

Full length article

Optical coherence measurement-based penetration depth monitoring of stainless steel sheets in laser lap welding using long short-term memory network

Leshi Shu, Deyuan Ma, Shenjie Cao, Yilin Wang^{*}, Ping Jiang, Shaoning Geng

State Key Laboratory of Intelligent Manufacturing Equipment and Technology, School of Mechanical Science and Engineering, Huazhong University of Science & Technology, Wuhan, Hubei 430074, China

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ABSTRACT

The industrial production site for laser lap welding of thin stainless steel plates puts strict requests on the level and fluctuation stability of penetration depth. Hence, the penetration depth monitoring is increasingly garnering attention. This research proposes an optical coherence measurement-based approach to monitor penetration depth utilizing machine learning in laser lap welding for stainless steel sheets. After the acquisition of the keyhole depth signal by the coherent light beam, it is found that there is a significant association relationship between the reconstructed keyhole depth obtained by empirical modal decomposition and the penetration depth curve, but meanwhile a penetration depth monitoring error also exists. Accordingly, based on the cross-correlation analysis and numerical simulation, it is revealed that the formation mechanism and sources of this error are related to the “bottom melt layer thickness”, “hysteresis property” and “multiple reflections”. On this basis, a long short-term memory network is built to memorize the historical information of the reconstructed keyhole depth for predicting the penetration depth at each moment. The experimental results demonstrate that the prediction model has high accuracy and good generalization ability, and thus effective monitoring for penetration depth can be achieved.

1. Introduction

As an advanced heat source for material joining manufacturing, laser is widely used in the welding stainless steel sheets [1,2] because of its advantages such as high speed, high energy density and small heat-affected zone [3]. Non-penetration laser lap welding can improve the aesthetics of the weld and the sealing of the component, which is often applied in train body side walls and power cell top covers [4,5]. In the non-penetration laser lap welding process, the penetration depth is a key factor to ensure the aesthetics of the weld and the mechanical properties of the components. If the penetration depth is too large, the lower plate will appear heat-affected traces, and the weld will be unsightly. If the penetration depth is too small, the strength of the welded joint will be reduced, and even the upper plate will not be penetrated. Therefore, it is very necessary to monitor the penetration depth of the non-penetration laser welding.

Penetration depth monitoring technology based on traditional sensors mainly collects various acoustic, optical and visual signals in the

laser welding process, extracts signal features, and establishes the corresponding relationship between them and penetration depth. Accordingly, it indirectly predicts penetration depth. With the aid of the built ultrasonic phased array system, Mizota et al. [6] measured the depth of the molten pool via computing the time of the receiving system. Huang and Kovacevic [7] defined two acoustic characteristics of sound pressure deviation and band frequency, and established the relationship between acoustic characteristics, welding parameters and weld penetration states, which can predict the overall penetration depth of each weld. Mrna et al. [8] used a photodiode to collect the light intensity signal of the plasma plume from 190 nm to 1110 nm, and investigated the correlation between the weld melt depth and the optical frequency characteristics. Sibillano et al. [9] used a spectrometer to collect the light intensity signal of the plasma plume from 400 nm to 530 nm and calculated and derived the electron temperature of the plasma plume, and then the correlation between the feature and the penetration depth is established. Finally, the laser power was adjusted in real time through the PI controller to ensure the penetration depth stability. Zhang et al.

^{*} Corresponding author.

E-mail address: wangelin@hust.edu.cn (Y. Wang).

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[10] built a set of high-speed camera coaxial online monitoring system, using the area growth algorithm to calculate the ratio of the diameter of the keyhole at the top and bottom. Subsequently, the penetration state of the weld was divided into “incompletely penetrated”, “moderately penetrated” and “over-penetrated”. Blug et al. [11] used a coaxial high-speed camera to acquire the images of the keyhole and molten pool during laser welding, and used an omnidirectional algorithm to count the number of keyhole pixels, which established a quantitative relationship between this pixel number and the penetration depth. In summary, the penetration depth monitoring technology based on traditional sensors is easily interfered by various noises. The most critical problem is that the correlation between the measured characteristic signals and the penetration depth is not obvious in many cases, and thus the error is large.

Plenty of studies have indicated that the most intuitive reflection of the fluctuation of penetration depth is the variation of keyhole depth to which it is directly related [12,13]. Among the few measurement techniques for keyhole depth, a coherence interferometry-based emerging imaging way called optical coherence tomography (OCT) can obtain morphological features of biological tissues, and it is now widely used in the clinical examination of medical diseases and the real-time monitoring of the manufacturing process status [14]. The main advantages of OCT are its non-contact measurement, high measurement frequency and high measurement accuracy [15]. In 2006, Precitec Germany introduced a distance sensor based on optical coherence measurement, which is suitable for long-distance measurement. The keyhole depth can be measured directly by this sensor in the laser welding process, and the measurement accuracy is not affected by metal vapor, factory gray layer and various materials [16]. Blecher et al. [17] used inline coherence imaging (ICI) to accomplish online measurement for the keyhole depth of five different materials during laser welding with an error of less than 5 % compared to the weld depth of metallographic sections, except for aluminum alloys. In 2018, the penetration depth monitoring technology based on optical coherence measurement achieved industrial application for the first time: it utilized the keyhole depth data collected by the OCT sensor to control the laser power, thereby controlling the stability of the weld penetration depth in the continuous laser welding production process [18]. However, the OCT sensor also collects a lot of invalid data during the laser welding process, because the keyhole is continuously generated and collapsed, and the keyhole depth then oscillates at high frequency, while the fluctuation of the penetration depth is smooth. Therefore, how to predict more accurate penetration depth from the keyhole depth data points is the most critical issue.

Currently, artificial intelligence (AI) technology has been proved to be applicable to online prediction of various states and targets in the laser welding process [19–21]. However, in the face of the penetration depth curve characterized by both strong time-varying and nonlinear properties, it is difficult for traditional AI models to achieve very ideal quantitative prediction results. Fortunately, many time series networks have flourished in recent years. As an impressive example, long short-term memory (LSTM) network that can carry time history information has been found to perform well in the field of intelligent laser manufacturing [22,23]. Accordingly, the LSTM model provides a powerful tool for real-time monitoring of the penetration depth curve during laser welding.

This research aims to build an online penetration depth monitoring system in laser lap welding of stainless steel sheets based on optical coherence measurement, which can accurately predict the penetration depth at each welding position in real time. The correlation between the keyhole depth and the penetration depth is investigated, and the mechanism and sources of penetration depth monitoring error are revealed by numerical simulation technique. On this basis, an AI model based on LSTM network for predicting penetration depth is constructed, and the prediction accuracy of the model is verified. Ultimately, it is worth mentioning in particular that unlike the qualitative detection of various penetration states, which has been widely studied, this research

achieves the quantitative monitoring of the penetration depth curve and can allow the prediction of the specific depth value at each moment.

Together four sections make up the remainder of this paper. In Section 2, the experimental setup with optimum process condition and the optical coherence measurement technology are presented. Section 3 explores the correlation relationship between keyhole depth and penetration depth, and provides the details of the implementation of numerical simulation. In Section 4, the construction process of the LSTM utilized to monitor the penetration depth are described along with the theoretical basis of the network model. Eventually, Section 5 summarizes the main research conclusions.

2. Experimental setup and OCT technology background

2.1. Experimental setup

The experiment platform of stainless steel laser lap welding and the penetration depth monitoring system are shown in Fig. 1. The fiber laser equipment installed here is IPG YLS-10000 with a maximum laser power of 10 kW and a wavelength of 1060 nm. A laser welding head IPG FLW-D50-W is used, and the diameter of the spot after collimation and focusing is 0.5 mm. A KUKA six-axis robot with repeat locating accuracy of ± 0.05 mm is used. The penetration depth monitoring system adopts the IPG LDD-700 coherent optical system with an imaging wavelength of 840 nm and a measurement frequency of 250 kHz. The experiments utilize a form of flat plate lap, the experimental material is 316L stainless steel, and the upper and lower plate sizes are 200 mm $\times$ 100 mm $\times$ 0.8 mm and 200 mm $\times$ 100 mm $\times$ 2 mm, respectively. Table 1 exhibits the 316L material's chemical composition. For removing the surface oil and oxide film before welding, a polishing machine is utilized to polish the surface of the workpiece, and anhydrous ethanol is used for cleaning.

2.2. Penetration depth monitoring technology based on optical coherence measurement

As exhibited in Fig. 2(a), the penetration depth monitoring system based on optical coherence measurement mainly consists of light source, beam splitter, reflector lens and photodetector, and the schematic diagram of the measurement principle is shown in Fig. 2(b). The beam emitted from the coherent light source is divided into two beams by the beam splitter. One beam is reflected at the surface of the workpiece through the reference path and the other beam is reflected at the bottom of the keyhole through the measurement path. The two reflected beams are recombined at the beam splitter, which is captured by the photodetector for evaluation and analysis. Coherent interference occurs when there is an optical range difference between the reference path and the measurement path within the coherence length of the light source. A larger optical range difference indicates a larger modulation frequency produced in the interference spectrum and a deeper distance. Subsequently, the keyhole depth data can be calculated by spectral analysis. Finally, the keyhole depth curve is fitted by the luminance threshold segmentation algorithm and the filter smoothing algorithm.

