

Determination of Injection Molding Process Parameters using Combination of Backpropagation Neural Network and Genetic Algorithm Optimization Method

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Abstract

The polymer matrix composite (PMC) in use today is generally made of synthetic fibers which are expensive and not environmentally friendly. The use of synthetic fibers can be replaced with natural fibers, which are more environmentally friendly at a lower price. The natural fiber material used in this study is made from husks, with a particle size of 500 μm (mesh 35). In the PMC manufacturing process, rice husks are mixed with polypropylene (PP) and maleic anhydride polypropylene (MAPP) with a composition of 10 wt% RH, 85 wt% PP and 5 wt% MAPP. PMC materials using natural fibers are called biocomposite materials. The result of mixing PMC with natural fibers in the form of pellets is then carried out by the injection process using an injection molding machine. The printed results are in the form of tensile test specimens based on ASTM D 638-03 type V testing standards and impact test specimens based on ASTM D 256-04 testing standards. The research was conducted by optimizing the responses i.e. tensile strength and impact strength of the biocomposite material in the injection molding machine process, whereas varied process parameters, namely barrel temperature, injection pressure, holding pressure, injection velocity were selected as process parameters. The backpropagation neural network (BPNN) training method is used to recognize the pattern of the relationship between process parameters and response parameters based on the previous experiment, while the genetic algorithm (GA) optimization method is to determine the variation settings for process parameters that can optimize tensile and impact strength. The results of the BPNN training have a 4-9-9-2 network architecture consisting of 4 input layers, 2 hidden layers with 9 neurons, and 2 neurons in the output layer. Optimization with GA produces a combination of variable process parameters barrel temperature 217°C, injection pressure 55 Bar, holding pressure 41 Bar and injection velocity 65 mm/sec. The results of statistical validation using one sample T test show that the average value of tensile strength and impact strength from the results of the confirmation experiment is the same as the value of the tensile strength and impact strength of the optimization prediction.

Keywords: injection molding process, Taguchi, BPNN, GA, tensile strength, impact strength

1. Introduction

Today's industrial world has used a lot of polymer materials to replace metal materials. This is due to the availability and low cost when compared to metal materials. The polymer material has properties that are easy to process, printable, fast, and have a long service life. In addition, polymer materials can also be combined with other materials in the form of a composite material called polymer matrix composite (PMC). The process of making PMC using synthetic fiber as reinforcement is still widely used. The use of synthetic fibers has begun to be reduced because they are not environmentally friendly and expensive, so it is necessary to look for natural fibers that are environmentally friendly and inexpensive.

One of the many natural fibers found in Indonesia

is rice husks. Rice husk is an inexpensive natural fiber material that can be used as a biocomposite to strengthen polypropylene polymers [1]. Rice husk is the remaining of rice processing whose utilization is not efficient and economical. Rice husk fiber can be used as a filler in natural PMC so that it becomes a high-value product [2]. The biocomposite molding process can be done with an open or closed molding process. The closed molding process can be done using an injection molding machine.

The expert staff of the minister of industry said that the development of the domestic plastic industry currently depends a lot on imported plastic raw materials. Therefore, it is necessary to develop biocomposite materials [3]. In East Java, there are several small industries engaged in the plastic industry, such as the industry that produces

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helmets. The industry in producing helmets still does it manually (hand layout) so that the products produced cannot meet the Indonesian National Standard (SNI).

Research on biocomposite molding has been carried out by several researchers using an injection molding system process. The study used pellets as a result of a mixture of sisal fiber and polypropylene [4]. Other studies have also been carried out with the injection molding process using pellets derived from kenaf and polypropylene fibers [5]. Furthermore, research on the injection molding process of recycled polymers mixed with two natural fibers, namely kenaf fiber and rice husk has also been carried out [6].

Injection molding process parameter settings greatly affect the quality of the final product such as mechanical properties. One method that can be used to optimize these parameters is the Taguchi method which aims to increase the tensile and impact strength in the optimization of the injection molding process [7]. They are the two most important mechanical properties because most of the mechanical component design should be based on their values.

In addition to the Taguchi method, several methods have been carried out to determine the value of process parameters on injection machines, namely the Taguchi parameter design method, the Backpropagation Neural Network (BPNN), and the Davidon-Fletcher-Powell (DFP) method [8]. The results show that an effective process in the proposed parameter optimization approach can avoid the inherent deficiencies in the application of the trial-and-error process or the conventional Taguchi parameter design method. The use of BPNN and GA methods has also been carried out to optimize the response parameters of plastic injection molding. The optimization results show that the BPNN and GA methods can adjust process parameters accurately and effectively [9].

