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스테인레스 박강판의 레이저 점용접부 형상예측에 관한 연구

강 형 식*, 홍 성 준*, 전 태 옥**, 장 원 석***, 나 석 주***

A Study on the Prediction of Laser Spot Weld Shapes of Thin Stainless Steel Sheet

H. S. Kang*, S. J. Hong*, T. O. Jun**, W. S. Jang***, S. J. Na***

ABSTRACT

본 논문에서는 Nd-YAG 레이저 용접 프로세스를 이용하여 두께가 다른 STS304스테인레스 박강판을 대상으로한 점용접에 관한 연구로서, 레이저 용접은 미소부위에 효율적인 접합가공이 가능한 공정으로 비접촉식 가열원을 이용하기 때문에 접합공정 중 기계적 변형이 없고, 레이저 빔을 국부가열원으로 하여 매우 좁은 부분에 제한적으로 열을 가할 수 있어서 강한 금속적 결합이 요구되는 소형부품의 접합에 이용될 수 있다. 뿐만 아니라 공정 변수들을 변화시켜 실제 접합부에 들어가는 입열량을 쉽게 제어할 수 있다는 등 많은 장점을 가지고 있다.

본 연구에서는 1mm 이하의 스테인레스 박판에 대한 레이저 점용접을 FDM과 신경회로망을 이용하여 해석하고 용접부의 너겟 크기, 용접부 깊이 등의 형상을 예측하였다.

또한 레이저 점용접에 있어서의 주요 변수인 펄스 에너지, 펄스 타임, 박판의 두께, 두 판사이의 간극크기 등을 변화시켜 실험하고 수치해석을 검증하기 위하여 여러 가지 강에 대한 레이저 점용접 실험을 수행하였다. 또한 수치해석 시뮬레이션을 위하여 윈도우 프로그래밍을 개발하였다

Key Words : Laser spot welding(레이저 점용접), Numerical analysis(수치해석), Neural network(신경회로망), Thin Stainless steel sheet(스테인레스 박강판) Nugget size(너깃크기), Penetration depth (용입깊이), Gap size (갭 간격)

1. INTRODUCTION

Laser beam welding offers a unique combination of high speed, precision and flexibility, compared with conventional resistance spot welding. This combination is especially attractive for electronic component joining. A wide range of research activities have been undertaken, including laser beam delivery systems and mechanical behavior of laser-welded sheet steels. However, research on the dimension of laser beam welds for given metal thickness remains virtually not extensively studied. The weld pool dimension and weld quality of spot welds produced by using a pulsed

* LG 전자 생산기술 센터
** 동아대학교 기계공학과
*** KAIST 기계공학과

Nd:YAG laser welding machine depend on various process parameters such as the spatial intensity distribution of incident laser beam, the peak power of pulse, the pulse energy, the pulse time, and the temporal shape of beam power during the pulse. When developing the welding procedure for a specific application, each of these parameters must be characterized and fully specified. This is usually done by using empirical techniques, since most analytical and numerical models for laser weld pool development ignore various aspects of the laser-material interaction[1], thus making it difficult to accurately predict the weld pool shape. Limited experimental studies of the effects of Nd:YAG laser process parameters on laser spot weld dimensions and weld quality have been reported.[2-3]

In this study, finite difference method and neural network were applied for predicting the bead shape in laser spot welding of thin stainless steel sheets with thickness smaller than 1mm. The penetration depth and nugget size of laser spot welds measured for the specimen with and without gap were compared with the predicted results to verify the proposed model.

2. FINITE DIFFERENCE ANALYSIS

2.1 Governing Equation and Boundary Conditions

Heat transfer problem of laser processing can be solved by applying the heat conduction theory. The thermal analysis of laser spot welding can be treated as an axisymmetric heat transfer problem, Fig. 1. Thermal energy changes due to the chemical reaction and evaporation of material during laser spot welding were not considered. The energy equation of the problem is :

$$\nabla^2 T = \frac{1}{x}\frac{\partial T}{\partial t} - \frac{G}{k} \tag{1}$$

$$G = \frac{2\alpha(1-R)P}{\pi\delta^2}\exp[-2\gamma^2/\delta^2 - \alpha Z] \tag{2}$$

where,

$T(r,z,t)$: temperature $\quad$ x : thermal diffusivity
k : thermal conductivity $\quad$ α : absorption coefficient
G: heat source function $\quad$ δ : effective beam radius
R : reflectivity $\quad$ P : laser power

