ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM APPROACH IN POLYPROPYLENE BUSINESS POLICY IN A PETROCHEMICAL PLANT IN INDIA

Dipak Kumar Jana, Sanghamitra Deya,

Department of Engineering Science, Haldia Institute of Technology, Haldia Purba Midnapur-721657, West Bengal, India

Sutapa Pramanik, Manoranjan Maiti

Department of Applied Mathematics with Oceanology and Computer Programming, Vidyasagar University, Midnapore, West Bengal, India Pin- 721 102

Emails: sutapaparamanik12@gmail.com, mmaiti2005@yahoo.co.in

Abstract: The polypropylene (PP) is a versatile thermoplastic resin available in an extensive range of formulation for engineering and industrial applications. In this paper, we have developed a new approach to predict the quality of polypropylene in petrochemical plants in India. The quality of polypropylene depends on the xylene- solubility of the product and the parameters controlling these two indices are *H2* ûow, donor ûow, pressure and temperature of polymerization reactors. Using these input and output parameters, we have proposed a new Adaptive Neuro-Fuzzy Inference System (ANFIS). The outcomes of proposed models are then compared and validated with the collected plant data. This new approach is surely beneûcial to predict the polypropylene quality just by controlling some parameters during the production phase and it saves both time and cost by reducing the yield of non-prime, oû-grade products. The experiment is performed with some real- life data from petrochemical ûrm. The results also suggest that ANFIS method can be successfully applied to establish PP quality prediction models. Statistical analysis is presented to determine the best ûtted model. Some sensitivity analysis are provided to the models.

Keywords: Adaptive Neuro-Fuzzy Inference System; Fuzzy-logic; Polypropylene; Product quality.

1. Introduction

Polypropylene (commonly called just PP) is a type of thermoplastic polymer resin. Polypropy- lene (PP) is an emergent polymer and its demand in various ûelds is increasing. The low cost, low density and good process characteristics make it even more signiûcant. To meet the growing expectations, various grades of PP with diûerent properties should be available. A single homopoly- mer grade of PP can not satisfy all the requirements. So new technologies are being used to get



Figure 1: House ware Sector Application: PP



Figure 2: Battery Sector Application: PP



Figure 3: Cast Film Application: PP



Figure 4: Material development Application: PP

al.[16]). But in practical ûeld where the polymer is produced, no such exact deûnitions have been followed and the variables take only linguistic values rather than some crisp values. One of the best method to make a mathematical model from it, is to apply fuzzy logic approach just like how Zhou et al.[6] applied fuzzy programming to create an integrated model for sustainable municipal energy system planning and management in Shenzhen, China. The fuzzy logic generally allows a simple knowledge representation of the production process in terms of if-then rules (Naderloo et al.[16]). Fuzzy inference systems (FIS) can properly describe the complex and non-linear phenomena with the precise rules. The rules are typically in if-then format with diûerent matching degrees for a given operational situation (Amiryouseû et al. [17]). Fuzzy inference is able to handle vague situ- ations and build model with words in the term of linguistic variables. This is especially valuable where models are developed based on experts knowledge and individuals without a mathematical background are involved (Cornelissen et al. [12], Prananik et al. [1], Chakraborty et al. [2]).

Fuzzy inference system (FIS) is one of the most eûcient computational method rather than other analytical and statistical techniques. Since PP production system and technologies are quite intricate and uncertain, they can widely be applied for modeling of diûerent components in this sector, because they can study new patterns which were not previously available in the trained data sets and they can also apprise knowledge over time as long as more training data sets are provided (Khoshnevisan et al. [18]). In the context of environmental management, the use of the fuzzy logic method is strongly suggested. Khoshnevisan et al. [18] estimated the yield of green- house strawberry with the help of adaptive neuro-fuzzy inference system (ANFIS). Ana et al. [3]

suggested an integrated recycling approach for GFRP pultrusion wastes using fuzzy logic. Sami et al. [19] had done a case study in cane farms in Iran using fuzzy logic. Khoshnevisan et al.[21] predicted the potato yield based on energy inputs by means of ANFIS. Alavi [22] had determined the quality of Mozafati dates using Takagi-Sugeno

fuzzy inference system. Abghari and Sadi [23] applied ANFIS for predicting the yield distribution of the main products in the steam cracking of atmospheric gasoil. Hosoz et al.[24] predicted the performance of a refrigeration system with the help of ANFIS. Wua et al. [4] introduces a technique of measuring performance of thermal power ûrms in China via fuzzy Enhanced Russell measure model. Similarly, Afrinaldi and Zhang [29] proposed an alternative methods for normalization and aggregation in life cycle assessment(LCA) using a fuzzy logic based aggregation method; Khoshnevisan et al. [5] appraised the environmental impact on tomato and cucumber cultivation in greenhouses using life cycle assessment and ANFIS. Khoshnevisan et al. [7] projected an environmental indices in potato production using artiûcial neural network; Nevertheless, uses of fuzzy inference system are still in its very early stages and there is the lack of applicable models.

In spite of the above mentioned development, lacunas still exist in the formulation and solution model as:

(i) The application polypropylene (PP) in a petrochemical chemical plant in India.

(ii) Adaptive Neuro-Fuzzy Inference System via Takagi-Sugeno fuzzy inference technique has been introduced for ûrst time.

(iii) A case study has been made to predicted plant data and observed data for four proposed models with some sensitivity analysis.

The present paper presents a complete fuzzy model which gives an essential indicator of parame- ters of production system of PP. There are so many possibilities to select functions and operators as well as inference, implication, aggregation and defuzziûcation methods, so the search for the perfect mathematical model can be included among the most vital topics in development of rules based models. Here we are concentrating on 3.5 MFI PP-powder because of its versatile and enormous application in polymer industry. The main purpose of this study is to develop a few FIS models and blue select the best model in order to predict the quality of 3.5 MFI PP. For this, we had made a primary investigation on the parameters controlling the production and choose the most appropriate input and output variables. A Takagi-Sugeno fuzzy inference system (MFIS) is then developed using these inputs and outputs. Depending on the membership functions (MF) 4 mod- els have been established and by sensitivity analyses we chose the best ûtted model among them. Finally, with some graphical representation we validate the chosen model with physical theoretical model.

1. Notations and abbreviations

The following notations and abbreviations are used to describe the proposed model.

(i) n = number of experiments.

(ii) *FIS* = fuzzy inference system.

(iii) *MFIS* = Takagi-Sugeno fuzzy inference system.

(iv) $R2$ = coeûcient of determination.

(v) *RMSE* = root mean square error.

(vi) *MAE* = mean absolute error.

(vii) *MAPE* = mean absolute percentage error.

(viii) *ypred* = predicted value.

(ix) *ypred* = mean of the predicted values.

(x) *yobs* = observed value from model.

(xi) *MF* = membership function.

