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"ANFIS Prediction of the Polymer and Polymer Composite properties and its Optimization Technique"

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Abstract.

Prediction and optimization of polymer properties and polymer composite properties are a complex and highly non-linear problem with no any easy method to predict polymer properties directly and accurately. The effect of modifying a monomer (polymer repeat unit) on polymerization and the resulting polymer properties is not an easy task to investigate experimentally, given the large number of possible changes. We utilize a database of polymer properties to train the ANFIS, which accurately predict specific polymer properties. In polymer composites, a certain amount of experimental results is required to train a well-designed ANFIS. The ANFIS approach for predicting certain properties of polymer composite materials are discussed here. These include fatigue life; wear performance, response under combined loading situations, and dynamic mechanical properties. Prediction of effective thermal conductivity (ETC) of different fillers filled in polymer matrixes is proposed. The finding shows that ANFIS demonstrates high prediction accuracy as reflected by the small root mean square error (RMSE) value and high correlation coefficient (r) and coefficient of determination (R^2) values. ANFIS prediction results are found to be compatible to linear regression estimations. The goal of this paper is to promote more consideration of using ANFIS in the field of polymer composite property prediction and design. The predicted results by ANFIS are in good agreements with experimental values. The predicted results also show the supremacy of ANFIS in comparison with other earlier developed models.

Keywords: ANFIS, Prediction, Polymer properties, Polymer Composites

Properties, Effective Thermal Conductivity (ETC)

1. Introduction

Experiments on the production of different characteristics of polymer composites are normally conducted in the labs. Lab research can be very costly and time consuming. Alternatively, researchers are looking into other methods of studying the properties of polymer composites produced by using computer application models. In our study presented in this paper, the physical properties of polymer composites modeled using ANFIS (Adaptive Neuro-Fuzzy Inference System). Identifying the suitable composition of polymer with other agents and filler in the production of polymer composites is essential in producing engineering products. The objectives of this study are:

(i) to develop a computer application model ANFIS that can be used to find the suitable combination of polymer with other agents and filler in the production of polymer composites with different physical characteristics.

(ii) to assess the ability of ANFIS in predicting the properties of polymer composites by comparison with Linear Regression prediction results.

The proposed computer application prediction tool ANFIS is not to replace the conventional lab experiments or substitute the traditional statistical modeling techniques; instead it is to strengthen the present system by providing a simple simulation tool which can be useful in studying the input-output relationship in prediction of properties of polymer composites Besides being highly non-linear, there are a large number of parameters that need to be accurately defined if such systems are to be properly characterized. The application of polymer composites as engineering materials has become state of the art. To design the characteristics of polymer composites is the most important advantage. In order to meet a special target of engineering application, e.g. concerning one or several measurable material properties, polymer composites can be designed by selecting the correct composition and choosing the appropriate manufacturing process, as schematically illustrated in Fig. 1. Property investigation plays a key role in materials science to evaluate composites designed for special engineering applications. All three stages shown in Fig. 1 are not separated, but interconnected, and the integration can be summarized as composite design, processing optimization and property relationships. The first two fields correspond to the interaction between the selected compositions or the manufacturing process and the properties investigated, whereas the last relates to possible correlations between some simple measured parameters (e.g. modulus, strength and failure strain) and more complex properties (e.g. fatigue, wear, combined loading and creep). The understanding of all these relationships is important in composite materials science, in order to meet the requirements for particular engineering applications. Modeling of these relationships generally involves the development of a mathematical tool derived from experimental data; once established it can significantly reduce the experimental work involved in designing new polymer composites. For this reason, ANFIS has recently been introduced into the field of polymer composites.

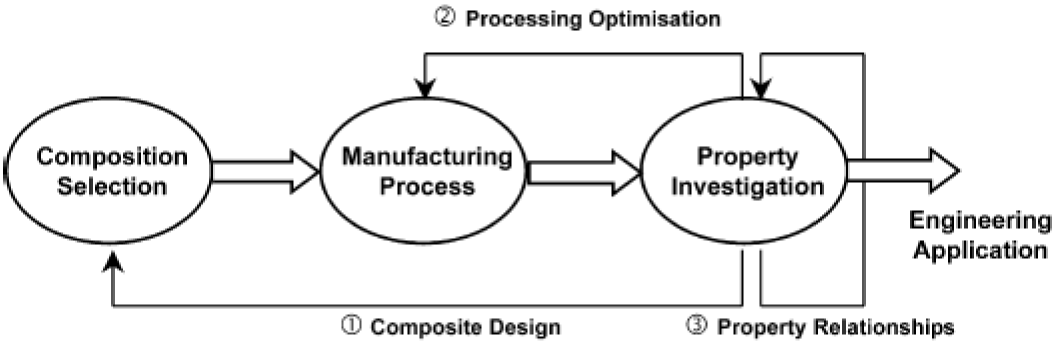

Fig. 1. Schematic presentation of composition selection, manufacturing process, and property investigation in composite materials science.