A special form of heat generation(Ref. 4) in the workpiece was adopted to simulate the laser beam heat source which has the characteristics of key-holing. The boundary condition is :

$$k\frac{\partial T}{\partial n} = -h(T_s - T_\infty) \tag{3}$$

where, n : unit vector outward normal to the boundary
h : convection heat-transfer coefficient
T_s: temperature of surface
T_∞ : temperature of atmosphere

Initial condition for the transient analysis is $T(t,z,0) = T_0(r,z)$ at $t=0$, where T_0 is the initial

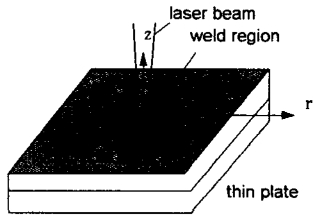

Fig. 1 Schematic diagram of laser spot welding

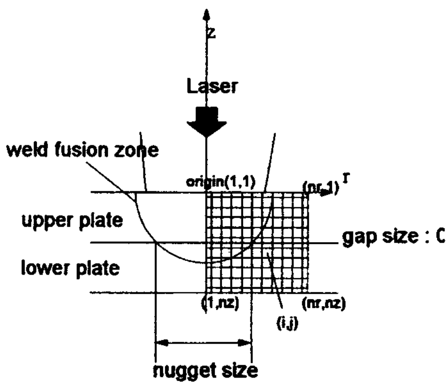

Fig. 2 Solution domain of finite difference model for thermal analysis

temperature. The solution domain of the finite difference model used for the thermal analysis is shown in Fig. 2.

2.2 Material thermal properties

The material used was type 304 stainless steel sheet. The thermal properties of the material were assumed to be homogeneous and independent of temperature. Thermophysical constants used in all calculations are presented in Table 1.

Table 1. Thermophysical constants used in finite difference analysis

Material	k, w/cm°C	κ, cm^2/sec	α, cm^{-1}	R	T_m, °C
STS 304	12	0.053	6	0.3	1450

where,
k : thermal conductivity κ : thermal diffusivity
α : absorption coefficient R : reflectivity
T_m : melting temperature

3. NEURAL NETWORK

3.1 Back-propagation Algorithm

The neural network based on the back-propagation algorithm consists of three layers, that is, the input, the output and the hidden layer. The purpose of the learning process is to decrease the error between the desired output and the actual one obtained from the output layer of the neural network, which can be expressed by a cost function as follows.[5]

$$J = (1/2)\sum_p \sum_k (d_k - a_k)^2 \tag{4}$$

where, p : the number of input patterns
k : the number of output patterns
d_k : desired outputs
a_k : actual outputs from the output layer

The hidden layer, output layer and the weights between the layers are expressed as follows.

$$h_j = S(\sum_i W_{ij} S_i) \tag{5}$$

$$a_k = S(\sum_k W_{jk} h_j) \tag{6}$$

$$S(x) = 1.0/(1.0 + e^{(-x-\theta)}) \tag{7}$$

where, h_j : output at the hidden layers
S_i : input according to each pattern
W_{ij}, W_{jk} : weights
θ : internal offset value
$S(x)$: Sigmoid function

3.2 Selection of Appropriate Input Variables to Neural Network

Three different combinations of process parameters were considered to find out the appropriate input variables to the neural network. Laser spot welding process parameters(focal length, energy, pulse time), sheet metal thickness(upper and lower plate), gap size and bead shape(penetration depth, nugget size) of the workpiece were selected as the input variables for the back-propagation learning algorithm of the neural network and the bead shape(penetration depth, nugget size) were considered as its output variables. In type 1, the focal length, pulse energy, pulse time, sheet metal thickness(upper and lower plate), gap size, penetration depth and nugget size were selected as the input variables, while in type 2 the sheet metal thickness(upper and lower plate), gap size, penetration depth and nugget size and in type 3 the gap size, penetration depth and nugget size were selected as the input variables.

