Online prediction of Composite Material Drilling Quality Based on Multi-sensor Fusion

Wei Liu · Jiacheng Cui · Yongkang Lu · Pengbo Yin · Lei Han · Yingxin Jiang · Yang Zhang

Abstract

~~Delamination damage of composite materials can have a significant impact on component performance, necessitating strict control over drilling quality. Traditional offline measurement methods for delamination damager do not fulfill the requirements of real-time quality control. To address this issue,~~The study introduces a novel online prediction method using a multi-sensor fusion approach ~~is proposed~~ for ~~online prediction of~~assessing the ~~processing~~drilling quality of composite materials~~. This method, named by the multi~~ in real-time. The Multi-sensor ~~fusion long short-term network~~Fusion Long Short-Term Memory (MFLSTM~~), is constructed by incorporating~~) model, which incorporates a ~~stacked sparse autoencoder~~Stacked Sparse Autoencoder (SSAE) ~~into~~within a Bayesian deep learning framework~~. It quantifies~~, was developed to manage the uncertainty ~~of prediction results, considering the randomness of drilling damage, and provides accurate and stable point predictions and interval predictions of the quality of holes being machined. The validity is demonstrated through~~ inherent in composite material processing. Experimental validation, utilizing a ~~composite hole-making~~ specifically constructed dataset~~, constructed by monitoring~~ from multi-sensor data~~,~~ including force, temperature, and vibration~~, and quantifying drilling quality. The results indicate~~ measurements, demonstrates that ~~the proposed method outperforms general methods used for~~our approach significantly enhances the predictability of hole quality during drilling. The MFLSTM model outperformed traditional machining process monitoring techniques by reducing prediction errors by over 25%, offering both accurate point predictions and reliable interval estimates. This method not only advances the intelligence of composite component manufacturing but also facilitates its industrial application through the development of supportive software.

Keywords Composite material · Multi-sensor fusion · Bayesian deep learning · Stacked sparse autoencoder (SSAE) · Drilling quality prediction

INTRUDUCTION

Composite materials have been recognized as having significant performance advantages over traditional materials, including high specific strength, high specific modulus, corrosion resistance, and fatigue resistance (Ashby et al., 1993). The utilization of composite materials, particularly fiber-reinforced materials, has gained widespread acceptance and success in various fields. However, during the mass production of composite material components, the coupling effect between the tool, material, and environment can lead to defects such as delamination and burrs (Xu et al., 2018). The drilling-introduced delamination is considered the most critical form of damage, causing substantial economic losses (Fleischer et al., 2018). It has been estimated that more than 60% of composite components are discarded due to delamination during assembly (~~Stone~~Zhang et al., ~~1996~~2020). Thus, controlling delamination is of utmost importance during processing.

The methods for obtaining drilling quality information of composite materials can be classified into offline measurement and online prediction. Offline measurement involves acquiring comprehensive information about the shape, size, and position of the material. This information can then be evaluated using suitable criteria to determine whether the damage exceeds the tolerance levels. The most commonly used measurement methods for offline measurement include optical microscopy (Xu et al., 2018; Su et al., 2018), ultrasonic C-scan (Jia et al., 2020), X-ray (Saoudi et al., 2018; Chabot et al., 2020), etc. Although these methods provide accurate information about delamination, they are limited by factors such as instrument size, measurement time, and detection range, making it challenging to achieve real-time and in-situ control.

In recent years, data-driven tool condition monitoring (TCM) has gained popularity in traditional material manufacturing as a means of ensuring product quality (Pimenov et al., 1996). Ross et al. (2024) developed a transfer learning based approach to predict flank wear of tools under different environmental conditions using a limited number of datasets. Liu et al. (2022) proposed a meta-invariant feature space learning method, which can achieve accurate tool wear prediction with a small number of samples. Liu et al. (2021) improve the hidden semi-Markov model by taking time-varying working mode into account and achieved better performance. In composite manufacturing, Date-driven TCM has also found some application. Pratama et al. (2021) proposed a tool condition monitoring method based on the metacognitive scaffolding theory, employing a recurrent classifier (rClass). Hegab et al. (2020) developed a smart TCM system that can predict the tool wear during drilling of woven composites.

In addition to predicting tool wear, there have also been attempts to directly map processing quality using sensor data. Zhang et al. (2021) develop the Gaussian process regression (GPR) model to predict delamination during drilling CFRP. Romoli et al. (2019) proposed a quality monitoring and control strategy for drilling CFRP based on fuzzy logic algorithm, but cannot give an accurate prediction value of delamination damage. Soepangkat et al. (2020) integrated back propagation neural network (BPNN) and particle swarm optimization (PSO) to predict and optimize multi-performance-characteristics. Compared with offline measurement, online prediction method has significant advantages in real-time performance. However, there are still unresolved issues with the current methods used for composite material drilling quality control:

(1) In industrial applications, it can be challenging to accurately analyze machining quality solely based on tool wear. Additionally, existing prediction methods that focus on processing quality only take into account information from a single stage of the process, making it difficult to apply these methods during continuous processing (Shen et al., 2021).

(2) The change pattern of processing quality has non-linear and stochastic characteristics, and feature extraction is easily impacted by noise interference. This is due to the presence of uncertain factors such as environment and materials during the processing of composite materials (Arul et al., 2006; Aich et al., 2019). As a result, it is crucial to consider multiple physical quantities and incorporate prediction uncertainty in the prediction process.

To address the aforementioned challenges in composite drilling quality control, a novel online prediction approach based on multi-sensor data is proposed. Our approach considers the discreteness of the drilling data and the stochastic nature of delamination damage, and is inspired by the SSAE and Bayesian deep learning frameworks (Ma et al., 2023; Zhu et al., 2017; Peng et al., 2022). Secondly, A multi-sensor test system is constructed to collect the information of force, temperature, and vibration during machining process. Finally, the online prediction of machining quality is achieved, and the prediction interval can be given. ~~The experimental results~~It is worth stating that the proposed method gives quantitative values of machining quality, which can be further combined with different quality requirements to assess the quality of machining, which provides greater adaptability of the algorithm. The experimental results also demonstrate that our method can effectively ensure drilling quality and improve final product performance. The major contributions of this study can be summarized as follows:

(1) The development of a multi-sensor fusion long-short term memory (MFLSTM) model is presented, capable of extracting deep features from discrete multi-sensor signals and evaluating the uncertainty of the predicted drilling quality.

(2) Considering the distinct characteristics of composite drilling quality prediction compared to traditional TCM, the proposed method improves upon prior knowledge, feature fusion method, and uncertainty assessment method.

(3) A comprehensive technical framework is proposed that integrates multi-sensor measurements, digital image processing, and deep learning techniques to predict the drilling quality of composite materials.