(xii) *ANFIS* = adaptive neuro-fuzzy inference system.

2. Plant Setup

Production process of PP is a very complex and intricate continuous process. The raw materials like propylene, ethylene, and any other desired copolymers are fed into the reactor. Hydrogen is then added to control the molecular weight. Teal is blended to activate the catalyst. At that point of time donor is mixed to the recontracting pot. Polymerization conditions (pressure, temperature and reactant concentrations) are set by the polymer grade being made. The reaction itself is exothermic and the cooling of the reactor is achieved by plate heat exchange, where liqueûed reactor gas (mainly propylene) is mixed with fresh feed and injected into the reactor. Flash evaporation of the liquid in the polymer bed ensures maximum heat exchange. The polymer powder is then discharged from the reactor and separated from the unrelated monomer in a discharge vessel at an atmospheric pressure. The production of PP is a very complex and as well as an elongated process. The plant set-up of a polypropylene unit (PP Unit) is presented in Figure 5.

The monomer is compressed and recycled into the reactors and partly returned to the upstream oû-gas unit for recovery in order to remove accumulated propane. The polymer is ûushed with nitrogen in a purge vessel to strip it of residual propylene. The purge vessel oû-gas is passed to a membrane unit to recover the remaining monomers and the nitrogen for reuse. The powder is transported to powder silos and is then converted into pellets that incorporate a full range of well dispersed additives. For highly demanding applications requiring extremely low volatile and odor levels, the Novolen process oûers an optional degassing unit to treat the pellets after extrusion.

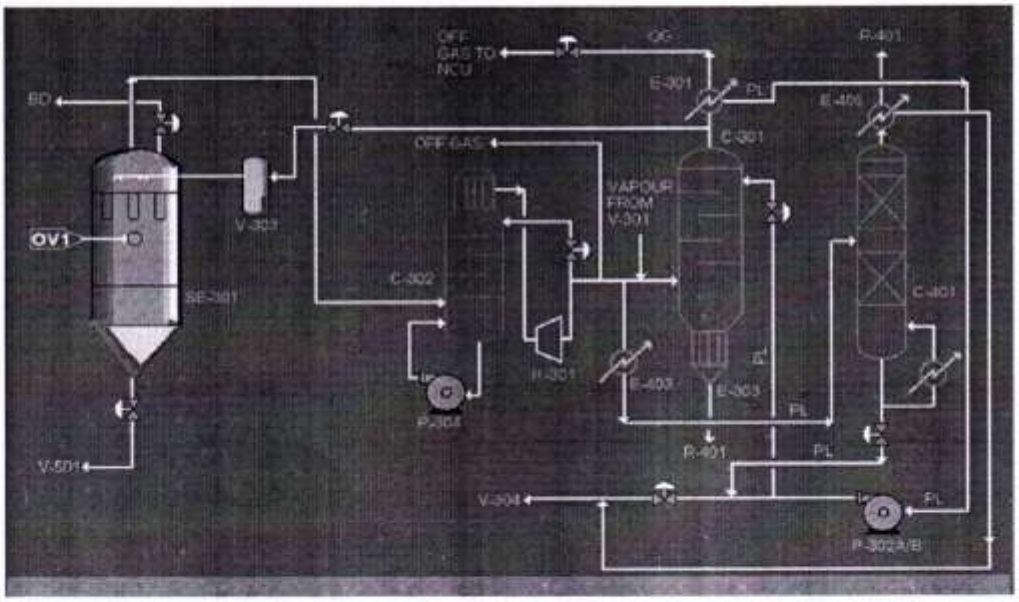


Figure 5: Systematic diagram of the Polypropylene Plant.

1. Materials selection and fuzzy logic modelling

The method to develop a prediction model from the plant data and applicability of fuzzy logic on that model is presented in this section.

4.1 Selection of input-output variables : Polypropylene production procedure involves a lot of parameters at a time. But the signiûcant parameters which aûect the production most are - hydrogen ûow, donor ûow, pressure of the reactor and temperature of the reactor. We therefore selected these 4 parameters as the input variables of our model. Again the diûerent grades of the polymer determine the quality of it and the basic diûerence between these grades is in the measurement of the melt ûow index (MFI) and the xylene solubility. So, we select these 2 as our output variables.

4.1.1. Hydrogen ûow : Hydrogen is used to maintain the polymer chain length, hence to control the MFI. For any kind of polymerization reaction hydrogen is required for chain termination part. In absence of hydrogen chain propagation will not be stopped, which results formation of very high molecular weight polymer. Hydrogen is used to cut the polymer chains into desired length, in this way the intrinsic viscosity, MFI, average molecular weight is controlled for polypropylene production. The rate of ûow of hydrogen is measured by *kg/h* unit. For 3.5 MFI powder hydrogen ûow ranges from 0.6*kg/h* to 1.5*kg/h*.

Donor ûow

Donor acts as a stereo regulating agent, which produces high concentration of isotactic polymers. Without donor, polymerization with high mileage catalyst would produce high concentration of atactic polymer, which is waxy in nature. Donor helps the polymerization reaction to be more stereospeciûc in nature by controlling the amount of atactic polymer production. Although a controlled amount of atactic material is needed in the ûnal product for obtaining good polymer process ability, the atactic content of the ûnal product is controlled by adjusting the donor addition rate. The rate of ûow of donor is measured by *kg/h* unit. For 3.5 MFI powder donor ûow ranges from 0.2*kg/h* to 0.5*kg/h*.

Pressure

PP production process is a slurry polymerization process and pressure plays a vital role in it. The main role of pressure is to soluble hydrogen in propylene medium which favors the polymerization

reaction. For 3.5 MFI powder the pressure of the reactor is keeping at 37.5*kg/cm2g* " 38.5*kg/cm2g*.

When it is increased hydrogen becomes more soluble and reaction rate of polymerization increases.

Temperature

Polymerization reaction, being a multiorder reaction, when temperature changes the rate of the reaction varies. For 3.5 MFI powder temperature of the reactor is maintained at 700*C* " 730*C*.

Reaction cannot be controlled at any temperature less or higher than this range.

Xylene solubility

This method is used to determine the percent of atactic polymer weight fraction in polypropylene. Atactic polymer is soluble in ortho-xylene at 250*C*. The method may also be used to obtain the amount of atactic polymer and oils present in the polymer. Both isotactic and atactic polypropy- lene are soluble in ortho-xylene at high temperature. Isotactic portion gets precipitated at 250*C*. Removal of this portion gives atactic por-

tion along with low molecular weight fractions remaining in the solution; from the low molecular weight fractions the amount of polypropylene soluble in xylene can be calculated.

