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Research Article

Using ANFIS by BA optimization for modeling of plastic injection molding process

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A b s t r a c t

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Product weight is one of the most important characteristics for quality monitoring in plastic injection molding (PIM) parts. Four parameters that most important on product weight in PIM are melting temperature, injection velocity, packing pressure and cooling time. In the present work,Adaptive Neuro Fuzzy Inference System (ANFIS)is used to model the weight of the plastic injecting molding parts.However, the results show that in ANFIS training, the vector of radius has a very important role for its predicting accuracy. Therefore, theBees Algorithm (BA) isused to find the best vector of radius.

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1. Introduction

Plastic injection molding is one of the notable processes in theplastic product industries.Each cycle of this process has four phases: plastication, injection, packing and cooling.Therefore, several process parameters such as melt temperature, mold temperature, injection pressure, injection velocity and cooling time influence the quality of injection molded plastic products.The quality of plastic injection moldedproducts can be roughly divided into three kinds: (1) thedimensional properties, (2) the surface properties, and (3)the mechanical or optical properties [1].Previously, researchers showed that product weight is acritical quality characteristic and a good indication of thestability of the manufacturing process in plastic injectionmolding [1, 2]. They also revealed that productweight is an important attribute for plastic injectionmolded products because the product weight has a closerelation to the other quality properties (e.g., surface andmechanical properties), particularly other dimensionalproperties (e.g., thickness). They also claimed that the performanceof a manufacturing process and quality controlcan be monitored by the product weight. Kamal et al. [2] showed that controlling the product weight is ofgreat commercial interest and can produce great value forproduction management.

So, It is very important to find better combination of process parameters for achieve better quality in PIM (plastic injection molding).Many researches have been tried to find the optimum process parameters during PIM [3-5].

Gao et al. [4, 5] proposed an optimization procedure to minimize of warpage in injection molding by using the Kriging model. Deng et al.[6] used Taguchi's parameter design method for determining the optimal process parameters.Altan[7] minimized the shrinkage of rectangular shaped specimens by Taguchiandexperimental design.AlsoNeural Network was used to predict the shrinkage of the parts. Chiang[8]usedgrey-fuzzy logic tooptimal process conditions of an injection-moldedthermoplastic.Cheng et al. [9]developed a fuzzy moldability evaluation approach for the optimizationof injection mold.

The main objective of the present study isto applyAdaptive Neuro-Fuzzy Inference System (ANFIS). For derive the best modelling, and furthermore BA algorithmwas used to find the optimum parameters in ANFIS.This modeling was very useful for predicting of product weight in plastic injection molding.

2.ExperimentalProcedures and Tooling

To apply experimental test an injection machinewith 30 ton clamping force and 70 cm3 volume per shot was used.The experimental test workpiece (washer) is made by EVA(ethylene-vinyl acetate) that is a thermoplastic copolymer of poly ethylene and poly vinyl acetate.The schematic of chemical construction and physical properties are shown in the Figure 1 and Table 1.

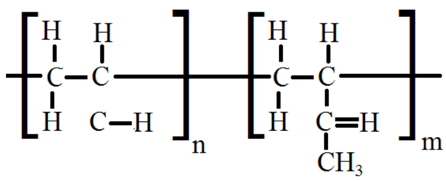

Fig. 1: Schematic of EVA chemical construction

Table1: Physical properties of EVA

Specific weight	0.93
Melting temperature	77-106
Process temperature	141-224
Impact resistance	Without fracture

This material has a very good flexibility and toughness with high sticky characteristic. These properties are very useful for sealing in the vibration systems. Figure2illustrates the schematic of the washer used as a sealing part.

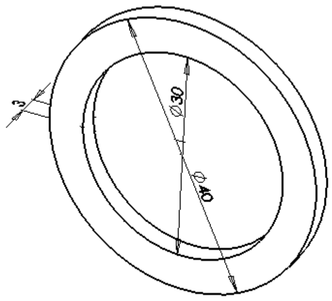

Fig. 2: Schematic view of washer part

Important parametersand their levels that were investigated in this paper have been listed in Table2.