The organization of this paper is as follows. ~~In Section "Preliminary work" provides an overview of the theories of SSAE and LSTM network.~~ In Section "Methodology", the proposed prediction method for composite drilling quality is described in detail. The experimental setup, dataset construction, and results are presented in Section "Experiment". In Section "Software Integration and Application", a software platform based on algorithmic integration is presented. Finally, Section "Conclusions" concludes the paper and summarizes its contributions.

~~PRELIMINARY WORK~~

~~Stacked Sparse Autoencoders~~

~~Sparse autoencoder (SAE) is an unsupervised machine learning algorithm, which minimizes the distance between the reconstructed vector and the output vector by calculating the error between the output and the original input. The cost function with respect to that signal example can be designed as~~

$$J(W,b,x)=\frac{1}{2}\left\|h_{W,b}(x)-x\right\|_2^2 \qquad (1)$$

~~where~~ $h_{W,b}(x)=f(W^T x)$ ~~is equal to the output~~ x' ~~and~~ x ~~is the input.~~

~~Give a training set of~~ m ~~examples, the overall cost function can be defined as~~

$$J(W,b)=\left[\frac{1}{2m}\sum_{i=1}^{m}\left(\left\|h_{W,b}\left(x^{(i)}\right)-x\right\|^2\right)\right]+\frac{\lambda}{2}\sum_{l=1}^{n_l-1}\sum_{i=1}^{s_l}\sum_{j=1}^{s_{l+1}}\left(W_{ji}^{(l)}\right)^2 \qquad (2)$$

~~where~~ n_l ~~represents the number of autoencoder layers,~~ $W_{ji}^{(l)}$ ~~is the weight matrix between~~ L_l ~~with~~ i ~~units and~~ L_{l+1} ~~with~~ j ~~units.~~

~~To avoid overfitting, a sparse constraint described by KL divergence is introduced~~

$$KL\left(\rho\|\hat{\rho}_j\right)=\rho\log\frac{\rho}{\rho_j}+(1-\rho)\log\frac{1-\rho}{1-\hat{\rho}_j} \qquad (3)$$

~~where~~ ρ ~~is the sparsity constant, and~~ $\hat{\rho}_j$ ~~is the average activation of the hidden unit~~ j ~~. The overall cost function can be formulated as~~

$$J_{\text{sparse}}(W,b)=J(W,b)+\beta\sum_{j=1}^{s_2}KL\left(\rho\|\hat{\rho}_j\right) \qquad (4)$$

~~Stacked sparse autoencoders (SSAE) is constructed by stacking multiple SAE to further mine the deeper features of the data. The operation mechanism of SSAE can be represented as~~

$$X^{n+1}=Y^{(n)}=f\left(W^{(n)}X^{(n)}+b^{(n)}\right) \qquad (5)$$

~~LSTM Network~~

~~Long short-term network, commonly known as LSTM, is a special type of RNN which can learn long-term dependencies. In many problems, LSTM has achieved considerable success and has widely used. The basic architecture of the LSTM memory cell is shown in Fig. 1, and the calculation formula of LSTM is as follows:~~

$$i_t=\sigma_i\left(x_tW_{xi}+h_{t-1}W_{hi}+b_i\right) \qquad (6)$$

$$f_t=\sigma_f\left(x_tW_{xf}+h_{t-1}W_{hf}+b_f\right) \qquad (7)$$

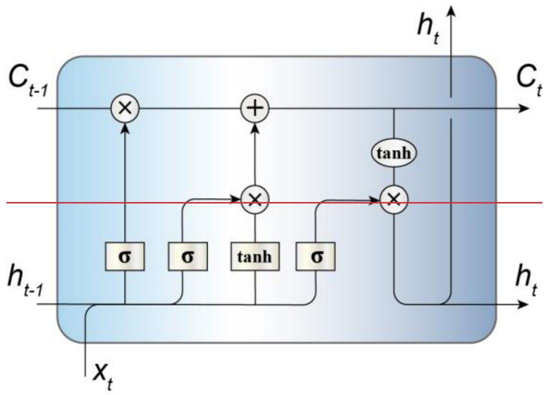
$$c_t=f_t\odot c_{t-1}+i_t\odot\sigma_c\left(x_tW_{xc}+h_{t-1}W_{hc}+b_c\right) \qquad (8)$$

$$o_t=\sigma_o\left(x_tW_{xo}+h_{t-1}W_{ho}+b_o\right) \qquad (9)$$

$$h_t=o_t\odot\sigma_h\left(c_t\right) \qquad (10)$$

~~where~~ i ~~,~~ f ~~,~~ c ~~,~~ o ~~and~~ h ~~are the input gate, forget gate, cell activation vector, output gate, and hidden layer output,~~

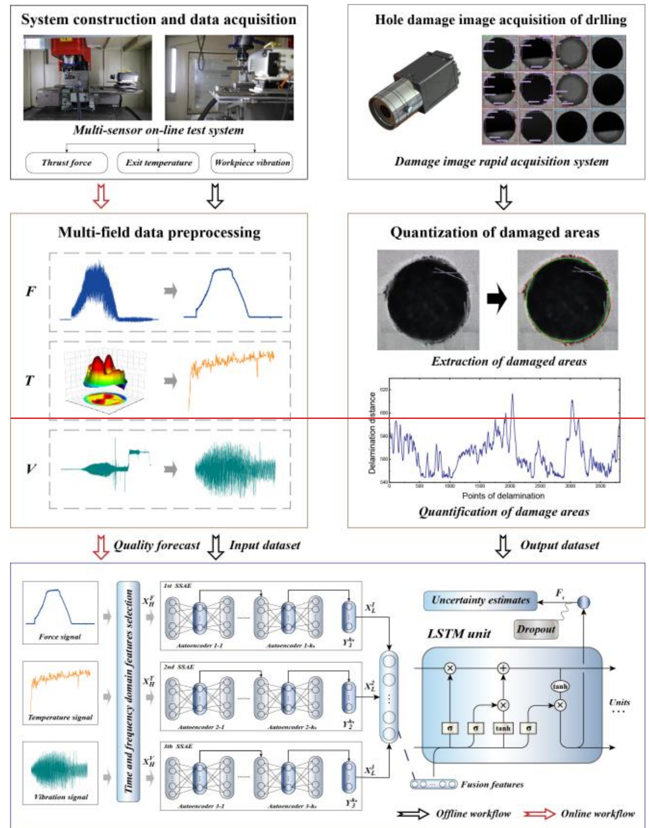
~~respectively.~~ W ~~and~~ b ~~represent the weight matrix and bias vector, respectively.~~ $\sigma(\cdot)$ ~~is the sigmoid function.~~



~~Fig. 1. The LSTM memory cell~~

METHODOLOGY

The framework of the proposed method is depicted in Fig ~~2~~1. The offline phase of the dataset construction consists of two primary stages: multi-sensor data collection and drilling quality evaluation. Firstly, a multi-sensor test system was established to simultaneously collect thrust force, exit temperature, and workpiece vibration signals. To mitigate the negative impact of noise and redundant data on subsequent processing, the acquired multi-sensor signals undergo an adaptive pre-processing step. Secondly, drilling damage images are captured through the image acquisition system. The damaged area is extracted, and drilling quality is evaluated using suitable criteria. Finally, the MFLSTM deep learning model is employed to establish the correlation between the multi-sensor signals from the machining process and the drilling quality of composite materials. During the online machining phase, multi-sensor data can be obtained and used to predict the evolution of quality. If the prediction results indicate an increased risk of damage, the risk can be effectively mitigated by changing the tool.