Fuzzy tool

An adaptive neuro-fuzzy inference system (ANFIS) is the combination of both Fuzzy Logic and Neural Network. An important property of a fuzzy system is that knowledge is represented in the form of the easily comprehensible logical rules. On the other hand, neural networks have the ability to use knowledge and experience. By combining both fuzzy and neural paradigms, neuro-fuzzy controllers can be developed. Fuzzy logic approach to incorporate the logical inputs of human and take decision much faster. Neural controllers learn the discrete input representations, which may cause such system unstable. The main objective of ANFIS is to borrow the learning capability from the Neural Network and put this in Fuzzy Inference System, i.e. superimpose of Fuzzy Inference System over a Neural layer architecture. Then the FIS will able to learn the training procedure as in Neural Network and after the learning mechanism the Fuzzy Inference System will behave exactly as the Neural Network. In NN there will be input layer, output layer and multiple hidden layers inside. The number inputs to the system are equal to the number of neurons that the network has. Each neuron behaves as a processing element.

The fuzzy logic toolbox in MATLAB was used for the entire process of training and evaluating the fuzzy inference system. Fig. 8 shows the ANFIS structure with four inputs of the proposed PP model. The output of the ith node in layer *l* is denoted as *Oil*. In this study, the ûrst-order Sugeno model with four input and fuzzy IF-THEN rules of Takagi and Sugeno type is used:

$$\text{If } x \text{ is } A \text{ then } f1 = p1x + q \qquad (1)$$

The ûrst layer consists of input variable membership functions (MFs). This layer supplies the input values to the next layer. The input comprises electrical properties of the one sensor. In the ûrst layer every node is an adaptive node with a node function.

$$Oi\ 1 = \mu(x)i, \text{ where } \mu(x)i \text{ is MFs.} \qquad (2)$$

In the present study, two bell-shaped MFs (8) with a maximum equal to 1 and minimum equal to 0 are chosen:

$$f(x,ab,c) = \frac{1}{1+(\underline{x-a})2b} \qquad (3)$$

where, the bell-shaped function depends on three parameters a, b and c.

The second layer (membership layer) checks for the weights of each MF. It receives the input values from the 1st layer and acts as an MF to represent the fuzzy sets of the respective input variables. Every node in the second layer is non-adaptive, and this layer multiplies the incoming signals and produces the following:

$$O^2 = wi = \mu(x)i + 1 \quad \text{where } i = 1, 2. \qquad (4)$$

Each node output represents the ûring strength of a rule or weight. The third layer is called the rule layer. Each node (neuron) in this layer performs the pre-conditional matching of the fuzzy rules, i.e. they compute the activation level of each rule. There are two fuzzy rules, A and B in this case since there are two MFs and one input. Each node in these layers calculates the weights,

which are normalized. The third layer is also non-adaptive and every node calculates the ratio of the rules ûring strength to the sum of all rules ûring strengths as follows:

$$O^i{}_3 = wi = \frac{wi}{w_1 + w_2} \quad \text{where } i = 1, 2. \qquad (5)$$

The outputs of this layer are generally called normalized ûring strengths or normalized weights. The fourth, defuzziûcation layer provides the output values resulting from the inference of rules. All nodes in the fourth layer are adaptive nodes with a node function:

$$O^{i}_{3} = wi^{\square} = \square\ fi = wi^{\square}\square(px + qi)$$

where $i = 1, 2.$ (6)

The ûfth layer is known as the output layer. It sums up all the inputs coming from the fourth layer and transforms the fuzzy classiûcation results into a crisp (binary). The single node in the ûfth layer is not adaptive and it computes the overall output as the summation of all incoming signals

Hybrid learning algorithms were applied to identify the parameters in the ANFIS architectures. In the forward pass of the hybrid learning algorithm, functional signals go forward until Layer 4 and the consequent parameters are identiûed by the least squares estimate. In the backward pass, the error rates propagate backwards and the premise parameters are updated by the gradient descent.

Model development

A fuzzy rule-based model is developed in several stages. In this paper, a ûve-step cycle is followed to complete the ûnal model as following:

(i) Determination of input and output parameters of the model.

(ii) Construction of MFs for each input and output parameters of the model.

(iii) Deûnition of rules.

(iv) Selection of operators and inference, implication, aggregation and defuzziûcation methods.

(v) Comparison of model outputs with predicted values and validity evaluation using sensitivity analysis. We can repeat this cycle as many times. Then we want to provide a reliable ûnal model and in each cycle, one or more factors may be modiûed. A block diagram of a fuzzy inference system is also shown in Figure 6. It is composed of ûve functional blocks as given below:

(i) A fuzziûcation interface: which transforms the crisp inputs into degrees of match with linguistic values.

(ii) A rule base: containing a number of fuzzy if-then rules.

(iii) A database: which deûnes the membership functions of the fuzzy sets utilized in the fuzzy rules.

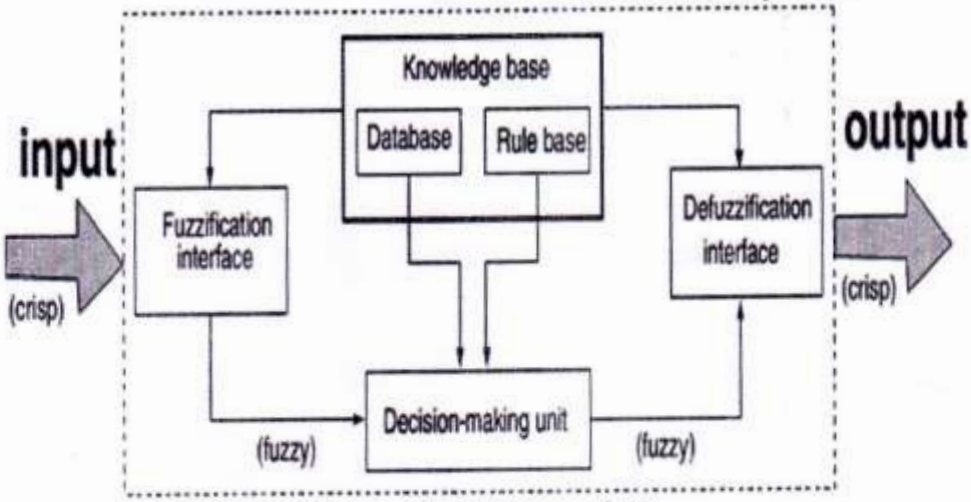


Figure 6: Block diagram of FIS

(i) A decision-making unit: that performs the inference operations on the rules.

(ii) A defuzziûcation interface: which transforms the fuzzy results of the interference into a crisp output.

