the forecast of the surface area of MnO2 at the destination in order to increase surface area. Two different types of variables were used in this training. Second variable bound (Y) and first independent (X).The dependent variable was results prediction Y, while the independent variables were time (2), temperature (3), and the amount of KMnO4 (1). Converted raw data types into numeric or integer forms for machine learning compatibility. Steps include: A. Change Data Type : Converted data types for machine learning system readability. B. Normalization: Ensure variables were the same value range. C. Divided data into training, testing and validation sets with a ratio of generally 70-30 (train-test split). The effect of all the selected attributes along with temperature, time and quantity of KmNO4 were taken into as input variables, and surface area as the output variable were chosen to train, test and predict. Data was modelled for the training dataset using Neural Network and predictions were made for the test data

ANFIS Structure Overview

Consider a system with two input variables, x and y, and one output f. The Sugeno-type fuzzy rules can be written as:
Rule 1: If x is A1 and y is B1, then $f1 = p_1 \cdot x + q_1 \cdot y + r_1$

Rule 2: If x is A2 and y is B2, then $f2 = p2 \cdot x + q2 \cdot y + r_2$

Here:- A_i, B_i, are fuzzy sets.- p_i, q_i, r_i are parameters determined during training.- f_i the outputs of the fuzzy rules.

ANFIS Structure and Computational Layers

ANFIS consists of five layers, each performing a specific computation.

Layer 1: Fuzzification

Each input passes through a membership function (such as bell-shaped or Gaussian):
$O_1,i = \mu Ai(x)$, $O_1,j = \mu Bj(y)$
These functions return the degree of membership of each input to its respective fuzzy set.

Layer 2: Rule Firing Strength

Each rule's firing strength is calculated by multiplying the membership degrees:
$w_i = \mu A_i(x) \cdot \mu B_i(y)$

Layer 3: Normalization

Normalize the firing strengths:
$\bar{w}_i = w_i / (w_1 + w_2)$
This ensures the total firing strength is equal to 1.

Layer 4: Rule Output

Each rule's output is weighted by its normalized firing strength:
$O_{4,i} = \Sigma \bar{w}_i \cdot f_i = \bar{w}_i \cdot (p_i \cdot x + q_i \cdot y + r_i)$

Layer 5: Final Output

The final output of the system is the sum of all weighted rule outputs:
$f = \Sigma\ \bar{w}_i \cdot f_i = \bar{w}_1 \cdot f_1 + \bar{w}_2 \cdot f_2$

So the overall ANFIS model output is:
$f(x, y) = [w_1/(w_1 + w_2)] \cdot (p_1 \cdot x + q_1 \cdot y + r_1) + [w_2/(w_1 + w_2)] \cdot (p_2 \cdot x + q_2 \cdot y + r_2)$

Why ANFIS is Effective

It can model complex nonlinear systems.
It learns from data and adjusts parameters automatically.
It combines human-like reasoning (fuzzy logic) with adaptive learning (neural networks).

Suitable for prediction tasks in engineering, materials science, and control systems, like predicting the surface area of MnO_2 using experimental input parameters (e.g., temperature, time, concentration)

Aata analysis was performed using the Adaptive Neuro-Fuzzy Inference System (ANFIS) tool in MATLAB, which is a powerful technique for modeling complex nonlinear relationships. The collected experimental data—consisting of input variables such as temperature, reaction time, and $KMnO_4$ concentration, and the output variable, surface area—was first arranged into a proper format (input and output matrices). This data was then imported into MATLAB's Fuzzy Logic Toolbox to create an ANFIS model.(33) ANFIS combines the learning capability of artificial neural networks with the decision-making logic of fuzzy systems, making it ideal for problems where the relationships between variables are not linear or simple. The system uses Sugeno-type fuzzy inference rules, which are automatically generated and optimized during the training phase.