Polymer composites with high thermal conductivity and low dielectric constant are highly desirable for use in various applications, such as electric stress control, electromagnetic shielding, and higher storage capability of the electric energy. Polymer matrixes are commonly used such as polyethylene, polypropylene, polyurethane, polyvinyl chloride etc. which are good thermally and electrically insulators. Due to the increasing use of composite materials in many industrials sectors, including transformation, electronic, and energy supply and production, there is a renewed interest in simulation techniques to estimate the ETC of fiber and particle filled polymer composites. Dependence of the ETC of these materials on porosity, shape factor and packing of the particles is a matter of concern to engineers, mathematicians, and physicists. Thermal conductivity of boron nitride (BN) reinforced high density polyethylene (HDPE) composites was investigated under a special dispersion state of BN particles in HDPE, and together with the influence on thermal conductivity of particle sizes of filler used by Zhou *et al.* Xu *et al.* investigated the use of aluminum nitride (AlN) and poly-vinylidene fluoride (PVDF) as the matrix. Gu *et al.* investigated the content of AlN influencing the thermal conductivity and ultimate mechanical properties of AlN/ linear low-density polyethylene (LLDPE) composites. Adaptive neuro-fuzzy inference system (ANFIS) has recently been introduced to predict the effective thermal conductivity of metal/non-metal filled polymer composites. The fillers used most frequently are particles of carbon, aluminum, copper, brass, graphite and magnetite. By the addition of fillers to polymer matrix the thermal conductivity of polymers can be increased remarkably. In this study, high-density polyethylene (HDPE), low-density polyethylene (LDPE), linear low-density polyethylene (LLDPE), and polyvinylidene fluoride (PVDF) with different metals/non-metals such as boron nitride (BN), copper (Cu) and aluminum nitride (AIN) are used as inclusions, because of its superior mechanical and physical properties. Here the variation of ETC of HDPE/BN composites with volume fraction of filler, the variation of ETC of LDPE/Cu composites with volume fraction of filler, the variation of ETC of LLDPE/Cu composites with volume fraction of filler, the variation of ETC of PVDF/AlN composites with volume fraction of filler and the variation of ETC of LLDPE/AlN composites with volume fraction of filler have been studied. HDPE is one of the most widely used commercial polymers. However, its toughness, weather resistance, and environmental stress cracking resistance are not good enough which limits its applications in many high-technology areas. Reinforcing HDPE with fillers (viz., aluminum and copper particles, short carbon fibers, carbon, graphite, aluminum nitrides and magnetic particles) has been found to improve its properties. Low-density polyethylene (LDPE) is a thermoplastic made from petroleum. Compared with LDPE, LLDPE possesses better strength, toughness, heat-resistance, cold resistance, environmental stress cracking resistance, and tearing resistance properties. Rule-based modeling, specifically using fuzzy logic rule is a soft-computing tool-based approach to construct a model for the systems that are highly complex and exhibit non-linear behavior in nature, for which no well-defined mathematical expression(s) exist. The effectiveness of the ANFIS approach is extensively tested by comparing its results with those obtained in real experimentations as well as with those of various existing empirical/semi-empirical models re-ported in literature.

2. Application of ANFIS in composite materials science

For materials research, a certain amount of experimental results is always needed first to develop a well performing ANFIS, After the ANFIS has learned to solve the problems based on these datasets, new data from the same knowledge domain can then be put into the trained neural network, in order to output realistic solutions. The process of creating ANFIS for materials research can, therefore, be summarized in terms of the following stages:

1. Database collection: analysis and pre-processing of the data.

2. Training of the neural network: this includes the choice of its architecture, training functions, training algorithms and parameters of the network.

3. Test of the trained network: to evaluate the network performance.

4. Use of the trained ANFIS for simulation and prediction.

The greatest advantage of ANFIS is its ability to model complex non-linear, multi-dimensional functional relationships without any prior assumptions about the nature of the relationships, and the network is built directly from experimental data by its self-organizing capabilities.

Evaluation of the ANFIS method

A dataset of measurement results will usually be divided into a training dataset and a test dataset. The training dataset is used to adjust the weights of all the connecting nodes until the desired error level is reached. Thereafter, the network performance is evaluated by using the test dataset. The quality of the prediction can normally be characterized by the root mean square error (RMSE) of the predicted values from the real measured data. The smaller the RMSE of the test dataset is the higher, is the predictive quality.

3. ANFIS for polymer composites

Fatigue life

Fatigue is one of the most complicated problems for fiber composites, and failure mechanisms are still not well understood. Extensive tests must be carried out because of the absence of a well-defined failure criterion that can be used to predict fatigue failure in polymer composites. ANFIS offer the possibility of developing models that will predict the behavior of composites without being linked to mechanistic arguments.

Unidirectional (UD) composites

It seems that the fiber orientation in UD composites plays a key role in fatigue performance. Applying fiber orientation as an input improves the ANFIS predictive quality significantly, even with a relatively smaller dataset. In order to improve the prediction accuracy, ANFIS was considered here using the same database employed in previous literatures.

Laminate composites

Three fatigue parameters, peak stress, minimum stress and probability of failure, and four monotonic mechanical properties, tensile strength, compression strength, tensile failure strain and tensile modulus, were selected as the ANFIS inputs, which were applied to predict the fatigue life of the composites as the output. ANFIS was finally optimized by evaluating the changes in RMSE of ANFIS output with the number of neurons in the intermediate layers. Once a well-trained ANFIS was obtained, the possibility for predicting fatigue life of new materials could be analyzed. Further, samples of two other materials, a fifth CFRP (HTA/982) laminate and a GFRP (E-glass/913) laminate of similar structure, were tested with regard to their mechanical and fatigue properties.

Wear of composites

The dataset are obtained from fretting tests with various material compositions under different wear measuring conditions. An ANFIS is proposed with the output of wear volume; the inputs were mechanical properties and test conditions, i.e. compressive strength, compression modulus, compressive strain to failure, tensile strength, tensile strain to failure, impact strength, environmental testing temperature, initial load, average load and average velocity. The design and the training of the ANFIS were performed using the 'ANFIS Toolbox' of MATLAB.

Dynamic mechanical properties

An ANFIS approach has been proposed for the complex problems of fatigue, wear and combined loading failure discussed earlier. Nevertheless, it is also interesting for dealing with some relatively simple material problems, which will be of help to understand the characteristics of ANFIS for polymer composite applications. Large training data are needed to reach a predictive quality to that in a one-output ANFIS.