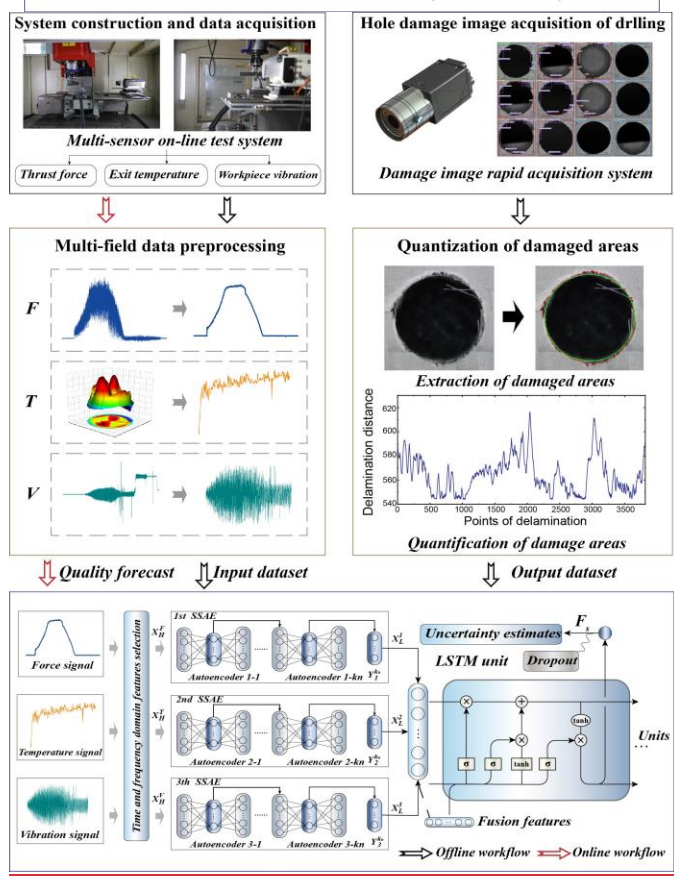


Fig. ~~2~~1. Composite material drilling quality prediction framework

Adaptive Pre-processing of Multi-sensor data

In the process of multi-sensor data acquisition, the acquired signals may contain outliers and noise due to environmental and other factors, as well as redundant information which could impact the speed and accuracy of subsequent predictions. To overcome these challenges, different data pre-processing methods must be designed to address the heterogeneity of multi-sensor data.

The pre-processing of the thrust force signals involves filtering the data using a low-pass filter. In the case of the exit temperature signals, the measurement result is a time-varying temperature field, leading to the presence of redundant information. To simplify the characterization of the global information, the maximum value in the temperature matrix is used. For vibration signals, the presence of environmental disturbances and potential anomalous signals in the acquisition process necessitates the use of an outlier detection algorithm based on root mean square (RMS) [8] to eliminate their impact on the subsequent analysis.

Extraction and quantification of damaged area

Extraction of damaged area

The process of damage area extraction is shown in Fig. ~~3~~2. First, after extracting the contour of the hole, the circle parameters such as center and radius can be obtained by combining with robust circle fitting. The circle parameter fitting is done by weight repeated least trimmed square algorithm (Nurunnabi et al., 2018). The algorithm follows an iterative process to obtain an outlier-free subset on which to perform the least trimmed square (LTS) regression (Jung et al., 2007). To save time, the algorithm start with a minimal subset of h_0 points, instead of h points of the full point set. The number of iterations I_n is determined by

$$I_n = \frac{\log\left(1 - p_k\right)}{\log\left(1 - (1-\epsilon)^{h_0}\right)}$$ (1~~11~~)

where $p_k = 1 - \left(1 - (1-\epsilon)^{h_0}\right)^{I_n}$ is the probability of getting at least one outlier free subset of h_0 points, and ϵ is the percentage of outliers. These two parameters can be selected adaptively according to the damage severity of composites.
After accurately obtaining the circular parameters, the damage area can be extracted according to the adaptive segmentation threshold. In this paper, the adaptive is determined by the following formula:

$$T(x,y) = m(x,y)\left[1 + pe^{-q\cdot m(x,y)} + k\left(\frac{s(x,y)}{R} - 1\right)\right]$$ (2~~12~~)

where $T(x,y)$ is the determined local threshold, $m(x,y)$ is the local mean value, $s(x,y)$ is the local standard deviation, p and q are constants, and R is usually set to 128.

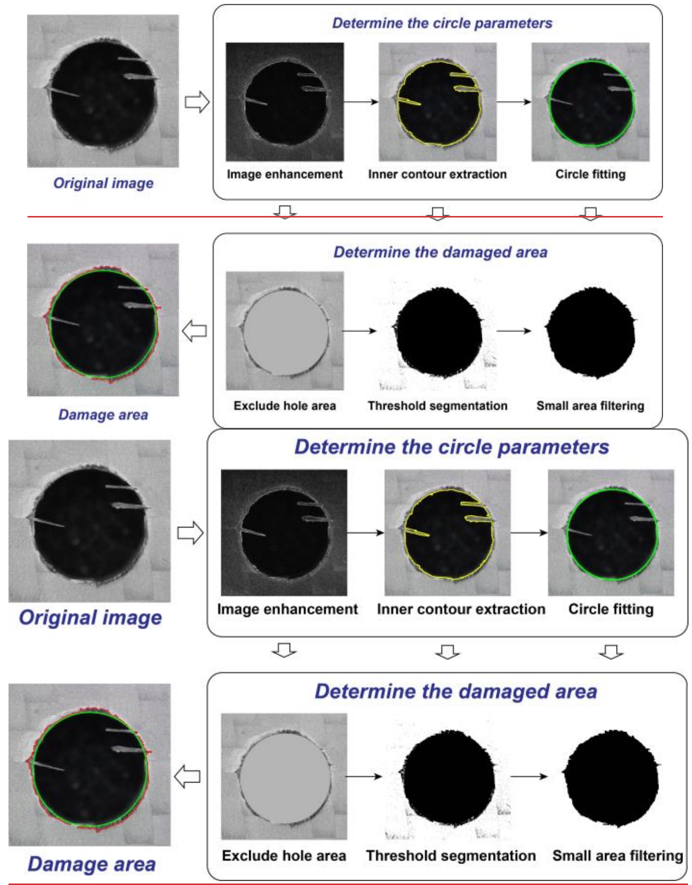


Fig. ~~3~~2. The process of damage area extraction of composite material

Quantification of damaged area

After extracting the damaged area, it needs to be quantified. The novel statistical delamination F_s (Cui et al., 2021) proposed by us is used to quantify the damaged area

$$F_s = \sqrt{l_0 \sum_{1}^{L/l_0} r^2 \Big/ L} + \sqrt{l_0 \sum_{1}^{L/l_0} \left(r - R\right)^2 \Big/ L}$$ (3~~13~~)

where L is the total length of the delamination contour, l_0 is the interval between points taken from the contour, and the number of points taken from the contour is L/l_0, r is the distance from a point on the contour to the center of the fitted circle, which can be called as delamination distance. R refers to the radius of the fitted circle. The visualization of qualifying the damage area by F_s is shown in Fig .~~4~~3. F_s considered the one-dimensional and two-dimensional information and the distribution of damage at the same time, which can be used to establish an accurate evaluation of drilling quality.

