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Determination of effecting process parameters with artificial neural network

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Abstract: The injection of PVC polimers with a molded has been studied. Experimentally, parameters were measured for different processing conditions. Injection molding is the most widely used process in manufacturing plastic products. An empirical model to decide the shrinkages of thermoplastic polymers in the injection process. Polyvnyl chloride was used in this study to test the effectiveness of the model. Comparing the calculated results, it was found that the shrinkage ratio obtained with the present model are in agreement with those obtained by using inline processes. ANN method, a Levenberg Marquardt algorithm neural network model is developed to map the complex non linear relationship between process conditions of the injection molded parts an ANN model. This method is used in the process optimization for an industrial part in order to improve the volumetric shrinkage variation in the part. The results show that the this method is an effective tool for the process optimization of injection molding. The simulations and calculations of the algorithms are done in MATLAB Packaged Program Environment. MPC is especially suitable for controlling these types of systems. MATLAB Packaged Program is utilized in all these studies.
Keywords: Plastic injection molding; Simulation; Optimization; Artificial neural network

INTRODUCTION

A continuously increasing number of commercial products are produced by polymer injection using plasticating injection, which are among the most widely used equipments in polymer process industry. The injection process has a standard setup including a feeding section, a barrel and a head with a die for shaping. In the feeding section, the solid polymer is fed into the injection through a hopper in the form of pellets or irregular small bits. The plasticating injection is one of the main pieces of equipment used in the polymer processing industries. As plastics is found more uses, with more stringent quality specifications, the methods of increasing polymer production while improving product quality are needed. İnjection molding is the most widely used process in manufacturing plastic products. Since the quality of injection coated plastic parts are mostly influenced by process conditions, how to determine the optimum process conditions becomes the key to improving the part quality. Injection molding is ideally suited to manufacture mass produced plastic parts of complex shapes requiring precise dimensions [1].

In this process, hot polymer melt is forced into a cold empty cavity of a desired shape and is then allowed to solidify under a high holding pressure. The entire injection molding cycle can be divided into three stages: filling, postfilling and moldopening. The complexity of the molding process makes it very challenging to attain desired part properties and thus causes difficulty in maintaining part quality during production. As the plastics exhibit extremely complicated thermo-viscoelastic material properties, In the actual operations, the molding process conditions are often selected from references or handbooks and then adjusted subsequently by atrial-and-error approach. This approach is very costly and time consuming, as well as highly dependent on the experience of the molding operators [2].

Computer aided designing (CAD) has made a major impact on the design and manufacturing process in the injection molding industry in terms of both quality improvement and cost reduction based on applications of various computer simulation techniques. The analyses and interpretations of the simulation results, however, are still empirical, and also the substantial computation time cannot meet the requirement of online control. The automatization of the plastic production process makes the molding optimization even more complex with the operations that move the products directly from the molding machine to assemble stations. Advanced methods are highly demanded to model and optimize the injection molding process with the purpose of manufacturing high quality plastic parts. ANN is the most promising natural computation techniques. In recent years, it has become a very powerful and practical method to model very complex nonlinear systems [3].

ARTİFİCİAL NEURAL NETWORK

The objective function was built by ANN technique to map the complex non-linear relationship between process conditions of injection molded parts. Artificial neural networks are widely accepted as a technology offering an alternative way to simulate complex and ill-defined problems. They have been used in diverse applications in control, robotics, pattern recognition, forecasting, power systems, manufacturing, optimization, signal processing, etc., and they are particularly useful in system modeling. A neural network is a computational structure, consisting of a number of highly interconnected processing units called neurons. The neurons sum weighted inputs and then applies a linear or non-linear function to the resulting sum to determine the output and the neurons are arranged inlayers and are combined through excessive connectivity. Levenberg Marquardt algorithm**(**LMA)is a typical neural networks that has been widely used in many research fields. LMA have hierarchical feed forward network architecture, and the outputs of each layer are sent directly to each neuron in the layer above [4].