Processing optimization

In this study, a Kohonen self-organizing map type of neural network was applied to classify the measured dataset. Another approach in a similar direction was performed for the optimization of the polymerization process of polyamide 6.6 by Nascimento and Giudici. It was shown in literatures that the optimal cure cycles of the ANFIS prediction were reasonably accurate in comparison of the mean-square-error to the results based on the numerical process models. The use of the ANFIS in lieu of the numerical models reduced the computational time for process simulations by several orders of magnitude.

4. Data Set and ANFIS

We concentrate on polymer composites properties (mechanical, thermal, magnetic, optical, electrical, environmental and deteriorative) and the relationships with their structures (microscopic, mesoscopic and macroscopic). The prediction of polymer properties from just the structure of the monomer is somewhat unreliable. But trained ANFIS that are given optimized input data do an excellent job of characterizing a new modified polymer.

Polymer Database

The polymer database we used was selected carefully so as to include all types of polymers available. Within each category, several different types of polymers were included to provide a comprehensive set of data. The total data set consisted of 400 individual polymers. For each polymer, information stored included its molecular weight (poly-dispersity), mechanical and thermal properties, chemical structure, and data reliability number.

Polymer Properties Selected

Impact resistance is very likely the most desired property of an engineering plastic. One indicator of good impact resistance is the $T\alpha$ / $T\gamma$ ratio and the dynamic elastic modulus. The higher this ratio is, the better the impact resistance is. However, high impact resistance with almost no elastic properties results in a brittle polymer that has no commercial use. Therefore, in the complete description of the overall mechanical properties of a polymer these properties must be included.

ANFIS and Linear Regression Models

Fuzzy systems and Artificial Neural Networks are computer application approaches that have been widely applied in various domains. The expressiveness of fuzzy if-then rules using linguistic variables can be combined with the learning capability of neural networks to produce Fuzzy Neural Network models. The input attributes of the developed ANFIS system are the ingredients needed to produce polymer. These imprecise attributes are called fuzzy linguistic variables and expressed as fuzzy linguistic labels such as Low (A1), Medium (A2) and High (A3).The research methodology undertaken is summarized in Fig.2.

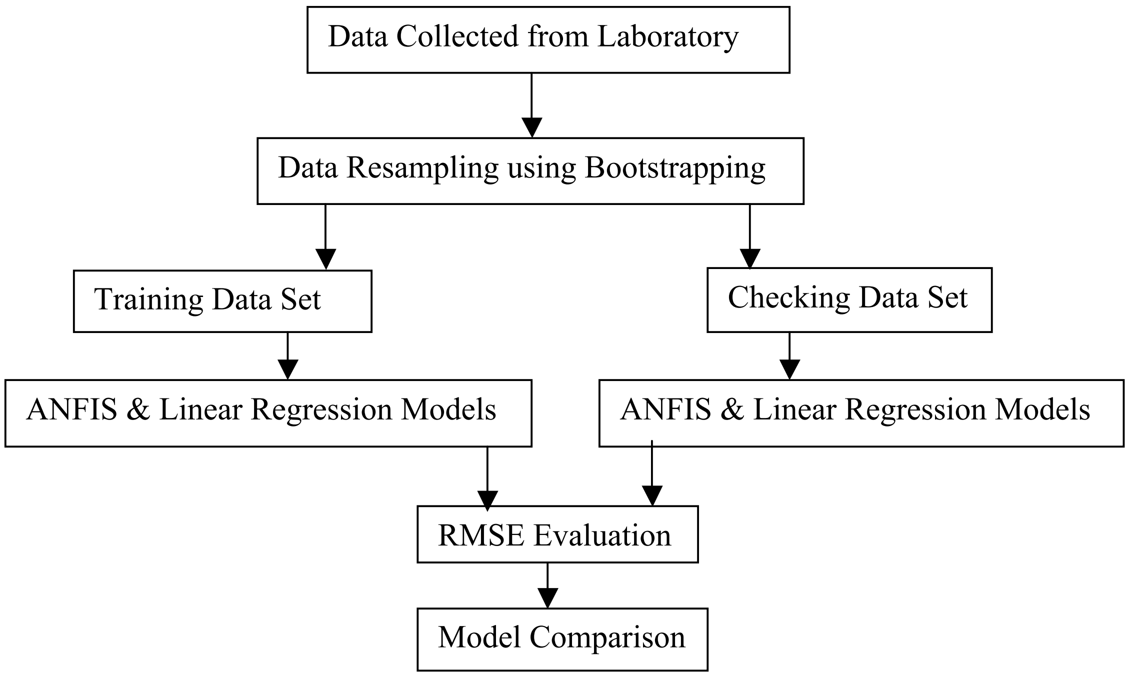

Fig.2 Summary of the research methodology.

The ANFIS model under consideration is a multi-input single-output (MISO) system with four inputs and one output. ANFIS and linear regression prediction accuracies are measured using the Root Mean Square Error (RMSE). The ANFIS structure generated in this study utilizes fuzzy clustering of the input and output data sets as well as the bell-shape membership function. Thus the number of rules is equal to the number of output clusters. In order to minimize the over fitting of the model developed, the complete data set was split into a training (50%) and testing data set (50%). The ANFIS model was first trained using the training data set followed by validation process using the remaining data. The errors associated with the training and checking processes are recorded. ANFIS training was found to converge after training with 95 epochs as shown in Fig.3. RMSE for both the training and testing of ANFIS are very small which reflects the ability of ANFIS to capture the essential components of underlying dynamics governing the relationships between the input and the output variables. Fig.4 shows the architecture of 4-input one-output ANFIS structure. The computation of membership functions (MFs) parameters is facilitated by a gradient descent vector.