Table2: Parameters that were investigated

Parameters \ level	1	2	3	4
Melt temperature(°C)	80	100	130	160
Injection velocity(mm/s)	10	15	20	40
packing pressure(MPa)	0	1.5	2	4
cooling time(s)	1	2	4	8

To construct an ANFIS model,first we need to form our input and output parameters.In order to make the network model as accurate as possible, number of sample fabrications were240 sets.160 sets were used for training purpose,80 sets were used for testing and validation of modelling process.Number of data was listed in Table3.

Table3:combination of parameters and corresponded results

Input parameters					
	Melt temperature(^{0}C)	Injection velocity(mm/s)	packing pressure(MPa)	cooling time(t)	Weight(gr)
1	80	15	0	1	0.2856
2	80	15	0	2	0.3093
….	….	….	….	…..	…..
70	100	15	1.5	1	1.0498
71	100	15	1.5	2	1.0496
….	….	….	…..	….	…..
160	130	20	4	4	1.1126
161	130	20	4	8	1.1129
….	….	….	….	….	…..
239	160	40	4	4	1.121
240	160	40	4	8	1.1275

3. AdaptiveNeuro-Fuzzy Inference System (ANFIS)

ANFIS represents a useful neural network approach for the solution of function approximation problems. Data driven procedures for the synthesis of ANFIS networks are typically based on clustering a training set of numerical samples of the unknown function to be approximated. Since introduction, ANFIS networks have been successfully applied to classification tasks, rule-based process controls, pattern recognition problems and the like. Here a fuzzy inference system comprises of the fuzzy model proposed by Takagi, Sugeno and Kang[10, 11] to formalize a systematic approach to generate fuzzy rules from an input -output data set.

3.1. ANFIS structure

For simplify, it is assumed that the fuzzy inference system under consideration has two inputs and one output.The rule base contains two fuzzy if-then rules of Takagi and Sugeno'stype [12] as follows:

$$\textit{If} \quad x \text{ is } A \text{ and } y \text{ is } B \quad \text{then} \quad z \text{ is } f(x,y)$$

Where A and B are the fuzzy sets in the antecedents and $z=f(x,y)$ is a crisp function in the consequent. $f(x,y)$ is usually a polynomial for the input variables X and Y. But it can also be any other function that can approximately describe the output of the system within the fuzzy region as specified by the antecedent. When $f(x,y)$ is a constant, a zero order Sugeno fuzzy model is formed, which may be considered to be a special case of Mamdaniet al. fuzzy inference system [13] where each rule consequent is specified by a fuzzy singleton.If $f(x,y)$ is taken to be a first order polynomial a first order Sugeno fuzzy model is formed. For a first order two-rule Sugeno fuzzy inference system, the two rules may be stated as:

Rule 1 : *If* x is A_1 and y is B_1 then $f_1=p_1x+q_1y+r_1$

Rule 2 : *If* x is A_2 and y is B_2 then $f_1=p_2x+q_2y+r_2$

Here type-3 fuzzy inference system proposed by Takagi and Sugeno [12] is used. In this inference system the output of each rule is a linear combination of input variables added by a constant term. The final output is the weighted average of each rule's output. The corresponding equivalent ANFIS structure is shown in Figure 3.

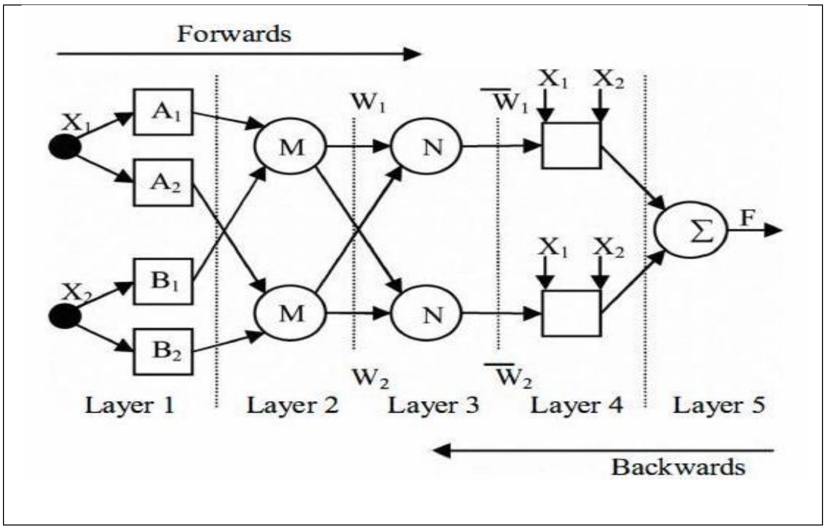

Fig. 3: ANFIS structure.

