ICCEPM 2024 https://dx.doi.org/10.6106/ICCEPM.2024.1188
The 10th International Conference on Construction Engineering and Project Management
Jul. 29-Aug.1, 2024, Sapporo

Design of considering distortion after high energy manufacturing with Finite element analysis & Deep learning

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Abstract: High-energy manufacturing processes, including laser welding, are actively being adopted not only in precision machinery industries but also in the shipbuilding and construction sectors. Laser welding, in particular, is gaining prominence in the industry due to its faster welding speed and reduced distortion compared to conventional arc welding methods. Integration of automated welding systems is anticipated to address challenges in shipbuilding and construction industries, which are currently facing a shortage of skilled labor. For successful implementation of automated welding systems, it is essential to predict and design for the post-welding effects, such as residual deformation and stresses. However, in the case of high-energy manufacturing like laser welding, the welding bead morphology differs from that of arc welding, and the heat load conditions applied during simulation are distinct. To facilitate accurate simulation predictions, the development of a suitable heat source for predicting welding bead morphology in high-energy manufacturing processes is crucial. The Block-dumping method is proposed for rapid simulation and on-site application, with the shape of the welding bead being imperative for its effectiveness. In this study, data on the welding bead morphology of Nickel-based steel was obtained. Using Deep Learning techniques, we successfully predicted the bead morphology and confirmed minimal discrepancies when compared to actual results. This outcome allows for the simulation of welding under untested conditions, offering practical applicability in the field. Additionally, we present a heat source model (heat load condition) to ensure a highly accurate interpretation of the results.

Key words: High energy manufacturing, Simulation, FEA, Deep learning, Estimation of distortion

1. INTRODUCTION,

High-energy manufacturing, characterized by rapid speed and minimal distortion, has expanded beyond precision machinery industries to find widespread application in the shipbuilding and construction sectors[1]. Welding, in particular, stands out as the most widely used fabrication process in industrial settings, owing to its relatively low processing costs and easy accessibility. While traditional arc welding has been extensively employed, it suffers from significant welding distortions. In contrast, fiber laser welding minimizes thermal deformation by concentrating heat in a narrow area for a short duration. This enables faster welding compared to arc welding, contributing significantly to improved productivity[2]. This addresses the shortcomings of traditional arc welding, such as slow processing speeds and significant distortions, and offers a solution by integrating with automated welding systems to overcome past challenges in relying on skilled labor.

However, in industries like shipbuilding and construction, where large volumes are involved, predicting and designing for laser welding distortions are crucial. Much research has been conducted in this area[5,6]. Various methods, such as simplified analysis based on inherent strain based equivalent load method[7], moving heat source methods through heat source modeling[8-10], and the use of Block dumping[11], have been employed to predict welding distortions. While the moving heat source method provides precise predictions, it requires accurate determination of the heat source, making it time-consuming for on-the-spot application in practical scenarios. To facilitate the aforementioned analysis, it is necessary to refine the mesh in the welding direction, which results in a significant consumption of time and memory in the analysis of 3D models[12]

The Block Dumping method is an analytical technique where the weld bead is discretized into a finite number of blocks in the welding direction, generating the blocks step by step for thermal deformation analysis. In this method, the heat source is assumed to be in the form of blocks, and volume heat flux is applied to the blocks generated at each step. The Block Dumping method offers advantages in terms of shorter analysis times compared to heat transfer models using moving heat sources, enabling efficient simulation of various models[11,13]. For the Block Dumping method, as illustrated in Fig. 1, the welding direction is divided into sections, and heat loads are applied to the modeled bead shape in a time-dependent manner, allowing for the prediction of welding distortions and residual stresses

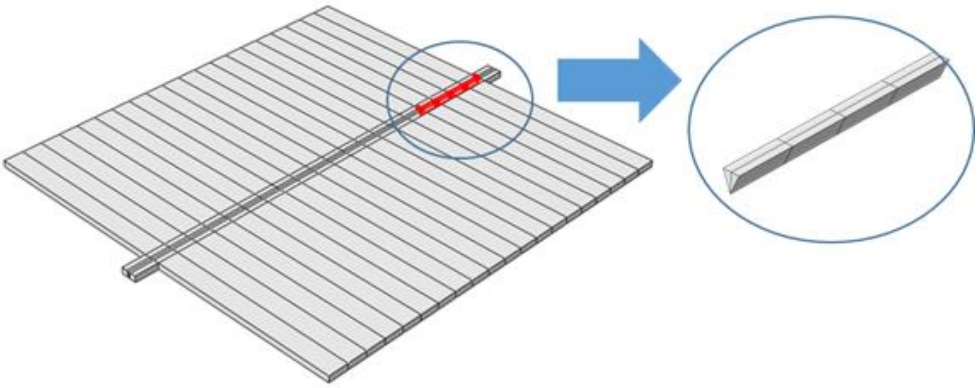


Fig.1. Block dumping method[14]