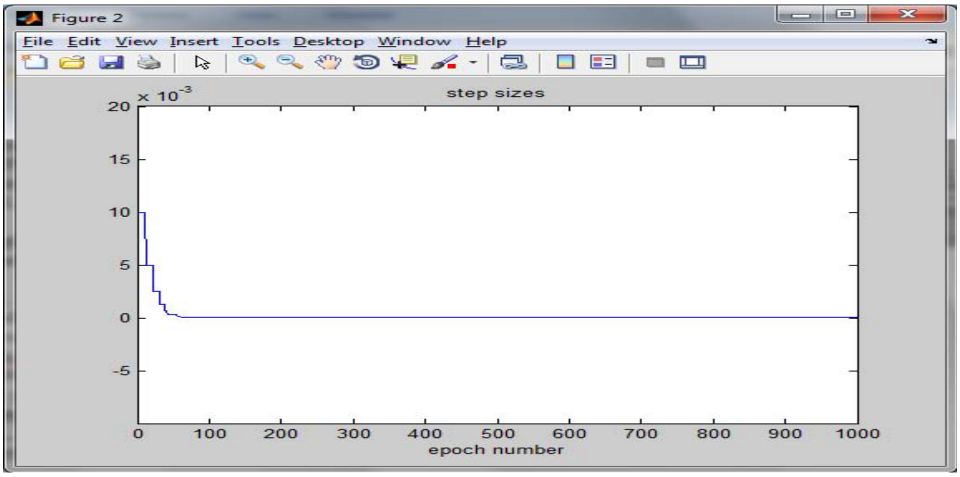

Fig.3 ANFIS training converges after 95 epochs.

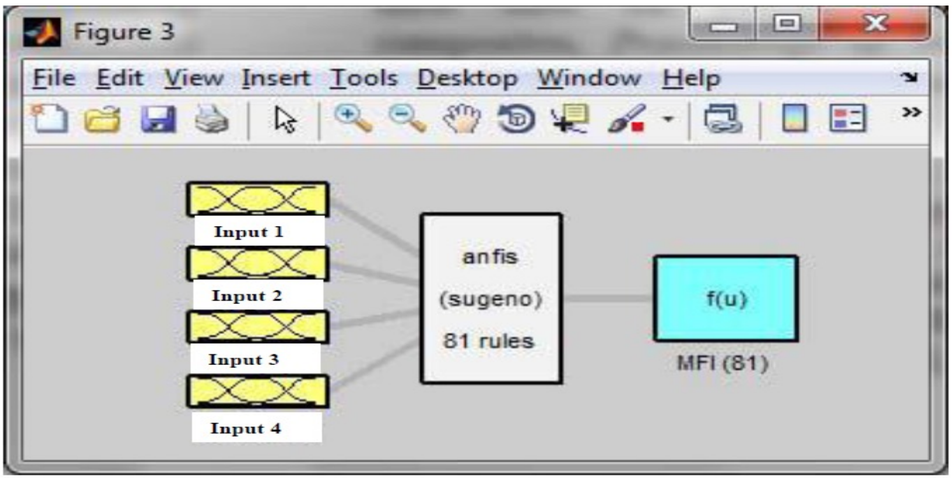

Fig.4 ANFIS architecture for a four input single-output Sugeno-fuzzy model.

ANFIS parameters are adjusted as to reduce the error measure defined by the sum of the squared difference between the actual and desired output. The root mean square error (RMSE) is calculated using

$$RMSE = \sqrt{\frac{1}{N}\sum_{t=1}^{N}(A_t - F_t)^2}$$

Where A_t and F_t are actual and fitted values, respectively and N is the number of training or testing sample. The parameters associated with MF's will change through the learning process of ANN. The output of the n^{th} node is given in Eq. (2).

Layer 1: Every node in this layer i is an adaptive node with a node function

$$O_{1,i} = \mu_{A_i}(x) \qquad for\ i = 1,2 \ldots\ldots\ldots\ldots\ldots\ldots.(1)$$

$$O_{1,i} = \mu_{B_i}(y) \qquad for\ i = 3,4 \ \ldots\ldots\ldots\ldots\ldots\ldots(2)$$

Where *m* and *n* are the inputs to node *i* and $A_{1,\ldots i}$ are the linguistic labels such as average, good, excellent associated with this node. O^1_{Ai} is the membership grade of fuzzy set $A_{1,\ldots i}$ and it denotes the degree to which the given inputs m or n satisfies the quantifier At. The membership grade can be calculated using Eq. (3)

$$\mu_A(x) = \frac{1}{1 + \left|\frac{x - c_i}{a_i}\right|^{2b_i}} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots..(3)$$

Where *ai, bi, ci* is the parameter set of a bell-shape figure. Parameters in this layer are referred as premise parameters.

Layer 2: Every node in this layer is a fixed node and the output is the product of all the incoming signals presented by Eq. (4).

$$O^2_{ij} = w_{ij} = \mu_{Ai}(m)\mu_{Bi}(n), \qquad i,j = 1,2 \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots..(4)$$

Each node of output represents the firing strength of a rule.

Layer 3: Every node in this layer is fixed. The nodes in this layer normalizes the weight functions by calculating the ratio of the i^{th} rule's firing strength to the sum of all rules' firing strengths using Eq.(5).

$$O^3_{ij} = \overline{w}_{ij} = \frac{w_{ij}}{W_{11} + W_{12} + W_{21} + W_{22}}, \qquad i,j = 1,2 \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots..(5)$$

Layer 4: The nodes in this layer are adaptive nodes. The output of this layer are represented as

$$O_{ij}^{4} = \overline{w}_{ij} f_{ij} = \overline{w}_{ij}\left(P_{ij}x + q_{ij}y + r_{ij}\right), \qquad i,j = 1,2 \quad \dots\dots\dots\dots\dots\dots\dots\dots\dots..(6)$$

Where *wi* is a normalized firing strengths from Layer 3 and (*Pi, qi,… mi, ri*) are the parameter sets referred as consequent parameters.

