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Response Prediction of Vulcanization Process on Rubber Sole Using Backpropagation Neural Network

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Abstract: Vulcanization process has been widely used in footwear industry due to the effect of rubber sole quality. This paper is focused on study the effect of vulcanization process parameters on mechanical properties of rubber sole. The vulcanization process parameters such as molding temperature, molding pressure, and holding time were used as factors. The mechanical properties of rubber sole such as tensile strength and elongation at break were used as responses. Full factorial design with three times replicated was implemented for the experiment. Response prediction was conducted by using backpropagation neural network. The network architecture was developed by using 3 neurons on input layer, 16 neurons on hidden layer, and 2 neurons on output layer. The mean absolute errors between experiment and predicted values were 1.485% for tensile strength and 0.6% for elongation at break. Therefore, backpropagation neural network was recommended for predicting the responses of vulcanization process on rubber sole with good agreement compared to experiment result.

Keywords:vulcanization process, rubber sole, backpropagation neural network, response prediction

I. INTRODUCTION

Currently, footwear industry has become well developed industry in Indonesia. Most of footwear industry used rubber as raw material for footwear sole manufacturing. There are several process to produce rubber sole such as compounding, mixing, cutting, vulcanizing, and finishing. Vulcanization process is the most important process that affects the mechanical properties of rubber sole. Vulcanization process was conducted by using hot press machine that has three parameters process such as molding temperature, molding pressure, and holding time. The mechanical properties of rubber sole such as tensile strength and elongation at break are some responses that used to evaluate the performance of vulcanization process. These responses are related to the quality of rubber sole.

Nowadays, backpropagation neural network (BPNN) is considered as a powerful and compelling practical method for modelling very complex non-linear systems. The BPNN application has been widely used for predicting the responses of machining systems [1]. Soepangkat et al [2] conducted a study to predict surface roughness, tool flank wear, and material removal rate in end milling process using BPNN. Nurcahyo et al [3] performed a study to predict thurst force and delamination in carbon fiber reinforced polymer (CFRP) drilling using BPNN. Sateria et al [4] conducted a study to predict thurst force and delamination in glass fiber reinforced polymer (GFRP) drilling using BPNN. Therefore, BPNN was proposed for predicting the responses of vulcanization process on rubber sole.

II. EXPERIMENT DESIGN

Vulcanization process was conducted by using hot press machine, while universal testing machine was used to measure the mechanical properties of rubber sole. Hot press machine and universal testing machine are shown in Fig. 1 and Fig. 2 respectively. The work piece material used in this experiment was rubber sole sheet with dimension of 295 mm x 215 mm x 10 mm. The vulcanization process parameters such as molding temperature, molding pressure, and holding time were used as factors with each of the factors has three levels. Table 1 shows the levels of vulcanization process parameters. The number of factor combination is 27 (3 x 3 x 3). There will be three observations taken for each trial to estimate the uncertainty of the result. Therefore, the total number of observations is 81. A random order was also determined for running the test. The mechanical properties of rubber sole such as tensile strength and elongation at break were used as responses.

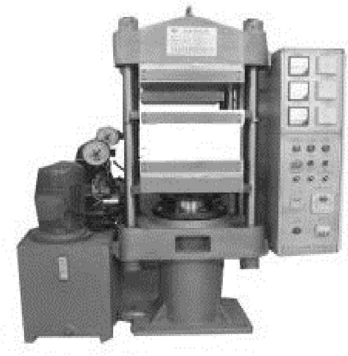

Fig. 1 Hot press machine

Fig. 2 Universal testing machine

Table 1. Levels of vulcanization process parameters

Parameter	Unit	Level 1	Level 2	Level 3
Molding Temperature	^{o}C	140	70	2
Molding Pressure	bar	155	80	3
Holding Time	minutes	170	90	4

III. BACKPROPAGATION NEURAL NETWORK

Artificial neural network (ANN) is a system which is used to process information. The characteristic of ANN resemble the biological neural network [5]. Mathematical models of the cognitive aspects human or biological nerves are generalized by developing ANN based on several assumptions, which are: (1) The processing of information takes place on nodes named neurons (2) Information propagates between neurons through interconnection as signals (3) Every interconnection owns a corresponding weight that on most neural networks serves to multiply the transmitted signal. Every neuron implements an activation function, which usually is not linear, on the network input to assign the output signal.

One of the architectures of artificial neural network that have high accuracy and speed is backpropagation neural network (BPNN). BPNN was first introduced in 1986 [6]. BPNN algorithm for neural network is commonly applied to multilayer perceptrons. They have at least an input section and several layers that are located between the input and the output. This middle layers, also known as hidden layers, can be one, two, three or more. The last layer output is directly used as the output of the neural network. The training on backpropagation method involves three stages that is feed forward, training pattern, error counting, and weight adjustment. After the training, the network applications only use the first stage of computing, i.e. feed forward to perform testing.

Although the training phase is slow, the network can produce outputs very quickly during the testing phase. Backpropagation method has been varied and developed to improve the speed of the training process. BPNN architecture consists of many layers (multilayer neural networks), namely [7]: (1) Input layer, which consists of a number of neurons of input unit (2) Hidden layer, which consists of a number of hidden unit (hidden unit 1 to hidden unit *n*) (3) Output layer, which consists of a number of neurons of output unit. The symbol *n* is arbitrary integer number according to the designed artificial neural network architecture.