5. Solution procedure

Fuzzy method is a procedure that is capable of taking into account ambiguous and vague think- ing. The fuzzy inference systems are recently more popular tools for solving engineering problems because of their unique features in predicting complex phenomena. The most important two types of fuzzy inference systems are Mamdani and Sugeno fuzzy inference methods. When the output variables are also fuzzy sets with membership function then MFIS is the most commonly used inference method. This method is introduced by Mamdani and Assilian in 1975 (Mamdani and Assilian[26]). Another known inference method is the Takagi- Sugeno-Kang method of fuzzy inference process. This method was introduced by Sugeno in 1985 (Sugeno [27]). A typical canonical fuzzy rule for this method has the following form:

If x is $\tilde{A}$ and y is $\tilde{B}$

then $z = f(x, y)$, where $\tilde{A}$ and $\tilde{B}$ are fuzzy sets in the antecedent and

$z = f(x, y)$ is a crisp function in the consequent. Generally, $f(x, y)$ is a polynomial in the input variables x and y (Castillo and Melin[28]). The main diûerence between the two methods lies in the consequent of fuzzy rules. In this paper, we are using ANFIS to predict the quality of PP. To compute the output of this FIS given the inputs, six steps have to be followed:

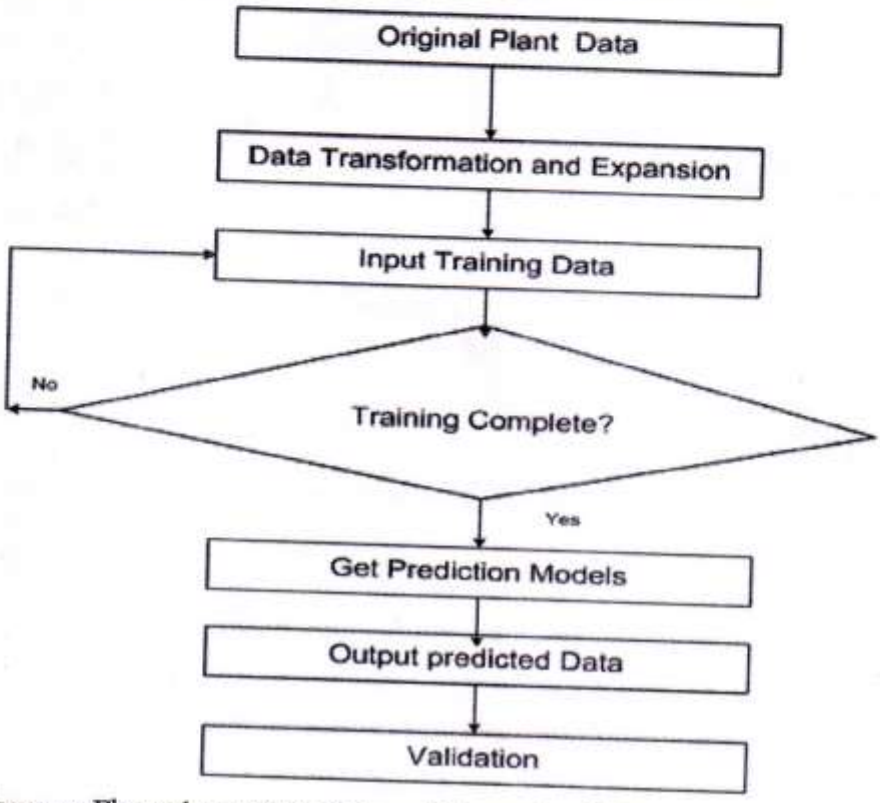


Figure 7: Flow-chart of ANFIS modeling and validation procedure.

(i) Determine a set of fuzzy rules.

(ii) Fuzzify the inputs using the input membership functions (converts the crisp input to a linguistic variable using the membership functions stored in the fuzzy knowledge base).

(iii) Combine the fuzziûed inputs according to the fuzzy rules to establish a rule strength (fuzzy operations).

(iv) Find the consequence of the rule by combining the rule strength and the output membership function (implication).

(v) Combine the consequences to get an output distribution (aggregation).

(vi) Defuzzify the output distribution (which converts the fuzzy output of the inference engine to crisp using membership functions analogous to the ones used by the fuzziûer).

The proposed Takagi-Sugeno fuzzy inference model with 4 input and 2 output variables is displayed in Figure 8. Hydrogen ûow, donor ûow, temperature and pressure are taken as the 4 input variables whereas xylene solubility is considered as output variables. In this model, we have applied 36 if-then rules, which is depicted in Figure 13. Min and Max operators employed to evaluate the logical conjunction AND and OR. We have used Min and Max operators for implication and aggregation method respectively. Centroid method is applied for the defuzziûcation.

Selection of MFs

Data for this research is collected from a renowned petrochemical plant in India in the year of 2014 during the month of May. We collected 70 sets of data of PP production process. Data are tabulated in the Table-1

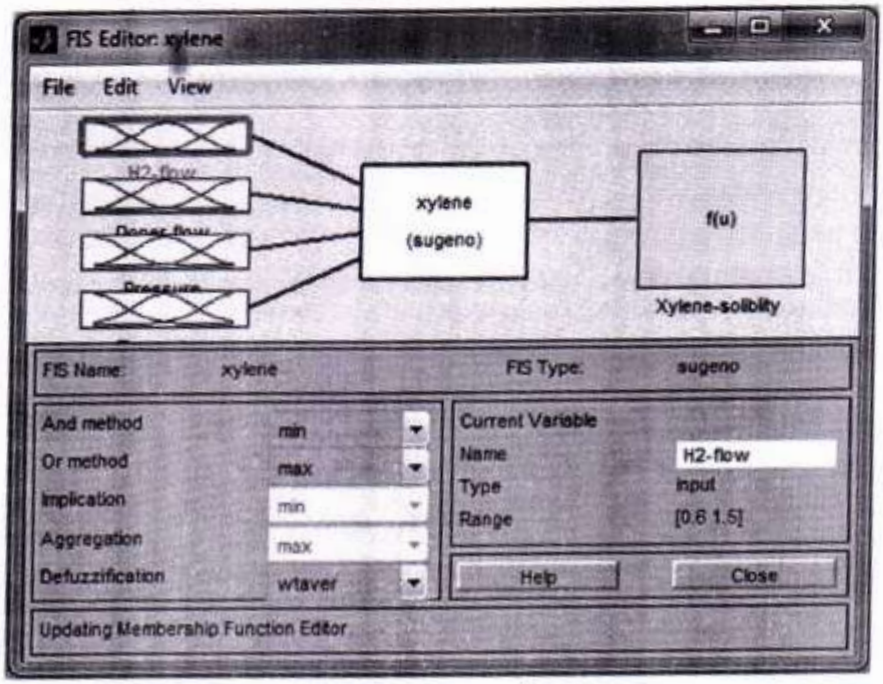


Figure 8: The structure of ANFIS.

Several studies have noted that the shape and type of MFs are the most inûuential factors for fuzzy model development (Li and Yen [11]; Cornelissen et al. [12]). MFs are at the core of inference models and their proper choice is important regarding the validation of the fuzzy models (Chang and Hall [13]). The membership functions of the fuzzy type input variables hydrogen ûow, donor ûow, pressure and temperature are recorded in respectively three and two quality features. Whereas the membership functions of the fuzzy type output variable Xylene solubility is set in one quality features.

