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Development of a Deep Neural Network Model for Predicting Operational Parameters in Plate Forming via Line Heating

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ABSTRACT

The line heating process is widely used in shipbuilding to form complex curvatures in steel plates, particularly in the bow and stern sections. However, the method's reliance on skilled operators often leads to inconsistent results. This study presents the development of a deep neural network (DNN) model to predict optimal operational parameters for plate forming via line heating, thereby improving precision, repeatability, and automation. A coupled thermomechanical finite element model was developed using ANSYS APDL to simulate temperature distribution and deformation for various heating configurations. The simulation results were used to train the DNN, which consists of multiple hidden layers with dropout regularization to enhance generalization. The model successfully learned the nonlinear relationships between input parameters (heat source speed, heat input, and the number of heating passes) and resulting deformations. The trained DNN achieved high predictive accuracy, demonstrating its potential as a real-time decision-support tool in automated plate forming systems. This integration of FEM-based simulation and AI enables more efficient, consistent, and cost-effective manufacturing in the shipbuilding industry. The proposed DNN model achieved an average predictive accuracy of 49.92%, with performance exceeding 80% for cases with distinct deformation patterns.

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1. Introduction

Bending steel plates is crucial in ship construction, ensuring both the hull's shape and hydrodynamic efficiency. About 15% of the plates used require curvature, with each exhibiting a unique geometry based on its position. The bow and stern sections often feature complex double curvatures, known as non-Gaussian and non-developable surfaces, which are difficult to form with traditional methods. These areas, along with stiffeners, require precise bending processes, making ship construction more challenging.

Shipyards typically use mechanical and thermal bending methods to achieve the desired curvature. Mechanical bending involves presses and molds that apply force to shape the plates. However, due to the variability in curvature, particularly in double-curved surfaces, this method becomes inefficient and expensive. As a result, thermal bending, particularly line heating, is more widely used. In this process, heat is applied along specific lines on the plate, followed by cooling, causing localized expansion and contraction that results in bending without the need for molds or dies. Although line heating is flexible and adaptable, its success historically depended on skilled workers, often leading to inconsistent results.

Despite its widespread use, line heating presents challenges related to precision, repeatability, and control. Traditionally, the process relied heavily on the expertise of workers to manually determine heating paths, leading to variations in outcomes. The complex nature of the process, influenced by variables such as plate thickness, heat input, and path geometry, makes accurate prediction difficult. These challenges have driven a surge in research toward modeling, automation, and predictive analytics to improve control over deformation outcomes. Recent research, including machine learning techniques, aims to model the behavior of steel plates under line heating, optimizing heating parameters and determination of paths. These innovations are crucial for automating the process, improving consistency, and enhancing efficiency and quality in shipbuilding.

This section categorizes and synthesizes the major research directions into four thematic areas: (1) heating techniques, (2) numerical modeling and simulation, (3) automation and intelligent optimization, and (4) parametric studies.

1.1. Linear Heating Techniques: Flame vs. Laser

Traditional flame-based line heating methods, typically using oxy-acetylene torches, are widely applied in shipyards due to their simplicity and low cost. However, as Anderson [1] notes, these methods suffer from excessive heat dispersion, high reliance on operator skill, and inconsistent deformation patterns. In contrast, laser-based heating offers several advantages, including localized heat input, high precision, and the ability to form complex geometries such as sinusoidal and conical surfaces. These benefits are particularly valuable in modern shipbuilding, where automation and reduced labor dependency are prioritized.

Barry [2] highlights both technical and economic merits of laser-based linear heating, including improved accuracy, lower post-processing demands, and reduced heat-affected zones. The controlled energy delivery of lasers also enables tighter tolerances and repeatability, which are essential for automated production lines.