The coherent light beam has a wavelength of 840 nm, which is in the near-infrared band, and has sufficient light intensity to easily break through the barrier of weak metal vapor and plasma, so that clear measurement results can be obtained at all times. For accurate measurement of the keyhole depth, determining the location of the deepest part of the keyhole is the most necessary condition. Different welding process parameters correspond to different locations of the deepest part of the keyhole. During laser welding, the metal material rapidly melts and evaporates to produce keyhole, and the sidewall of the keyhole continuously expands outward under the action of steam recoil pressure. However, the front of the keyhole is the area to be welded, and the rear of the keyhole is the melted metal material. On the one hand, the expansion resistance in front of the keyhole is greater than that in the rear, so the deepest location of the keyhole lags behind the laser beam

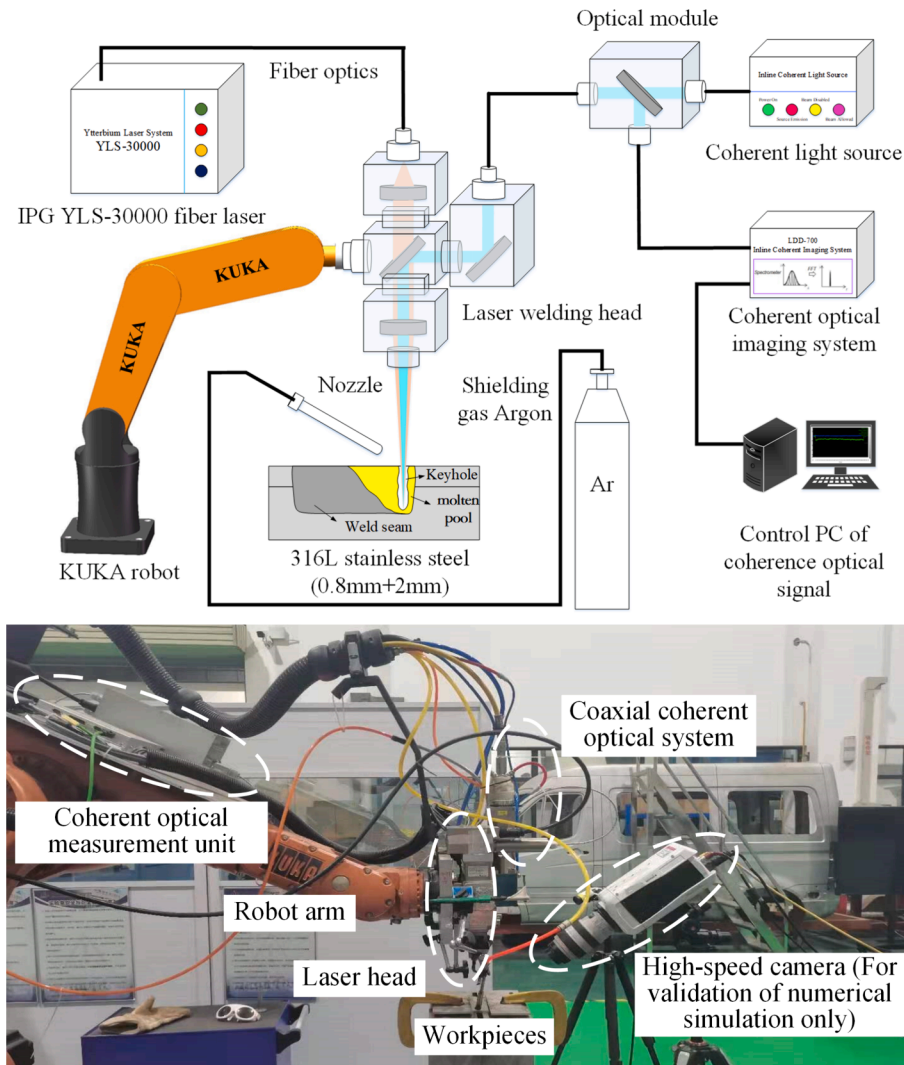


Fig. 1. The stainless steel laser lap welding platform and penetration depth monitoring system.

Table 1
The chemical composition of 316L stainless steel.

Element	C	Ni	Mo	Cr	Mn	Si	N	Fe
Wt(%)	0.023	13.1	2.66	17.3	1.74	0.73	0.1	Balance

location. On the other hand, the laser beam is coaxial with the coherent light beam. The 3D morphology of the keyhole is obtained by coherent light surface scanning, as shown in Fig. 3. The redder color of the data points indicates that the coherent light beam is more likely to directly irradiate to the deepest part (maximum depth) of the keyhole. The location of the data point with the reddest color is saved as the deepest location of the keyhole, which is used for subsequent real-time measurement of the keyhole depth under the same process parameters. In addition, it is worth noting that the keyhole opening marked in Fig. 3 is flush with the workpiece surface, serving as the starting position of the keyhole depth in the vertical direction.

In the practical engineering application site of this research, it is required that the penetration depth should be as large as possible but no heat-affected marks should be allowed on the backside of the lower plate. Therefore, the exploration of the process parameters is first conducted. As exhibited in Fig. 4, the experiments are carried out under varying laser power and varying welding speed respectively, and the front and back images of welds with their size data are acquired. The

optimum combination of process parameters is finally determined as displayed in Table 2.

3. Analysis on the formation mechanism of penetration depth monitoring error

With the development of computer techniques in recent years, many scholars have used numerical simulation methods to analyze the dynamic behavior of the molten pool and keyhole during laser welding, so as to reveal its inherent laws. Liu et al. [24] established a numerical simulation model for high-power laser welding of 316L stainless steel, revealing the correlation between three typical weld morphologies and the dynamic behavior of the molten pool. Wang et al. [25] used a modified ray-tracing method to numerically simulate a 10-mm-thick 316L laser welding process and investigated the effect of energy density decay on the stability of the molten pool and keyhole. This chapter mainly studies the dynamic behavior of the keyhole and the process of penetration depth curing from the perspective of numerical simulation, and clarifies the formation mechanism of the penetration depth monitoring error.

3.1. Relationship between keyhole depth and penetration depth

Before performing numerical simulation for the welding process, it is of great necessity to explore the relationship between keyhole depth and

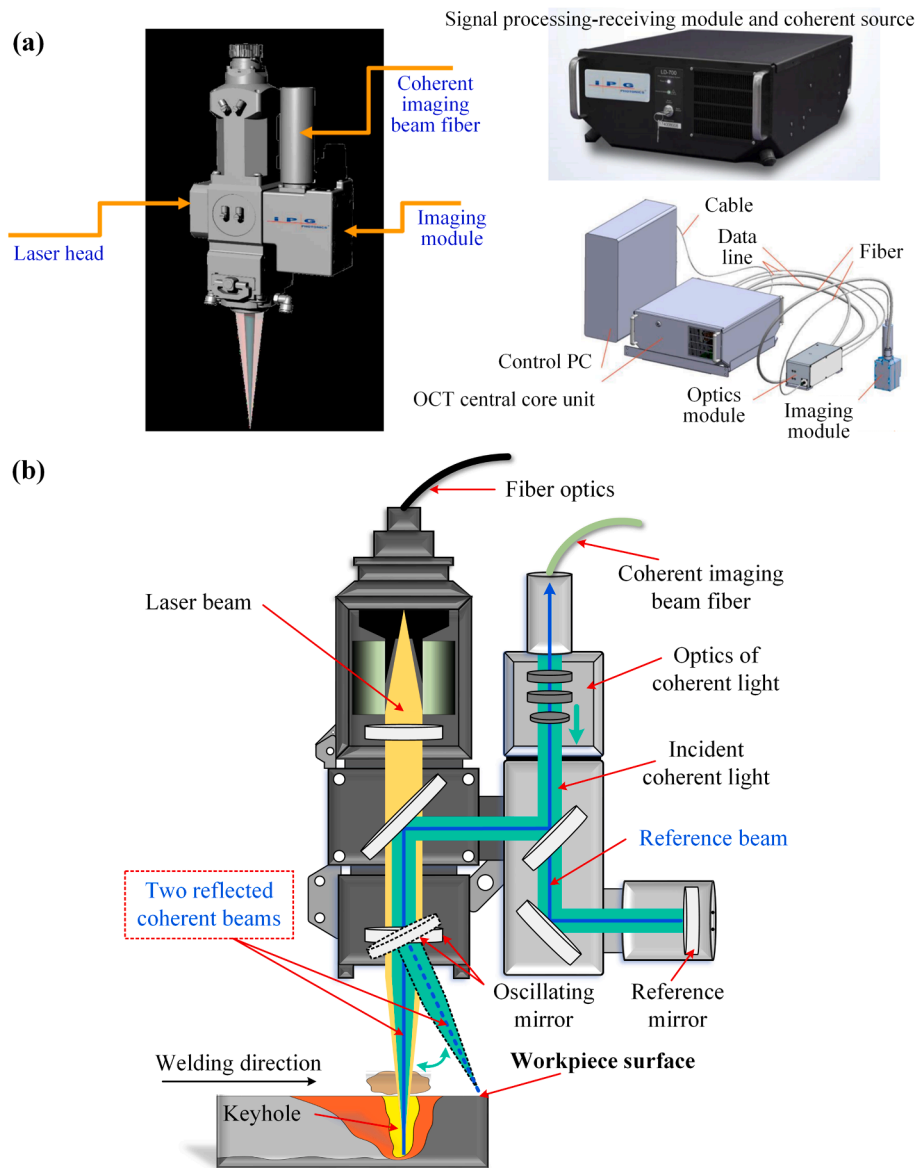


Fig. 2. Optical coherence measurement: (a) Components of OCT equipment; (b) Measuring principle.