Table-1: Plant data for proposed models

Sl .No.	H_2 Flow(kg/h)	Donor Flow (kg/h)	Preassure kg/cm^2g	Temparature (^0C)	Xylene Solubility(wt%)
1	1.0573	.348	38	73	3.5
2	1.0612	.374	38	72.99	3.15
3	0.948	.262	38.02	73	3.75
4	0.9934	.353	37.97	72.98	3.6
5	1.1535	.317	38	73	3.75
6	0.9665	.372	38.01	73	3.2
7	0.9786	.325	38.05	73.01	3.5
8	0.9915	.349	38	73	3.6
9	0.9385	.245	38.03	72.98	3.95
10	0.9876	.36	38	73	3.4
11	0.959	.264	38.01	73	4
12	0.9875	.365	37.98	73.05	3.5
13	0.993	.34	37.86	73	3.4
14	0.983	0.348	38	72.98	3.6
15	0.9075	0.276	37.99	73.01	3.45
16	0.9677	0.336	38	73	3.55
17	0.9426	0.312	37.98	73.02	3.56
18	0.9445	0.315	38	72.98	3.5
19	1.034	0.293	37.99	73	3.4
20	1.0235	0.27	38	73.01	3.8
21	0.985	0.346	38.05	73.01	3.4
22	1.107	0.252	38.01	73.01	3.8
23	0.9425	0.272	38	73	3.76
24	0.994	0.236	38	73	4
25	0.9695	0.245	38.05	73	3.8
26	0.9838	0.246	38.01	73	3.89
27	0.948	0.245	38	72.99	3.8
28	0.9735	0.334	38	73	3.55

Sl .No.	H_2 Flow(kg/h)	Donor Flow (kg/h)	Preassure kg/cm^2g	Temparature (^0C)	Xylene Solubility(wt%)
29	0.8765	0.259	38	72.99	3.75
30	1.0423	0.274	38.02	73	3.75
31	1.0357	0.243	38.02	73.01	3.9
32	0.9035	0.284	37.98	73	3.55
33	0.974	0.278	38	73	3.7
34	0.972	0.271	38.01	73	3.8

Table-2: Nature of Linguistic variables for input and output data

Input/ output	Linguistic variables
H_2	(low, medium, high)
Donor	(low, medium, high)
Pressure	(low, adequate, high)
Temparature	(low, high)
MFI	(low, required, high)
Xylene	(low, required, high)

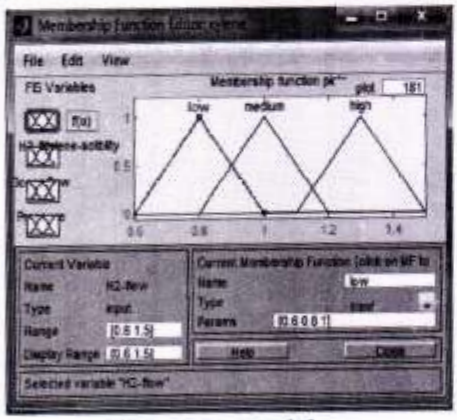


Figure 9: Model-1:

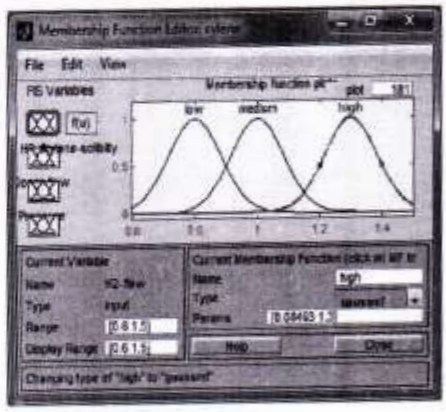


Figure 10: Model-2:

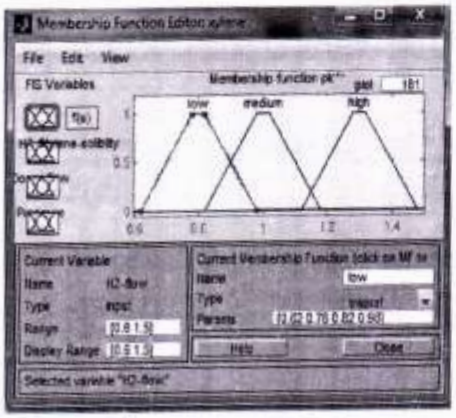


Figure 11: Model-3:

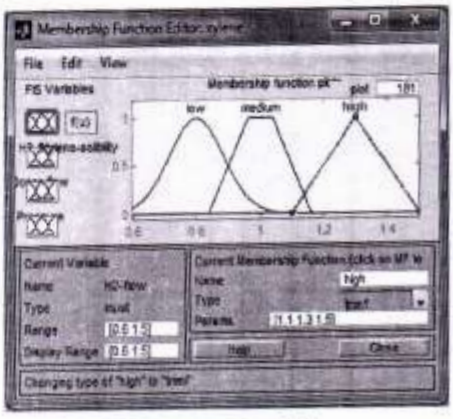


Figure 12: Model-4:

The nature of linguistic variables are diûerent for the proposed Models. Hence, from the practical knowledge the above Table 1 has been considered for the membership functions of the input and output variables. Depending on the MFs, we have developed four diûerent ANFIS models. In the ûrst model, all the input variables are considered as trapezoidal type fuzzy variables, which are depicted in Figure-9. In Model-2, the inputs are Gaussian type fuzzy variables (depicted in Figure 10. All the inputs are all trapezoid fuzzy variables in Model-3 (Figure 11) and Model-4, all the inputs are mixed type fuzzy variables in Fig. 12. Based on the linguistic variables, we have construct an ANFIS model structure (in Fig. 8) using Seugeno inference fuzzy system, which consisted of four input variables and one output variable. The graphical representation of ANFIS structure is depicted in Fig. 14.