While LMA can have many layers, but all pattern recognition and classification tasks can be accomplished with a three-layer LMA. LMA are trained by repeatedly presenting a series of input, output pattern sets to the network. The neural network gradually 'learns' the governing relationship in the data set by adjusting the weights between its neurons to minimize the error between the actual and predicted output patterns of the training set. A separate set of data called the test set is usually used tomonitor network's performance. When the mean squared error(MSE) of the test set reaches a minimum, network training is considered complete and the weights are fixed. In essence, an eural network is a function that maps input vectors to output vectors [5].

ANN model

The three layers are fully connected with five nodes in the input layer, four nodes in the hidden layer and one node in the output layer. This network can be termed a 3-7-1 feed-forward network, referring to the number of nodes in the input, hidden and output layers, respectively. All the nodes are allowed several input signals and only one output signal, just as a biological neuron. Scaled data usually scaled to the range of 0–1 is introduced into the input layer of the network and then is propagated from input layer to hidden layer and finally to the output layer. The nodes in the input layer act only as a buffer, sending out scaled inputs to the hidden layers (Fig. 5.). In the hidden layers and output layer, each node firstly acts as a summing junction which combines and modifies the inputs from the previous layer using:

$$y_j = \sum_i x_i w_{ji} + \theta_j \quad (1)$$

Where y_j is the total weighted input of the *j* th node in the layer, say layer L, x_i is the output of the *i*th node in thei previous layer, say layer L-1, and w_{ji} is the weight representing the strength of the connection between the *i*th node and *j*th node while θ_j is a threshold value.

Then each node transfers the summation $y_j$to the output of the*j* node z_j through, typically, a sigmoid function:

$$z_j = \frac{1}{1 + e^{-y_j}} \quad (2)$$

z_j , the output of node *j*, is also an element of the inputs to the nodes in the next layer [6].

The values of the interconnection weights are deter-mined by a neural network training or learning procedure using a set of data. The objective is to find the value of the weight that minimize differences between the actual output and the desired output in the output layer. The Levenberg Marquarth algorithm firstly adjusts weights connected to the output layer. Then, working backward towards the input layer, the algorithm adjusts weights in each successive layer to reduce the errors at each level. The delta learning rule is one of the well known weight update rules, which is based on the simple idea of continuously modifying the strengths of the connections to reduce the difference the delta between the desired output value and the current output value of a processing element. It is expressed as:

$$\Delta w_{ji}(n+1) = \eta d_j x_i + \mu \Delta w_{ji}(n) \quad (3)$$

Where w_{ji} is the connection weight between nodes *i* and *j*,*n* is discrete time cycle number , η is the learning rate, d_j is the difference between actual and predicted values, $x_i$is the current output of processing element *i* and μ is momentum factor. The larger the learning rate, the larger the weight changes on each epoch (training cycle), and the quicker the network learns. However, the size of the learning rate can also influence whether the network achieves a stable solution. The concept of momentum is that previous changes in the weights should influence the current direction of movement in weight space. The effect of the learning rate and the momentum on network performance was discussed by Li and Bridg water [7].

Many different process parameters affect the quality of the injection molded products. Variables with greater influence on the part quality need to be selected in order to simplify the problem by saving both the sample collecting time and the computing time. The selection of process variables as inputs of ANN model is based on the relative significance of each variable on the objective performance. In this paper, the DOE technique is used to obtain the near optimum process. The neuron number of the input layer of ANN is determined by the number of variables selected, and the neuron number of the output layer is determined by the number of the objective indexes. In this paper, a three-layer ANN model with one hidden layer was used, where the neuron number of the hidden layer was determined by trials. The transfer function between the input layer and the hidden layer is 'Logsig', while the transfer function between the hidden layer and the output layer is 'Purelin' [8].

Train and Test

A neural network model with a Levenberg Marquardt algorithm was employed for the network training and simulation in MATLAB 2014 b program. The model was firstly constructed by determining the number of nodes and layers. The number of nodes in the input layer is dependent on the requirement of the simulation. A varied step of each variable is set to obtain a series of set-point values of variables inside the varied range based on baseline. The samples of all set points are then assigned as input, output data to train and test the ANN. The samples are randomly divided into two groups. Those samples including the baseline set were methodically assigned to the training set, and all the remaining samples were assigned to the test set. After being trained, the ANN model can map the nonlinear relationship between quality indexes and variables of injection molding. It can then be used in the optimization of online process conditions and the part quality control of molded products [9].