Table 1. Chemical composition of rice husk

Composition	Percentage(%)
Cellulose	31.12
Hemicellulose	22.48
Lignin	22.34
Mineral ash	13.87
Water	7.86
Chemical analysis of mineral ash	
SiO ₂	93.13
K ₂ O	3.84
MgO	0.87
Al ₂ O ₃	0.78
CaO	0.74
FeO ₃	0.58

Optimization of the injection molding machine process parameters using the Taguchi-gray-fuzzy method to increase the tensile strength and impact of the biocomposite material has been carried out [3]. The process parameters used in this study are barrel temperature, injection pressure, holding pressure, and injection velocity. While the constant parameters are hooper temperature, nozzle temperature, holding time, injection time, and cooling time. The research response parameters were tensile and impact strength. The orthogonal matrix design used is L₂₇.

Based on the things that have been explained, research on optimization of injection molding process parameters needs to be carried out with an integrated procedure involving the backpropagation neural network method and genetic algorithm to find optimal solutions with the right process parameter values to increase the tensile strength and impact strength of the biocomposite material.

2. Experimental Study

2.1. Rice Husk

Biocomposites with fillers can be formed from polymeric materials (as a matrix) and natural fibers as fillers which function to improve their mechanical properties. Biocomposites like this are classified as polymer matrix composite (PMC) materials. In the PMC manufacturing process, rice husks, which each have a particle size of 500 μm (mesh 35), are mixed with polypropylene (PP) and maleic anhydride polypropylene (MAPP) with a composition of 10 wt% RH, 85 wt% PP, and 5 wt% MAPP.

Rice husk is the outermost layer of rice grains covering the cariopsis and consists of two parts called lemma and palea. Rice husks have strong and rigid properties because rice husks contain a lot of lignocellulose and others [10], as shown in Table 1. Because of these properties, rice husks can be used as a composite material [11].

Apart from having strong and rigid properties based on the content in Table 1 as in [10], rice husks are also high in silica content in the outer layer (lemma). Lemma hardness values can be in the range of ± 5.5 to 6.5 Mohs scale. This reason can also strengthen the use of rice husk for the biocomposite mixture as a filler material [3]. In Table 2, we can see the characteristics of rice husks as in [10].

Table 2. Characteristics of rice rusk

Composition	Percentage(%)
Bulk density (g/ml)	0.79
Solid density (g/ml)	1.48
Moisture content (%)	5.98
Ash content (%)	48.81
Surface area (m ² /g)	320.90
Surface acidity (meq/g)	0.15
Surface basicity (meq/g)	0.53



Figure 1. ASTM D 638-03 Tensile Testing Specimen V type.



Figure 2. ASTM D 256-04 Impact Testing Specimens.

2.2. Results of the Injection Molding Machine Process

The result of the injection system molding process is a tensile test specimen based on the ASTM D 638-03 type V test standard with a specimen length of 63.5 mm and a specimen width of 9.53 mm, while the impact test specimen is based on ASTM D 256-04 test standards with a specimen length of 63.5 mm and the width of the specimen is 12.7 mm. The printed results can be seen in Figure 1 for the tensile test specimen and Figure 2 for the impact test specimen.

The tensile test specimen shown in Figure 1 is the standard ASTM D 638-03 type V tensile test with a cross-sectional area of 10.176 mm^2 . In this test, the specimen is subjected to a continuous tensile force load in the direction of the axis until it breaks. The results obtained are the value of tensile strength and changes in specimen length (Δl). Figure 2 shows the standard impact test specimen ASTM D256-04 with a cross-sectional area of 32.51 mm^2 and a notch shape V. The tensile and the impact strength data as the experiment result have been proposed in the previous study [3].

3. Numerical Study

3.1. Backpropagation Neural Network (BPNN) Method

Artificial neural networks (ANN) are information processing systems that have similar characteristics to biological neural networks. ANN is formed as a generalization of a mathematical model of biological neural networks, with the assumption that [12]:

1. Information processing occurs in many simple elements (neurons).
2. Signals are sent between neurons through links.
3. The links between neurons have a weight that will amplify or weaken the signal.
4. To determine the output, each neuron uses an activation function (usually not a linear function) which is assigned to the sum of the received inputs. The amount of this output is then compared with a threshold.

BPNN consists of an input layer, hidden layer, and output layer, where each layer has several neurons that

are interconnected between layers and have weight. The results (output) of BPNN are based on experience during the training process. The BPNN training process begins by giving initial weight values. The information that is already known to the result is entered into neurons in the input layer. These weights are used to remember the information patterns that have been given. The weight setting is adjusted continuously until the expected results are obtained. The objective of BPNN training is to achieve the ability to perfectly recall a learned pattern (memorization) and produce acceptable output values for similar patterns which are called generalizations [13].

The BPNN network was selected based on the experiment using Taguchi method with the chosen orthogonal matrix L27. Four process parameters i.e. barrel temperature, injection pressure, holding pressure, and injection velocity were used as network input, while two response variables i.e. tensile strength and impact strength were used as network output. The selection of the structure, activation function, and training function of the BPNN network used in this study has been discussed and proposed in previous studies, namely using a 4-9-9-2 network architecture consisting of 4 input layers, 2 hidden layers with 9 neurons, and 2 neurons in the output layer. The activation function used is "tansig" and the training function is "trainrp" [14].