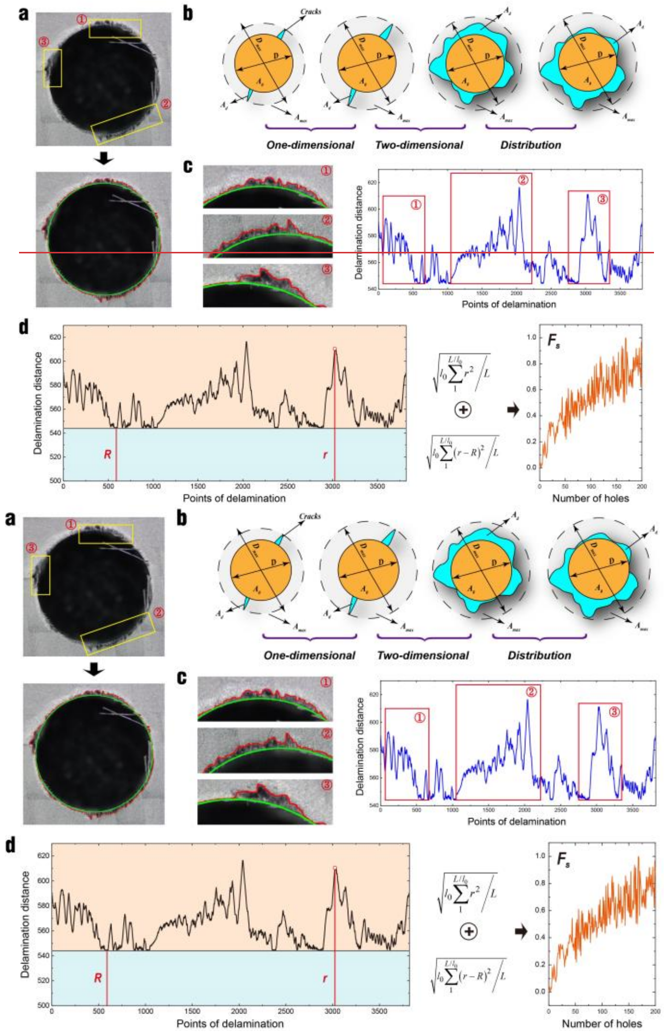


Fig. ~~4~~3. Quantification of damaged area: (a) Extraction of damaged area, (b) Diverse information of damaged area, (c) Convert the damaged area to delamination distance data line, (d) Quantification process

Proposed MFLSTM model

In this section, we introduce the proposed MFLSTM network, which employs the novel Stacked Sparse Autoencoder Ensemble (SSAEs) method to achieve effective fusion of multi-source signals. Leveraging this Bayesian LSTM framework, the network harnesses the integrated features to predict the machining quality of holes. This approach effectively synthesizes data from multiple sensors, enhancing predictive accuracy during high-volume continuous machining processes.

Multi-sensor fusion based on SSAEs

~~After undergoing signal acquisition and preprocessing, the original signals still contain a significant amount of redundant information. Therefore, it is necessary to perform dimensionality reduction and fusion of the multi-sensor signals. Existing methods may not effectively extract the key features of the multi-sensor data, resulting in inaccurate predictions of processing quality. To address this issue, a collaborative analysis approach for the force, temperature, and vibration data is proposed. By leveraging the capabilities of SSAE, deep features from the multi-source heterogeneous data are adaptively extracted.~~

In the field of TCM, traditional methods typically focus on monitoring tool wear in milling processes. The signals in these cases are continuous and their dimensions can be easily reduced ~~by using the SSAE~~ to extract deeper features. However, in the task of drilling quality prediction, the signals are intermittent and show great variations in amplitude, frequency, and even duration under different processing parameters. To address this challenge, this study aims to unify signals of varying durations by directly extracting both time and frequency domain features.

After undergoing signal acquisition and preprocessing, the original signals still contain a significant amount of redundant information. Therefore, it is necessary to perform dimensionality reduction and fusion of the multi-sensor signals. Existing methods may not effectively extract the key features of the multi-sensor data, resulting in inaccurate predictions of processing quality. To address this issue, a collaborative analysis approach for the force, temperature, and vibration data is proposed. By fully integrating time-frequency characterization with SSAE, deep features from the multi-source heterogeneous data are adaptively extracted.

Fig. ~~5~~4 illustrates the constructed multi-sensor data fusion framework. The collected force, temperature and vibration signals are input to the frame in parallel. After features extraction, the feature matrix can be obtained as

$$X_H = \left[X_H^1, X_H^2, X_H^3\right] = \left[X_H^F, X_H^T, X_H^V\right] \qquad (~~4~~14)$$

where X_H is the features matrix before dimensionality reduction~~, and~~.

Sparse autoencoder (SAE) is the foundation of SSAE, which minimizes the distance between the reconstructed vector and the output vector by calculating the error between the output and the original input. The cost function with respect to that signal example can be designed as

$$J(W,b,x) = \frac{1}{2}\left\|h_{W,b}(x) - x\right\|_2^2 \qquad (5)$$

where $h_{W,b}(x) = f(W^T x)$ is equal to the output x' and x is the input.

Give a training set of m examples, the overall cost function can be defined as

$$J(W,b) = \left[\frac{1}{2m}\sum_{i=1}^{m}\left(\left\|h_{W,b}\left(x^{(i)}\right) - x\right\|^2\right)\right] + \frac{\lambda}{2}\sum_{l=1}^{n_l-1}\sum_{i=1}^{s_l}\sum_{j=1}^{s_{l+1}}\left(W_{ji}^{(l)}\right)^2 \qquad (6)$$

where n_l represents the number of autoencoder layers, $W_{ji}^{(l)}$ is the weight matrix between L_l with i units and L_{l+1} with j units.