The individual layers of this ANFIS structure are described below:

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

$$O_i^1 = \mu_{A_i}(x) \tag{5}$$

Where x is the input to node i, A_i the linguistic variable associated with this node function and μ_{A_i} is the membership function of A_i. Usually $\mu_{A_i}(x)$ is chosen as

$$\mu_{A_i}(x) = \frac{1}{1+[(\frac{x-c_i}{a_i})^2]^{b_i}} \tag{6}$$

or

$$\mu_{A_i}(x)=\exp\left\{-(\frac{x-c_i}{a_i})^2\right\} \qquad (7)$$

Where x is the input and $\{a_i,\ b_i,\ c_i\}$ is the premise parameter set.

Layer 2: Each node in this layer is a fixed node which calculates the firing strength w_i of a rule. The output of each node is the product of all the incoming signals to it and is given by

$$O_i^2=w_i=\mu_{A_i}(x)\times\mu_{B_i}(x) \quad , \quad i=1,2 \qquad (8)$$

Layer 3: Every node in this layer is a fixed node. Each ith node calculates the ratio of the ith rule's firing strength to the sum of firing strengths of all the rules. The output from the ith node is the normalized firing strength given by

$$O_i^3=\overline{w}=\frac{w_i}{w_1+w_2} \quad , \quad i=1,2 \qquad (9)$$

Layer 4: Every node in this layer is an adaptive node with a node function given by

$$O_i^4=\overline{w_i}f_i=\overline{w_i}(p_i x+q_i y+r_i) \qquad (10)$$

where $\overline{w_i}$ is the output of Layer 3 and $\{p_i,\ q_i,\ r_i\}$ is the consequent parameter set.

Layer 5: This layer comprises of only one fixed node that calculates the overall output as the summation of all incoming signals, i.e.

$$O_i^5=overall\ \text{output}=\sum_{i}\overline{w_i}f_i=\frac{\sum_i w_i f_i}{\sum_i w_i} \qquad (11)$$

3.2. Learning algorithm

From the proposed ANFIS structure, it is observed that given the values of premise parameters, the final output can be expressed as a linear combination of the consequent parameters. The output f in Fig. 3 can be written as:

$$f=\frac{w_1}{w_1+w_2}f_1+\frac{w_2}{w_1+w_2}f_2=\overline{w_1}f_1+\overline{w_2}f_2=$$
$$(\overline{w_1}x)p_1+(\overline{w_1}y)q_1+(\overline{w_1})r_1+(\overline{w_2}x)p_2+(\overline{w_2}y)q_2+(\overline{w_2})r_2 \qquad (12)$$

f is linear in the consequent parameters $\{p_1, q_1, r_1, p_2, q_2, r_2\}$.

In the forward pass of the learning algorithm, consequent parameters are identified by the least squares estimate. In the backward pass, the error signals, which are the derivatives of the squared error with respect to each node output, propagate backward from the output layer to the input layer. In this backward pass, the premise parameters are updated by the gradient descent algorithm [14].

4.Bees Algorithm (BA)

Bees Algorithm is an optimization algorithm inspired by the natural foraging behavior of honey bees to find the optimal solution. Figure 4 shows the flowchartfor the algorithm in its simplest form. The algorithm requires a number of parameters to be set, namely: number of scout bees (n), number of sites selectedout of n visited sites (m), number of best sites out of m selected sites (e), number of bees recruited for best sites (nep), number of bees recruited for the other (m-e) selected sites (nsp), initial size of patches (ngh) which includes site and its neighbourhood and stopping criterion [15].