3.3 Combined model of FDM and Neural Network

Various combinations of stainless steel sheet metal thickness were considered to calculate the laser spot weld bead shape of the workpiece with no gap, which was then used as the input variable of the neural network for predicting the bead shape in the case of sheet metals with various thicknesses and gap sizes.

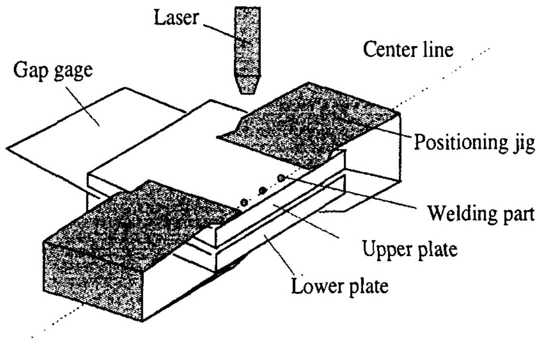

Fig. 3 Experimental setup of laser spot welding

Table 2. Laser spot welding conditions for neural network input parameter

Specimens upper/lower (mm)	Laser Spot Size (mm)	Gap (mm)	Energy (J/S)	Pulse Duration (ms)	Focus Position (mm)
0.30/0.33 0.33/0.50 0.40/0.60 0.60/0.50 0.50/0.50	φ0.6	0 0.06 0.12	2.5 3.0 3.5	2.0, 4.0	1, 2

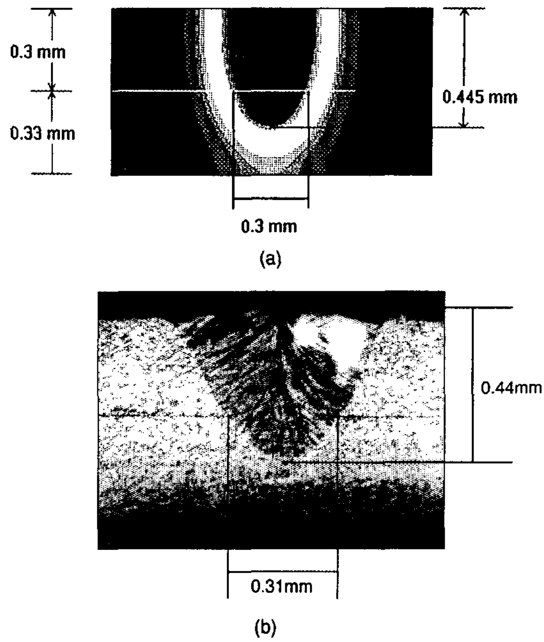

Fig. 4 Comparison of calculated (a) and experimental (b) results (pulse time : 4ms, pulse energy : 2J/s)

4. EXPERIMENTS

Experiments were designed to test the finite difference model and to determine the input and output variables appropriate to the neural network. An experimental set-up for Nd:YAG laser spot welding is shown in Fig. 3. A pulsed type Nd:YAG laser welding machine was used for all experiments. The beam oscillator was capable of the maximum output power 400W. And the laser spot welding conditions are summarized in table 2. Type 304 stainless steel specimens with 5 different combinations of thickness(0.3mm+0.33mm, 0.33mm+0.5mm, 0.4mm+0.6mm, 0.6mm+0.5mm and 0.5mm+0.5mm) were prepared for experiments.

5. RESULTS AND DISCUSSIONS

Fig. 4 shows a typical example of cross-sections of experiments and calculations obtained for the stainless steel thickness combination of 0.3mm+0.33mm with laser energy of 2J and pulse time of 4ms. In the calculated result(Fig. 4a), it is shown that the nugget size and penetration depth agree fairy well with the experimental result(Fig. 4b), while the experimental result shows a somewhat wider top bead size than the calculated one. It is thought that the temporal pulse shape, plasma formation and laser-material interaction influence the formation of top bead, which cannot be considered in the developed finite difference model. However, the top bead size is less important in determining the weld quality such as joining strength than the nugget size and penetration depth. Consequently, this study is mainly dealing with the prediction of nugget size and penetration depth.