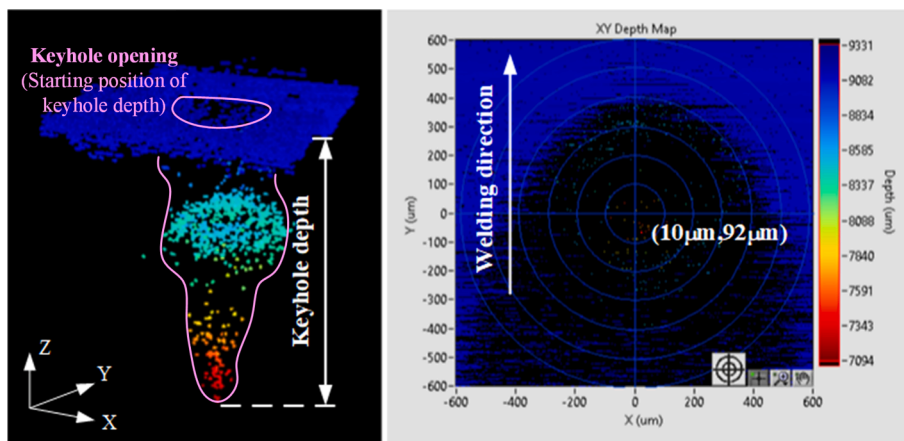


Fig. 3. Keyhole 3D morphology imaging.

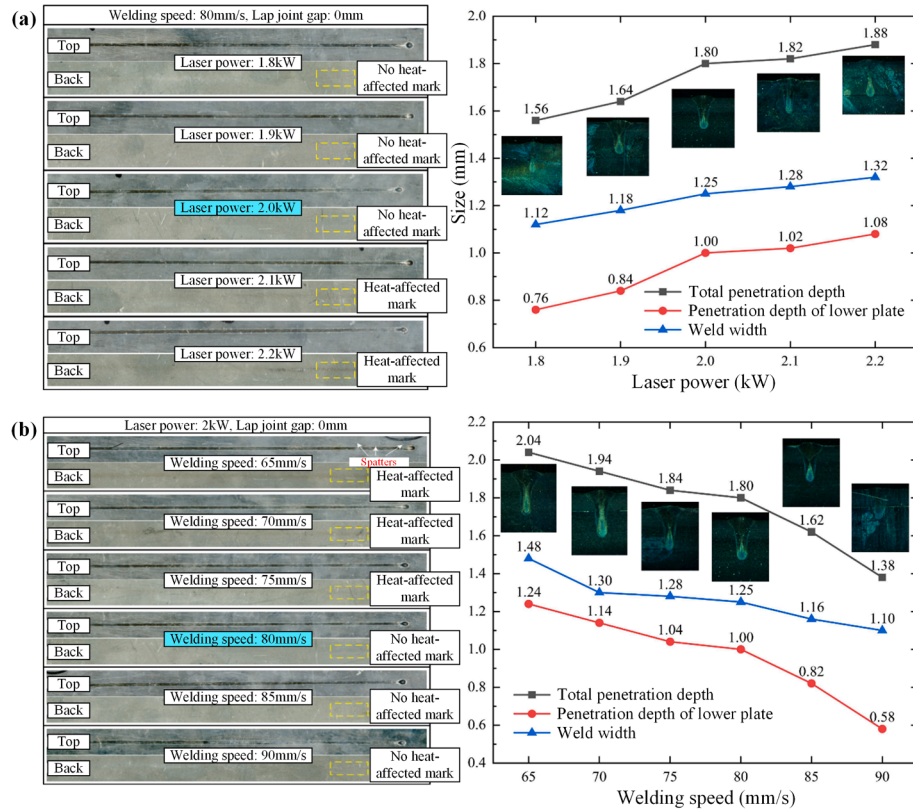


Fig. 4. Front and back images of welds with their size data under different combinations of process parameters: (a) Varying laser power; (b) Varying welding speed.

Table 2

The optimum combination of process parameters.

Welding parameters	Value
Laser power	2000 W
Welding speed	80 mm/s
Defocusing amount	0 mm
Shielding gas and its flow	Ar and 25 L/min
Laser deflection angle	+5°

penetration depth at the signal aspect for more data information guidance. The raw signal of the keyhole depth measured by the IPG LDD-700 optical coherence measurement system is shown in Fig. 5, with dramatically oscillating waveform and many interstitial peaks and valleys. Apparently, it is a non-smooth signal, and its negative values denote that the workpiece surface with a value of zero is the reference plane. Empirical modal decomposition (EMD) algorithm is used to filter and denoise the original keyhole depth signal to extract the local real features.

As an adaptive time–frequency analysis tool, the major advantage of EMD is that its basis function can be derived from the signal itself [26,27], rather than relying on manual selection like wavelet packet transform and other traditional methods. Especially for signals whose frequency characteristics are completely unknown beforehand, such as the keyhole depth data during laser welding, the EMD algorithm that can adaptively and automatically determine the basis function is more suitable.

As formulated in Eq. (1), a non-stationary signal $x(t)$ can be converted into multiple single-frequency waves (with a series of different frequencies) and a remainder term by EMD:

$$x(t) = \sum_{i=1}^n c_i(t) + r_n(t) \quad (1)$$

where $c_i(t)$ represents each of intrinsic mode functions (IMFs), $r_n(t)$ denotes the remainder term. Here, after decomposition, a total of 9 IMFs expressed in descending frequency order and a remainder term are obtained. Among them, IMF 1 to IMF 3 are regarded as high-frequency detail components, and IMF 4 to IMF 9 are regarded as low-frequency approximate components which finally realize reconstruction together with the remainder term. The keyhole depth signal reconstructed by the EMD algorithm is shown in Fig. 5, and the effect of filtering and denoising is obvious.

An issue deserving clarification in industrial production is that

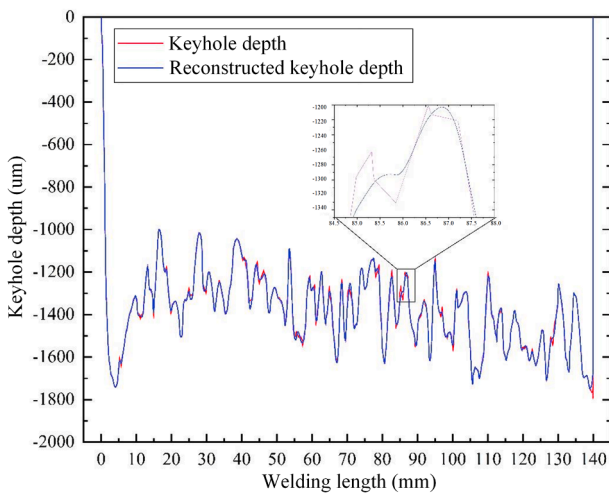


Fig. 5. Comparison of the original keyhole depth signal and the EMD-reconstructed keyhole depth signal.

during the penetration depth monitoring process, the IPG LDD-700 optical coherence measurement system actually measures the keyhole depth, rather than the penetration depth. The procedure of collecting true penetration depth data is provided here. Longitudinal section, grinding, and etching are performed on each weld in turn. The Epson Perfection V33 scanner is used to acquire the weld longitudinal section image, and the resolution can reach 2400 dpi. Finally, Photoshop is used to key out the melting area, and the penetration depth value at each position of the weld is computed, as shown in Fig. 6.

Fig. 6 also shows the relationship between the reconstructed keyhole depth signal obtained by EMD and the actual penetration depth curve. A clear correlation can be seen to exist, and the degree of correlation between keyhole depth and penetration depth is measured by cross-correlation analysis.