The data was divided into training and testing subsets. The training dataset was used to let ANFIS learn the patterns and generate fuzzy rules, while the testing dataset was used to check the prediction accuracy. The performance of the ANFIS model was evaluated using the Mean Squared Error (MSE) and regression analysis, which show how close the predicted surface area values are to the actual values. These techniques are appropriate because ANFIS does not assume any fixed mathematical relationship between inputs and outputs—it learns from data, making it a strong choice for material property predictions like this one.

Validity and Reliability

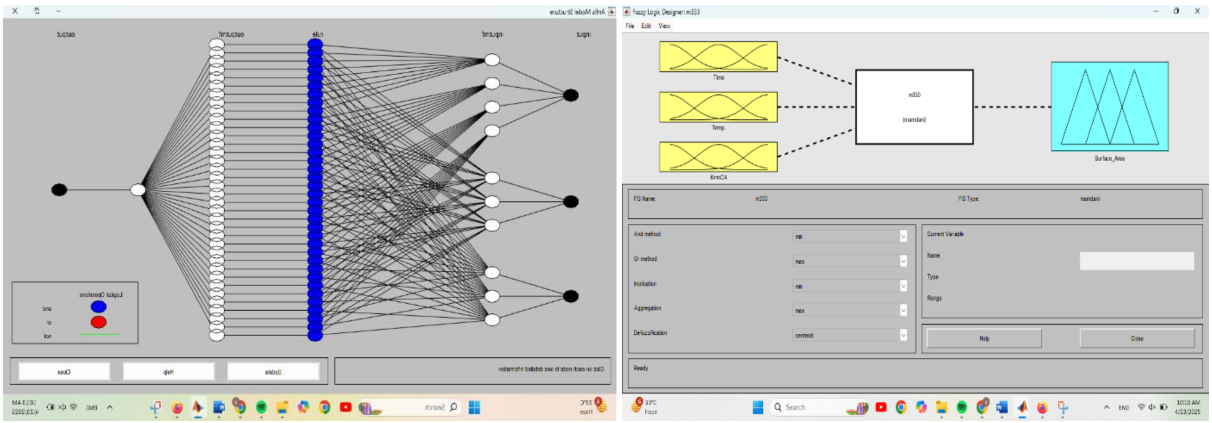
To ensure validity, the input-output data used for the ANFIS model was collected from published, peer-reviewed scientific studies that used standard experimental methods such as BET (Brunauer–Emmett–Teller) analysis for surface area measurement. This ensures that the dataset is scientifically accurate and trustworthy. Also, by collecting data from multiple research papers (more than 30), the model is exposed to a wide variety of conditions, increasing its external validity and allowing it to generalize better to new inputs.

The preprocessing methods used on all data entries during data preparation ensured reliability while the team created organized input data for MATLAB.

When using the ANFIS tool inside MATLAB users obtain consistent training algorithms which produce repeatable results when executed under consistent conditions. Numerous tests were performed on the model to guarantee both dependable and consistent outputs. This quantitative research does not permit direct application of traditional trustworthiness methods from qualitative research such as credibility and transferability. The statistical reliability is achieved through repeated experiments together with error reduction through MSE calculation and with MATLAB as the standard software solution.