To employ the Block Dumping method, it is essential to model the shape of the weld bead, and the derivation of the bead shape based on welding conditions must precede the analysis. In such cases, the inconvenience arises from the need to confirm the weld bead shape through Bead on Plate welding for welding distortion simulation. Consequently, there has been a request for solutions to address this issue in practical scenarios.

In this study, we performed the prediction of weld bead shapes using Deep Learning to alleviate the need for tedious Bead on Plate welding for weld distortion simulation. We conducted Bead on Plate welding under approximately 50 processing conditions for Nickel-based steel, analyzing the bead shapes. Based on the analyzed data, we created a database and utilized it for training Deep Learning models. Subsequently, we predicted results for conditions not included in the training data and compared them with actual experimental results to analyze the validity of the predictions. With this research as a foundation, we anticipate a more straightforward prediction of welding distortion and residual stresses during laser welding in practical field applications.

2. METHOD

2.1. Bead on plate welding

In this study, Bead on Plate (BOP) welding was conducted using a 9% nickel steel with dimensions of 600mm x 300mm x 6mm. The chemical composition of the 9% nickel steel is provided in Table 1[15]. A fiber laser welding machine (Miyachi, Japan) capable of delivering a maximum output of 5 kW was employed. The focal length was set at 148.8 mm, focal depth at 6 mm, and defocus at 0, with nitrogen (N_2) used as the shielding gas at a flow rate of 15 L/min. Both tilting and working angles were fixed at 0°, and welding was performed under various welding power and speed conditions.

Table 1. Chemical Compostion of 9% Nickel Steel (wt%)

Component	C	Si	Mn	Cr	S	P	Ni	Fe
Requirement	0.05	0.67	0.004	-	0.003	0.25	9.02	Bal.

After performing the welding, the cross-sectional shape was examined. For this purpose, a section of 10mm in the welding direction and 25mm in the width direction from the center was cut. Subsequently, polishing was carried out, followed by etching with Nital solution (10% HNO3, Ethanol). The welded cross-section was then examined using a digital optical microscope with a resolution of 2 megapixels.

The analysis of the cross-section is depicted in Fig.2. During the cross-sectional analysis, the dimensions of the melt line were examined, and classifications were made based on parameters such as bead width, penetration depth, and changes in position.