Cross-correlation analysis is a signal processing method used to measure the degree of correlation of time series and to estimate the time delay. The cross-correlation function between the reconstructed keyhole depth signal $f(t)$ and the penetration depth curve $g(t)$ is defined as Eq. (2). The larger amplitude of the cross-correlation function denotes the stronger correlation between the two signals.

$$R(\tau) = \lim_{T \rightarrow \infty} \frac{1}{T} \int_0^T f(t)g(t+\tau)dt \quad (2)$$

The amplitude image of the cross-correlation function between the reconstructed keyhole depth signal and the penetration depth curve is shown in Fig. 7. The amplitude of the cross-correlation function obtains the maximum value when $\tau = 6.8\text{ms}$. This means that the penetration depth fluctuation lags behind the keyhole depth fluctuation with a latency time of 6.8 ms. In the following numerical simulation, the value of this latency time is verified and explained.

3.2. Numerical model building

The physical process of laser welding is very complex. In order to improve the computational efficiency, it is necessary to simplify some of the minor factors that are not very decisive for the simulation results. The liquid stainless steel metal is regarded as a type of incompressible fluid with Newtonian viscosity, and the laser source is assumed to be Gaussian distributed. The mathematical and physical models for laser lap welding of thin stainless steel plates established in this paper are as follows.

(1) Governing equations

In order to analyze the heat and mass transfer and fluid flow processes during laser lap welding of stainless steel, numerical simulations are performed by solving the mass continuity equation, the momentum conservation equation, and the energy conservation equation,

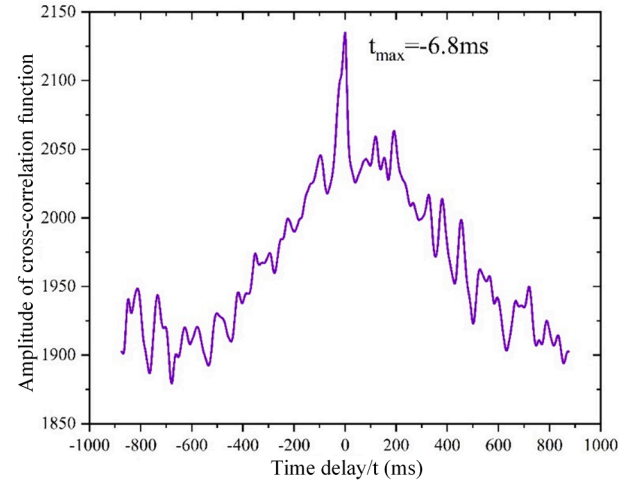


Fig. 7. The amplitude image of the cross-correlation function between the reconstructed keyhole depth signal and the penetration depth curve.

respectively.

Mass continuity equation:

$$\frac{\partial \rho}{\partial t} + \nabla \cdot (\rho \vec{v}) = 0 \quad (3)$$

where $\vec{v}$ is the vector of the fluid velocity, and ρ is the fluid density.

Momentum conservation equation:

$$\rho \left(\frac{\partial \vec{v}}{\partial t} + \vec{v} \cdot \nabla \vec{v} \right) = -\nabla P + \mu \nabla^2 \vec{v} - \rho K \vec{v} - F_b + \rho g + F_L \quad (4)$$

where K , P , μ , F_b and F_L are the Carman-Kozeny coefficient, the fluid pressure, the fluid dynamic viscosity, the thermal buoyancy and the volumetric Loren magnetism, respectively.

Energy conservation equation:

$$\rho \left(\frac{\partial h}{\partial t} + \vec{v} \cdot \nabla h \right) = \nabla \cdot (k \nabla T) + Q_J \quad (5)$$

where h represents the enthalpy, k denotes the thermal conductivity, and Q_J is the fluid Joule heat.

(2) Free surface tracking

In this research, the Volume-of-Fluid (VOF) method is utilized to track the free surface's dynamic evolution. The VOF control equation is as follows:

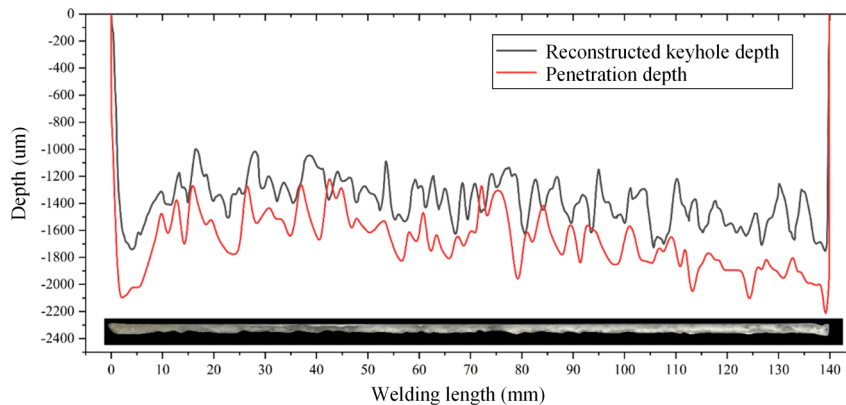


Fig. 6. The weld longitudinal section image, the calculation result of penetration depth, and the reconstructed keyhole depth signal obtained by EMD.

$$\frac{\partial F}{\partial t} + \vec{v} \cdot \nabla F = 0 \quad (6)$$

where F is the volume fraction in the computational cells. And the keyhole surface is deemed to be located at cells where $F = 0.5$.

(3) Driving force model

Recoil pressure and shear force of vapor, surface tension, buoyancy and gravity together drive the flow of the molten pool. The vapor recoil pressure P_r , surface tension τ and buoyancy F_b are expressed as:

$$P_r = 0.54P_0 \exp\left(L_v M \frac{T - T_b}{RTT_b}\right) \quad (7)$$

$$\tau = \tau_0 + \frac{d\tau}{dT}(T - T_l) \quad (8)$$

$$F_b = \rho g \beta (T - T_l) \quad (9)$$

where P_0 is atmospheric pressure, L_v is evaporation latent heat, M is atomic mass, T_b is the boiling temperature and R is an universal gas constant.

(4) Heat source model

The laser beam reflection and absorption mechanism are simulated by ray-tracing algorithm in this research. The laser heat source is distributed in a Gaussian-like axisymmetric distribution. The heat flux q_L of the laser beam at the point (x, y, z) is as follows:

$$q_L(x, y, z) = \frac{Q}{\pi r_z^2} \exp\left(-\frac{x^2 + y^2}{r_z^2}\right) \quad (10)$$

where Q is the laser power, and the laser radius along the beam axis and energy ray direction can be calculated by:

$$r_z = r_f \left[1 + \left(\frac{z - z_f}{z_r} \right)^2 \right]^{\frac{1}{2}} \quad (11)$$

where r_z represents the Rayleigh length, z_f is the focal plane's position, and r_f denotes the focal radius of the laser beam.

The keyhole wall absorbs the incident beam energy based on the Fresnel absorption mechanism. Absorption ratio R is calculated by:

$$R = \frac{1}{2} \left(\frac{1 + (1 - \varepsilon \cos \theta)^2}{1 + (1 + \varepsilon \cos \theta)^2} + \frac{\varepsilon^2 - 2\varepsilon \cos \theta + 2\cos^2 \theta}{\varepsilon^2 + 2\varepsilon \cos \theta + 2\cos^2 \theta} \right) \quad (12)$$

where θ is the angle between the keyhole wall's normal vector and the inclined ray, ε is radiation emissivity. The ray χ_r reflected by the free surface is calculated as:

$$\chi_r = \chi_i - 2(\chi_i \cdot \vec{n}) \quad (13)$$

where χ_i is the ray before reflection.

3.3. Implementation and validation of numerical simulation

Fig. 8 exhibits the geometric model of the numerical simulation case. The size of the entire computational domain is $13.7 \text{ mm} \times 6.2 \text{ mm} \times 3.3 \text{ mm}$. For ensuring the output accuracy while improving the computational efficiency, the melting and heat-conduction regions are divided into a fine mesh and a coarse mesh, respectively. The edge lengths of the coarse and fine meshes are 0.2 mm and 0.05 mm , respectively. In the initial situation, the upper plate area is $-0.8 \text{ mm} \leq z \leq 0 \text{ mm}$; the lower plate area is $-2.8 \text{ mm} \leq z \leq -0.8 \text{ mm}$; the protective gas area is $0 \text{ mm} \leq z \leq 0.5 \text{ mm}$. The whole boundary surface is defined as the wall condition. Flow-3D software is adopted for solving the numerical simulation model. Table 3 displays the physical properties utilized in the simulation.