EXPERİMENTAL PARAMETERS

In this paper, an industry example, shown in Fig. 1, was studied. The PVC plastic part is a cup of drinking water. The main plane of the part has a thickness of 2–3mm, and the frame work have the thickness of 1–1.5 mm. The primary objective of the present research is to study the possibility of modeling and predicting the quality of injection molded parts and optimizing the process conditions so as to improve the part quality by using the ANN method. CAD simulations are used to replace real experiments for thesake of cost saving [10].

The other useful of CAD simulations is that the time required to train a network is much less than that with real experiments because there is no noise existing in the computation data compared to the experimental data. Anonly way is used for the mold as shown in Fig. 1. The polymer material used formolding the cover is PVC. Numerous frame works on the main plane and large dimension variations of the part may lead to nonuniform shrinkage of the part, which is attributed as the main cause for part war page. Thus, the volumetric shrinkage variation (the difference between the maximum and the minimum volumetric shrinkages) in the part is selected as the objective function, and the objective is a minimum problem.

The volumetric shrinkage variation is influenced by many process variables, and those variables that have significant influences on the volumetric shrinkage variation are selected by the Taguchi DOE technique. The selected variables and the process window for the injection molding process are as follows:

Fig-1: Phsycal model (CAD Scale:1/3)

Melt temperature : 190◦C -230 ◦C
Mold temperature : 45◦C - 65◦C
Holding pressure: 35 MPa -42 MPa
Injection time : 6 s - 4 s
Packing time : 8 s - 13 s

Fig.2. shows the evolution of the mean square error of the ANN model during training. The trained network model was validated for its predictive capability.The result indicates that the ANN has a good performance graphics in Fig.2.

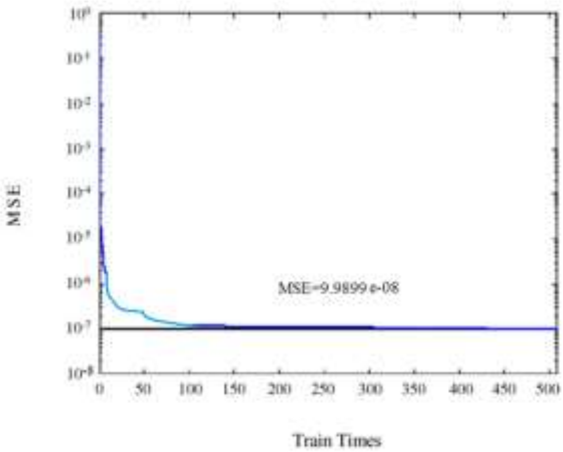

Fig-2: ANN Performance

Experimental and Predicted Values

Among the 275 samples obtained based on the theory discussed in the previous section, 180samples were used to train the ANN as shown in Fig. 3.

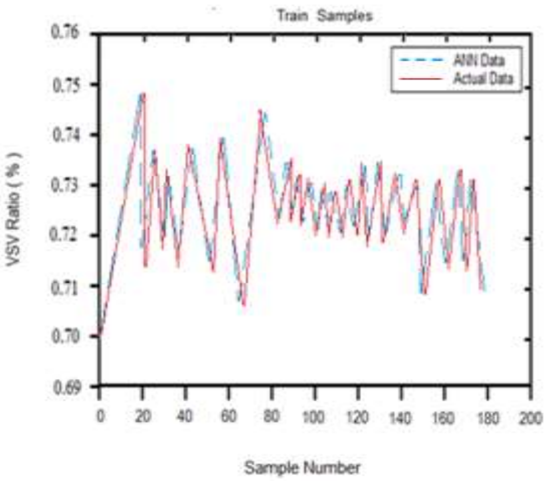

Fig-3: Training

After the training, the mean square error of all 180 samples was 9.9899e–8. The remaining95 samples were then used to test the performance of the ANN.As shown in Fig. 4, most of the samples have consistent outputs of ANN prediction and numerical experiment, and the result is quite satisfactory.