3.2. GA Optimization Method

The basic concept of algorithmic genetics is based on the genetic process that is owned by living things, where the development of generations in a natural population, will gradually follow the principle of natural selection "strong will survive". By imitating this theory of evolution, genetic algorithms can be used to find solutions to problems in the real world. This algorithm works with a population that includes individuals where each individual presents a possible solution to an existing problem. In this connection, individuals are represented by a fitness value that will be used to find the best solution to existing problems.

Genetic algorithms as a branch of evolutionary algorithms include adaptive methods that are commonly used to solve a search for value in an optimization problem. In its application, the genetic algorithm will involve several

operators, namely the operation of evolution, which involves a selection process in it, and genetic operations, which involve crossover and mutation operators [13]. In this study, the initial population = 150, the maximum generation = 20, the selection process = Roulette Wheel, the crossover probability = 0.6, and migration probability = 0.4 were used to obtain the optimal result.

4. PNN/GA for optimization

This study uses a combination of the BPNN and GA methods to obtain the best setting for the injection molding process parameters, namely barrel temperature, injection pressure, holding pressure, injection velocity so that the process results have optimal tensile and impact strength. In the combined method of BPNN and GA, the GA generates a population consisting of many individuals. Each individual carries a chromosome with genes in the form of certain process parameter values. Then each individual predicted its tensile strength and impact strength using the BPNN prediction of the training results. Based on these predictions, each individual is analyzed for his proximity to optimal conditions. If the closeness to optimal conditions is not sufficient, then some individuals from the population are selected, crossed, and/or mutated to generate a new generation, so that they are iterated again starting from the predicted tensile strength and im-

pact strength until their proximity to the optimal condition is analyzed. This iteration process is carried out continuously until the termination criteria such as population size and error gradient are reached.

5. Results and Discussion

The GA optimization process is carried out several iterations to obtain the optimal parameter setting results. From several iterations until the termination criteria are reached, the optimum setting of the barrel temperature, injection pressure, holding pressure, and injection velocity parameters in the injection molding machine process using the IBRA and GA methods is shown in Table 3.

Because the results shown in Table 3 are the predictive results of the BPNN-GA method, these results still need to be confirmed through experimental testing. Experiments were carried out using the optimum process parameter settings generated from BPNN-GA, then the response value of the process parameter settings from the BPNN-GA results with the response value of the experimental results was compared. This experiment is called a confirmation test experiment and was carried out by replicating 5 times on the HAITIAN-MA900 / 260e injection molding machine. The experimental response data is shown in Table 4.

Table 3. Optimal settings parameters in the injection molding machine process using GA optimization method.

Process parameters	Combination GA optimization	GA response	
		Tensile strength (MPa)	Impact strength (kJ/m ²)
Barrel temperature	217		
Injection pressure	55	32.99	5.10
Holding pressure	41		
Injection velocity	65		

Table 4. Experimental response data.

GA optimum parameter combination	Replication to-	Response	
		Tensile strength (MPa)	Impact strength (kJ/m ²)
Barrel temperature = 217°C	1	31.22	5.33
Injection pressure = 55 Bar	2	34.50	5.33
	3	32.67	4.48
Holding pressure = 41 Bar	4	32.77	5.33
	5	31.61	4.48

To find out the comparison between the response value from BPNN-GA with the response value from the experiment, statistical validation was carried out using the one sample t-test average test. This test aims to test whether the response data to the experimental result is significantly different or not from the response data from BPNN-GA. Testing is done by using the hypothesis:

$$H_0 : \mu_T = 32.99$$

$$H_0 : \mu_T \neq 32.99$$

With rejection criteria: Reject H_0 , if the value of Pvalue $< \alpha$, with $\alpha = 0.05$. Based on calculations using Minitab software, Pvalue was obtained at 0.48. Because Pvalue > 0.05 , then H_0 failed to be rejected, which means that the average value of tensile strength from the confirmation experiment was not significantly different from the tensile strength of the predicted results.

Apart from tensile strength, a one sample t-test testing experiment for impact strength was also carried out. The hypothesis used is:

$$H_0 : \mu_I = 5.10$$

$$H_0 : \mu_I \neq 5.10$$

The criteria for rejection used is: reject H_0 if the value of Pvalue $< \alpha$, with $\alpha = 0.05$. The result for Pvalue is 0.63, so the Pvalue is also greater than 0.05. Therefore, H_0 fails to be rejected, which means that the average value of the impact strength of the confirmation experiment results is also not significantly different from the value of the predicted impact strength.

6. Conclusions

The results of optimization and confirmation experiments carried out on the response parameters of tensile strength and impact strength of specimens resulting from the injection molding process using BPNN-GA are in the form of process parameter settings that produce optimal response parameters, with barrel temperature of 217°C, injection pressure 55 bar, holding pressure 41 bar and an injection velocity of 65 mm/sec. The results of the confirmatory experimental test using the one sample t-test method show that the average tensile strength and impact strength of the confirmation experiment results are not significantly different from the tensile strength and impact strength values of the GA optimization prediction.

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