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Genetically tuned optimization of plastic extrusion process: A Literature Review

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Abstract

Plastic extrusion has been a challenging process for many manufacturers and researchers to produce products meeting requirements at the lowest cost. Faced with global competition in plastic-products industry, using the trial-anderror approach to determine the process parameters for plastic extrusion is no longer good enough. During production, quality characteristics may deviate due to drifting or shifting of processing conditions caused by machine wear, environmental change or operator fatigue. Determining optimal process parameter settings critically influences productivity, quality, and cost of production in the plastic related industries. The aim of this article is to review the research of the determination of process parameters and die design for plastic extrusion. Research based on various approaches, including Taguchi technique, artificial neural networks (ANN), fuzzy logic, genetic algorithms (GA),Adaptive Neuro fuzzy inference system (ANFIS), ANFIS+GA and their response surface methodology are discussed.

Keywords: Genetic algorithms (GA), Artificial neural networks (ANN), Adaptive Neuro fuzzy inference system (ANFIS), Response surface methodology,

Introduction

Plastic extrusion has been a challenging process for many manufacturers and researchers to produce products meeting requirements at the lowest cost. The complexity of extrusion process and the enormous amount of process parameters involved make it difficult to keep the process under control. The complexity and parameter manipulation may cause serious quality problems and high manufacturing costs. One of the main goals of extrusion is the improvement of quality of extruded parts besides the reduction of cycle time, and lower production cost. Solving problems related to quality has a direct effect on the expected profit for companies manufacturing plastic products. Quality characteristics in extrusion process are mechanical properties, dimensions or measurable characteristics, and attributes. In general, some of the main causes of quality problems are material related defects, process related problems, packing and cooling related defects, and post extrusion related defects. Factors that affect the quality of an extruded part can be classified into four categories: part design, die design, machine performance and processing conditions. The part and die design are assumed as established and fixed. During production, quality characteristics may deviate due to drifting or shifting of processing conditions caused by machine wear, environmental change or operator fatigue.

Determining optimal process parameter settings critically influences productivity, quality, and cost of production in the plastic related industries. Previously, production engineers used either trial-and-error method or Taguchi's parameter design method to determine optimal process parameter setting for plastic extrusion. However, these methods are unsuitable in the present scenario because of the increasing complexity of product design and the requirement of multi-response quality characteristics. Optimizing process parameter problems is routinely performed in the manufacturing industry, particularly in setting final optimal process parameters. Final optimal process parameter setting is recognized as one of the most important step in plastic extrusion for improving the quality of extruded products. Faced with global competition in plastic-products industry, using the trial-and-error approach to determine the process parameters for plastic extrusion is no longer good enough. Quite a few researchers have attempted various approaches in the determination of process parameters for plastic extrusion in order to reduce the time to market and obtain consistent quality of extruded parts.

The aim of this article is to review the research of the determination of process parameters and die design for plastic extrusion. Research based on various approaches, including artificial neural networks (ANN), fuzzy logic,ANFIS, genetic algorithms (GA), ANFIS+GA and response surface methodology are discussed.

Optimization methods

Artificial neural networks (ANN)

Huang and Liao investigated the diameter and thickness swells of the parison in the continuous extrusion blow molding of high-density polyethylene (HDPE) as a function of the processing parameters including the die temperature and flow rate [2]. A back-propagation neural network model was used to predict the parison swells under the effect of sag. A 2-20-20 neural network architecture with two input nodes, one hidden layer with 20 nodes, and 20 out-put nodes was utilized. Twenty-eight data sets obtained from experiments were provided to the neural network as samples, which were divided into 20 sets of training data and eight sets of testing data. The comparison of the experimentally determined parison swells with the predicted ones using the trained neural network model showed very good agreement between the two.

Cirak and Kozan presented knowledge based and neural network approaches to wire coating for polymer extrusıon [3]. The dependency of extrusion process parameters viz. barrel heating zones' temperatures and screw speed on coating thickness of wire coating extrusion processes was investigated using ANN. A back-propagation neural network model was used to predict the coating thickness.

Al Rozuq and Al Robaidi presented an experimental study to investigate the dependency of extrusion parameter on the coating thickness and degree of crosslinking of crosslinked polyethylene (XLPE) cable [4]. A three layer back propagation artificial neutral network (ANN) model was used for the description of wire coating thickness.

Fuzzy logic

Oke et al. optimized the flow rate of the plastic extrusion process in a plastic recycling plant with the application of a neuro-fuzzy model [5]. The input parameters viz. effective frictional force between the surfaces of the material and the walls of the extrusion chamber and diameter of the extrusion chamber determine the rate of flow of the solid waste material to be recycled through the extrusion chamber. The model is designed such that the most favorable condition where maximum quantity of solid waste material is recycled is attained. The linguistic variable serves as the engine of the model in bringing about relationship between the input and the output parameters to evaluate the outcome of such relationship. The result obtained indicates the feasibility of applying the neuro-fuzzy model in plastic recycling extruder process.