To avoid overfitting, a sparse constraint described by KL divergence is introduced

$$KL\left(\rho \| \hat{\rho}_j\right) = \rho \log\frac{\rho}{\rho_j} + (1-\rho)\log\frac{1-\rho}{1-\hat{\rho}_j} \qquad (7)$$

where ρ is the sparsity constant, and $\hat{\rho}_j$ is the average activation of the hidden unit j. The overall cost function can be formulated as

$$J_{\text{sparse}}(W,b) = J(W,b) + \beta \sum_{j=1}^{s_2} KL\left(\rho \| \hat{\rho}_j\right) \qquad (8)$$

Stacked sparse autoencoders (SSAE) is constructed by stacking multiple SAE to further mine the deeper features of the data. The operation mechanism of SSAE can be represented as

$$X^{n+1} = Y^{(n)} = f\left(W^{(n)} X^{(n)} + b^{(n)}\right) \qquad (9)$$

(10)The loss function ~~in (4)~~of the SSAE can be ~~modified~~formulated as

$$E_t^n = J_t^n\left(W_t^n, b_t^n\right) + \beta_t \sum_{i=1}^{S_t^n} KL\left(\rho_t \| \hat{\rho}_{t,i}^n\right) \qquad (11\cancel{15})$$

$$J_t^n\left(W_t^n, b_t^n\right) = \frac{1}{2m} \sum_{i=1}^{m} \| f_k'\left(W_t'^n f_k\left(W_t^n \left[X_H^t\right]_{n,i} + b_t^n\right) + b_t'^n\right) - \left[X_H^t\right]_{n,i} \|^2 + \frac{\lambda_t}{2} \sum_{l=1}^{n} \sum_{c=1}^{s_t^{l+1}} \sum_{r=1}^{s_t^l} \left(\left[W_t^l\right]_{c,r}\right)^2$$

(~~16~~)(12)

where $t = 1,2,3$ is the SSAE corresponding to the $t-th$ sensor, and $n = 1,2,\ldots,k_n$ is the $n-th$ autoencoder, so E_t^n is the cost function of $t-th$ SSAE and $n-th$ autoencoder. $f_k(\cdot)$ is the activation function. Therefore, W_t^n and b_t^n can be obtained by minimizing E_t^n.

Finally, the features matrix X after dimensionality reduction can be calculated by the following formula

$$\begin{cases} Y_t^1 = \left[X_H^t\right]_1, X_L^t = Y_t^{k_n} \\ Y_t^{j+1} = W_t^n Y_t^j + b_t^n \\ X = \left[X_L^1, X_L^2, X_L^3\right] \end{cases} \qquad (13)$$

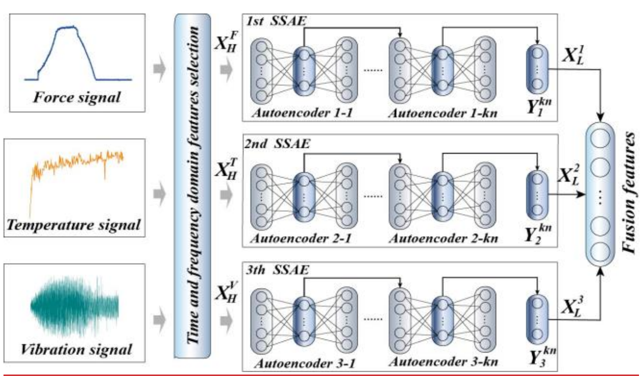


Fig. 4. The constructed multi-sensor data fusion framework

Bayesian LSTM

To further achieve quality prediction in the continuous processing context, a time-series forecasting network based on Bayesian LSTM was developed upon the foundation of feature fusion. Given the significant uncertainties associated with the processing environment and materials, the damage in composite materials processing exhibits high unpredictability. With this in consideration, a Bayesian inference mechanism was incorporated on top of the conventional LSTM framework. This enhancement not only improves the model's resistance to overfitting but also provides a quantification of uncertainty, which is particularly crucial for making informed decisions about processing quality.

The basic architecture of the LSTM memory cell is shown in Fig. 5, and the calculation formula of LSTM is as follows:

$$i_t = \sigma_i\left(x_t W_{xi} + h_{t-1} W_{hi} + b_i\right) \qquad (14)$$

$$f_t = \sigma_f\left(x_t W_{xf} + h_{t-1} W_{hf} + b_f\right) \qquad (15)$$

$$c_t = f_t \odot c_{t-1} + i_t \odot \sigma_c\left(x_t W_{xc} + h_{t-1} W_{hc} + b_c\right) \qquad (16)$$

$$o_t = \sigma_o\left(x_t W_{xo} + h_{t-1} W_{ho} + b_o\right) \qquad (17)$$

$$h_t = o_t \odot \sigma_h\left(c_t\right) \qquad (18)$$

where i, f, c, o and h are the input gate, forget gate, cell activation vector, output gate, and hidden layer output, respectively. W and b represent the weight matrix and bias vector, respectively. $\sigma(\cdot)$ is the sigmoid function.

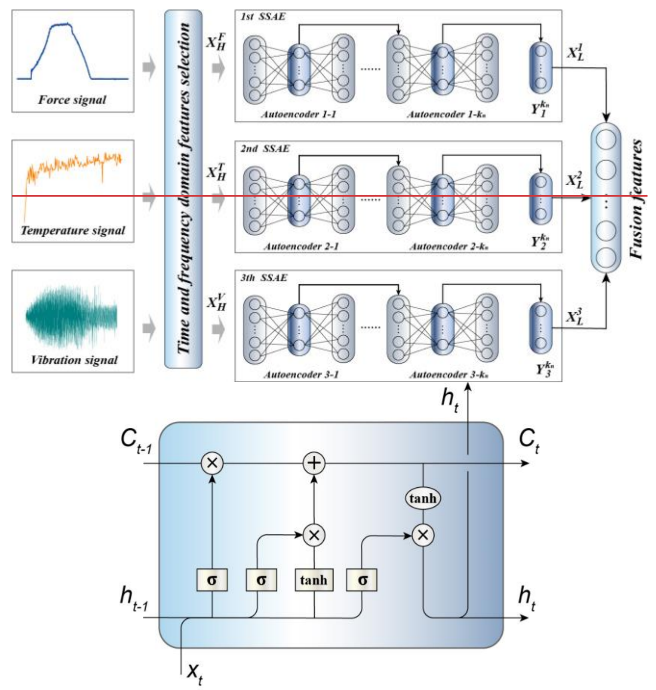


Fig. 5. The ~~constructed multi-sensor data fusion framework~~ ~~Bayesian~~ LSTM memory cell

Compared to traditional LSTM, the Bayesian LSTM can obtain the prediction uncertainty. In a Bayesian neural network, a prior assumption is introduced for the distribution of the weight parameters W. In regression, we often assume

$$y | W \sim N\left(f^W(x), \sigma^2\right) \qquad (19\cancel{18})$$

where the neural network is denoted as $f^W(\cdot)$, and σ is the noise level.