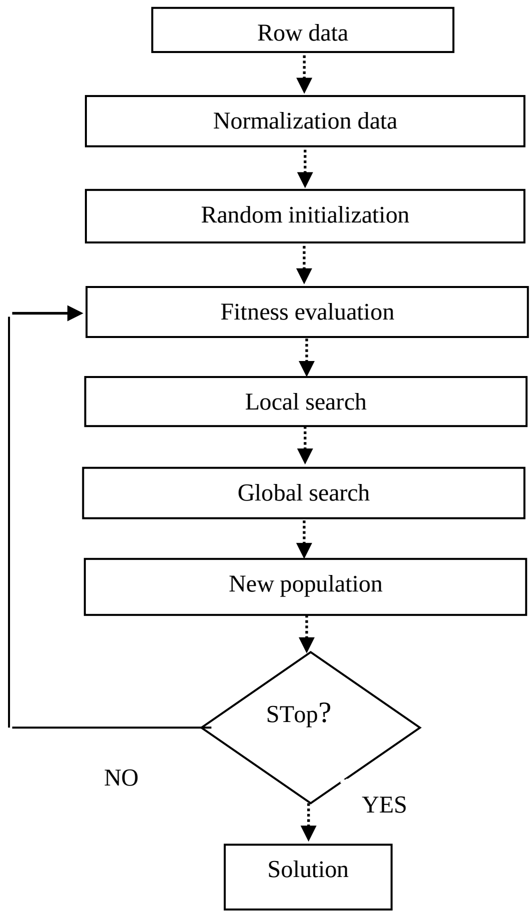

Fig. 4: Flowchart of the proposed method

5. Proposed approach

Inthe current study, it would have been better to use the mean absoluteerror (MAE) as network performance, using the formula:

$$MAE = \frac{1}{T}\sum_{K=1}^{T} \left(\left|t_K - a_K\right|\right)$$

Where T is the number of testing patterns, t_k is the target value, anda_k is the network output value.

It is noted that before the **ANFIS** can be trained, it isimportant to normalize the variables. Normalizing of the data toa value between s_{min} and s_{max} is performed using the followingequation:

$$V_{nor} = S_{\min} + \frac{V_i - V_{\min}}{V_{\max} - V_{\min}}\left(S_{\max} - S_{\min}\right)$$

Where $V_{nor}$is the normalized value, Vi is the value of a certain variable,V_{max} and V_{min} are the maximum and minimum values of thevariable.

The input data normalized 0.1-1. The ranges of weight product were .1-1.3gr.

6. Simulation results

6.1. Modeling by ANFIS:

The model designed by ANFIS to predict the product weight. The ANFIS model was developed using MATLAB Fuzzy Logic Toolbox. A subtractive fuzzy clustering was generated to establish a rule base relationship between the input and output parameters.There is many parameters affecting the reliability, prediction accuracy and convergence speed of an ANFIS. In this work,modeling by ANFIS training process, parameter that investigated was the vector of radius. Five radii was (0.2, 0.4, 0.6, 0.8) used to considerate the variation of MAE. Therefore, by means of MAE evaluation through testing datawas (0.0983, 0.1017,0.1222,and 0.1024). Fig.5also shows the comparison of experimental results andthe values which were predicted by ANFIS in constant vector of radius. As can be seen from Fig.5, the variations of radii parameter were resulted to various performance of modeling. Therefore choosing appropriate radii parameter for enhancing the performance of ANFIS modeling is really crucial.