Layer 5: The single node in this layer labelled Σ computes the overall output. The output is calculated

using Eq.(7).

$$O_{ij}^{5} = \sum_{i=1}^{2} \overline{w}_{ij} f_{ij} = \sum_{i=1}^{2}\sum_{j=1}^{2} \overline{w}_{ij}\left(P_{ij}x + q_{ij}y + r_{ij}\right), \qquad i,j = 1,2 \quad \dots\dots\dots..(7)$$

Fuzzy reasoning which is made up of fuzzy if-then rules together with fuzzy membership functions is the main feature of fuzzy inference systems (R. Jang, 1993). Fuzzy reasoning derives conclusions from the set of rules which are either data driven or provided by experts (E. Neilsen, 1991). Fig.5 shows the reasoning procedure for a first order Sugeno fuzzy model. Each rule has a crisp output and the overall output is a weighted average. For example;

“If Input-1 is High and Input-2 is Low and Input-3 is Medium and Input-4 is Low THEN the output MF1 will be Medium is a complete rule defining the relations of input and output linguistic variables”.

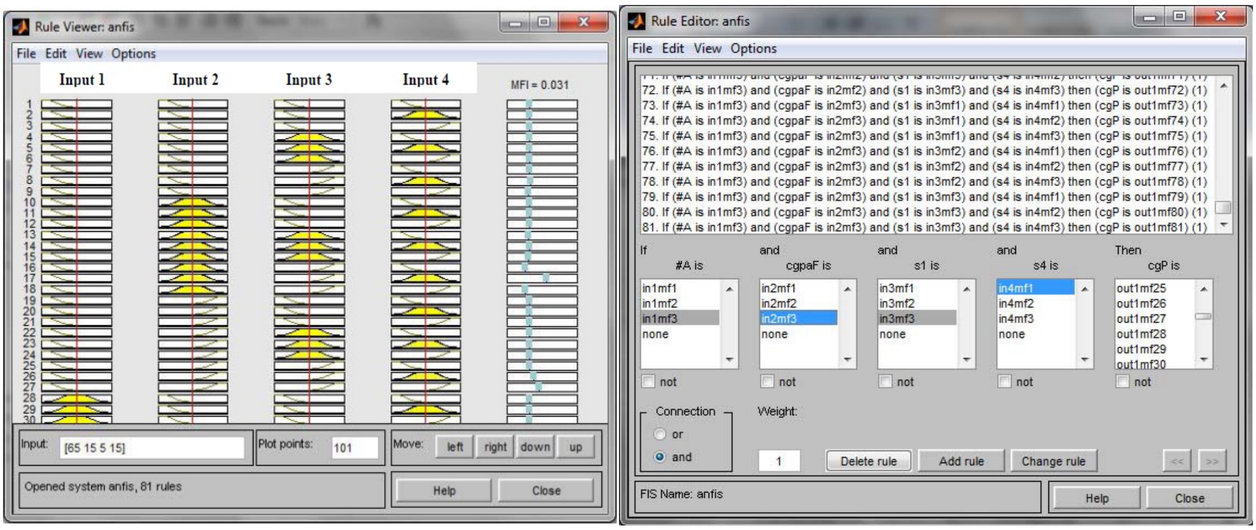

Fig.5 (a) Fuzzy reasoning procedure for Sugeno model of physical properties of degradable plastics (b) If-Then rules derived by ANFIS.

The rule set given below illustrates the reasoning mechanism and the corresponding equivalent ANFIS architecture where the nodes of the same layer have similar functions.

5. Result and Discussion

Initially the training data set was used to develop ANFIS models with 2-input, 3-input and 4-input. The models were run for 800 epochs before the best models are identified based on the smallest RMSE values. Next, the testing data set are fed into the trained ANFIS models. ANFIS outputs are recorded and the error is calculated by comparing ANFIS predicted values with the actual lab values. Similar training data sets are used to generate linear regression equations which are then tested on similar testing data set as used for ANFIS. Linear regression outputs are recorded and the error is also calculated by comparing linear regression predicted values with the actual lab values. Table1 shows observed data, predicted data and percentage error in training ANFIS for prediction of dielectric constants of various polymers.

Table.1. Observed data, Predicted data and Percentage Error in training ANFIS

Die electric Constants			
Name of Polymer	Observed Data	Predicted Data	Error %
Poly(tetrafluoroethylene)	2.00	1.87	6.50
Polyisobutylene	2.23	2.32	-4.00
Polyethylene	2.30	2.19	4.80
Polypropylene	2.30	2.41	-4.80
Polyisoprene	2.40	2.37	1.70
Polybutadiene	2.51	2.44	2.80
Polysiloxane	3.04	2.87	5.60
Poly(vinyl acetate)	3.50	3.39	3.10
Poly(methyl methacrylate)	3.60	3.06	15.0
Poly(oxymethylene)	3.70	2.54	31.4
Polyacrylonitrile	6.50	4.12	36.6
Poly(vinyl alcohol)	7.80	3.25	58.3
Poly (vinylidenefluoride)	8.40	3.04	63.8

All ANFIS and linear regression predicted outputs on the physical properties of polymer are recorded and analyzed. Tables 2 tabulate the RMSE values for the prediction of Melting Point, Melt Flow Index and Density of polymer**.** The best predictor set (Optimized) is determined based on the smallest RMSE values. The results showed that ANFIS model prediction has very low RMSE values which indicate high prediction accuracies in predicting the physical properties of polymer.

Other combinations could also be predicted using the developed ANFIS model to suit the needs of the polymer industry. ANFIS prediction outputs are found to be compatible to linear regression estimations.