1.2. Numerical Modeling and Simulation

Accurate prediction of thermal and mechanical behavior is key to understanding and controlling line heating. Clausen [3] developed finite element (FE) tools for simulating heat transfer and predicting temperature fields, thereby reducing dependence on empirical methods. Building on this, Anderson [1] and Bai-chen [4] introduced simplified Gaussian heat source models to estimate temperature distribution and residual stresses more efficiently. Their approaches enabled the coupling of thermal-mechanical simulations using ANSYS. Shahidi [5] advanced this methodology by performing thermal simulations in Fluent and mechanical analysis in MAPDL. Their work emphasized the critical role of cooling both natural and forced in influencing final deformation.

Shabani [6] has carried out a study on the simulation of thermal distribution during the welding process using ANSYS software, focusing on residual stresses and the deformation of plates.

Lee et al. [7] conducted thermo-elastic-plastic FEM simulations on EH36 steel saddle plates, effectively quantifying the influence of geometric and process parameters on shrinkage and deflection, thereby providing critical insights for lightweight ship design and automated forming processes.

1.3. Automation and Optimization through AI and Robotics

To overcome limitations associated with manual operation, several industrial and academic efforts have focused on automation. Tango, et. al from IHI Corporation [8] and Jang, et. Al [9] introduced robotic systems like Alpha-IHIMU, which automate torch handling and process execution. These systems offer repeatability and efficiency but face challenges such as the need for worker retraining, offline programming, and limited flexibility in adapting to plate variations.

The integration of machine learning into prediction and optimization tasks has opened new frontiers. Li & Wang [10] employed an Improved Sparrow Search Algorithm with Extreme Learning Machine (ISSA-ELM) to model and predict plate deformation. Their data-driven approach captured the nonlinear relationships between process parameters and deformation outcomes with high accuracy and demonstrated the feasibility of applying ML to substitute or supplement conventional simulations.

Masahito Takezawa [11] developed a support system for ship-hull plate forming using a laser scanner. Their method constructs a B-spline surface from scanned point cloud data and uses differential geometry to analyze the current plate shape.

1.4. Influence of Operational Parameters

Understanding the impact of process parameters is vital for both simulation accuracy and real-time control. Das [12] used the Taguchi method to analyze the influence of laser power, scan speed, and plate thickness on bending angle, developing regression models for deformation prediction. Their findings underscored the sensitivity of deformation to thermal input and process speed.

Lee & Lim [13] investigated the effect of multi-line heating and spacing between heat lines on the angular deviation and flatness of the final product. Their work provided practical guidelines for torch arrangement in complex curvature generation, highlighting the need to consider thermal overlap and mechanical interaction between adjacent lines.

The reviewed studies collectively demonstrate the evolution of line heating from manual, empirical practice to a data-driven, automated, and simulation-based discipline. Flame heating remains widely used due to its low cost and ease of implementation, yet laser heating is gaining ground in precision applications. Simulation tools, particularly finite element models, have enabled accurate prediction of temperature and stress fields, though their computational cost can be prohibitive in large-scale use.

Artificial intelligence and machine learning present a promising alternative, offering faster predictions and the potential for real-time process control. However, most existing ML models are still limited by the availability of high-quality training data and lack physical interpretability. Robotic systems offer consistency and speed, but challenges in adaptability and user-friendliness remain.

In this study, an AI-based system is developed to automatically predict the optimal heating parameters for shaping the sail-plates. The goal is to improve the accuracy, repeatability, and speed of the bending process, reduce costs, and enhance the quality of production.

2. Methods and Theories

2.1. Coupled Thermomechanical Simulation of the Line Heating Process in FEM

Thermomechanical simulation of the line heating process in an FEM environment, such as ANSYS, models the heat application and the thermal and mechanical responses of steel plates during the bending process. This approach enables the prediction of deformation due to localized heating.

The process begins with thermal analysis, where heat is applied along predefined lines on the plate’s surface. This heat induces non-uniform temperature distribution, which propagates through the material. Once the thermal analysis is complete, a mechanical analysis is performed. The temperature distribution from the thermal model is used to simulate thermal expansion, which induces internal stresses. Material properties such as yield strength and stiffness, which vary with temperature, are included to accurately simulate deformation.