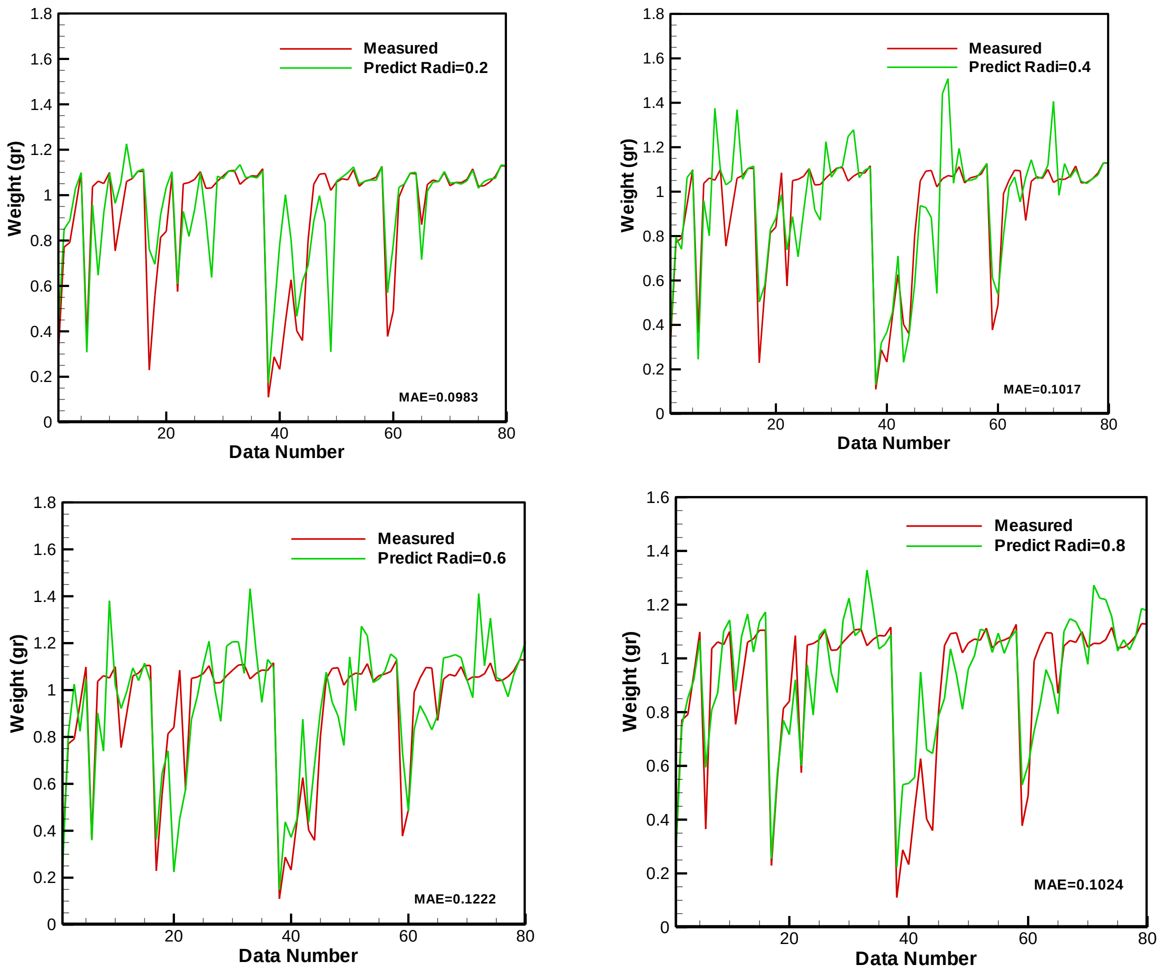

Fig. 5: comparison of experimental results by predicted by several of radii

6.2. BA_ANFIS

In optimizedANFIS, BA is applied for finding the optimum parameter radii ofANFIS.Table 4 shows the coefficient values in the BAalgorithm.

Table4: Coefficient values in the Bees optimizationalgorithm BA

Number of bees	20
Elite bees	5
number of bees recruited	2
Maximum iteration	100

The BA finds the best parameter ofANFIS (radii) and the best features to gain the minimum of MAE. By 30 iterations in BA algorithm the vector of radius was optimized.in Figure6 show the change vector of radius.