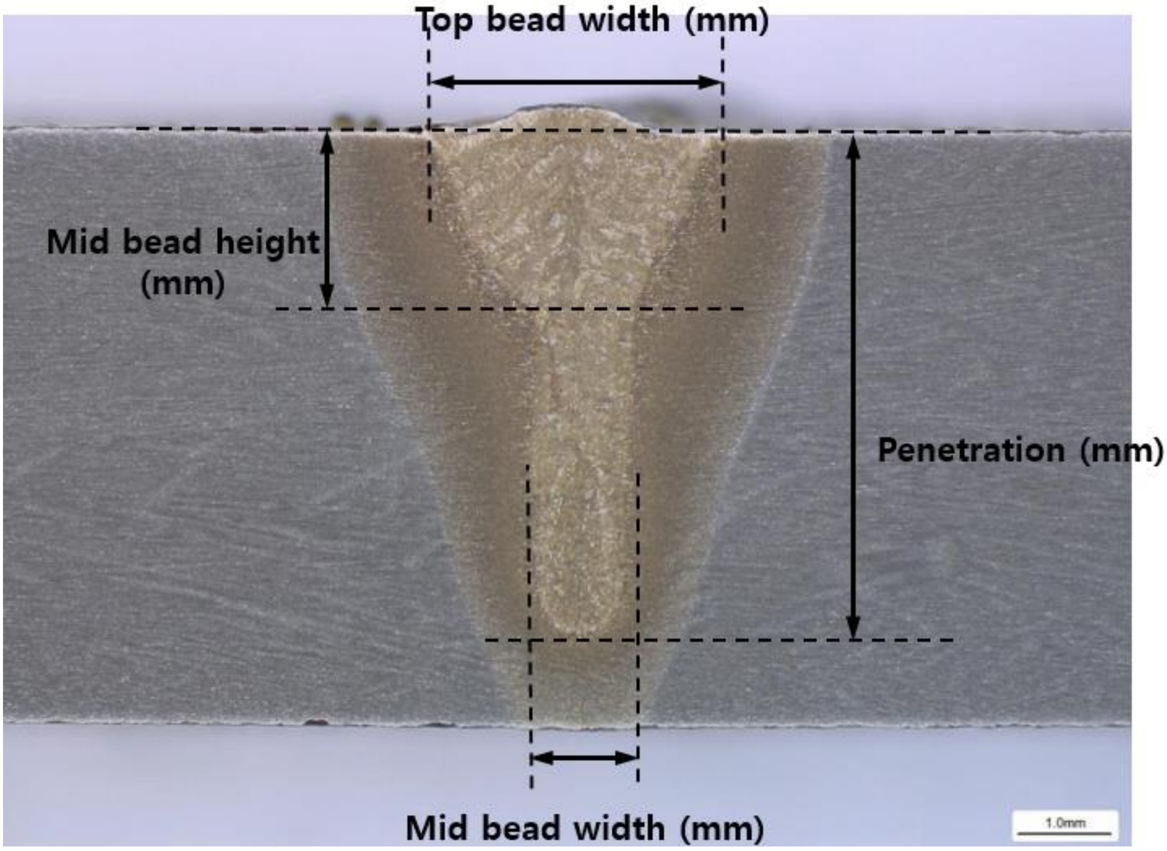


Fig.2 Bead shape and dimension[16]

2.2. Result of diverse condition

Bead on Plate welding was performed on 9% nickel steel, and cross-sectional examinations were conducted, classifying key parameters based on the cross-section. The values of major parameters were observed for 50 different conditions, varying welding power and speed (see Table 2). Subsequently, a deep learning model was utilized to compare the bead shapes for 10 conditions not used in the model

Table 2. Bead shapes of diverse condition

	Condition				Bead shape					
	Power (kW)	Velocity (mpm)	Defocus (mm)	Tilting angle (°)	Top bead width (mm)	Top HAZ width (mm)	Middle bead width (mm)	Concave depth (mm)	HAZ depth (mm)	Penetration (mm)
case 1	3.0	0.3	0	90	5.063	9.063	3.625	2.267	6.750	5.563
case 2	3.0	0.5	0	90	4.250	7.625	2.938	3.000	6.250	5.313
case 3	3.0	0.8	0	90	3.000	5.750	1.875	2.356	5.500	5.063
case 4	3.0	1.0	0	90	3.000	5.125	1.500	2.333	5.125	4.563
case 5	3.0	1.2	0	90	2.625	4.750	1.250	2.133	4.938	4.563

case 6	3.0	1.5	0	90	2.625	4.250	1.125	1.867	4.375	4.250
case 7	3.0	1.8	0	90	2.375	3.875	0.750	1.333	4.000	3.688
case 8	3.0	2.0	0	90	2.125	3.750	0.875	1.422	4.125	3.938
case 9	3.0	2.2	0	90	2.000	3.375	0.750	1.356	4.000	3.813
…..										
case 49	2.0	3.0	0	90	0.911	1.851	0.508	0.392	2.225	2.060
case 50	5.0	3.5	0	90	1.239	2.672	0.567	0.784	4.643	4.464

3. RESULT

Based on the database compiled in Section 2.2, predictions were made for conditions not tested in the experiments. In this study, predictions were conducted for 10 cases under the condition where the welding power was 4.5 kW, and the results are presented in Table 3.

Table 3. Estimated bead shapes

	Condition				Bead shape					
	Power (kW)	Velocity (mpm)	Defocus (mm)	Tilting angle (°)	Top bead width (mm)	Top HAZ width (mm)	Middle bead width (mm)	Concave depth (mm)	HAZ depth (mm)	Penetration (mm)
case 1	4.5	0.5	0	90	4.830	8.065	2.704	2.650	7.747	6.923
case 2	4.5	0.8	0	90	4.126	7.081	2.221	2.321	7.046	6.358
case 3	4.5	1.0	0	90	3.656	6.425	1.899	2.102	6.579	5.982
case 4	4.5	1.2	0	90	3.186	5.769	1.576	1.883	6.112	5.606
case 5	4.5	1.5	0	90	2.601	4.976	1.169	1.597	5.584	5.174
case 6	4.5	1.8	0	90	2.356	4.387	1.083	1.456	5.189	4.878
case 7	4.5	2.0	0	90	2.232	4.080	1.040	1.380	4.999	4.738
case 8	4.5	2.2	0	90	2.120	3.802	1.004	1.309	4.830	4.615
case 9	4.5	2.5	0	90	1.967	3.407	0.944	1.208	4.583	4.435
case 10	4.5	3.0	0	90	1.886	3.025	0.778	1.101	4.285	4.184

To validate the predicted results, experiments and cross-sectional analyses were conducted based on the content of Section 2 for the 4.5 kW condition. The results are presented in Table 4, and the error rates comparing the predicted values with the actual values are provided in Table 5.