The thermal and mechanical analyses are coupled, where the output of the thermal analysis (temperature distribution) serves as input for the mechanical analysis. This coupling ensures the accurate simulation of thermomechanical behavior. Additionally, material models are chosen to account for nonlinear behavior, including plasticity and phase changes, which are crucial for high-temperature conditions common in line heating.

In this study, a Gaussian heat source model (eq. 1) is employed to simulate the localized heat input during the line heating process.

$$q_r = q_{max} exp\left(\frac{-3r^2}{R^2}\right)(1) \qquad (1)$$

where q_r is the heat flux at a distance r from the center of the arc, Q is the total heat input, R is the characteristic radius that defines the heat distribution and q_{max} is the maximum heat flux at the center.

The parameter R depends on the heat source and other process variables. However, for simplicity and based on common practice, it is assumed to be 8 mm, which corresponds to approximately 95% of the total arc energy being delivered within this area.

Once the heat source is defined, the temperature distribution across the steel plate is obtained by solving the heat conduction equation using finite element analysis (FEA) in ANSYS, where both the heat source and boundary conditions (such as convection or forced cooling) are applied. By solving this equation over time, the temperature distribution is calculated across the plate at any given time during the heating process. This temperature field serves as the input for the subsequent mechanical analysis, where the induced thermal stresses and deformations are computed.

3. Finite Element Simulation

3.1. General Assumption

The finite element analysis in this study was carried out using ANSYS APDL 2024 R2. A three-dimensional steel plate, measuring 1000 × 1000 mm with a thickness of 8 mm, was modeled. A circular heating path with a radius of 240 mm from the center of the plate was considered for the application of heat considering a 10 mm radius torch.

SOLID70, an eight-node three-dimensional thermal element, and SOLID45, a three-dimensional structural element capable of modeling nonlinear material behavior, were employed for the thermal and structural analyses, respectively. To ensure precise heat application, a circular region with a width of 20 mm and an inner radius of 230 mm was defined, allowing for the generation of a fine and structured mesh.The element edge lengths in this region were set to 5 × 10 mm and were gradually increased up to 40 mm toward the outer edges of the plate.

As indicated in validation section and some previous studies [14,15], one element along the thickness is enough, however in this study, two numbers are considered.The finite element model, along with the boundary conditions of the mechanical analysis, is shown in Figure 1. To accurately simulate the boundary conditions, contact elements are defined beneath the plate surface, with their nodes constrained in the Z (vertical) direction. This configuration allows the steel plate to deform freely in all other degrees of freedom. Additionally, a node at the center of the plate is fully constrained in the X, Y, and Z directions to prevent rigid body motion during the simulation.

Free convection boundary conditions were considered for all steel surfaces in contact with air and ground.