These must be predicted extremely accurately for predicting miscibility. We have seen that the ratio $T\alpha / T\gamma$ is extremely sensitive and important to predicting good mechanical properties. The main advantage of this comparison is that it enables us to select ANFIS that train quickly and provide acceptable results as compared to the best network we found. In Figure 6, points on the straight line indicate that the actual and predicted output were identical. If most of the points lie on this line, there is a danger of memorization and lack of generalization by the network. Similarly, wide deviations from the straight line indicate a poorly trained ANFIS that may not give accurate predictions.

Table 2: RMSE values of ANFIS models for the prediction of Melt Flow Index, Melting Point and Density.

Input	RMSE Melt Flow Index		RMSE Melting point		RMSE Density	
	Train	Test	Train	Test	Train	Test
Polyethylene	0.0050	0.0049	0.0991	0.1519	0.0056	0.0055
Polypropylene	0.0259	0.0239	0.3581	0.3359	0.0279	0.0266
Polyisoprene	0.0144	0.0157	0.5764	0.5545	0.0117	0.0123
Polybutadiene	0.0348	0.0342	0.2905	0.3109	0.0409	0.0385
Polysiloxane	0.0155	0.0187	0.4799	0.5120	0.0134	0.0139
Poly(vinyl acetate)	0.0197	0.0183	0.4754	0.5168	0.0177	0.0176
Poly(methyl methacrylate)	0.0030	0.0030	0.0820	0.1344	0.0043	0.0044
Poly(oxymethylene)	0.0030	0.0030	0.0820	0.1343	0.0043	0.0044
Polyacrylonitrile	0.0030	0.0030	0.1089	0.1639	0.0043	0.0044
Poly(vinyl alcohol)	0.0030	0.0030	0.0820	0.1344	0.0043	0.0044
Poly(vinylidenefluoride)	0.0030	0.0030	0.0820	0.1344	0.0043	0.0044

Predicted Properties

Table 2 gives the results when the final selected ANFIS model is used. We found that for these modifications better $T_{\alpha}/T\gamma$ ratios and dynamic mechanical modulus values were predicted as compared to the parent polymers. On the basis of these results, we were able to conclude that both steric factors, and the intra- and intermolecular polarities of the polymer play a vital role in the final outcome of the prediction of the mechanical properties of the polymers tested.

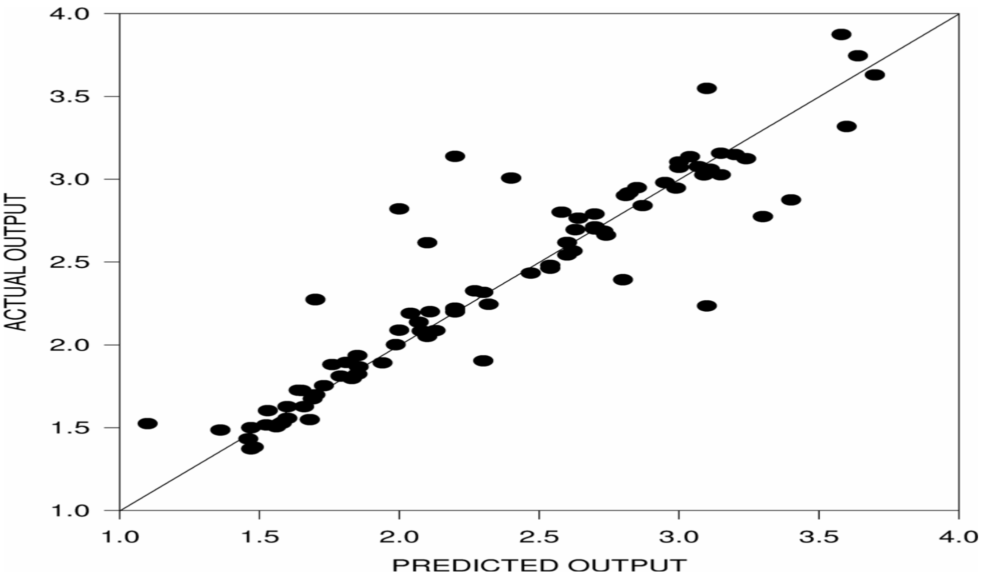

Fig. 6: Actual versus predicted output when final ANFIS model is applied to the 96 testing set.

Table 2: a) Results of applying the final model to 20 modified bisphenol-A polycarbonates. b) Results of applying the final model to 15 modified poly (2, 6-dimethyl-1, 4-phenylene oxide)

Monomer	T_{α}/T_{γ}	Dynamic Modulus (20^0C, dynes/cm^2)
(a)		
Modification PC-1	3.13	5.67×10^9
Modification PC-2	2.70	5.22×10^9
Modification PC-3	2.74	5.38×10^9
Modification PC-4	3.37	6.39×10^9
Modification PC-5	2.58	5.06×10^9
(b)		
Modification PPO-1	1.98	6.32×10^9
Modification PPO-2	2.29	6.59×10^9

The dielectric constants of polymers

The dielectric constants of polymers used in this study were obtained from the literature

(Brandrup and Immergut, 1975). Out of the available 13 conductive polymers, 12 were used for training and one was left for testing or to validate the training. In the next run, a different set of 12 polymers was used for training, and the remaining polymer was used for testing. A total of 13 sets of training were conducted in this manner and the results have been presented in Fig. 7.

However, when the dielectric constant data was large, the percent error was also getting large. The reason for this, we feel, was the small number of compounds tested. If you don't provide enough information to train the ANFIS, it won't learn properly.

Polymer Composites

Thermal conductivity of boron nitride reinforced high density polyethylene composites was investigated under a special dispersion state of boron nitride particles in high density polyethylene, and together with the influence on thermal conductivity of particle sizes of filler used by Zhou *et al.* Xu *et al.* investigated the use of aluminum nitride (AN) and poly-vinylidene fluoride (PvF) as the matrix. Gu *et al.* investigated the content of AN influencing the thermal conductivity and ultimate mechanical properties of AN/ linear low-density polyethylene (LldP) composites.