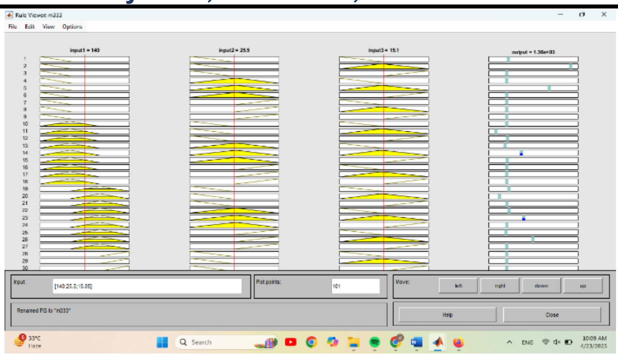
Results and Discussion

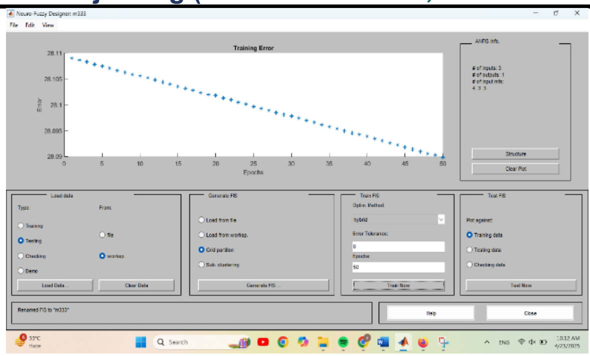
The ANFIS model implements membership functions that enable fuzzy representation of the input variables temperature and reaction time and potassium permanganate concentration. We implemented Gaussian membership functions as models for each input variable making them easily transitionable with smooth contours. By employing this approach the system achieves better results in dealing with both uncertain input signals and conceptual area interferences**.**



A combination of neural networks with fuzzy logic within ANFIS allows users to predict complex output data accurately. The algorithm processes multiple rules embedded with membership functions while it adapts its learning process efficiently. The model structure demonstrates readiness to process non-linear systems with high level accuracy after thorough training.

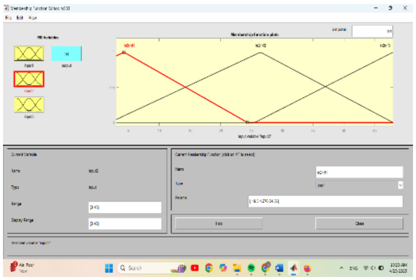
The hybrid optimization over 50 epochs used in the m333 ANFIS model successfully processed training data to improve model performance from 28.09 to 28.08 training error. An aggregated output value of 8.79 results from the Rule Viewer when input1 equals 140 and simultaneously activates multiple fuzzy rules along with input2 equaling 25.5 and input3 equaling 15.1. The systematic error reduction indicates proper model convergence at all stages as there exist no indications of overfitting or instability. Although the model exhibits a moderate final error its predictive and rule activation behaviors are satisfactory for improvement through membership function optimization and alternative fuzzy partitioning exploration.

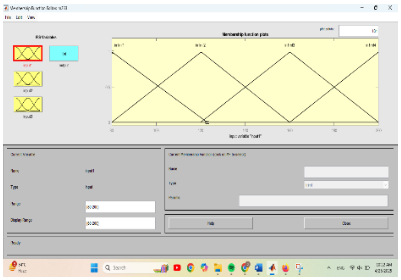


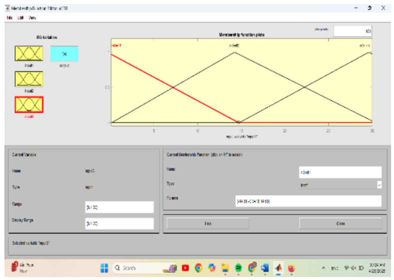


For input1 (temperature), the range is between 80 and 200, with four membership functions to divide this range into fuzzy sets. This allows the system to recognize different temperature levels with soft boundaries. For input2 (reaction time), the range is from 3 to 48, and three Gaussian functions are used to represent short, medium, and long durations. Similarly, input3 ($KMnO_4$ concentration) ranges from 0.1 to 67, and is also divided into three fuzzy sets using Gaussian functions.