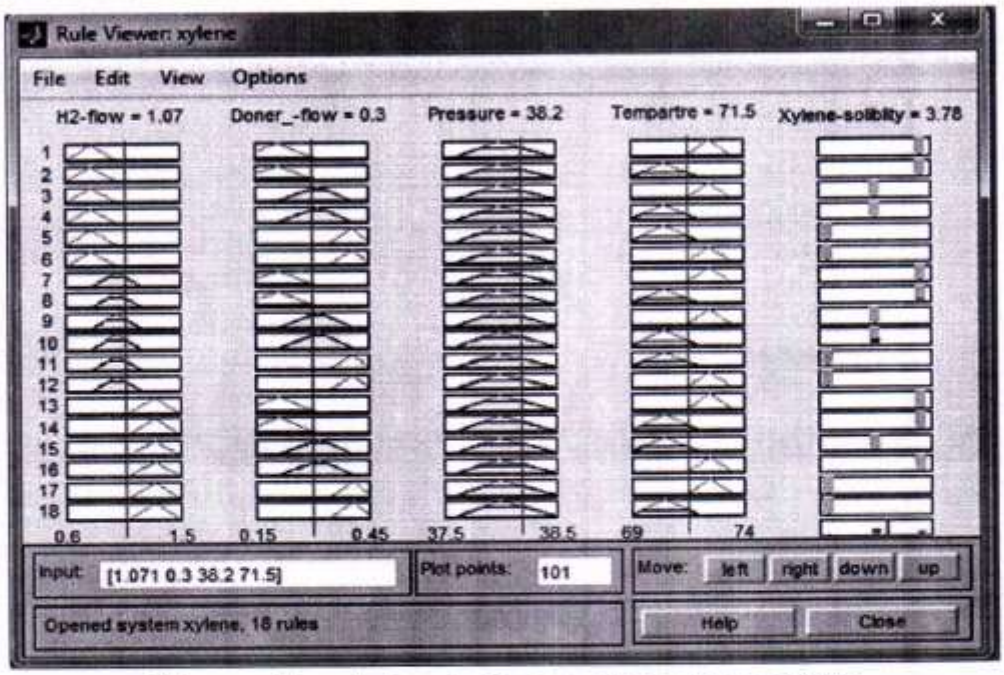


Figure 13: Fuzzy logic rules for controlling xylene solubility.

Results and discussion

Corresponding to every input data, collected from the plant, we recorded the output values observed from each of the 4 models. Considering the plant data as predicted value and the model output as observed value. In order to control the business performance of the predictive models, we have deûned some statistical parameters. The prediction capability of proposed models is evaluated by using the test data in the trained data and comparing the outputs and measured values. In addition, the statistical parameters such as the root mean square error (RMSE) and the determination coeûcient ($R2$) are used to compare predicted and measured values of ûexible modulus. The RMSE is deûned by the following Eq. (8):

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(ypred_i - yobs_i)^2}$$

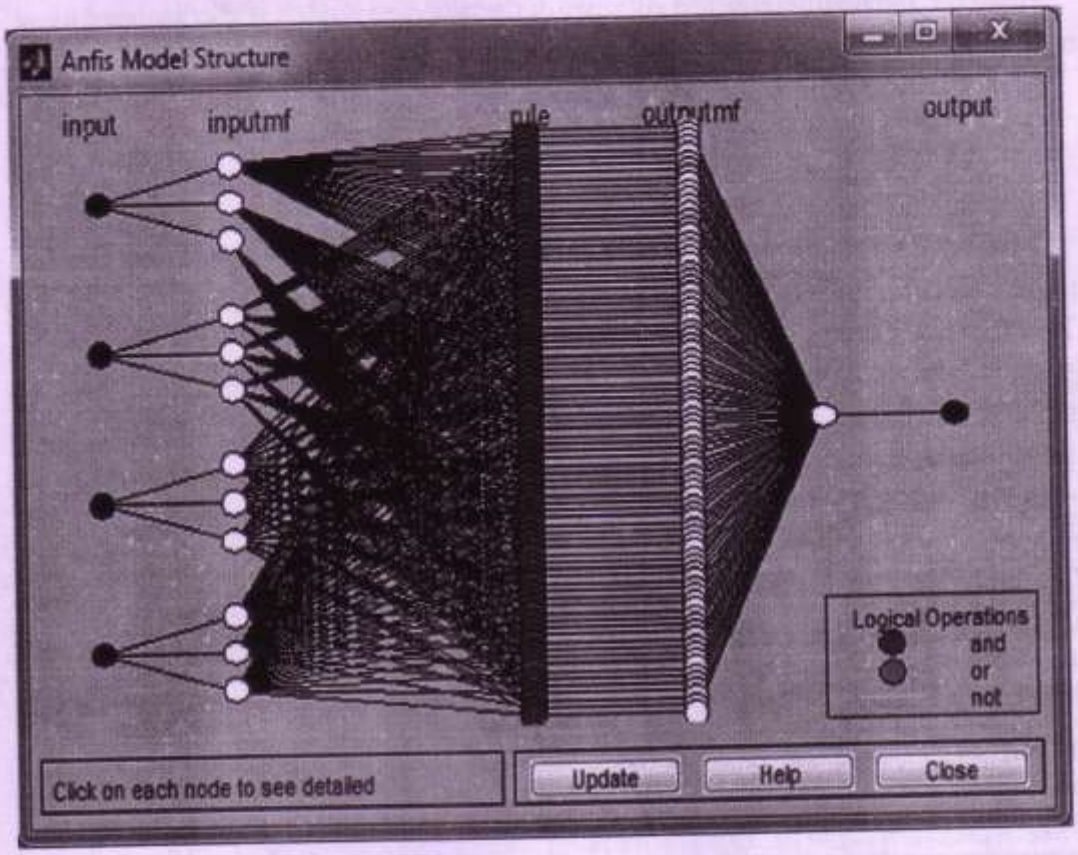


Figure 14: The ANFIS model structure consisted of 4 input variables and 1 output variables.

In addition, the determination coeûcient ($R2$) can be calculated using Eq. (9) that is given by:

$$R^2 = 1 - \frac{\sum_{i-1}^{n} (ypred_i - yobs_i)^2}{\sum_{i=1}^{n} y^2 obs_i} \tag{9}$$

Mean absolute percentage error (MAPE) measures the average of the squares of the errors. The smaller values of MAPE ensure the better performance of the proposed models. The MAPE is calculated by the following Eq. (10):

$$MAPE = \frac{1}{n} \sum_{i=1}^{n} \frac{\left| (ypred_i - yobs_i) \right|}{ypred_i} \times 100\% \tag{10}$$

However, the performance and eûciency of the proposed models is also analyzed using mean abso- lute error (MAE), which is deûned by the Eq. (11):

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|ypred_i - yobs_i| \tag{11}$$

where n is the number of data patterns in the data set, *ypredi* indicates the predicted value of one data point i and *yobsi* is the observed value of one data point i. Fuzzy logic is now a wide ûeld of study and diûerent tools have been developed over the last 15 years. The important aspect of the present research work is that the decision maker can control both input and output data by using Fuzzy logic controller. The graphical representation of such type fuzzy logic controller is shown in Figure 10 for input and output data.