Fig. 5 shows that the error of predicted nugget size and penetration depth determined by comparing them with experimental ones is less than 15% for the type 1 of the neural network, where the focal length, pulse energy, pulse time, sheet

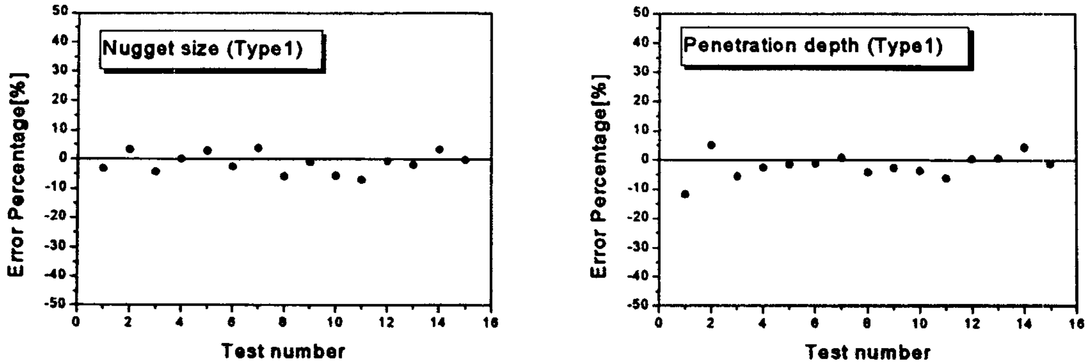

Fig. 5 Estimated error of bead shape predicted in type 1

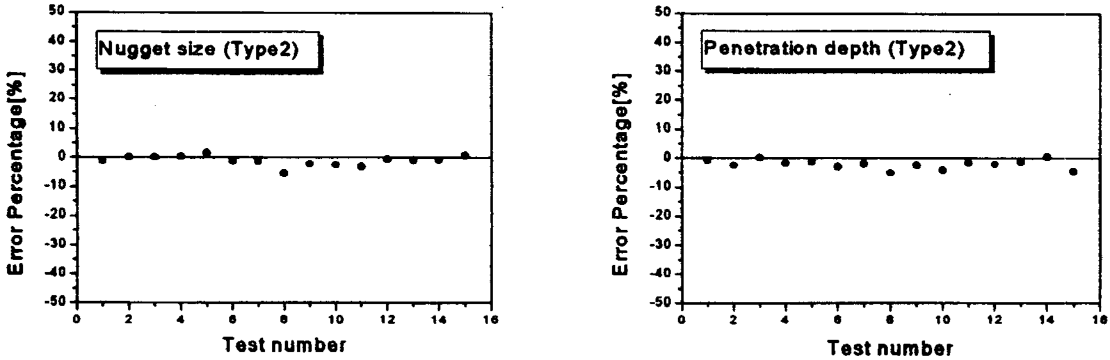

Fig. 6 Estimated error of bead shape predicted in type 2

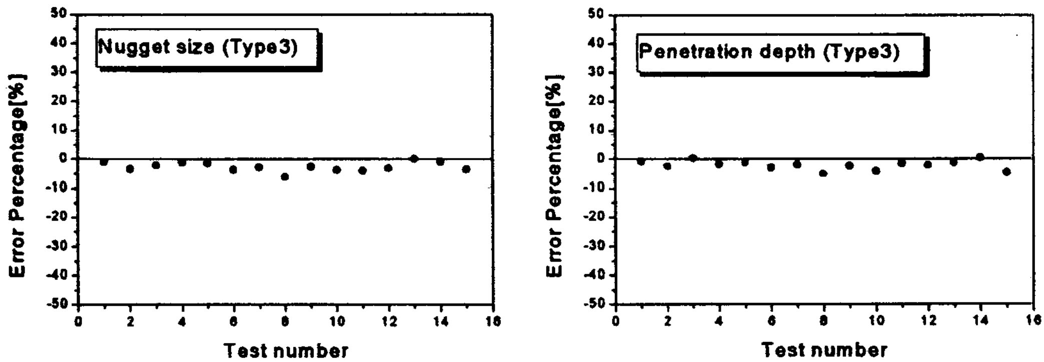

Fig. 7 Estimated error of bead shape predicted in type 3

metal thickness(upper and lower plate), gap size, penetration depth and nugget size were selected as the input variables.

Fig. 6 and 7 show that the neural network model of type 2 and type 3 can estimate the bead shape of laser spot welds such as nugget size and penetration depth. From these results it could be revealed that the process parameters adopted in type 2 and type 3 are also appropriate input variables to the neural network.

