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# Optimization Analysis between Processing Parameters and Physical Properties of Geocomposites

## 지오컴포지트의 공정인자와 물성의 최적화 분석

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**ABSTRACT**

Geocomposites of needle punched and spunbonded nonwovens having the reinforcement and drainage functions were manufactured by use of thermal bonding method. The physical properties (e.g. tensile, tear and bursting strength, permittivity) of these multi-layered nonwovens were dependent on the processing parameters of temperatures, pressures, bonding periods etc. – in manufacturing by use of thermal bonding method. Therefore, it is very meaningful to optimize the processing parameters and physical properties of the geocomposites by thermal bonding method. In this study, an algorithm has been developed to optimize the process of the geocomposites using an artificial neural network (ANN). Geocomposites were employed to examine the effects of manufacturing methods on the analysis results and the neural network simulations have been applied to predict the changes of the nonwovens performances by varying the processing parameters.

**요 지**

열융착법을 이용하여 보강과 배수기능을 가진 니들펀치 및 스펀본딩 부직포의 지오컴포지트를 제조하였다. 이 다층 부직포의 물성(인장, 인열 및 파열강도, 투수도 등)은 열융착법을 사용하여 제조될 경우 온도, 압력, 접착시간 등의 공정인자에 좌우된다. 따라서, 열융착법으로 제조된 지오컴포지트의 공정인자와 물성의 최적화는 매우 중요하다. 본 연구에서는 인공신경망(ANN)을 사용하여 지오컴포지트의 제조공정 최적화를 위한 알고리즘이 개발되었다. 지오컴포지트의 공정인자를 변화시켜 부직포 성능변화를 예측하기 위한 신경망 모사가 적용되었으며, 분석결과에 대한 제조방법의 효과를 조사하였다.

***Keywords*** **:** Multi-layered nonwovens, Thermal bonding method, Processing parameters, Optimization analysis

## 1. INTRODUCTION

The function of nonwoven geotextiles are reinforcement, seperation, filteration, drainage and when impregnated acting as a liquid barrier. Multi-layered nonwovens as a kind of geocomposites are manufactured by needle punching or thermal bonding method to develop the above one or two functions of geotextile (Lnenschloss 등, 1981; Gourc 등, 1982). Especially, in the case of application to thermal bonding method to manufacture geocomposites (multi- layered nonwovens), the processing parameters e.g. temperature, pressure, time etc, one influenced the physical properties of this geosynthetics. And the optimization analysis is applicated to examine this effect (Ingold 1994; Koerner 2005).

Process optimization is one of the most important topics in modern non-woven research because it directly influences many physical properties of the thermal bonded nonwoven geocomposite. It has been known that there exist very complicated interaction between processing

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parameters and material properties. The popular regression approaches always neglects some significant interactions between processing parameters in order to simplify the model and often have some difficulty in finding a reliable multivariable nonlinear model which must be considered as a model.

Very recently, the feed-forward multi-layered neural network approach has been widely used in many areas of engineering and science (Hornik, 1989). Commonly, the neural networks can be employed in order to analyze some of the most complex non-linear system. The recent theoretical work has proven that neural networks can be successfully applied to express most classes of continuous functions with bounded inputs and outputs with any specified precision (Sharpe, 1994).

In this paper, a neural network algorithm for optimizing multi-layered nonwovens to be manufactured at the different processing condition was used and the optimum condition of these was derived from analytical results.

## 2. EXPERIMENTAL

### 2.1 Manufacturing of Geocomposites

Spunbonded nonwoven (18g/$m^2$) of polypropylene filament (7d) and needle punched nonwoven (163g/$m^2$) of polypropylene staple fiber (12d) were used as raw materials for geocomposite composed of multi-layered nonwovens. And thermal bonding apparatus having to bond these nonwovens protrusions within the plate which are available to heat and press.