Table-3: Outcomes of xylene solubility from diûerent proposed models

Sl. No.	Model-1	Model-2	Model-3	Model-4	Sl. No.	Model-1	Model-2	Model-3	Model-4
1	3.5	3.5	3.48	3.46	36	3.5	3.5	3.44	3.44
2	3.05	3.11	3.15	3.16	37	3.82	3.79	3.8	3.79
3	3.82	3.79	3.8	3.79	38	3.5	3.5	3.5	3.49
4	3.5	3.5	3.42	3.43	39	3.85	3.81	3.81	3.8
5	3.78	3.7	3.77	3.74	40	3.5	3.5	3.64	3.61
6	3.11	3.17	3.17	3.18	41	3.77	3.74	3.78	3.76
7	3.5	3.5	2.5	3.51	42	3.72	3.69	3.76	3.73
8	3.5	3.5	3.47	3.45	43	3.76	3.72	3.77	3.75
9	3.97	3.91	3.87	3.87	44	3.74	3.7	3.76	3.74
10	3.45	3.47	3.33	3.36	45	3.82	3.79	3.8	3.79
11	3.82	3.79	3.8	3.79	46	3.95	3.9	3.86	3.86
12	3.31	3.35	3.27	3.3	47	3.59	3.56	3.71	3.68
13	3.5	3.5	3.5	3.49	48	3.92	3.87	3.85	3.85
14	3.5	3.5	3.48	3.46	49	3.52	3.5	3.68	3.65
15	3.72	3.68	3.76	3.73	50	3.84	3.8	3.81	3.8
16	3.5	3.5	3.5	3.5	51	3.63	3.61	3.71	3.67
17	3.5	3.5	3.51	3.54	52	3.73	3.71	3.75	3.73
18	3.5	3.5	3.5	3.53	53	3.5	3.5	3.64	3.61
19	3.5	3.5	3.65	3.62	54	3.5	3.5	3.62	3.59
20	3.78	3.74	3.78	3.76	55	3.5	3.5	3.65	3.62
21	3.5	3.5	3.5	3.47	56	3.5	3.5	3.5	3.53
22	3.87	3.83	3.82	3.82	57	3.05	3.11	3.15	3.15
23	3.75	3.72	3.77	3.75	58	3.5	3.5	3.37	3.4
24	4.15	4.08	3.92	3.93	59	3.5	3.5	3.5	3.51
25	3.95	3.9	3.86	3.86	60	3.55	3.54	3.36	3.64
26	3.94	3.89	3.85	3.86	61	3.5	3.5	3.67	3.64
27	3.96	3.9	3.86	3.87	62	3.76	3.74	3.77	3.75
28	3.5	3.5	3.5	3.5	63	3.5	3.5	3.67	3.63
29	3.83	3.8	3.81	3.8	64	4.5	4.5	4.5	4.29
30	3.73	3.7	3.76	3.74	65	4.21	4.15	3.95	3.97
31	3.98	3.92	3.87	3.87	66	4.5	4.49	4.29	4.15
32	3.59	3.57	3.71	3.68	67	3.57	3.55	3.71	3.67
33	3.68	3.65	3.74	3.71	68	3.9	3.86	3.84	3.84
34	3.76	3.73	3.77	3.75	69	3.76	3.71	3.77	3.75
35	3.78	3.75	3.78	3.76	70	3.81	3.78	3.8	3.78

Table 4: Statistical data analysis for Xylene Solubility.

Parameter	Model-1	Model-2	Model-3	Model-4
RMSE	0.104232	0.094166	0.122171	0.104922
MAE	0.074714	0.068714	0.090571	0.080857
MAPE(%)	1.9835	1.825969	2.478427	2.209297
R^2	0.99202	0.999341	0.9989	0.999184

Similarly, it is very much evident from Table-5 that the RMSE and MAE are minimum for Model- 2 for xylene solubility and they are very near to 0. Again, MAPE of Model-2 is recorded just 1.825969% and *R*2 is almost 1.

On the basis of statistical data analysis of xylene solubility, we can elect the Model-2 as the best ûtted model among the four for determining the quality of PP. Regarding fuzzy model, it is observed that the ANFIS algorithm can quite eûectively predict the quality of PP. Comparison of simulation and experimental results has been shown in Fig. 15 and Fig. 16. The experiments have been carried out for four PP models. The best result of 70 trails during experiment and simulation has been shown in the ûgure. To compare the results, several experiments have been carried out considering the same position of obstacles.

6. Sensitivity analysis

Sensitivity analysis measures the changes in parameter values and errors and their impacts on model conclusions. To develop a model, it can be useful for *i*) validity or accuracy of the model,

ii) ûnding errors in the model, *iii*) simplifying the model, *iv*) calibrating the model, *v*) coping with poor or missing data and *vi*) ranking acquisition of information (Pannell[8]).

Sensitivity analysis methods can be classiûed in many ways such as: mathematical, statistical and graphical (Frey and Patil[9]). In this paper, the sensitivity analyses has been made by graphical method. This method gives the representation of sensitivity in the form of graphs, charts, or surfaces. Generally, graphical methods are used as a screening method before further analysis of a model or to represent complex dependencies between inputs and outputs (McCamley and Rudel [10]). To validate the model outcomes with the predicted plant data it is very important to do a sensitivity analysis. Here using some graphical representation we have tried to veriûed the model with the actual plant set-up. Again, physically xylene solubility is inversely proportionate with donor ûow, i.e,

$$\text{Xylene solubility} \propto \frac{1}{\text{Donor flow}} \qquad (8)$$

The validation of equation (12) is completed in Figure 16, where we plot input data of donor ûow on x-axis and the plant data and Model-2 output of xylene solubility against y-axis. The ûgure depicts that the increment in the value of donor ûow results a fall in the value of xylene solubility.

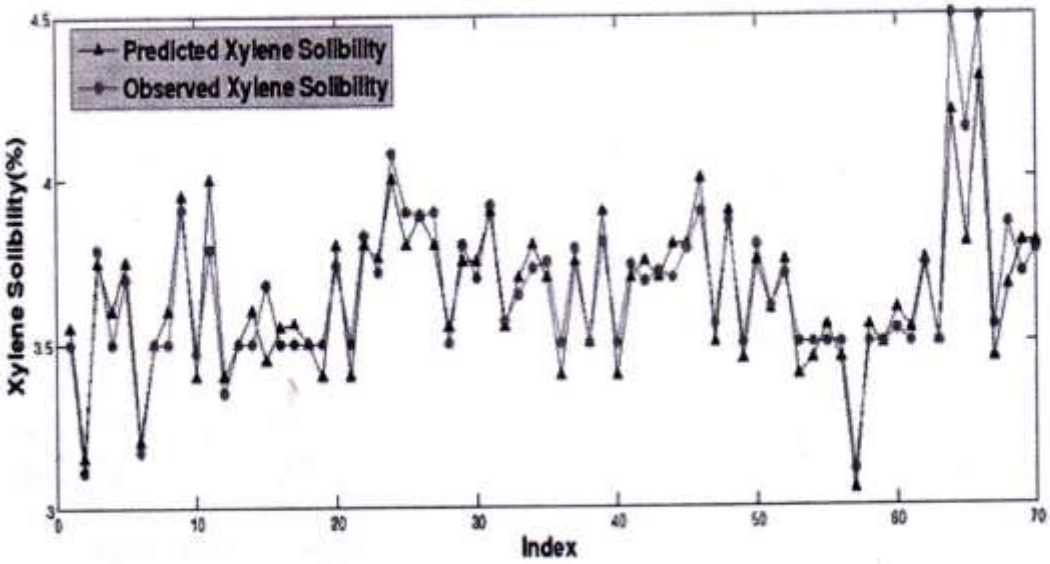


Figure 15: Comparison between predicted and observed values of xylene solubility.