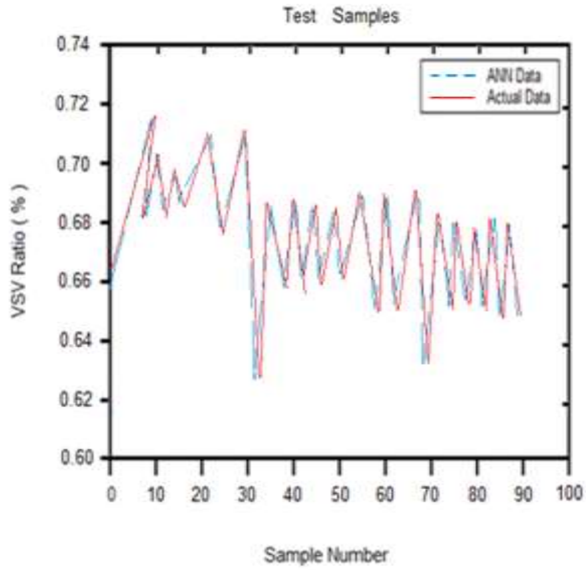

Fig-4: Testing

The ANN model for the volumetric shrinkage variation of the part built by the above methods is shown in Fig. 5. The node number of the hidden layer was determined by train trials and the final value obtained was 7, that made the configuration of ANN as 5–7–1. The log sigmoid transfer function LOGSİG was used as the activation function for the hidden layers and linear transfer function was used for the output layers.

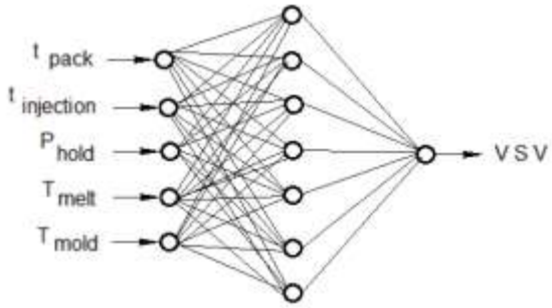

Fig-5: ANN model of VSV

The result indicates that the ANN has a good performance, and it can accurately map the relationship between the volumetric shrinkage variation ratio and the process parameters. The simulation function based on the ANN was used as the objective function of the optimization problem, and the process window for each variable as given above was used as the boundary restrictions. The contrast of prediction results and numerical experiment results of relationship between VSV and melt temperature are shown in Fig. 6.

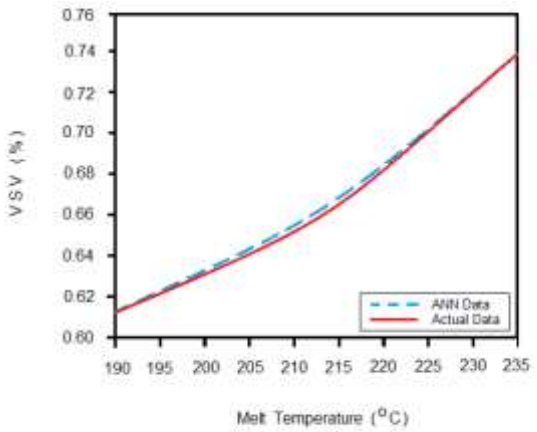

Fig-6: Relationship of VSV ratio between melt temperature

The contrast of prediction results and numerical experiment results of relationship between volumetric shrinkage variation VSV and mold temperature are shown in Fig. 7.

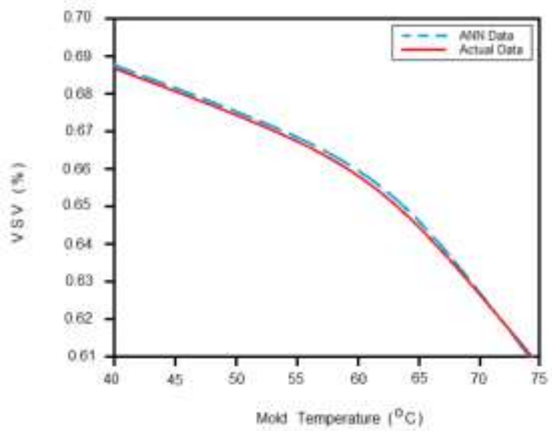

Fig-7: Relationship of VSV ratio between mold temperature

The contrast of prediction results and numerical experiment results of relationship between volumetric shrinkage variation VSV and injection time are shown in Fig. 8.