Table 4. Real bead shapes

	Condition				Bead shape					
	Power (kW)	Velocity (mpm)	Defocus (mm)	Tilting angle (°)	Top bead width (mm)	Top HAZ width (mm)	Middle bead width (mm)	Concave depth (mm)	HAZ depth (mm)	Penetration (mm)
case 1	4.5	0.5	0	90	5.938	11.125	4.375	3.400	10.000	8.688
case 2	4.5	0.8	0	90	5.125	9.375	4.063	2.289	7.750	6.688
case 3	4.5	1.0	0	90	4.625	7.563	2.438	1.911	6.875	6.313
case 4	4.5	1.2	0	90	3.875	6.563	1.750	1.600	6.375	5.688
case 5	4.5	1.5	0	90	3.938	6.000	1.875	1.756	5.813	5.375
case 6	4.5	1.8	0	90	3.188	5.188	1.500	1.711	5.375	4.938

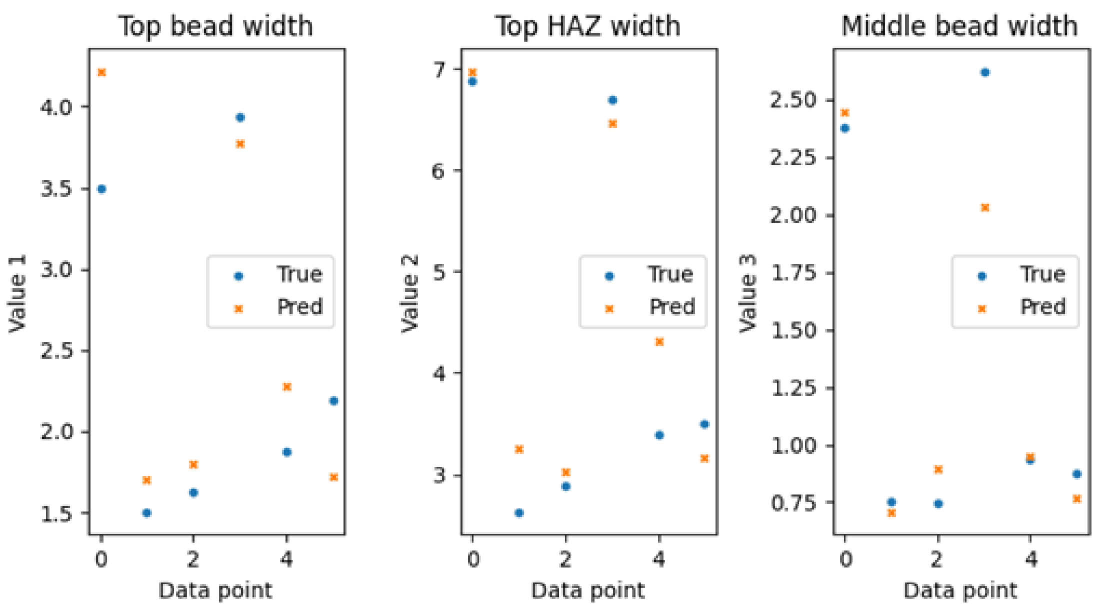
case 7	4.5	2.0	0	90	3.250	4.750	1.000	1.356	5.125	4.813
case 8	4.5	2.2	0	90	3.000	4.438	0.938	1.644	5.000	4.688
case 9	4.5	2.5	0	90	2.625	4.188	0.875	1.756	4.875	4.563
case 10	4.5	3.0	0	90	2.625	3.813	0.813	1.422	4.688	4.438