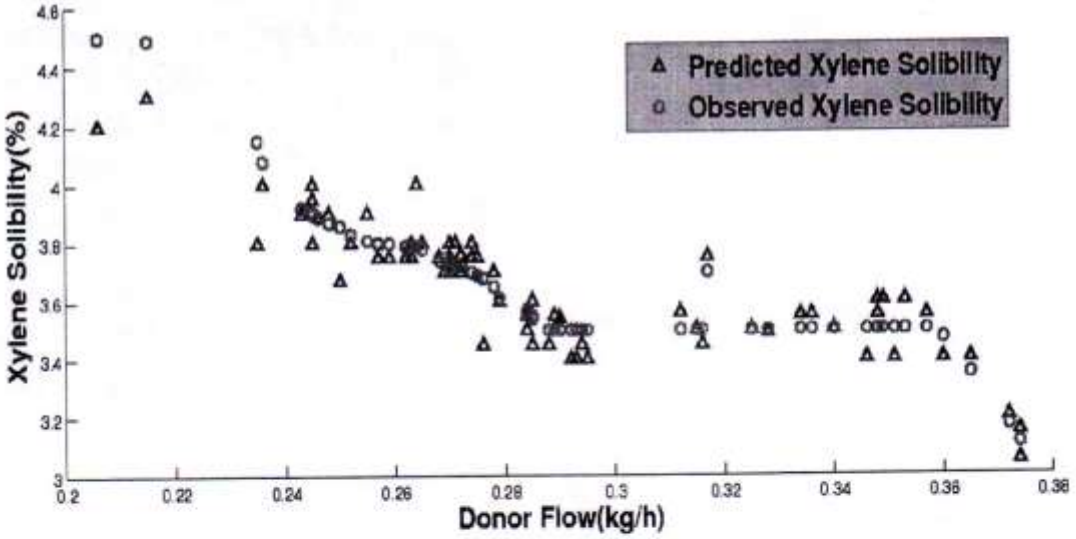


Figure 16: Relation between Xylene solubility and Donor ûow.

Again if we consider three dimension views of relationship between any two input variables with any one output variable, then we can see how they are related to each other and whether they satisfy the physical theory of the PP production process. The preview of the surface generated by hydrogen ûow, donor ûow and xylene solubility is illustrated in Figure 18. It is evident from the ûgure that in spite of all ranges of hydrogen the xylene solubility decreases step by step as donor ûow varies from lower range to higher range. This veriûes the Equation 12 quite eûciently. Figure 18 presents the surface created by donor ûow, pressure and xylene solubility. As shown, in the ûgures, the increment

in the value of donor ûow eûects a fall in the value of xylene solubility step by step, in view of the entire range of pressure.

The surface produced by donor ûow, temperature and xylene solubility shown in the Figure 17, a step wise drop in the value of xylene solubility is observed as the donor ûow is increased gradually

throughout the entire range of temperature. Thus, we can conclude that the donor ûow controls the xylene solubility mostly and they satisfy the relation in equation (12). The achieved results of

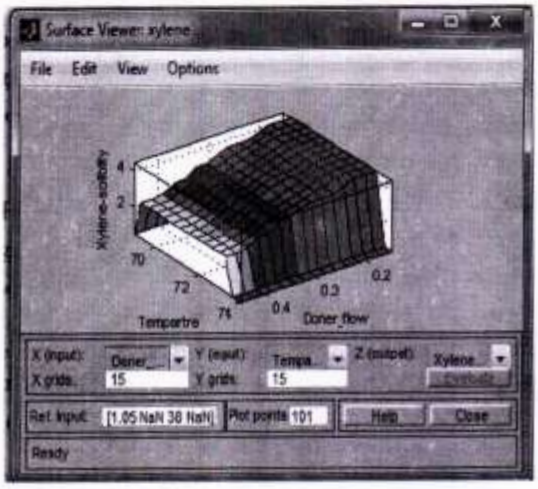


Figure 17: Surface view of temperature, donor flow and xylene solubility

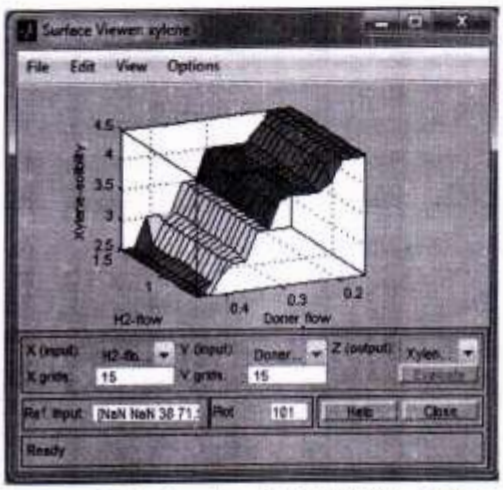


Figure 18: Surface view of hydrogen ûow, donor flow and xylene solubility

the study can be compared with some relevant studies discussed in the literature. The obtained result of the research identiûed that the proposed ANFIS models are capable to predict the PP quality parameters utilizing limiting data sets.

6. Conclusions and Future Research work:

From the research, it is found that using adaptive neuro-fuzzy inference system for PP quality modelling could be successfully demonstrated. Research works are going on with PP, where makers experiment with diûerent methods for producing it. This paper presents a Takagi-Sugeno fuzzy inference approach to control the quality of polypropylene during its production period. Sensitivity analysis selects the best MFIS model that gives more precise results compared to the plant data. In general the production engineers have to opt for a trial and error process to set the input param- eters for attaining the desired quality of PP. But if the proposed mathematical model is applied in petrochemical plant, it will surely beneût the engineers to set the input parameters promptly to achieve the desired quality of PP. The prediction of the quality of the yield during the production phase will help the production farm and as well as the end user to estimate the class of product in advance. Moreover, sometimes due to trial and error process sometimes the required speciûcation is not achieved, resulting the production of non-prime, oû-grade products of inferior quality which increases the price of non-conformance. The use of our projected model will certainly protect the valuable time and

reduce the cost of the accomplished product.

For further research work, we will utilize and integrate other intelligent methods, such as interpre- tative structural modelling method, fuzzy artiûcial neural network, etc., to evaluate the scale of eûciency of our current study. Furthermore, the product quality of other petrochemical plants and chemical industries can be evaluated and beneûted by this proposed method also.

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