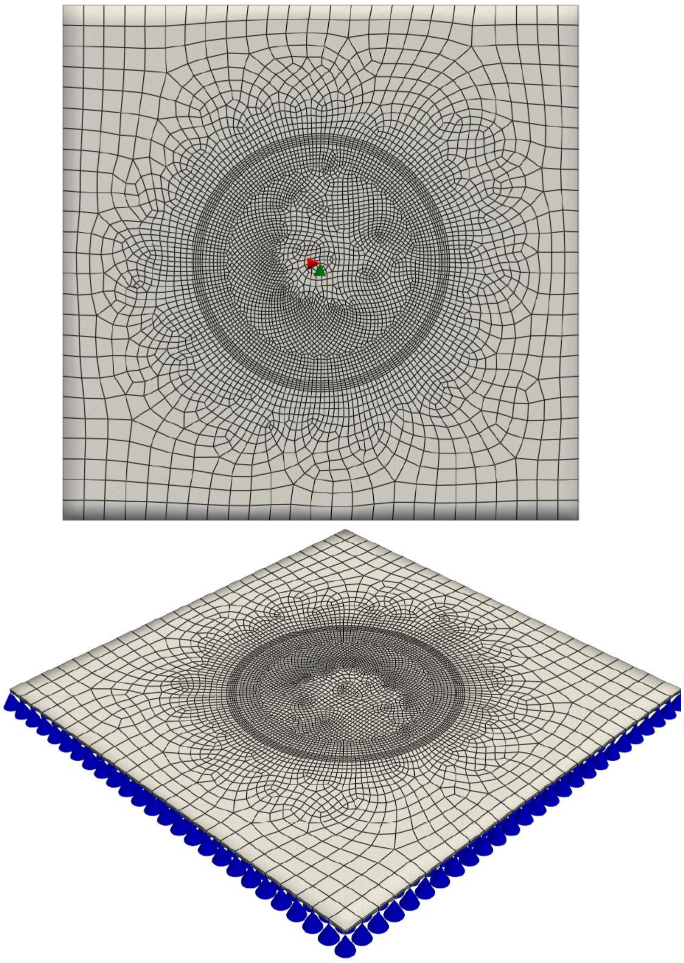

Figure 1. Model Geometry and Boundary condition

3.2. Extent of the Models

While the plate's length, width, thickness, and heating path location were kept constant, three key operational parameters were varied independently: heat source speed (4 levels), heat input (4 levels), and number of heating passes (3 cases). The values of the varying parameters are presented in Table 1. This resulted in a total of 48 simulation cases. However, due to the imposed maximum temperature limit of 700 °C, only 36 cases remained within the permissible range and were therefore considered for prediction of line heating parameters.

Table 1. Numerical data

Variable Parameters	Values
Heat Source Speed [*mm/s*]	5, 6, 7 and 8
Heat Input [*W*]	4000, 5000, 6000 and 7000
Number of Passes	1, 2 and 3

3.3. Material Properties

Material properties were adopted from the work of Biswas [15]. Table 2 presents the temperature-dependent properties of C-Mn-III steel used in the transient heat transfer and elastoplastic analyses. Additionally, Figure 2 illustrates the variation of yield strength with temperature for C-Mn steel, as reported in Biswas [15].

Table 2. Temperature-dependent properties of C-Mn-III steel

T [°C]	E [GPa]	ν -	α [10^{-6}/°C]	K [W/m·K]	c [J/kg·K]
0 °C	200	0.28	10	51.9	450.0
100 °C	200	0.31	11	51.1	499.2
300 °C	200	0.33	12	46.1	565.5
450 °C	150	0.34	13	41.5	630.5
550 °C	110	0.36	14	37.5	705.5
600 °C	88	0.37	14	35.6	773.3
720 °C	88	0.37	14	35.6	773.3
800 °C	20	0.42	14	26	931.0
1450 °C	2	0.47	15	29.45	437.9

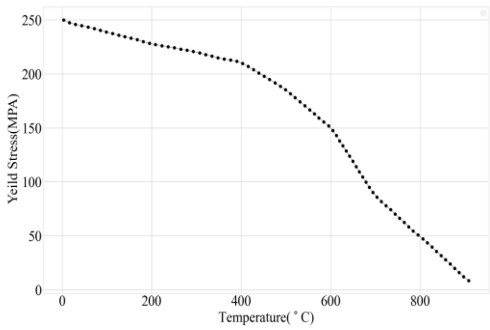

Figure 2. Variation of Yield Strength with Temperature

3.4. Validation

The developed numerical model was validated against the experimental and numerical results reported by Biswas. In his study, line heating was applied to a steel plate with dimensions 300 × 250 × 8 mm using a 5500 W torch with an 8 mm radius at a speed of 6 mm/s for a total of 50 seconds. The simulation results of the present study, including residual deformation, showed close agreement with Biswas' findings, confirming the accuracy of the model (Figure 3). Further details of the experimental setup, procedure and plate properties can be found in Biswas [15].