IV. RESULT AND DISCUSSION

In this study, the data used as input layer is a combination of vulcanization process parameters or factors, i.e. molding temperature, molding pressure, and holding time. The data used as output layer is the mechanical properties of rubber sole or responses, i.e. tensile strength and elongation at break. Experiment data should be normalized according to the output interval of the activation function. Normalization is a process to change the data to a value of between -1 to 1. Calculation of normalization of input and output data can be performed using Eq. 1 as follows [8]:

$$p_n = \frac{2(p - \min(p))}{(\max(p) - \min(p))} - 1 \quad (1)$$

where:

p = experiment data

p_n = normalization data

Determining the best network architecture to obtain the smallest value of mean square error (MSE) was conducted by trial and error. Calculation of MSE can be performed using Eq. 2 as follows [9]:

$$MSE=\frac{1}{n}\sum_{i=1}^{n}\left(d_i - y_i\right)^2 \quad (2)$$

where:
d_i = experiment value
y_i = predicted value
n = combination number

In training process, parameters of BPNN are shown in Table 2. All combination used learning rate of 0.05 and performance goal of 0.0001 [10].

Table 2. Parameters of BPNN

Parameter	Value
Maximum Iteration	10,000
Maximum Iteration Time	200 s
Minimum Performance Gradient	0.00001
Maximum Validation Failure	1,000

The calculation results to obtain the network architecture of BPNN show that the smallest value of MSE can be obtained by using 3-16-2 network. The activation functions of the hidden layer, the output layer, and the network training were tansig, purelin, and trainlm respectively. The 3-16-2 network means that the network consists of 3 neurons on input layer, 16 neurons on hidden layer, and 2 neurons on output layer. The best network architecture of BPNN is shown in Fig. 3.

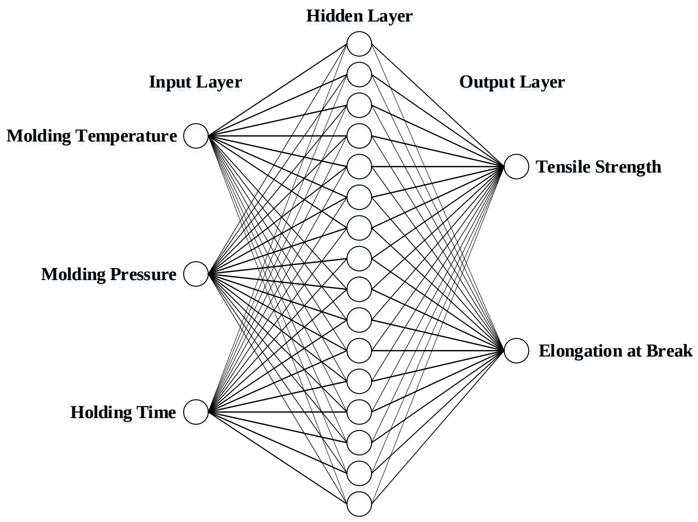

Fig. 3 Best network architecture of BPNN

Generally, the data used in the BPNN process consists of training, testing, and validation. Percentage of data used for training, testing, and validation are respectively 70%, 15%, and 15% of experiment data. The data used as training, testing, and validation are 57, 12, and 12 respectively. Error (the difference between experiment and predicted result) was calculated to evaluate the performance of BPNN model. Calculation of error can be performed using Eq. 3 as follows [10]:

$$Error=\frac{d - y}{d} x\ 100\% (3)$$

where:
d = experiment value
y = predicted value

The comparison between the experiment and predicted value of tensile strength and elongation at break are shown in Fig. 4 and Fig. 5 respectively. The mean absolute errors between experiment and predicted values were 1.485% for tensile strength and 0.6% for elongation at break.

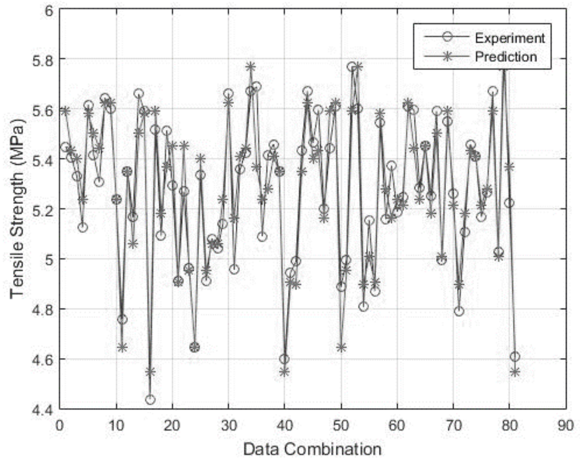

Fig. 4 Comparison between the experiment and predicted value of tensile strength

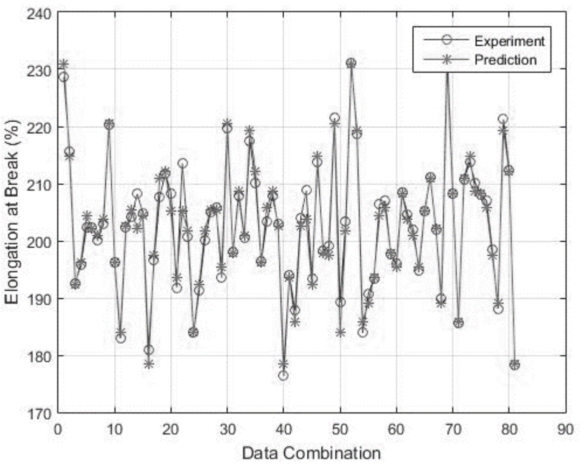

Fig. 5 Comparison between the experiment and predicted value of elongation at break

V. CONCLUSION

In this study, response prediction was investigated in vulcanization process on rubber sole. BPNN was applied to predict the tensile strength and elongation at break of rubber sole. The best network of BPNN for predicting these responses was 3-16-2. The mean absolute errors between experiment and predicted values were 1.485% for tensile strength and 0.6% for elongation at break. Therefore, backpropagation neural network was recommended for predicting the responses of vulcanization process on rubber sole with good agreement compared to experiment result.

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