The top surface of the mesh model in Fig. 8 is set as the pressure/temperature outlet boundary, and the boundary conditions should satisfy Eqs. (14–16):

$$P_{\text{outlet}} = P_0 \quad (14)$$

$$T_{\text{outlet}} = T_0 \quad (15)$$

$$G \frac{\partial T}{\partial n} = h_c(T - T_0) + \delta \varepsilon (T^4 - T_0^4) \quad (16)$$

where P_0 and T_0 are the ambient pressure and temperate, G is the drag coefficient, h_c represents the convection coefficient, and δ denotes the Stefan-Boltzmann constant.

With the purpose of verifying the numerical model's accuracy, the laser lap welding process of stainless steel in a practical experimental situation needs to be observed, and the simulation results should be compared with the experimental results. In terms of the weld morphology, the numerically simulated penetration depth (1.80 mm) is very close to the actual penetration depth (1.79 mm), and the numerically simulated melt width (1.0 mm) is slightly smaller than the actual melt width (1.25 mm), as shown in Fig. 9(a). In terms of the dynamic behavior of the molten pool and keyhole, it is obvious that the melt pool-keyhole morphology in the numerical simulation shot is essentially the same as in the high-speed camera shot, as shown in Fig. 9(b). The high agreement between the experimental and simulation results indicates

Table 3

The physical properties utilized in the simulation.

Parameter	Symbol	Value/unit
Liquid density	ρ	$7249 \text{ kg} \cdot \text{m}^{-3}$
Solid density	ρ_s	$7050 \text{ kg} \cdot \text{m}^{-3}$
Specific heat of liquid phase	C_l	$830 \text{ J} \cdot \text{kg}^{-1} \text{K}^{-1}$
Specific heat of solid phase	C_s	$470 \text{ J} \cdot \text{kg}^{-1} \text{K}^{-1}$
Liquid temperature	T_l	1697 K
Solidus temperature	T_s	1674 K
Boiling temperature	T_v	3273 K
Surface tension coefficient	τ	1.533
Latent heat of evaporation	L_v	$6.08 \times 10^6 \text{ J} \cdot \text{kg}^{-1}$
Latent heat of melting	h_{st}	$2.77 \times 10^5 \text{ J} \cdot \text{kg}^{-1}$
Dynamic viscosity	μ	$8 \times 10^{-3} \text{ kg} \cdot \text{m}^{-1} \text{s}^{-1}$

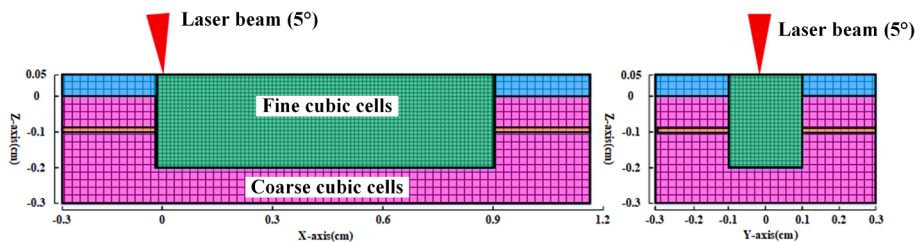


Fig. 8. The geometric model of numerical simulation.

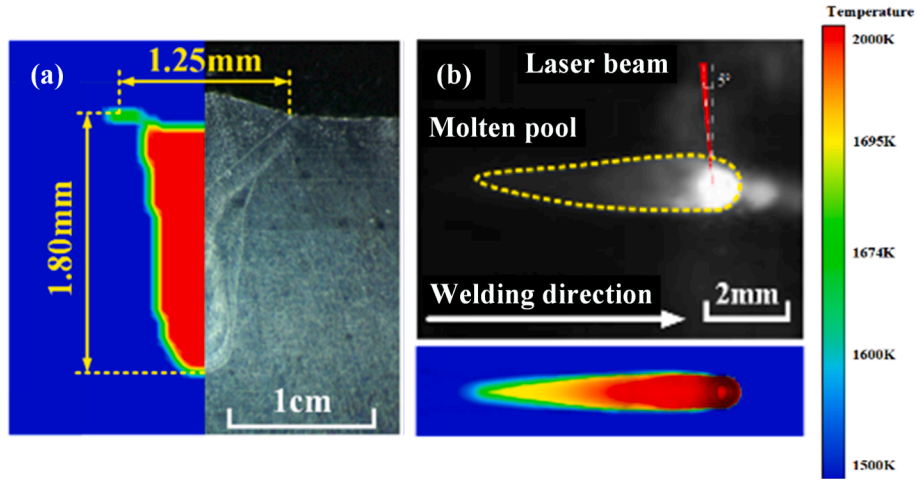


Fig. 9. Comparison of experimental and numerical simulation results of laser lap welding process for stainless steel: (a) The weld morphology; (b) The dynamic behavior of the keyhole and molten pool.

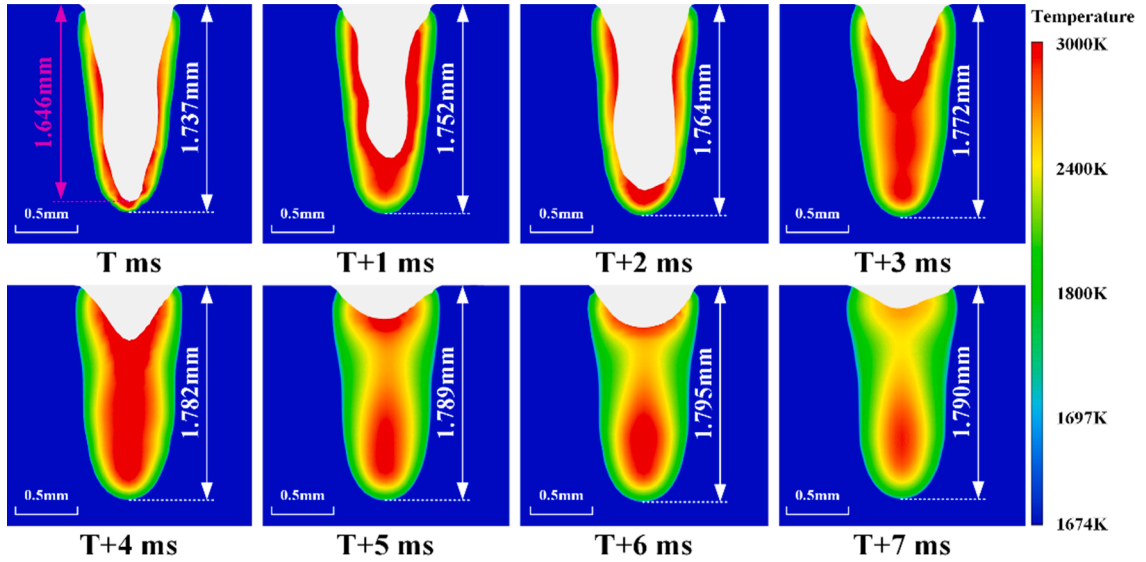


Fig. 10. The keyhole depth and penetration depth at different moments of the same weld position.

that the numerical model is reliable.

3.4. Sources of the penetration depth monitoring error

In the numerical simulation result, the keyhole depth and penetration depth at different moments of the same weld position are shown in Fig. 10. As the laser continues to act on the keyhole and the energy input continues, the molten pool expands deeper until it starts to cool and solidify at the moment of $T + 6$ ms. During laser welding, the optical coherence measurement system measures the keyhole depth at the moment of T , corresponding to the maximum melt depth at the moment of $T + 6$ ms. Hence, from the numerical simulation result, the lag time of reaching the maximum melt depth is approximately 6 ms, which is close to the time delay (6.8 ms) obtained from the correlation analysis in subsection 3.1.

Besides, in a few other welding positions, we also find that the simulated keyhole depth exceeds the simulated penetration depth, and this phenomenon also occurs occasionally in the signal sensing result exhibited in Fig. 6. Theoretically, due to the presence of the bottom melt layer, the keyhole depth is absolutely less than the penetration depth. In order to explore the keyhole depth measurement error, a total of 500

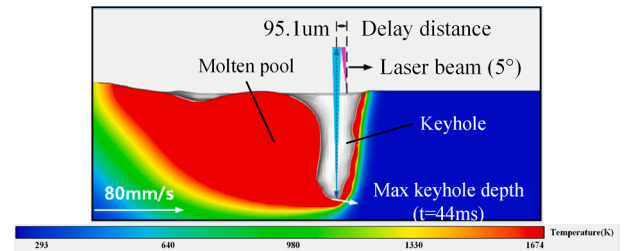


Fig. 11. The keyhole longitudinal section characteristic with the hysteresis distance.

images of the simulated keyhole longitudinal section are acquired with 0.2 ms intervals for a welding period of 0.1 s. The image feature is extracted, and the distance from the deepest part of the keyhole to the focus of the laser beam is defined as the hysteresis distance which is initially described in subsection 2.2, as shown in Fig. 11, and the value of this obtained distance is also displayed. During the first 5 ms when the laser beam acts on the workpiece surface, the hysteresis distance at the deepest part of the keyhole is in a process of steady growth, followed by

a process of high-frequency oscillation with an oscillation frequency of approximately 500 Hz.