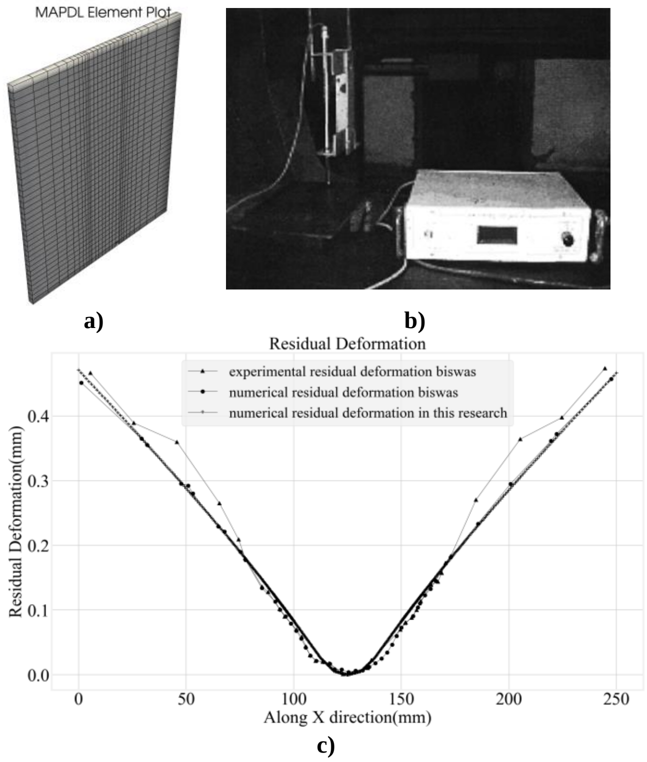

Figure 3. (a) FE Model (Present Study). (b) Biswas Test Setup [15]. (c) Residual deformation pattern along the width of the plate.

4. Results and Discussion

4.1. Model Deformations (Based on FEA Results)

As mentioned earlier, a fully transient analysis was conducted for both thermal and mechanical simulations. The temperature distribution and the resulting plate deformation were calculated at each time step during the heating process. An example of the deformed shape due to circular line heating is presented in Figure 4 (heat source speed: 5 mm/s, heat input: 5000 W, number of heating passes: 3). A total of approximately 700,000 deformation data points were extracted across the plate during the heating process. These data points serve as input for the machine learning model, which is trained to predict deformation based on the heat source speed, heat input, and number of heating passes.

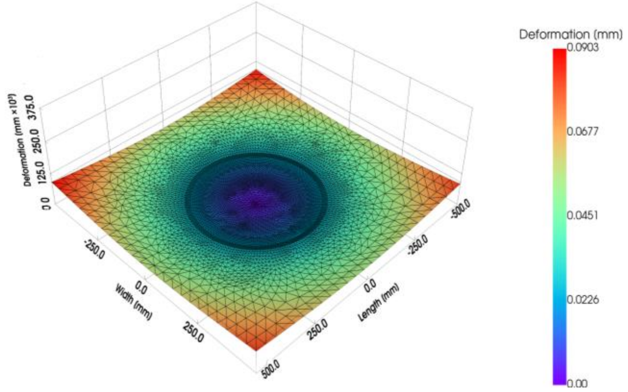

Figure 4. Plate Deformation (5 mm/s heat source speed, 5000 W heat input and 3 number of heating passes)

4.2. Machine Learning

Deep neural networks (DNNs) (Figure 5) have significantly transformed the field of artificial intelligence, often outperforming conventional machine learning techniques. Modeled after the human brain, these sophisticated architectures are adept at managing complex tasks such as image recognition and natural language understanding.

The model consists of multiple hidden layers, each designed to progressively extract and learn hierarchical features from the input data. To reduce the risk of overfitting and improve the model's generalization capability, dropout regularization is applied after certain hidden layers. This technique randomly deactivates a portion of neurons during training, ensuring the network does not rely too heavily on specific paths.