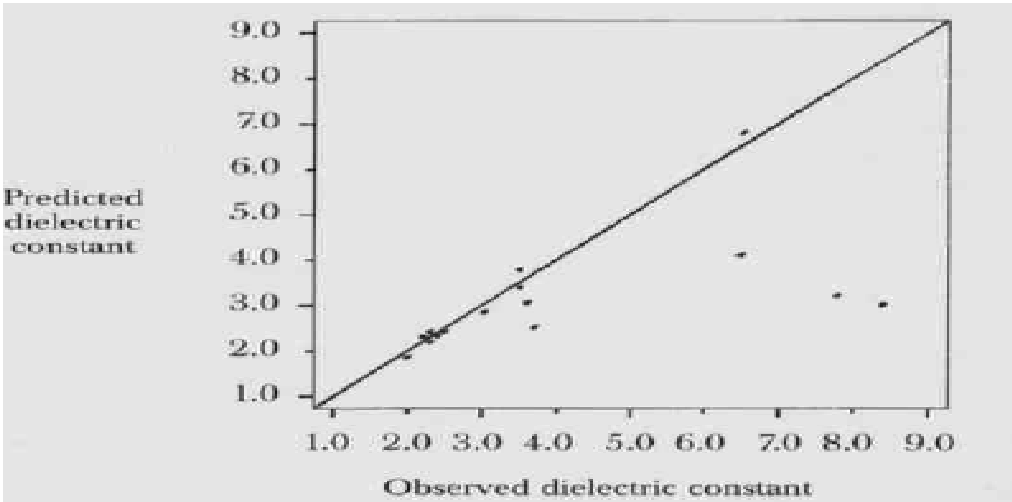

Fig.7 Correlation between the actual values and predicted values by the ANFIS of dielectric constant.

In this study, high-density polyethylene (HdP), low-density polyethylene (LdP), linear low-density polyethylene (LldP), and polyvinylidene fluoride (PvF) with different metals/non-metals such as boron nitride (BrN), copper (Cu) and aluminum nitride (AN) are used as inclusions, because of its superior mechanical and physical properties.

Effective Thermal conductivity of boron nitride reinforced high density polyethylene composites

Fig.8 shows the variation in experimental values of effective thermal conductivity of boron nitride reinforced high density polyethylene composites and those predicted by the ANFIS, and other theoretical models with volume fraction of dispersed phase (filler). It is seen that with the increase in filler loading the ETC of the composite increases. The ETC of 1.129 W/m K is achieved by ANFIS for HdP containing 29 % volume fraction of BrN, more than four times of pure HdP.

Effective Thermal Conductivity of Copper reinforced low-density polyethylene and linear low-density polyethylene Composites

Fig.9 show the experimental values of effective thermal conductivity of LdP/copper composites and those predicted by the ANFIS and other theoretical models over a wide range of volume fraction of dispersed phase (filler) between 0% to 24%. It is clear that the effective thermal conductivities.

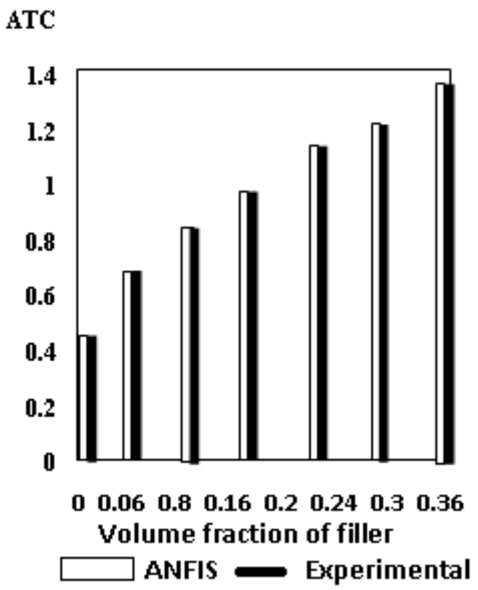

Fig. 8 Effective Thermal Conductivity of boron nitride reinforced high density polyethylene composites

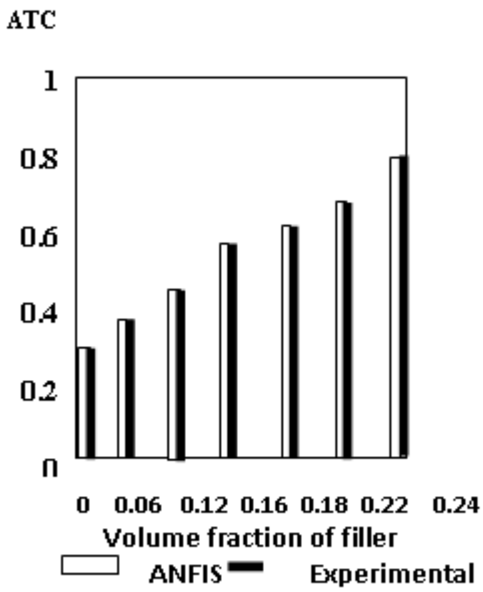

Fig.9 Effective Thermal Conductivity of Copper reinforced low-density poly ethylene and linear low-density poly ethylene

Effective Thermal Conductivity of polyvinylidene fluoride with aluminum nitride Composite

The effective thermal conductivity of PvF/AN composites with volume fraction of dispersed phase (filler) over the range between 0% to 75% is shown in Fig.10. It is noticed that the effective thermal conductivity of the composite increases with the increase in filler loading, except that the ETC decreased when the AN volume fraction is increased from 70% to 75% (due to increase in porosity). The highest values of effective thermal conductivity 5.101 W/m K and 3.654 W/m K are predicted by ANFIS for PvF containing 70% and 75% volume fraction of AN, respectively. It is also shown that the calculated results by the Singh *et al*. equations are in better agreement with the experimental and ANFIS results.