According to the principle of optical coherence measurement, the position of the coherent light beam is always constant, while the position of the deepest part of the keyhole is in dynamic fluctuation. When the coherent light beam position coincides with the deepest position of the keyhole, the coherent light is directly reflected after a single reflection, and the keyhole depth measurement is accurate. However, when the coherent light beam is shifted out of the deepest position of the keyhole, the coherent light beam is directly irradiated to the side wall of the keyhole, which causes the keyhole depth measurement value to increase after multiple reflections inside the keyhole. The effects of single reflection and multiple reflections are shown in Fig. 12.

In summary, the penetration depth monitoring error mainly comes from the thickness of the bottom melt metal layer between the keyhole and the molten pool, the hysteresis property of the penetration depth and the multiple reflections of the coherent light beam.

At the end of this chapter, it is worth further emphasizing that numerical simulation is only used for qualitative mechanism explanation and not for quantitative prediction, and the penetration depth curve obtained by simulation cannot be regarded as the reality. The main reason is that the multiple simulation results under a fixed combination of process parameters are always constant and rough, whereas the corresponding real penetration depth curves of the multiple welds formed differ in detail from each other. Therefore, the detailed real-time penetration status with randomness during actual welding cannot be reflected quantitatively via numerical simulation and can only rely on online monitoring.

4. Long short-term memory network-based penetration depth prediction

4.1. Penetration depth prediction method

As mentioned above, the presence of the monitoring error means that a suitable and effective AI algorithm must be selected to accurately predict penetration depth from keyhole depth (reconstructed data). Since there is a non-linear correlation between keyhole depth and penetration depth, the penetration depth prediction can be regarded as a regression fitting process. Machine learning has excellent learning ability to approximate any nonlinear functions at any set accuracy levels, and is now widely used in areas such as weld forming prediction and weld defects identification [28,29].

In this research, the input data space of the reconstructed keyhole depth obtained by EMD can be mapped to the output data space of the penetration depth by using machine learning, so as to realize the penetration depth prediction of unknown data samples.

When building a machine learning-based penetration depth prediction model, the welding thermal history must be considered [30,31]. On

the one hand, the variation of the penetration depth lags behind the fluctuation of the keyhole depth because of the hysteresis property of the penetration depth; on the other hand, due to the continuity of the penetration depth, the penetration depth at the current moment is influenced not only by the keyhole depth at the current moment, but also by the keyhole depth at the previous moment. In this research, the penetration depth is predicted by the LSTM network, which can optionally and automatically memorize historical information about the keyhole depth for predicting the penetration depth at the current moment.

The process of the penetration depth prediction based on the LSTM network is shown in Fig. 13. Firstly, the original keyhole depth signal is filtered and reconstructed by EMD. The dataset is normalized to eliminate dimensional differences, as in Eq. (17). Then the LSTM network is constructed, trained and tested. Finally, the penetration depth prediction accuracy of the LSTM network is verified under the same welding process parameters.

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (17)$$

4.2. Theoretical basis of LSTM model

The LSTM network is a kind of temporal recurrent neural network (RNN), which is capable of mining the deep features of time series information autonomously [32]. Meanwhile, it has the ability to memorize long-term dependencies, which is suitable for dealing with regression prediction problems of nonlinear time series. Compared with traditional RNNs, the LSTM network utilizes LSTM units instead of the original hidden layer units, which can choose to remember, retain and forget historical information, thus avoiding the problem of gradient disappearance or gradient explosion [33].

A typical LSTM architecture is exhibited in Fig. 14. The LSTM network consists of multiple LSTM cells connected in series, and each LSTM cell mainly consists of input gates, forget gates, output gates and cell state update sites. Among them, the cell state update sites remove or add information to memory states through input gates, forget gates, and output gates, and they record the historical information of all nodes and are the long-time memory of the LSTM network. The current input gate determines how much of the current input is saved to the current memory state. The current forget gate determines how much of the previous moment's memory state is saved to the current memory state. The output gate determines how much of the current memory state is controlled to be output to the current state value.

For LSTM cells, the output variables of the input gates and forget gates, the states of the update sites and the output variables of the output gates are as follows:

$$i_t = \sigma(\omega_i \cdot [x_t, H_{t-1}] + b_i) \quad (18)$$

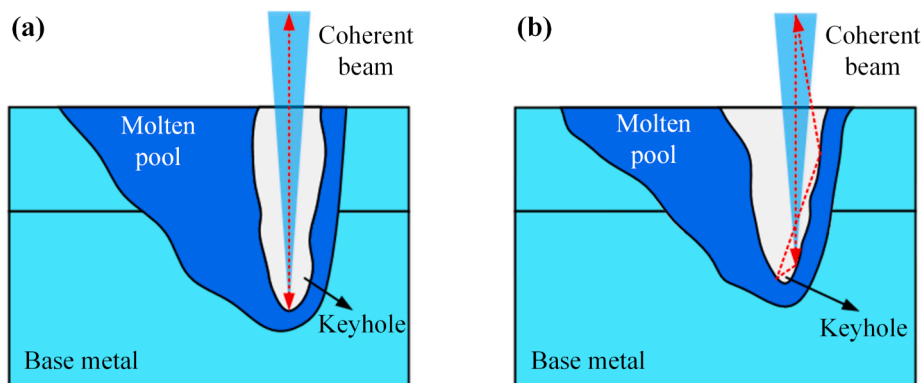


Fig. 12. Different reflection modes of coherent beam: (a) Single reflection; (b) Multiple reflections.

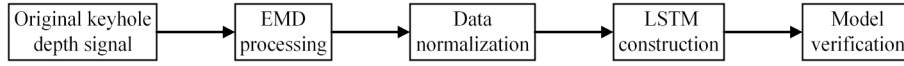


Fig. 13. The process of penetration depth prediction based on the LSTM network.

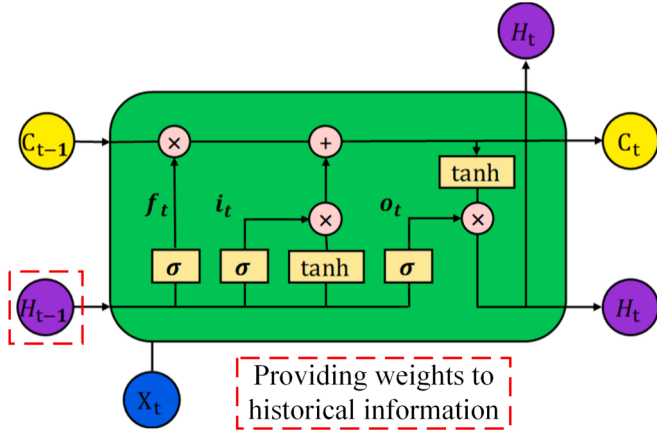


Fig. 14. The typical architecture of LSTM.

$$f_t = \sigma(\omega_f \cdot [x_t, H_{t-1}] + b_f) \quad (19)$$

$$c_t = f_t c_{t-1} + i_t \tanh(\omega_c \cdot [x_t, H_{t-1}] + b_c) \quad (20)$$

$$o_t = \sigma(\omega_o \cdot [x_t, H_{t-1}] + b_o) \quad (21)$$

$$H_t = o_t \tanh(c_t) \quad (22)$$

where, ω_i , ω_f , ω_c , ω_o are weights of the input and forget gates, cell state update and output gates, respectively; b_i , b_f , b_c , b_o are their bias terms, respectively; σ is the sigmoid-type activation function; $\tanh$ is the hyperbolic tangent activation function.

4.3. Implementation of LSTM-based penetration depth prediction

In the constructed LSTM network structure, the time series of keyhole depth acts as the input layer and the time series of penetration depth is the output layer. The number of neurons in both the input layer and the output layer is one. To reduce the complexity of the model, a single hidden layer is installed in the LSTM network. The data set is divided into a training set and a test set by the ratio of 4:1 to train the LSTM network. After fine tuning, the sample sizes of the training and test sets are 438 and 110, respectively. Table 4 displays the parameters of the LSTM network. The penetration depth prediction result for the test set is displayed in Fig. 15, and it is obvious that the penetration depth prediction values are close to the penetration depth expectation values.

For quantitatively evaluating the prediction accuracy of the model, the maximum absolute error (MAE) and root mean square error (RMSE) are introduced in this paper to characterize the local prediction performance and global prediction performance of the model, respectively. The MAE and RMSE are calculated by Eqs. (23) and (24).

$$MAE = \max\{|y_i - Y_i|\}, i = 1, 2, 3, \dots, m \quad (23)$$

Table 4
Parameters of the LSTM network.