Training is conducted over multiple epochs, during which the entire dataset is repeatedly passed through the network to refine its internal parameters. Instead of feeding all the data at once, the dataset is divided into smaller batches, which helps improve computational efficiency and stabilize learning.

A suitable loss function is employed to measure the difference between the model's predictions and the actual labels. This loss guides the optimization algorithm in updating the model weights. The final output layer is responsible for generating a probability distribution over all target classes, enabling accurate classification. The model's performance is evaluated using accuracy, reflecting the proportion of correctly predicted instances.

In this study, regression-based approaches were initially considered to predict deformation values directly from the input parameters. However, each of the 36 simulation cases (samples) contained multiple variables and only a single output per case, which limited the feasibility of conventional regression models. Conducting separate regressions for each variable would have been inefficient and prone to error. Therefore, each simulation case was instead treated as a distinct class, and the task was reformulated as a classification problem.

The neural network was designed to identify the inherent patterns of each class from the large number of deformation records available within a single simulation. This approach enabled the model to learn the distribution of patterns corresponding to different operational parameters, despite having only one overall output per simulation. While this strategy improved the ability of the model to generalize, the inherent limitation of single-output-per-sample simulations caused a performance drop. Ultimately, the model achieved an average prediction accuracy of 49.92%, with variations of up to 80% depending on the sample.

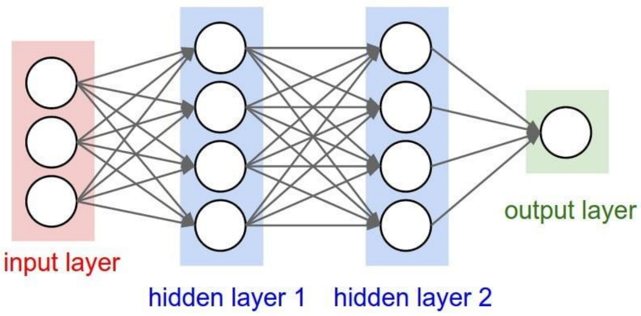

Figure 5. Deep Neural Network (DNN)

4.3. Prediction of Line Heating Parameters (Based on DNN Algorithm)

The objective of this model is to predict thermal parameters based on the desired deformation—a process herein referred to as prediction. The thermal parameters considered in this study include heat source speed, heat input, and the number of heating passes, all of which significantly affect the resulting deformation. The dataset comprises approximately 700,000 data points collected from 36 different models, each containing deformations at each node and their corresponding location.

A key challenge in this modeling task lies in the inability to designate specific coordinates as training or testing data, as each model corresponds to a single simulated sample, and experimental data is essential for proper validation. To mitigate this limitation, a small random value, drawn from a uniform distribution in the range of (−0.001, 0.001), was added randomly to a subset of records. This slightly modified version of the original dataset was then used as the database.

To prevent overfitting, dropout techniques were applied at various stages of the neural network. The data first passed through a layer of 256 neurons with a dropout rate of 0.3, followed by a 128-neuron layer with the same dropout rate. In the final hidden layer, the data flowed through a layer with 64 neurons and a dropout rate of 0.2. The output from this layer was connected to the final output layer, which consisted of 36 neurons corresponding to the number of classes in the problem and was designed to predict the probability distribution across these classes.

The model was trained over 100 epochs, meaning the entire training dataset was presented to the model 100 times. A batch size of 64 was employed to accelerate the training process while maintaining predictive accuracy. An appropriate loss function was selected for training, and accuracy was used as the evaluation metric, representing the percentage of correct predictions. As shown in Table 3, all 700,000 data points were used for training. It should be noted that the dataset presented in Table 3, which contains the deformation coordinates and displacements, was directly used as the input to the DNN. These features enabled the network to learn the relationship between deformation patterns and the corresponding simulation cases.