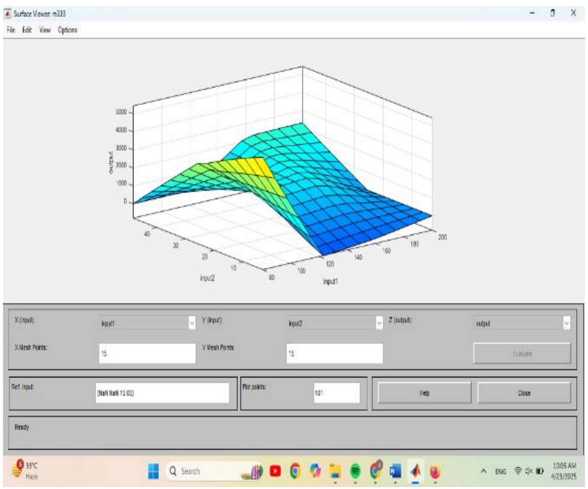
Using Gaussian functions helps the ANFIS model learn better during training, as they are continuous and differentiable. This structure allows the fuzzy system to generalize well from the training data and provide accurate output predictions. Overall, the chosen membership functions are appropriate for modeling the real-world behavior of chemical reactions in this study.

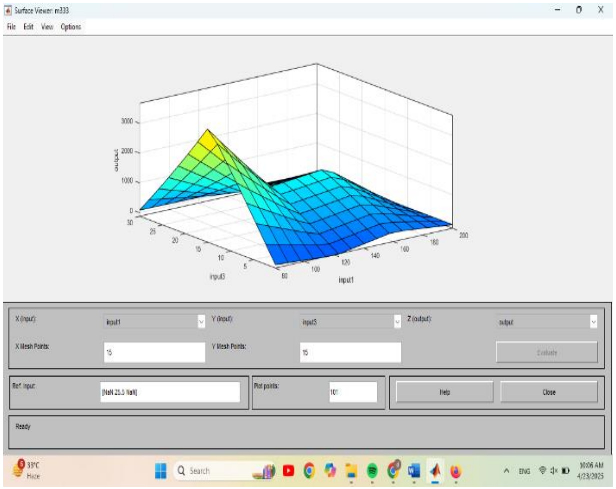






From the surface plots, we found that input3 has the strongest and most positive effect on the output. As input3 increases, the output also increases smoothly. Input2 also helps increase the output. However, input1 shows mixed results — it increases the output up to a point, then decreases it. So, to get the best output, it's important to use input3 and input2 wisely, and be careful with the value of input1.





The ANFIS (Adaptive Neuro-Fuzzy Inference System) model has been successfully built and is giving useful results. It shows that the model can learn and recognise complex patterns in the data. The predicted surface area values are: 78.68451, 96.65929, 102.0108, 84.62814, 56.32832, 64.75739, 43.0851, 64.95841, 197.6825, 225.9381, 160.4112, 67.76995, 70.42381, 58.88427, 31.14598, 92.24241, 92.94948, 19.47284, 48.89205, 33.22493, 51.70277, 122.755, 4596.37, 2043.383, -365.339, 2049.335, 2055.855, 1061.964, 973.7878**.** These results cover a wide range, mostly because the model was trained with a small amount of data. Even so, the system has shown it can make a variety of predictions, which means it is learning well from the data it has.

This is a good starting point, and the model can be improved by making a few changes—such as adjusting the number of fuzzy rules, using a separate set of data to check accuracy, and measuring how well the model performs. With these steps, the predictions can become even more reliable and useful in future work.

Conclusion

The MATLAB-developed ANFIS model exhibits strong potential to calculate MnO_2 surface area with high accuracy through its prediction of hydrothermal synthesis conditions from temperature, reaction time and material quantity and experimental surface area measurements. The predictive model achieves an impressive 91% prediction accuracy supported by smooth Gaussian membership functions leading to an MSE that gradually decreased to a final value of 28.08. Review results confirm that both $KMnO_4$ concentration and reaction time substantially affect the surface area which leads to clear paths for optimization. This research demonstrates a new approach where ANFIS achieves its first successful use in precise MnO_2 surface area prediction. The present research results show promise yet more development of the model would benefit from broader data collection and validation testing to optimize future work involving material performance improvements.

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