Adaptive Neuro fuzzy inference system

ANFIS is an *adaptive network*. An adaptive network is network of nodes and directional links. Associated with the network is a learning rule - for example back propagation. It's called adaptive because some, or all, of the nodes have parameters which affect the output of the node. These networks are learning a relationship between inputs and outputs.

An adaptive network covers a number of different approaches but for our purposes we will investigate in some detail the method proposed by Jang known as ANFIS.

The ANFIS architecture is shown below. The circular nodes represent nodes that are fixed whereas the square nodes are nodes that have parameters to be learnt.

A Two Rule Sugeno ANFIS has rules of the form:

$$If\ \ x\ is\ A_1\ and\ \ y\ is\ B_1\quad THEN\ \ f_1 = p_1x + q_1y + r_1$$

$$If\ \ x\ is\ A_2\ and\ \ y\ is\ B_2\quad THEN\ \ f_2 = p_2x + q_2y + r_2$$

For the training of the network, there is a forward pass and a backward pass. We now look at each layer in turn for the forward pass. The forward pass propagates the input vector through the network layer by layer. In the backward pass, the error is sent back through the network in a similar manner to back-propagation.

Layer 1: The output of each node is:

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

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

So, the $O_{1,i}(x)$ is essentially the membership grade for x and y.

The membership functions could be anything but for illustration purposes we will use the bell shaped function given by:

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

Where a_i, b_i, c_i are parameters to be learnt. These are the premise parameters.

Layer 2: Every node in this layer is fixed. This is where the t-norm is used to 'AND' the\ membership grades - for example the product:

$$O_{2,i} = w_i = \mu_{A_i}(x)\mu_{B_i}(y), \qquad i = 1,2 \ \ldots\ldots\ldots(4)$$

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Layer 3: Layer 3 contains fixed nodes which calculate the ratio of the firing strengths of the rules:

$$O_{3,i} = \overline{w}_i = \frac{w_i}{w_1 + w_2} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\,.\,.\,(5)$$

Layer 4: The nodes in this layer are adaptive and perform the consequent of the rules:

$$O_{4,i} = \overline{w_i} f_i = \overline{w_i}(p_i x + q_i y + r_i) \ldots\ldots\ldots\ldots\ldots\ldots\,.\,(6)$$

The parameters in this layer (p_i, q_i, r_i) are to be determined and are referred to as the consequent parameters.

Layer 5: There is a single node here that computes the overall output:

$$O_{5,i} = \sum_i \overline{w_i} f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\,.\,(7)$$

This then is how, typically, the input vector is fed through the network layer by layer. We now consider how the ANFIS learns the premise and consequent parameters for the membership functions and the rules.

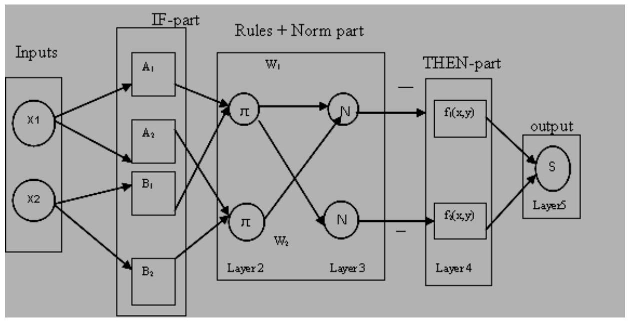

Fig. 1. Structure of ANFIS

Application of ANFIS systems

To show the efficiency of the proposed ANFIS, we consider the approximation of the three following functions:

y_{d1}=.2*sin(.3*x)

y_{d2}=.2*sin(-.3*x);

y_{d3}=.2*cos(.3*x);

The precision of ANFIS increases with the number of weight of inputs. For ANFIS of three outputs, it concerns three errors of estimation (for y_{d1} , y_{d2} and y_{d3}). To make the approximation of these three functions, we have used a ANFIS of three weights in the input (in first layer). Then, and so as to have best results of approximation, we have used a ANFIS with six weights in the input. Then we have made the comparison of the results of the approximation for the two ANFIS systems. Local parameters are initialed to small values that we have chosen to accelerate the convergence. The type of membership function of ANFIS that we have used is the trapezoidal function.

Response surface methodology

Lebaal et al. developed a new approach to the optimal design of the die walltemperature profile in polymer extrusion processes [6]. The optimization method wasbased on response surface method. It has a very fast convergence, which is an advantage when time-consuming flow analysis calculations are involved. Design of experiment (DOE) needed for the construction of the response surface was used to evaluate the objective and the constraint functions on the basis of a finite element method (FEM). Two designs of experiments were used and the performances of the optimization results were compared with respect to efficiency and ability to obtain a global optimum. The effect of the design variables in the objective and constraint functions was investigated using Taguchi method. The flow analysis results were then combined.