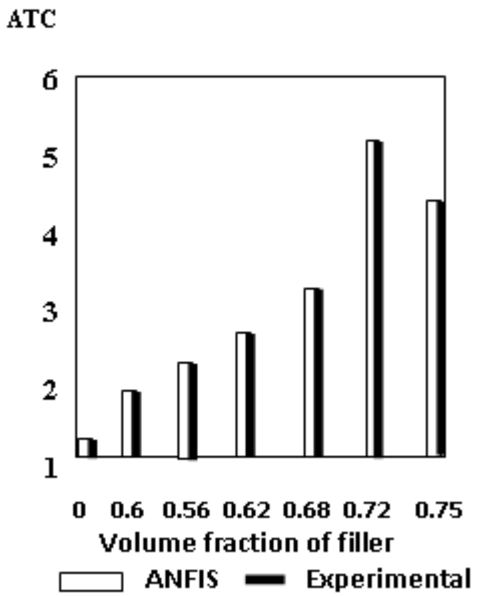

Fig.10 Effective Thermal Conductivity of polyvinylidene fluride with aluminum nitride Composite.

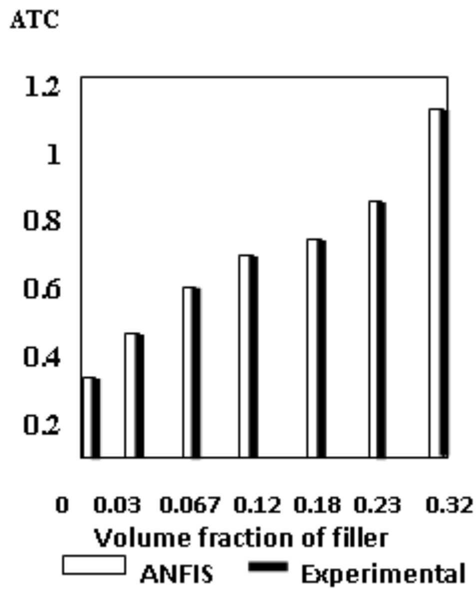

Fig.11 Effective Thermal Conductivity of linear low-density polyethylene with aluminum nitride Composites

Effective Thermal Conductivity of linear low-density polyethylene with aluminum nitride Composite

Fig.11 shows the variation in experimental ETC of LldP/AN composites over a wide range of volume fraction of dispersed phase (filler) between 0% to 32% and those predicted by the ANFIS and calculated by various model with volume fraction of dispersed (filler) phase. It is clear that the effective thermal conductivities of composites are higher than that of pure LldP matrix. The ETC of composites increases considerably with the increase of volume fractions of inclusions. The results are satisfactory in agreement with the experimental and ANFIS results.

In Fig.8-11, it is noticed that the ETC of different metal/non-metal filled polymer composites increases with the increase in volume contents of filler in polymer composites. The enhancement in the effective thermal conductivity of present composites with increase in volume content of metal/non-metal is mainly due to more interaction between metal/non-metal particles as they come in contact with each other, resulting in the ease in transfer of heat and consequent enhancement of the effective thermal conductivity. Highly conductive different metal/ non-metal like BrN, Cu, and AN are used as fillers into polyethylene (HdP, LdP, and LldP) and polyvinylidene fluoride (PvF) composites as matrix in this study. All the predictions of the ETC by ANFIS are in good agreement with the available experimental results and calculated by the Singh *et al*. model. Clearly, there are many benefits of using ANFIS for prediction, including the following: 1) It is a general framework that combines two technologies, namely neural networks and fuzzy systems; 2) By using fuzzy techniques, both numerical and linguistic knowledge can be combined into a fuzzy rule base; 3) The combined fuzzy rule base represents the knowledge of the network structure so that structure learning techniques can easily be accomplished; 4) Fuzzy membership functions can be tuned optimally by using learning methods; 5) The architecture requirements are fewer and simpler compared to neural networks, which require extensive trails and errors for optimization of their architecture; and 6) ANFIS does not require extensive initializations through several random starts before training, as always happens in neural networks. Other advantages of the two-phase neuro fuzzy hybrid technique in the ANFIS model also include its nonlinear ability, its capacity for fast learning from numerical and linguistic knowledge, and its adaptation capability.

4. Conclusions

In this paper we had described the development of a data driven ANFIS model using real data set obtained from the polymer laboratory. The developed ANFIS is a soft computing approach utilizing a feed-forward multilayer neural network for fuzzy modeling. This study had shown that ANFIS models are highly robust and compatible. ANFIS models are found to have good prediction ability for the prediction of physical properties of polymer is recommended. It is noticed that the ETC of different metal/non-metal filled polymer composites increases with the increase in volume contents of filler in polymer composites. The enhancement in the effective thermal conductivity of present composites with increase in volume content of metal/non-metal is mainly due to more interaction between metal/non-metal particles as they come in contact with each other, resulting in the ease in transfer of heat and consequent enhancement of the effective thermal conductivity. Highly conductive different metal/ non-metal like BrN, Cu, and AN are used as fillers into polyethylene (HdP, LdP, and LldP) and poly-vinylidene fluoride (PvF) composites as matrix in this study. All the predictions of the ETC by ANFIS are in good agreement with the available experimental re-sults and calculated by the Singh *et al*. model. Max-well as well as Hamilton and Crosser models are calculated fairly well the ETC only for low concentration of present composites. The predicted results show that using a hybrid intelligent approach, in particular ANFIS, gives good prediction ac-curacies for the ETC of metal/non-metal filled polymer composites. The resultant predictions of effective thermal conductivity by the ANFIS agree well with the available experimental data. The ANFIS exhibit the capability to use for the predictions of effective thermal conductivity of various types of tailored complex materials.

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