#### 2.1.1 The processing conditions

Processing conditions for multi-layered nonwovens one as following:

(1) Temperatures: 180～190℃(at 2℃ intervals)
(2) Pressures: 4, 5, 6 kgf/$m^2$
(3) Times: 2, 3, 4 seconds

#### 2.1.2 Types of geocomposites

The following types of geocomposites were manufactured at the above conditions.

(1) Needle Punched - thermal bonded
(2) Needle Punched/Spun Bonded
(3) Needle Punched/Needle Punched
(4) Spun Bonded/Needle Punched/Spun Bonded

### 2.2 Physical Properties

Physical properties of multi-layered nonwovens were estimated in accordance with the following test method:

(1) Tensile strength for MD (machine direction) and CD (cross direction) - ASTM D 4632
(2) Tear strength - ASTM D 4533
(3) Bursting strength - ASTM D 3786
(4) Permittivity - ASTM D 4491

## 3. NEURAL NETWORK

In this paper, the feed forward back propagation algorithm is applied to model manufacturing process of non-woven materials. A basic multi-layer neural network structure is shown in Fig. 1 depicting the hidden layer, and output layer.

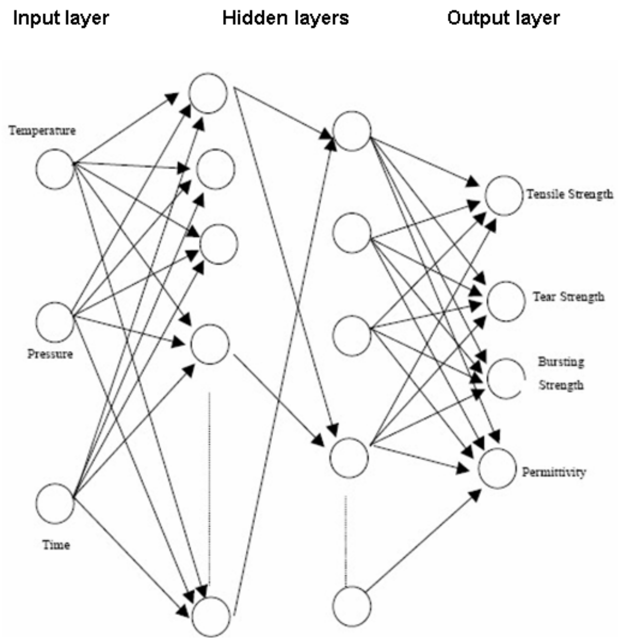


Fig. 1 Architecture of a neural network having two layers.

This neural network has one input layer, one output layer, and any number of hidden layers. Each network consists of nodes (neurons). The input layer of the neural network takes information from the outside world and sends it to the nodes in the hidden layers. Similarly, the output layer of the neural network transmits the processed information to the external world.

To apply an m-variate signal input to a one-layer neural network consisting of n neurons each having m weights, we multiply an m-variate vector X ($x_1$, $x_2$, ... $x_{m-1}$, 1) with the (nxm)-variate weight matrix W. The result is an n-variate net input vector s ($s_1$, $s_2$, ... $s_n$).

Then, we can show how each component $s_j$ is calculated for layer l:

$$s_j = \sum_{i=1}^{n} w_{ji} v_i + b_j = w_j T \cdot v + b_j,\ j = 1,2,..k \tag{1}$$

The index j spans the n neurons, while i spans the m weights in the jth neuron. The number of weights in the neuron is one of more than the number of input variables, $x_i$ the remaining one input variable is the bias, which is always equal to 1.