Table 5. Error rate of real and estimated case

	Condition				Bead shape					
	Power (kW)	Velocity (mpm)	Defocus (mm)	Tilting angle (°)	Top bead width (%)	Top HAZ width (%)	Middle bead width (%)	Concave depth (%)	HAZ depth (%)	Penetration (%)
case 1	4.5	0.5	0	90	22.9	37.9	61.8	28.3	29.1	25.5
case 2	4.5	0.8	0	90	24.2	32.4	82.9	-1.4	10.0	5.2
case 3	4.5	1.0	0	90	26.5	17.7	28.4	-9.1	4.5	5.5
case 4	4.5	1.2	0	90	21.6	13.8	11.0	-15.0	4.3	1.5
case 5	4.5	1.5	0	90	51.4	20.6	60.4	9.9	4.1	3.9
case 6	4.5	1.8	0	90	35.3	18.2	38.5	17.5	3.6	1.2
case 7	4.5	2.0	0	90	45.6	16.4	-3.8	-1.8	2.5	1.6
case 8	4.5	2.2	0	90	41.5	16.7	-6.6	25.6	3.5	1.6
case 9	4.5	2.5	0	90	33.5	22.9	-7.3	45.3	6.4	2.9
case 10	4.5	3.0	0	90	39.2	26.0	4.4	29.2	9.4	6.1

4. Discussion

This study focuses on predicting the shape of the weld bead for welding distortion analysis, employing the deep learning method. Typically, to minimize error rates in deep learning, a sufficient amount of data needs to be gathered based on hundreds of cases. In this study, due to time and cost constraints associated with BOP welding and cross-sectional analysis, the training was conducted based on approximately 50 cases, resulting in a somewhat higher anticipated error rate. To facilitate a straightforward verification of the errors between actual and predicted values, visualization was performed, as depicted in Fig.3.



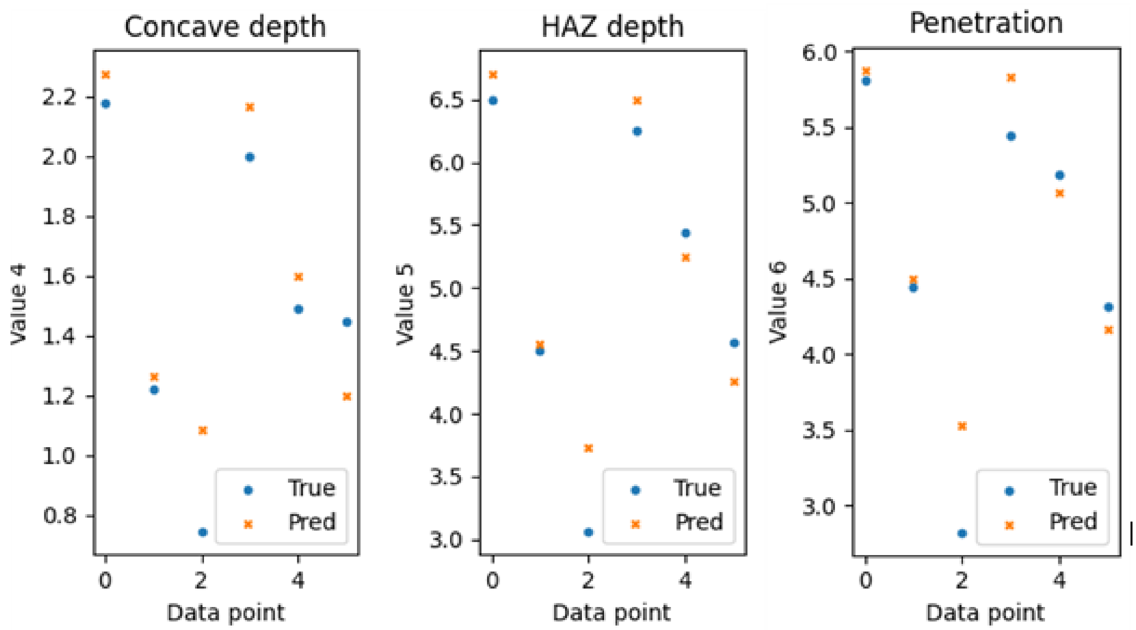


Fig 3. Graph for real and estimated case

According to Fig. 3, a trend is observed, but there seems to be some level of error. While the approach of this study holds significance, to derive more meaningful results, it is suggested that further research be conducted by accumulating more data for training. Alternatively, even with limited data, using Physics Informed Neural Network (PINN) could yield more meaningful and accurate results, calling for subsequent studies in this direction.

ACKNOWLEGEMENTS

This work was supported by Technology Innovation Program (project name : Equipment technologies for 50cm2 all solid state battery cell, project Number : 20012349) funded by the Ministry of Trade, Industry & Energy (MOTIE, Korea).

This research was supported by National R&D Program through the National Research Foundation of Korea(NRF) funded by Ministry of Science and ICT(2021M3H4A3A02098099)

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