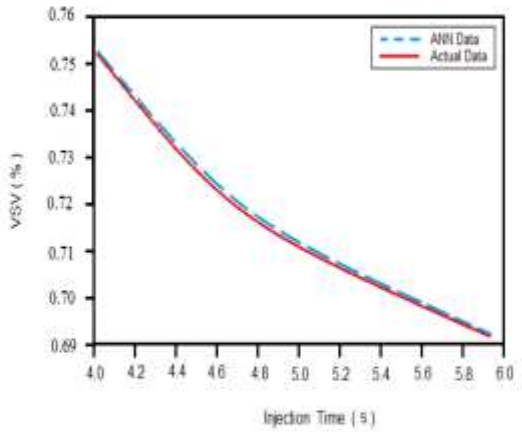

Fig-8: Relationship of VSV ratio between injection time

The contrast of prediction results and numerical experiment results of relationship between volumetric shrinkage variation VSV and packing time are shown in Fig. 9.

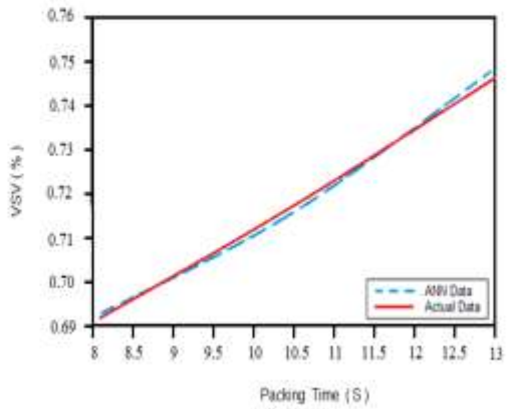

Fig-9: Relationship of VSV ratio between packing time

The contrast of prediction results and numerical experiment results of relationship between volumetric shrinkage variation VSV and holding pressure are shown in Fig. 10.

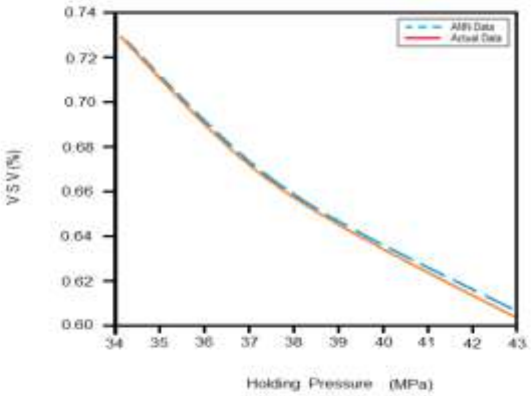

Fig-10: Relationship of VSV ratio between holding pressure

CONCLUSİONS

1. The ANN technique has been shown as an effective method to the process conditions of injection molding parts.
2. An ANN method proposed in this paper gives satisfactory result for the optimization of the injection molding process. An ANN model of volumetric shrinkage variation versus process conditions for injection molding with a 5–7–1 configuration has been developed.
3. The modeling and optimization methods proposed in this paper show the great potential in complicated industrial applications.
4. The difference between the maximum value and the minimum value is 0.489 which is lager than the ANN predicted result under optimization parameters, but smaller than all the samples. The result shows that the volumetric shrinkage distribution of the injection molded part has been improved under the optimized process conditions.

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NOMENCLATURE

PVC	Poly Vinyl Chloride
MSE	Mean Squared Error
CAD	Computer Aided Design
ANN	**A**rtificial Neural Network
DOE	Design Of Experiment Taguchi Methods
VSV	Volumetric Shrinkage Variation
LMA	Levenberg Marquardt algorithm
LOGSİG	Logarithmic Sigmoid Transfer Fonction

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