The quantity $s_j$ is processed by an activation function to give the output $o_j$ of the jth neuron:

$$o_j = f(s_j) \tag{2}$$

The input consists of process variables such as pressure, temperature and processing time. The network output are predicted values of physical properties at possible process conditions. The network training is performed using the nonlinear least square methods. The error at the output neuron can be defined as

$$E = \frac{1}{2}(t_k - o_k)^2 \tag{3}$$

where $t_k$ is the target value of the output neuron. The backpropagation algorithms make use of the gradient descent methods for minimizing E. The error signal defined by

$$\delta_j = -\frac{\partial E}{\partial o_j} \tag{4}$$

leads to the result of general delta rule

$$\Delta w_{ji} = \eta \delta_j o_i \tag{5}$$

where $\eta$ is an adaptation gain and $\delta_i$ is computed based on whether or not neuron j is in the output layer. If neuron j is one of the output neurons, then

$$\delta_j = (t - o_j) o_j (1 - o_j) \tag{6}$$

On the other hand, if neuron is not in the output layer,

$$\delta_j = o_j (1 - o_j) \sum_i \delta_i w_{ji} \tag{7}$$

For a fast convergence, the momentum with gain $\alpha$ will be introduced by following equation:

$$\Delta w_{ji}(k+1) = \eta \delta_j o_i + \alpha \Delta w_{ji}(k), \tag{8}$$

where k is the iteration step.

## 4. RESULTS AND DISCUSSIONS

The feedforward back propagation algorithm based on the generalized delta rule and the minimum mean squared error (MSE) principle were used for the data sets. In a feedforward network, the processing units can be divided into several layers: input layer, hidden layers and output layer. The input components consist of process variables such as pressure, temperature and processing time which are considered to be important parameters. Outputs of the network are the predicted physical properties at the given process condition. The number of units in the hidden layers was set to be 16 following a series of optimization experiments. The networks have been used for training hundreds of experimental data sets, namely, pairs of process conditions and physical properties of different multi-layered nonwovens produced by varying the process conditions.

The prediction results are shown in Figs. 2-5. As shown in the figures, several physical properties were predicted quite well with small errors. Fig. 2 shows predicted permittivity at different process conditions. It has been found that high permittivity can be obtained when materials are made at 180℃ or same values attained for short processing time and lower temperature. But in