Iterations	Learning rate	Batch size	Dropout	Optimizer	Number of neurons in hidden layer
500	0.005	32	0.5	Adam	12

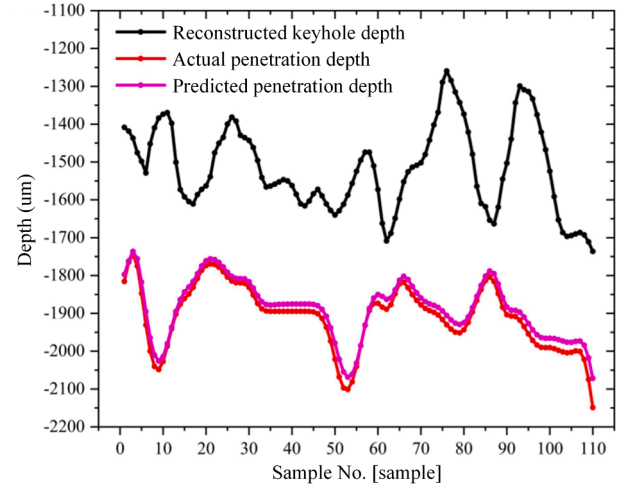


Fig. 15. The penetration depth prediction result for the test set.

$$RMSE = \sqrt{\frac{\sum_{i=1}^m (y_i - Y_i)^2}{m}}, i = 1, 2, 3, \dots, m \quad (24)$$

where y_i are the penetration depth prediction values of the test set samples, Y_i is the penetration depth expectation values of the test set samples, m is the number of sample points in the test set. A smaller MAE indicates a higher local prediction accuracy of the model, and a smaller RMSE denotes a higher global prediction accuracy of the model.

The prediction accuracy of the LSTM network is shown in Table 5. It is found that the LSTM network is accurate to within 80 μm (MAE) for the penetration depth and can control the RMSE to within 30 μm . Accordingly, the penetration depth monitoring by LSTM can meet the accuracy requirement in the practical engineering application.

To further demonstrate the advantages of the LSTM model in continuous monitoring of the penetration depth, three other classical neural network models are additionally utilized, including RNN, deep belief network (DBN) and adaptive neuro fuzzy inference system (ANFIS). Their accuracy indicators for the penetration depth prediction are displayed in Table 5. It should be noted that for these three newly added neural networks (non-time series prediction models), the structures and capacities of the hidden and output layers and all the training options are consistent with those of the LSTM, with the only difference lying in the input layer.

As mentioned before, during laser welding, heat transmission and thermal history cause the slight hysteresis between the keyhole fluctuation and the penetration change. Thus, here, in predicting the penetration depth value at T moment, each input layer of these three non-

Table 5

Prediction accuracy indicators of the LSTM and three other neural network models.

Model\Criterion	MAE	RMSE
LSTM	77.31 μm	23.14 μm
RNN	80.94 μm	27.16 μm
DBN	83.69 μm	29.95 μm
ANFIS	88.13 μm	32.52 μm

Bold indicates optimal performance.

time series prediction models must contain the keyhole depth values at both T moment and (T-1) moment. In contrast, for the LSTM as a time series prediction model, this extra operation is not required because it already automatically takes into account the time-domain recursive information, but interestingly, its prediction accuracy is the highest. Hence, LSTM is more suitable for being applied in real-time penetration depth monitoring than the other neural networks used.

4.4. Validity verification of LSTM-based penetration depth prediction

Penetration depth monitoring requires good adaptability of the machine learning model for the same process parameters during laser welding. To verify the accuracy of the LSTM network in monitoring the penetration depth under the same process parameters, the method is used to predict all data in the penetration depth curve of another complete weld under this optimum combination of process parameters, and the LSTM no longer needs to be retrained. Fig. 16 exhibits the penetration depth prediction result of the validation experiment, and the accuracy indicators are displayed in Table 6. It can be noticed that the penetration depth monitoring accuracy in the validation experiment is also satisfactory. Therefore, the penetration depth prediction model based on the LSTM model has good generalization ability. Furthermore, it can be seen from Table 6 that in this case, the LSTM still has the two best accuracy indicators among all the prediction models adopted.

5. Conclusions

In this paper, the penetration depth monitoring in laser lap welding of thin stainless steel plates is performed. Based on the optical coherence measurement technology and EMD for obtaining and reconstructing the keyhole depth signal respectively, we explore the mechanism of the generation of penetration depth monitoring error utilizing numerical simulation, and build a LSTM model to realize the penetration depth prediction at each position of the weld. The main conclusions can be summarized as follows:

- (1) There is a correlation between keyhole depth and penetration depth. The penetration depth monitoring error mainly comes from the thickness of the melt metal layer between the keyhole and the molten pool, the hysteresis property of the penetration depth and the multiple reflections of the coherent light beam.
- (2) Considering the continuity and hysteresis of penetration depth, the LSTM network-based model for monitoring the penetration depth from the reconstructed keyhole depth can be built successfully and can narrow the MAE in the prediction to a scale of 80 μm and the RMSE in the prediction to a scale of 25 μm .
- (3) Under the optimum combination of process parameters, the constructed LSTM model also has high accuracy of penetration depth prediction facing the same process condition, demonstrating the existence of the strong generalization ability of the model.

In the future, we will carry out online feedback control for penetration depth and integrate it with the real-time monitoring research, so that the process parameters can be regulated by timely feedback to control the penetration depth within the specified range, thus ensuring the mechanical properties and aesthetics of the weld joint.

CRediT authorship contribution statement

Leshi Shu: Methodology, Conceptualization. **Deyuan Ma:** Writing – original draft, Software, Investigation, Funding acquisition. **Shenjie Cao:** Visualization, Formal analysis, Data curation. **Yilin Wang:** Resources, Project administration. **Ping Jiang:** Supervision, Funding acquisition. **Shaoning Geng:** Writing – review & editing, Validation.

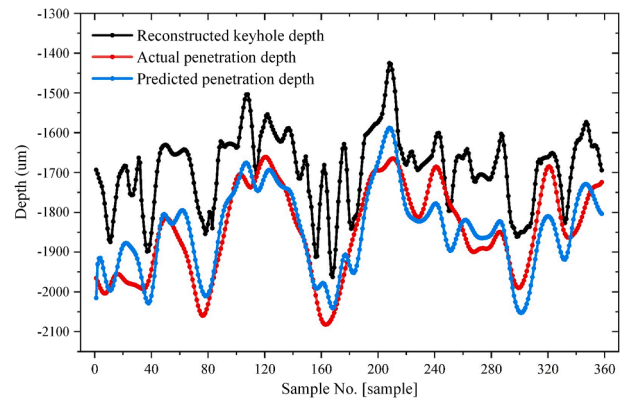


Fig. 16. The penetration depth prediction result of the validation experiment.

Table 6

Prediction accuracy indicators of the LSTM and three other neural networks (Validation experiment).

Model\Criterion	MAE	RMSE
LSTM	227.84 μm	77.42 μm
RNN	236.18 μm	80.59 μm
DBN	241.74 μm	87.03 μm
ANFIS	248.69 μm	90.35 μm

Bold indicates optimal performance.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data that has been used is confidential.

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References

- [1] D. Rizzi, T. Sibillano, P.P. Calabrese, A. Ancona, P.M. Lugarà, Spectroscopic, energetic and metallographic investigations of the laser lap welding of AISI 304 using the response surface methodology, Opt. Lasers Eng. 49 (2011) 892–898, <https://doi.org/10.1016/j.optlaseng.2011.02.014>.
- [2] Y. Zhang, D. You, X. Gao, N. Zhang, P.P. Gao, Welding defects detection based on deep learning with multiple optical sensors during disk laser welding of thick plates, J. Manuf. Syst. 51 (2019) 87–94, <https://doi.org/10.1016/j.jmsy.2019.02.004>.
- [3] D. Ma, P. Jiang, L. Shu, Y. Qiu, Y. Zhang, S. Geng, DBN-based online identification of porosity regions during laser welding of aluminum alloys using coherent optical diagnosis, Opt. Laser Technol. 165 (2023) 109597, <https://doi.org/10.1016/j.optlaseng.2023.109597>.
- [4] D. Colombo, B.M. Colosimo, B. Previtali, Comparison of methods for data analysis in the remote monitoring of remote laser welding, Opt. Lasers Eng. 51 (2013) 34–46, <https://doi.org/10.1016/j.optlaseng.2012.07.022>.
- [5] W. Meng, X. Yin, J. Fang, L. Guo, Q. Ma, Z. Li, Dynamic features of plasma plume and molten pool in laser lap welding based on image monitoring and processing techniques, Opt. Laser Technol. 109 (2019) 168–177, <https://doi.org/10.1016/j.optlaseng.2018.07.073>.
- [6] H. Mizota, Y. Nagashima, T. Obana, Fundamental study of molten pool depth measurement method using an ultrasonic phased array system, Jpn. J. Appl. Phys. 54 (2015) 07HC03, <https://doi.org/10.7567/JJAP.54.07HC03>.
- [7] W. Huang, R. Kovacevic, A neural network and multiple regression method for the characterization of the depth of weld penetration in laser welding based on