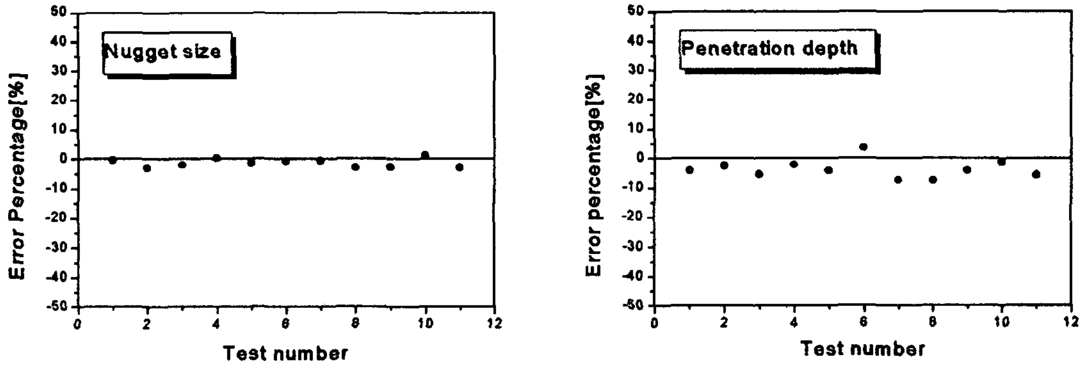

Fig. 8 Estimated error of bead shape predicted by combined model of FDM and neural network

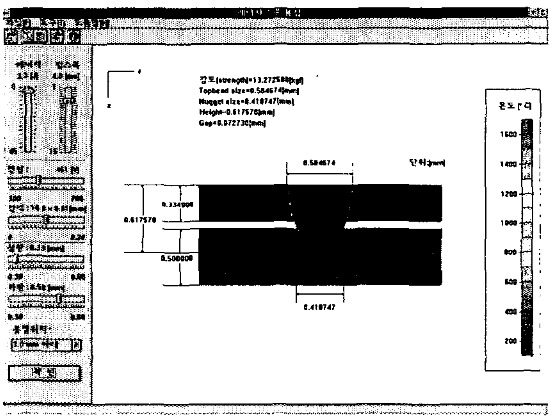

Fig. 9 Windows program for simulations of bead shape by combined model of FDM and neural network

Fig. 8 shows the error of nugget size and penetration depth predicted by using the combined model of finite difference analysis and neural network. Predicted results were compared with the experimental ones of the specimen with thickness combination of 0.5mm+0.5mm. It shows that the error was smaller than 10%. From these results, the combined model could be effectively applied for the prediction of laser spot weld bead shape such as nugget size and penetration depth.

Fig. 9 shows the windows program developed for the simulation and display of the combined model of finite difference analysis and neural network. In this program, the user can select the process parameters such as sheet thickness, gap size, pulse time, pulse energy, focal length and the bead shape calculated for no gap and then the bead shape is simulated for various gap sizes by using the neural network and displayed.

Type 1 is the result of inputting the most parameters, and type 3 is the result of inputting the least. These are obtained by comparing the deviations between the estimation obtained from carrying out the neural network by means of changing the input parameters and real test.

From these, we can see that the deviation from the estimation by type 1 is larger than those of type 2, 3 and the deviation of type 3 is somewhat larger than that of type 2. These results show that the exact estimation of shape must not be obtained even if we input many parameters in neural network, and it is also difficult when we input few parameters. In result, type 2 has the least deviation and it is used to estimate in the situation which has a gap.

6. CONCLUSIONS

From the results of finite difference analysis, neural network and experiments for laser spot welding of thin stainless steel sheets, the following conclusions may be drawn:

1) The proposed finite difference model can estimate the laser spot weld bead shape of thin

stainless steel sheets considerably precisely, if they are layered tightly.

2) The developed neural network which uses the bead shape data of the specimen with no gap and a few data of specimen with gap can predict the laser spot weld bead shape of thin stainless steel sheets with various gap sizes fairly well.

3) The combined model of finite difference analysis and neural network could be effectively applied for the prediction of laser spot weld bead shapes, because the numerical analysis of laser spot weld bead shape for the workpiece with a gap between two sheet metals is highly limited.

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