As for drilling quality prediction task, Given a set of N input $X = \{x_1, \ldots, x_N\}$ and output $Y = \{y_1, \ldots, y_N\}$, Bayesian inference can be used to find the posterior distribution over model parameters $p(W | X, Y)$ with a new sample x^*, the predictive probability density can be calculate as

$$p\left(y^{*}|\ x^{*}\right)=\int_{W}p\left(y^{*}|\ f^{W}\left(x^{*}\right)\right)p(W|\ X,Y)dW \qquad \text{(19)}$$

~~And the prediction distribution which quantifies the uncertainty is expressed as~~

$$\mathrm{Var}\left(y^{*}|\ x^{*}\right)=\mathrm{Var}\left[\mathbb{E}\left(y^{*}|\ W,x^{*}\right)\right]+\mathbb{E}\left[\mathrm{Var}\left(y^{*}|\ W,x^{*}\right)\right]$$
$$=\mathrm{Var}\left(f^{W}\left(x^{*}\right)\right)+\sigma^{2}$$

(20)

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$$\mathrm{Var}\left(y^{*}|\ x^{*}\right)=\mathrm{Var}\left[\mathbb{E}\left(y^{*}|\ W,x^{*}\right)\right]+\mathbb{E}\left[\mathrm{Var}\left(y^{*}|\ W,x^{*}\right)\right]$$
$$=\mathrm{Var}\left(f^{W}\left(x^{*}\right)\right)+\sigma^{2}$$

(21)

where $\mathrm{Var}\left(f^{W}\left(x^{*}\right)\right)$ reflects modeling uncertainty, which is also called as epistemic uncertainty. And σ^{2} reflects the inherent noise which is the noise level during data generating process.

However, due to the complicated non-linearity and non-conjugacy of deep model, it is difficult to perform exact posterior distribution. So a distribution $q(W)$ is used to approximate to approximate the posterior $p(W|\ X,Y)$, Thus the goal is to minimizing the Kullback-Leibler (KL) divergence between $p(W|\ X,Y)$ and $q(W)$

$$KL(p(W|\ X,Y)\|\ q(W))=-\sum_{n=1}^{N}\int q(W)\log p\left(y_{n}|\ x_{n},W\right)dW$$
$$+KL(q(W)\|\ p(W))$$

(22~~21~~)

Then, the approximate predictive distribution can be formulated as

$$p\left(y^{*}|\ x^{*}\right)=\int p\left(y^{*}|\ x^{*},W\right)q(W)dW \qquad \text{(23\sout{22})}$$

By Monte Carlo dropout, the training of the network can be viewed as determining $q(W)$ (Gal et al., 2021), and by performing T stochastic forward passes through the LSTM and averaging the results, the prediction is estimated via

$$\mathbb{E}_{q\left(y^{*}|\ x^{*}\right)}\left(y^{*}\right)=\hat{y}^{*}(x^{*})\approx\frac{1}{T}\sum_{t-1}^{T}f^{W^{t}}\left(x^{*}\right) \qquad \text{(24\sout{23})}$$

where $\hat{y}^{*}(x^{*})$ is the predicted quality corresponding to x^{*}.

Probabilistic drilling quality forecasting

To further conduct probabilistic drilling quality forecasting, an α-level prediction interval (PI) is introduced to measure the uncertainty.

According to (20), the uncertainty consists of modeling uncertainty and inherent noise. With true value estimated by $\hat{y}^{*}$ calculated by (23), the modeling uncertainty can be approximated by sample variance

$$\sigma_{m}^{2}=\mathrm{Var}\left(f^{W}\left(x^{*}\right)\right)=\frac{1}{T}\sum_{t}^{1}\left(f^{W^{t}}\left(x^{*}\right)-\hat{y}^{*}\left(x^{*}\right)\right)^{2} \qquad \text{(25\sout{24})}$$

In the process of composite drilling, there is a priori that the more serious the damage, the stronger the damage fluctuation. Therefore, combined with prior knowledge, the inherent noise can be calculated as

$$\sigma_{i}^{2}=\beta\exp\left(f^{W}(x^{*})\right) \qquad \text{(26\sout{25})}$$

where β is a constant, which can be determined according to the different materials and environment.

Combining the modeling uncertainty and the inherent noise, we can obtain the total uncertainty by the form of standard deviation

$$\sigma_{t}=\sqrt{\sigma_{m}^{2}+\sigma_{i}^{2}} \qquad \text{\sout{(26)}}$$

~~Thus, the PI can be expressed as~~

$$\cancel{\left[\hat{y}^{*}-z_{\alpha/2}\sigma,\hat{y}^{*}+z_{\alpha/2}\sigma\right]} \qquad \text{(27)}$$

Thus, the PI can be expressed as

$$\left[\hat{y}^{*}-z_{\alpha/2}\sigma,\hat{y}^{*}+z_{\alpha/2}\sigma\right] \qquad \text{(28)}$$

Therefore, through the further application of Bayesian LSTM, not only more stable prediction results can be given, but also interval estimation can be carried out through uncertainty evaluation, so as to obtain more comprehensive drilling quality prediction results.

EXPERIMENT

Experimental Setup

Fig. 6 illustrates the experimental setup. The thrust force during the drilling process was measured using a Kistler 9257B dynamometer and amplified with a Kistler 5080B signal amplifier. The force range of the instrument is 0 to 5000N in both the X and Y directions and 0 to 10000N in the Z direction, and the force sensitivity is -7.5pC/N in both the X and Y directions and -3.7pC/N in the Z direction. To capture the dynamic temperature information at the exit area, an infrared camera (Telops-MW) was used to acquire low-noise infrared thermal images at high frequencies. The instrument's measurement error is within 1% between -15°C and 324°C. The temperature measurement accuracy of this thermal imaging system is essentially the same as that of a thermocouple. The vibration of the workpiece was also measured during drilling using the OFV-505 laser vibrometer, located on the same side as the temperature measurement. The velocity resolution of the instrument is better than 0.02μm/s and the displacement resolution is better than 0.15 nm, which can provide sufficiently high precision vibration measurement information.

The experiment utilized a carbon fiber reinforced plastic (CFRP) material with a thickness of 8 mm and comprised of 44 layers of carbon fiber. The carbon fiber is made up of CYCOM977-2 epoxy resin matrix and Toshiba T300 carbon fiber, and both the upper and lower surfaces are reinforced with a 0°/90° glass fiber/epoxy resin layer. The images of the holes were recorded using a custom-designed vision system.

In this study, two spindle speeds and three feed rates were selected as the main processing parameters during drilling. The specific experimental parameters are listed in Table 1., and a total of 220 holes (8 mm diameter) were drilled in each group.