- acoustic signatures, *J. Intell. Manuf.* 22 (2011) 131–143, <https://doi.org/10.1007/s10845-009-0267-9>.
- [8] L. Mrňa, M. Šarabot, Š. Řeřucha, P. Jedlička, Feedback control of laser welding based on frequency analysis of light emissions and adaptive beam shaping, *Phys. Procedia* 39 (2012) 784–791, <https://doi.org/10.1016/j.phpro.2012.10.101>.
 - [9] T. Sibillano, D. Rizzi, F.P. Mezzapesa, P.M. Lugarà, A.R. Konuk, R. Aarts, B.H. i'. Veld, A. Ancona, Closed loop control of penetration depth during CO₂ laser lap welding processes, *Sensors* 12 (2012) 11077–11090, <https://doi.org/10.3390/s120811077>.
 - [10] Y. Zhang, C. Zhang, L. Tan, S. Li, Coaxial monitoring of the fibre laser lap welding of Zn-coated steel sheets using an auxiliary illuminant, *Opt. Laser Technol.* 50 (2013) 167–175, <https://doi.org/10.1016/j.optlastec.2013.03.001>.
 - [11] A. Blug, D. Carl, H. Höfler, F. Abt, A. Heider, R. Weber, L. Nicolosi, R. Tetzlaff, Closed-loop control of laser power using the full penetration hole image feature in aluminum welding processes, *Phys. Procedia* 12 (2011) 720–729, <https://doi.org/10.1016/j.phpro.2011.03.090>.
 - [12] C. Stadter, M. Schmoeller, L. von Rhein, M.F. Zaeh, Real-time prediction of quality characteristics in laser beam welding using optical coherence tomography and machine learning, *J. Laser Appl.* 32 (2020) 022046, <https://doi.org/10.2351/7.0000077>.
 - [13] W. Ke, X. Bu, J.P. Oliveira, W.G. Xu, Z. Wang, Z. Zeng, Modeling and numerical study of keyhole-induced porosity formation in laser beam oscillating welding of 5A06 aluminum alloy, *Opt. Laser Technol.* 133 (2021) 106540, <https://doi.org/10.1016/j.optlastec.2020.106540>.
 - [14] D. Ma, P. Jiang, L. Shu, S. Geng, Real-time porosity monitoring during laser welding of aluminum alloys based on keyhole 3D morphology characteristics, *J. Manuf. Syst.* 65 (2022) 70–87, <https://doi.org/10.1016/j.jmsy.2022.08.011>.
 - [15] D. Wu, P. Zhang, Z. Yu, Y. Gao, H. Zhang, H. Chen, S. Chen, Y.T. Tian, Progress and perspectives of in-situ optical monitoring in laser beam welding: Sensing, characterization and modeling, *J. Manuf. Process.* 75 (2022) 767–791, <https://doi.org/10.1016/j.jmapro.2022.01.044>.
 - [16] T. Bautze, M. Kogel-Hollacher, Keyhole depth is just a distance: The IDM sensor improves laser welding processes, *Laser Tech. J.* 11 (2014) 39–43, <https://doi.org/10.1002/latj.201400040>.
 - [17] J.J. Blecher, C.M. Galbraith, C. Van Vlack, T.A. Palmer, J.M. Fraser, P.J.L. Webster, T. DebRoy, Real time monitoring of laser beam welding keyhole depth by laser interferometry, *Sci. Technol. Weld. Join.* 19 (2014) 560–564, <https://doi.org/10.1179/1362171814Y.0000000225>.
 - [18] M. Kogel-Hollacher, S. André, T. Beck, New horizons in laser material processing: how OCT sets new standards, High-power laser materials processing: applications, diagnostics, and systems VIII, SPIE 10911 (2019) 81–91, <https://doi.org/10.1117/12.2516967>.
 - [19] L. Cao, J. Li, L. Zhang, S. Luo, M. Li, X. Huang, Cross-attention-based multi-sensing signals fusion for penetration state monitoring during laser welding of aluminum alloy, *Knowl.-Based Syst.* 261 (2023) 110212, <https://doi.org/10.1016/j.knosys.2022.110212>.
 - [20] J. Günther, P.M. Pilarski, G. Helfrich, H. Shen, K. Diepold, First steps towards an intelligent laser welding architecture using deep neural networks and reinforcement learning, *Procedia Technol.* 15 (2014) 474–483, <https://doi.org/10.1016/j.protcy.2014.09.007>.
 - [21] G. Masinelli, T. Le-Quang, S. Zanolli, K. Wasmer, S.A. Shevchik, Adaptive laser welding control: A reinforcement learning approach, *IEEE Access* 8 (2020) 103803–103814, <https://doi.org/10.1109/ACCESS.2020.2998052>.
 - [22] Z. Mao, W. Feng, H. Ma, Y. Yang, J. Zhou, S. Liu, Y. Liu, P. Hu, K. Zhao, H. Xie, G. Guo, Z. Liu, Continuous online flaws detection with photodiode signal and melt pool temperature based on deep learning in laser powder bed fusion, *Opt. Laser Technol.* 158 (2023) 108877, <https://doi.org/10.1016/j.optlastec.2022.108877>.
 - [23] Q. Wang, X. Lin, X. Duan, R. Yan, J.Y.H. Fuh, K. Zhu, Gaussian process classification of melt pool motion for laser powder bed fusion process monitoring, *Mech. Syst. Signal Process.* 198 (2023) 110440, <https://doi.org/10.1016/j.ymssp.2023.110440>.
 - [24] Y. Liu, P. Jiang, Y.W. Ai, C. Yue, Prediction of weld shape for fiber laser welding based on hybrid heat source model, 3rd International Conference on Material, Mechanical and Manufacturing Engineering, 2015. Pp. 1868–1873. doi: 10.2991/ic3me-15.2015.360.
 - [25] Y. Wang, P. Jiang, J. Zhao, S. Geng, B. Xu, Effects of energy density attenuation on the stability of keyhole and molten pool during deep penetration laser welding process: A combined numerical and experimental study, *Int. J. Heat Mass Transf.* 176 (2021) 121410, <https://doi.org/10.1016/j.ijheatmasstransfer.2021.121410>.
 - [26] Y. Lei, Z. He, Y. Zi, Application of the EEMD method to rotor fault diagnosis of rotating machinery, *Mech. Syst. Signal Proc.* 23 (2009) 1327–1338, <https://doi.org/10.1016/j.ymssp.2008.11.005>.
 - [27] D. Ma, P. Jiang, L. Shu, S. Geng, Multi-sensing signals diagnosis and CNN-based detection of porosity defect during Al alloys laser welding, *J. Manuf. Syst.* 62 (2022) 334–346, <https://doi.org/10.1016/j.jmsy.2021.12.004>.
 - [28] D. Bacioiu, G. Melton, M. Papaelias, R. Shaw, Automated defect classification of Aluminium 5083 TIG welding using HDR camera and neural networks, *J. Manuf. Process.* 45 (2019) 603–613, <https://doi.org/10.1016/j.jmapro.2019.07.020>.
 - [29] C. Gonzalez-Val, A. Pallas, V. Panadeiro, A. Rodriguez, A convolutional approach to quality monitoring for laser manufacturing, *J. Intell. Manuf.* 31 (2020) 789–795, <https://doi.org/10.1007/s10845-019-01495-8>.
 - [30] D. Wu, H. Chen, Y. Huang, Y. He, M. Hu, S. Chen, Monitoring of weld joint penetration during variable polarity plasma arc welding based on the keyhole characteristics and PSO-ANFIS, *J. Mater. Process. Technol.* 239 (2017) 113–124, <https://doi.org/10.1016/j.jmatprotec.2016.07.021>.
 - [31] D. Wu, H. Chen, Y. Huang, S. Chen, Online monitoring and model-free adaptive control of weld penetration in VPPAW based on extreme learning machine, *IEEE Trans. Ind. Electron.* 15 (2018) 2732–2740, <https://doi.org/10.1109/TII.2018.2870933>.
 - [32] Z. Li, J. Bai, M. Jiang, J. Feng, X. Chen, R. Wei, K. Jia, Continuous monitoring of tissue oxygen metabolism based on multi-wavelength diffuse correlation spectroscopy using LSTM-based RNN model, *Opt. Laser Technol.* 171 (2024) 110384, <https://doi.org/10.1016/j.optlastec.2023.110384>.
 - [33] X.J. Luo, L.O. Oyedele, Forecasting building energy consumption: Adaptive long-short term memory neural networks driven by genetic algorithm, *Adv. Eng. Inform.* 50 (2021) 101357, <https://doi.org/10.1016/j.aei.2021.101357>.