Table 3. Sample Input Data For DNN

model -	X mm	Y mm	Z mm	DispX mm	DispY mm	DispZ mm
1	500	-500	8	0.12	-0.12	0.09
	….	….	….	….	….	….
2	500	-500	8	0.04	-0.04	0.01
	….	….	….	….	….	….
….	….	….	….	….	….	….
36	500	-500	8	0.15	-0.15	0.05
	….	….	….	….	….	….

As shown in Figure 6, some FEM-simulated samples achieved an accuracy exceeding 80%, indicating that the DNN successfully recognized deformation patterns when the differences between cases were relatively large. These results are promising and demonstrate the capability of the model to capture distinct deformation behaviors. However, since the dataset was generated from finite element simulations, each input case corresponded to only one fixed output. This limitation reduced the overall accuracy, particularly for samples with highly similar deformation patterns. In such cases, the network had difficulty distinguishing between them, which directly resulted in lower accuracy.

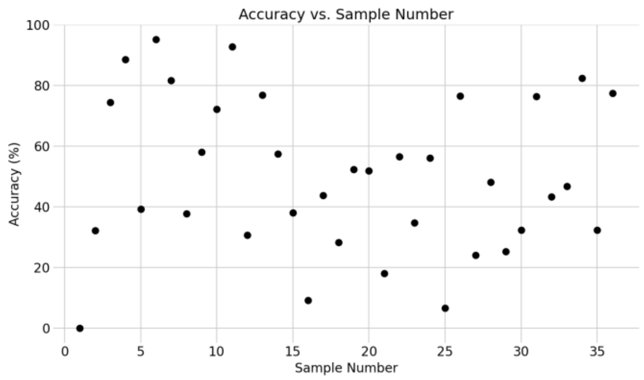

Figure 6. Accuracy of All Samples

5. Conclusions

In this study, previous works related to the line heating process as well as research involving the application of artificial intelligence in predicting the process were reviewed. A numerical model was then developed and validated using both experimental data and existing simulations to assess its accuracy. Subsequently, A new method has been proposed to predict the operational parameters (output data) for line heating process to obtain the required deformation in the plates (input data), contributing to improved control of the forming process in shipbuilding. The thermal parameters considered in this study include heat source speed, heat input, and the number of heating passes, all of which significantly affect the resulting deformation. At the final stage, machine learning technique (Deep Neural Network) was employed as a tool to enhance the accuracy of deformation prediction.

In the final conclusion, it is important to emphasize the range of accuracies achieved by the DNN model, culminating in an average accuracy of 49.92%. The lowest classification accuracies were observed in cases where deformation patterns were highly similar, while the highest accuracies (above 80%) corresponded to samples with distinct deformation characteristics. The selected DNN architecture, with layered dropout regularization, demonstrated the best balance between generalization and predictive capability**.**

For future work, it is recommended to extend this approach to more complex geometries such as saddle plates, enabling broader application of the method under more realistic industrial conditions. Additionally, to improve prediction accuracy, several strategies can be considered. First, adding real samples and accurately labeling them can significantly enhance the model's learning capability. Second, increasing the number of simulated models can provide a more diverse dataset for training. Third, redundant or common points across all samples can be removed to reduce noise and improve model focus. Finally, fine-tuning the model may lead to better results; however, this step requires access to high-performance computing resources.

Furthermore, to overcome the limitation of having only one deformation output per simulation sample, a deformation-based data augmentation strategy can be applied. By introducing small artificial distortions into each sample and labeling them consistently with the original class, it becomes possible to create multiple variations from a single simulation. For instance, generating around 100 distorted versions of each sample would provide a richer dataset, enabling the DNN to better learn deformation patterns. This approach is expected to significantly improve the model's predictive accuracy and robustness in subsequent studies.

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7. List of Symbols

E	Young's Modulus [Gpa]
K	Conductivity [W/m·K]
T	Temperature[°C]
c	Specific Heat [J/kg·K]
α	Thermal Expansion [10^{-6} / °C]
ν	Poisson's Ratio

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