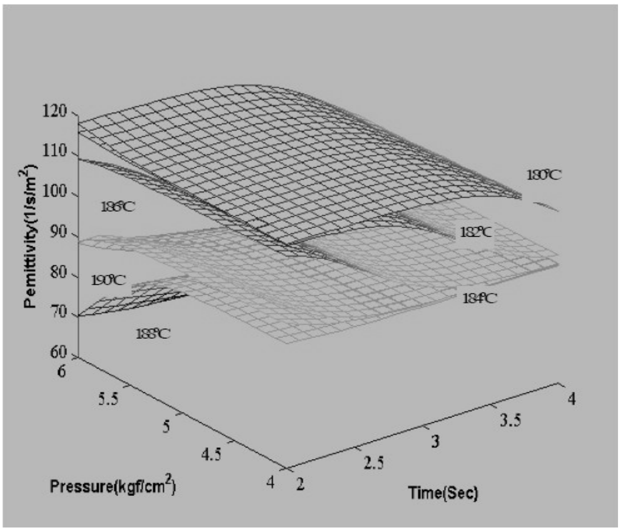


Fig. 2 Prediction of permittivity using neural network

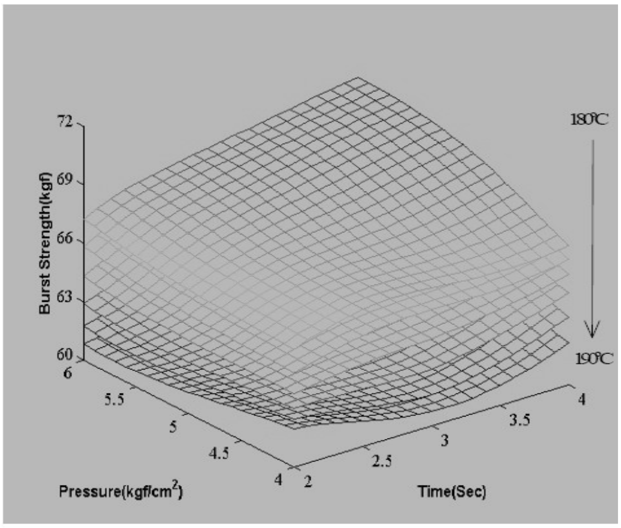


Fig. 5 Prediction of burst strength using neural network

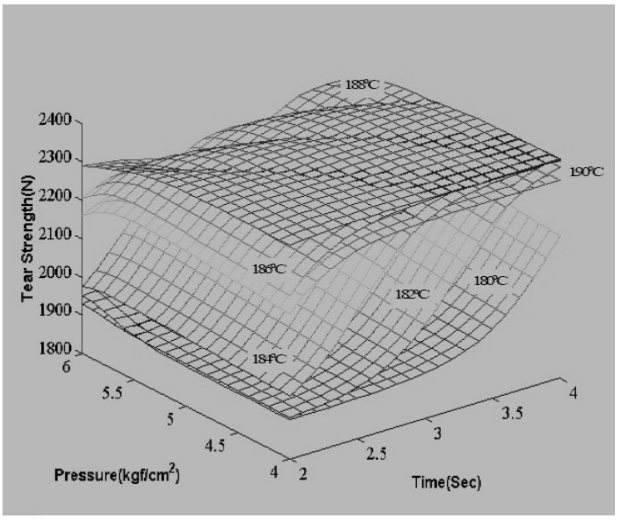


Fig. 3 Prediction of tear strength using neural network

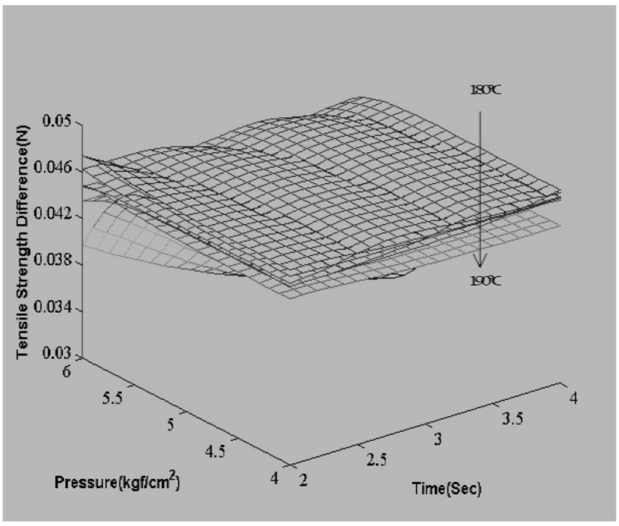


Fig. 4 Prediction of tensile strength difference

very high pressure and long processing time, the property is deteriorated significantly below unacceptable region. For tensile strength difference (difference between MD and CD), the property doesn't depend much on process condition except the case on very high temperature. In 188℃, tensile strength in machine direction shows significantly high values but one in cross direction doesn't increase when compared to lower temperature. Fig. 3 shows effect of process condition on tear strength of nonwovens. It was clearly seen that process time affect significantly the tear strength in such a way that longer process time enhance the tear strength over whole temperature regions investigated. But pressure effect is really negative, that is, high pressure caused the decrease of tear strength of nonwovens. Tensile and burst strength of geocomposites was shown in Fig. 4 and Fig. 5., it shows the same tendency of tear strength. Using simulation model, we tried to find some optimal process conditions which optimize several physical properties in such a way that permittivity, tensile, tear strengths are maximized and tensile strength difference is minimized. From this, it is known that the optimum condition is found to be 182℃, 3sec and 4.9 kgf/cm$^2$, respectively

## 5. CONCLUSION

The optimization analysis by neural network was applied to examine the relations between processing parameters and physical properties of multi-layered nonwovens.

A neural network model was developed by analyzing the experimental data and this simulation shows that ANN model was found to be accurate and highly robust for modeling the process performance. Using the tool, we developed an algorithm for optimization the nonwovens performances without a significant loss of physical properties. The simulated response surfaces were found to highly effective in predicting the qualities of resulting geocomposites without actually producing them.

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