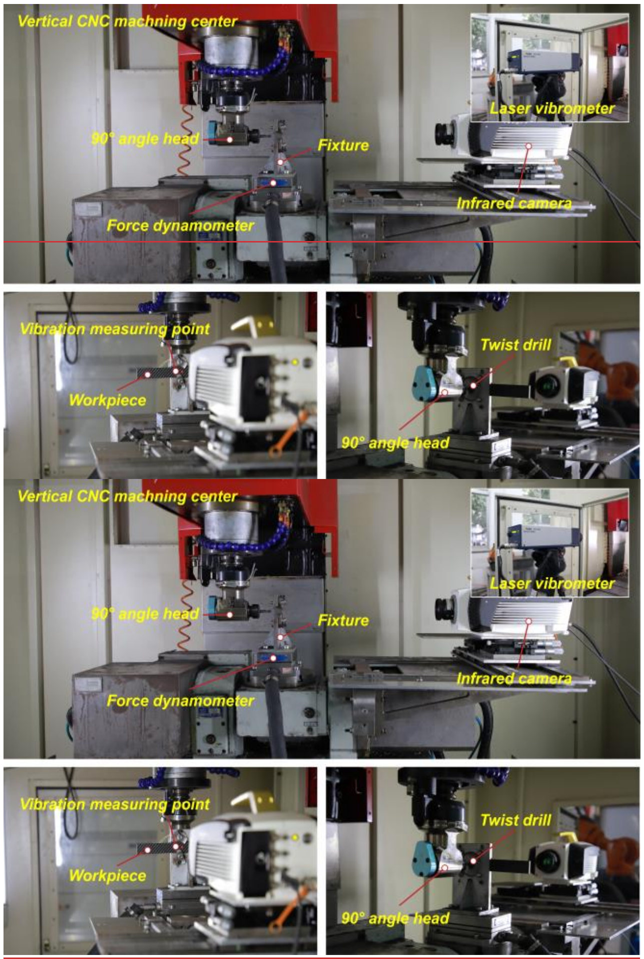


Fig. 6. The experimental layout

Table 1 Experimental parameters

Test no.	1	2	3	4	5	6
Spindle Speed (rpm)	3000	4000	3000	4000	3000	4000
Feed speed (mm/min)	150	150	250	250	350	350

Dataset Construction

As mentioned in the previous section, there is heterogeneity in the collected multi-sensor signals, and different adaptive preprocessing strategies need to be designed. The analysis results are shown in Fig. 7. After preprocessing, the noise of the signals is eliminated, and the redundancy is reduced. The matching of multi-sensor data is accomplished by the initial time of machining, i.e., each hole begins to be machined at essentially exactly the same time that the sensors begin to collect.

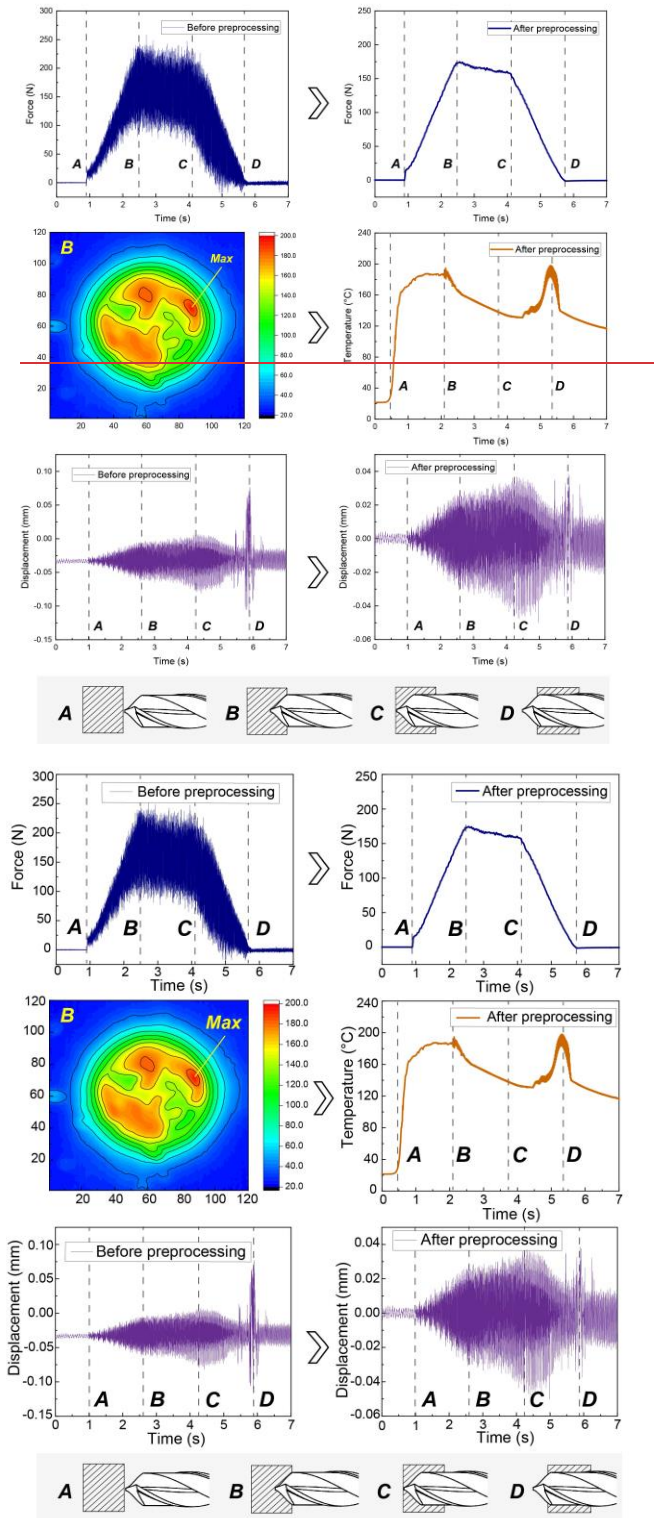


Fig. 7. The preprocessing of multi-sensor signals

The results of extraction and quantification of damaged area are shown in Fig. 8. The four images are selected from test no.1. The ordinal number of holes is displayed in the upper left corner of the picture, and the corresponding value of F_s displayed in the lower right corner. As the number of machined holes increases, the severity of the damage gradually increases.

The procedure of sample generation is illustrated in Fig. 9.

Samples are constructed using a sliding window with step size one, where each sliding window contains the previous 5 signal features as input and aims to forecast the quality of hole which has not yet been machined. ~~The test no.1 and test no.2 are used to verify the proposed method.~~

Considering the characteristics of the dataset's time series, a specific form of cross-validation was employed to validate the proposed model, namely "Leave-One-Group-Out Cross-Validation." Each group contains a complete time series of data obtained from independent processing operations, and in each iteration, one group is left out as the validation set. In the subsequent experimental results, test no.1 and test no.2 are used to verify the proposed method. This is because groups with higher feed rates exhibit particularly strong randomness in damage, and in practical machining processes, lower feed rates are also preferred to control the damage. This validation method ensures the applicability and accuracy of the proposed method under different machining conditions.