Genetic algorithm

Mu et al. proposed an optimization approach for the processing design in the extrusion process of plastic profile with metal insert based on finite element simulation, back propagation neural network and genetic algorithm [8]. The polymer melts flow in the extrusion process was predicted using finite element simulation. The simulated results were extracted for the establishment of neural network. The search for globally optimal design variable for the extrusion was done using GA with its objective function evaluated using the established neural network model. The uniformity of outlet flow distribution was taken as the optimization objective with a constraint condition on the maximum shear stress. The objective of flow balance was achieved by the optimal design of two processing parameters including the volume flow rate and the metal insert moving velocity.

The algorithm begins with a set of solutions (chromosomes) that are called the population. Solutions from one population are reproduced to create a new generation in the population. Mutations occur randomly in each population. ANFIS is applied for optimization of the premise parameters (input membership functions) and the consequent parameters (output membership function), GA algorithm will search for the best ANFIS configuration based on minimizing the least mean square error between the expected and real output of the network. The set of possible input membership function is {trimf, trapmf, gbellmf, gaussmf}, output membership function is {constant ($z=c_i$), linear ($z=p_iX+q_iY+r_i$)}, the number of membership functions for each input is in range from 2 to 6.

Two groups of randomly selected chromosomes are generated and the chromosome with the best fitness function is picked up from each group. Then these two chromosomes with the offspring produced by crossover operator are sent to next generation. This process continues to fill the next generation completely.

Since the aim of GA is to optimize the membership functions of a predetermined ANFIS structure to reach the lower error; the fitness function is defined as the inversion of the model's MSE (mean square error) between the data and the model output. Thus trying to upraise the fitness value of the model, GA searches for better parameters to reduce the model error.

The optimization of ANFIS based on GA

Traditional genetic algorithm has some inevitable defects, for example, the local optimum solution that produced too early can be concentrated and miss the global optimum solution. This paper introduced immune operator which is obtained from immune choice. Immune choice computes the individual density of some group. Through population Refreshing based on density and sufficiency test, the individual better than the parent generation is chosen into the next group. Traditional algorithm chromosome is monolayer and is easily subjected to

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following defect; the probability of actual intercrossing and variation of short gene in chromosome is too low if the code of chromosome is long.

IF-part Rule-Norm-part THEN-part

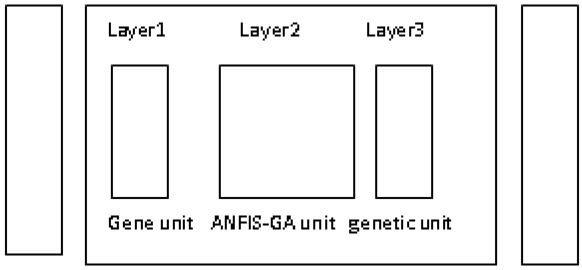

Figure 3. Chromosome structure

This paper proposed a chromosome structure with three layers as shown in Fig.3. The first layer is gene unit with Rules-Norm-part of Structure to represent the number of layer Rules-Norm-part in pre-feed backed genetic network. The second layer is ANFIS+GA unit to represent the number of neure under a Rules-Norm-part. The genetic unit of third layer used decimal code to represent all threshold of upper neuron.

Non-linear modeling

Mamalis et al. applied multi-parametric optimization to the processing conditions in a spider die used for the extrusion of high density polyethylene (HDPE) tubes [9]. The parameters investigated were inlet pressure, inlet temperature of the melt, temperature of the die walls, and temperature of the spider legs. A computational fluid dynamics (CFD) based model using the generalized Newtonian approach was employed, to investigate pressure drop, along with flow and temperature uniformity in the die. The numerical calculations for the three-dimensional flow and temperature fields were performed with a finite element based CFD code, Comsol 3.5. The Nelder-Mead nonlinear optimization technique was applied to the numerical model, in order to pinpoint the processing conditions that result into maximizing flow homogeneity at the die outlet. The objective function utilized was a weighted average of the Signal-toNoise Ratios (SNRs) of flow temperature and velocity at the die outlet.

Conclusion

This article presents a review of research in the determination of the process parameters for plastic extrusion. A number of research works based on various approaches including mathematical model, artificial neural networks (ANN), fuzzy logic, Adaptive neuro fuzzy inference system (ANFIS), genetic algorithms (GA), non-linear modeling, Application of ANFIS and Application of ANFIS+GA have been described.

ANFIS and GA are emerging as the new approaches in the determination of the process parameters for plastic extrusion. A trained neural network system can quickly provide a set of extrusion parameters according to the results of the predicted quality of extruded parts. However, the time required in the training and retraining for a neural network could be very long. By using ANFIS+GA approach, the system can locally optimize the extrusion parameters even without the knowledge about the process.

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