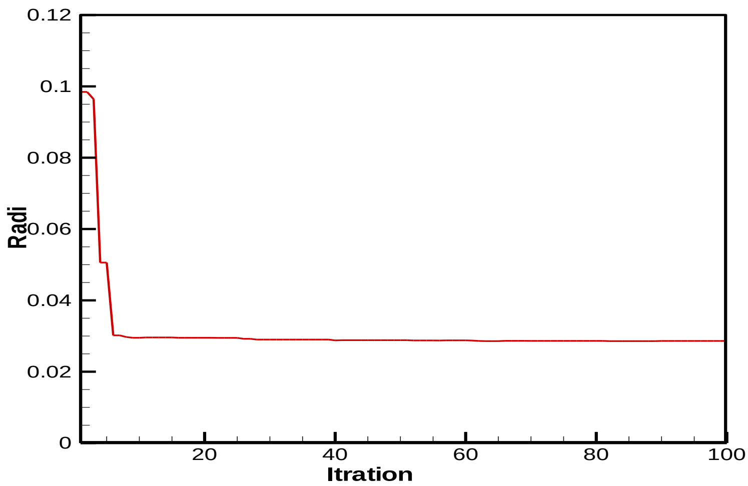

Fig.6: Change the vector of radius in the 100 iteration

Figure7also shows the comparison of experimental results andthe values which were predicted by BA_ANFIS. In Figure7 shows, most of the predictive valuescan agrees with the numerical experimental values very well. The MAE was 0.0475.

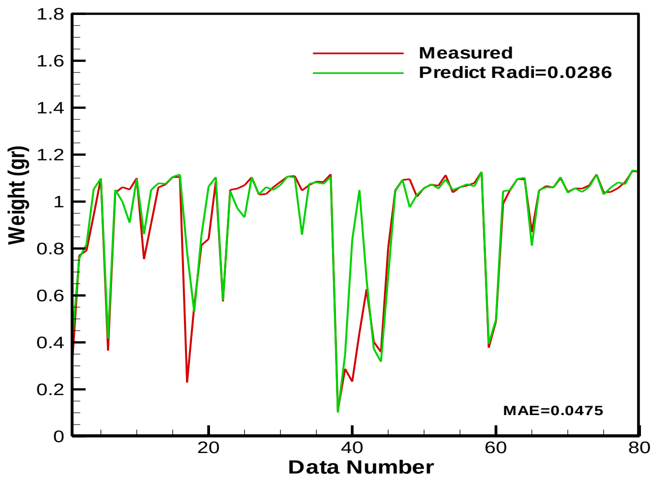

Fig.7: comparison of experimental results by predicted that optimized by BA-ANFIS

6.3. Optimizationof process using BA

After optimizing model the optimization algorithms are used to obtain optimal PIM setup parameters. In fact, now we are able to optimize the input matrix of our ANFIS to achieve the minimum dimensional error, which can be derived from the output matrix. Best weight for PIM part is 1.1gr. Lower than 1.1gr the part was incomplete and defect in PIM part was accord. Therefore if the weight of product was higher of 1.1gr,time, materials and defect were accord.That is causes to higher of pierce in part. In this phase, we tried to obtain the optimal results by bees' algorithm. Parameters used for optimization of BA algorithm similar to optimization ofANFISmodelling.In table5 shows the parameters and weight product of 5 elitebees. In plastic injection process, time is very important ruleto cast of product. Most time cycle in PIM depended to cooling time.Therefore lower cooling time is better in PIMas well as little cooling time reason to warpage in part.Moreover the Process temperature of EVA is 141 to 224(^{0}C). In number1though the cooling time is lower, but the melt temperature not enough that causes to not suitable connection in line joint. The best condition for this part is in number2.

Table.5:optimization result of BA

Number	Melt temperature(^{0}C)	Injection velocity(mm/s)	packing pressure(MPa)	cooling time(s)	Product weight(gr)
1	104.5	29.03	3.968	2.34	1.1
2	158.3	36.25	3.73	3.06	1.1
3	115.37	39	3.7	4.282	1.1
4	141.8	23.93	3.92	3.07	1.1
5	93.51	26.42	3.973	3.333	1.1016

7. Conclusions

There are many parameters in plastic injection molding accomplish the quality of part. In present study used ANFIS for modeling and predicting of product weight in plastic injection molding.For improving ANFIS performance in twoaspects: feature selection and parameter optimization.Thenew method that proposed in this paper is the combinationof ANFIS and BA (BA‑ANFIS).BA algorithm was used to find the best vector of radius in ANFIS modeling for predicting of product weight in PIM. The simulation resultsindicate that the BA‑ANFIS method wassuitable for modelling and predicting of PIM.After optimizing model the optimization algorithms are used to obtain optimal PIM setup parameters. Also BA optimization method used to find the parameters.

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