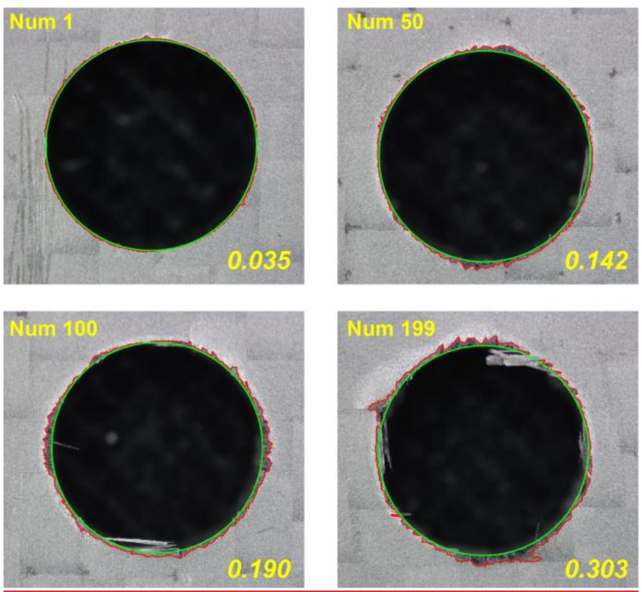


Fig. 8. The extraction and quantification of damaged area

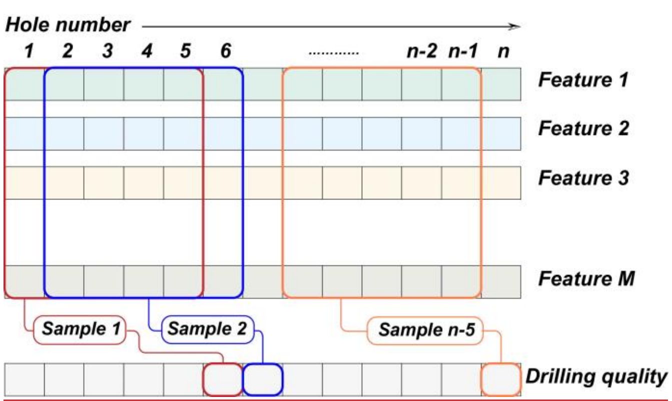
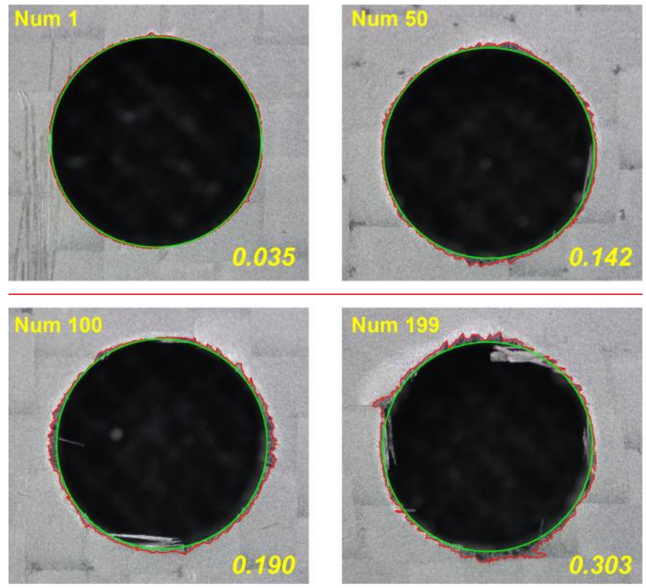


Fig. 9. Data samples generation

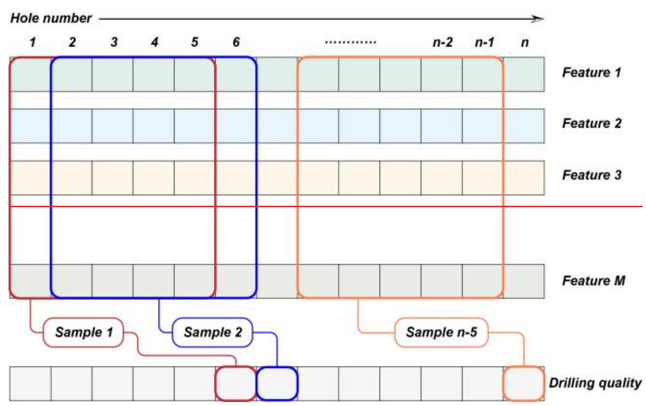
Model Construction

After dataset construction, 30 time-domain and frequency-domain features are selected for the subsequent analysis process by referring to the most frequently used eigenvalues. Therefore, the dimensionality of the input feature matrix X_H is 90. After feature fusion by formula (~~15) (174)-~~(13), 6-dimensionanl deep features are obtained.

The Bayesian LSTM is constructed with two-layer LSTM cells, with 64 and 32 hidden states, respectively. The dropout probability is set to 0.1. The model uncertainty is estimated by the model trained with 100 epochs. The experiments are conducted on a 64-bit desktop, which is equipped with an Intel Core i7-10700 CPU and a 64 G RAM.



~~Fig. 8. The extraction and quantification of damaged area~~



~~Fig. 9. Data samples generation~~

Comparison with Other Methods

In this section, the proposed MFLSTM is compared with five benchmark methods: extreme gradient boosting (XGBoost), support vector regression (SVR), Multilayer Perceptron (MLP), gated recurrent neural network (GRU), and traditional LSTM. In addition, as an effective dimension reduction method, kernel principal component analysis (KPCA) is applied to model comparison. The hyperparameters of all the models involved in the comparison were carefully calibrated to allow for optimal prediction results. This initiative ensures the fairness of the comparisons. The results involved in the comparison are the average of the ten predictions of the model, and the compared metrics are Root Mean Square Error (RMSE~~,~~), Coefficient of Determination (R^2 SCORE) and Mean Absolute Error (MAE~~.~~).

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{29}$$

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{30}$$

$$R^2 = 1 - \sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \Big/ \sum_{i=1}^{n}(y_i - \bar{y})^2 \tag{31}$$

These three indicators are widely used in the evaluation of deep learning regression models, providing a comprehensive perspective for model assessment. The results of the model comparison are shown in Fig .10. It can be seen from the figure that the prediction result of proposed MFLSTM can accurately reflect the trend of composites quality evolution under the high randomness. In contrast, none of the other methods can perform an accurate fit. Table 2 shows the results of the quantitative comparison of the prediction errors (RMSE) for each model. In the no.2 experiment, dimensionality reduction using KPCA can significantly reduce the prediction error of the model. However, in the no.1 experiment, the prediction error is not significantly reduced, which indicates that the key features of the data are not accurately extracted by the KPCA dimensionality reduction method. Compared to other methods, the proposed method reduces the machining quality prediction error by more than 25% (from 0.0470 to 0.0352). In addition, the distribution of the box-line plots in Fig. 11 show that the MFLSTM is more stable, and the proposed MFLSTM method preforms better than other methods on SCORE and MAE. Training time is not a concern, so there is no comparison here.

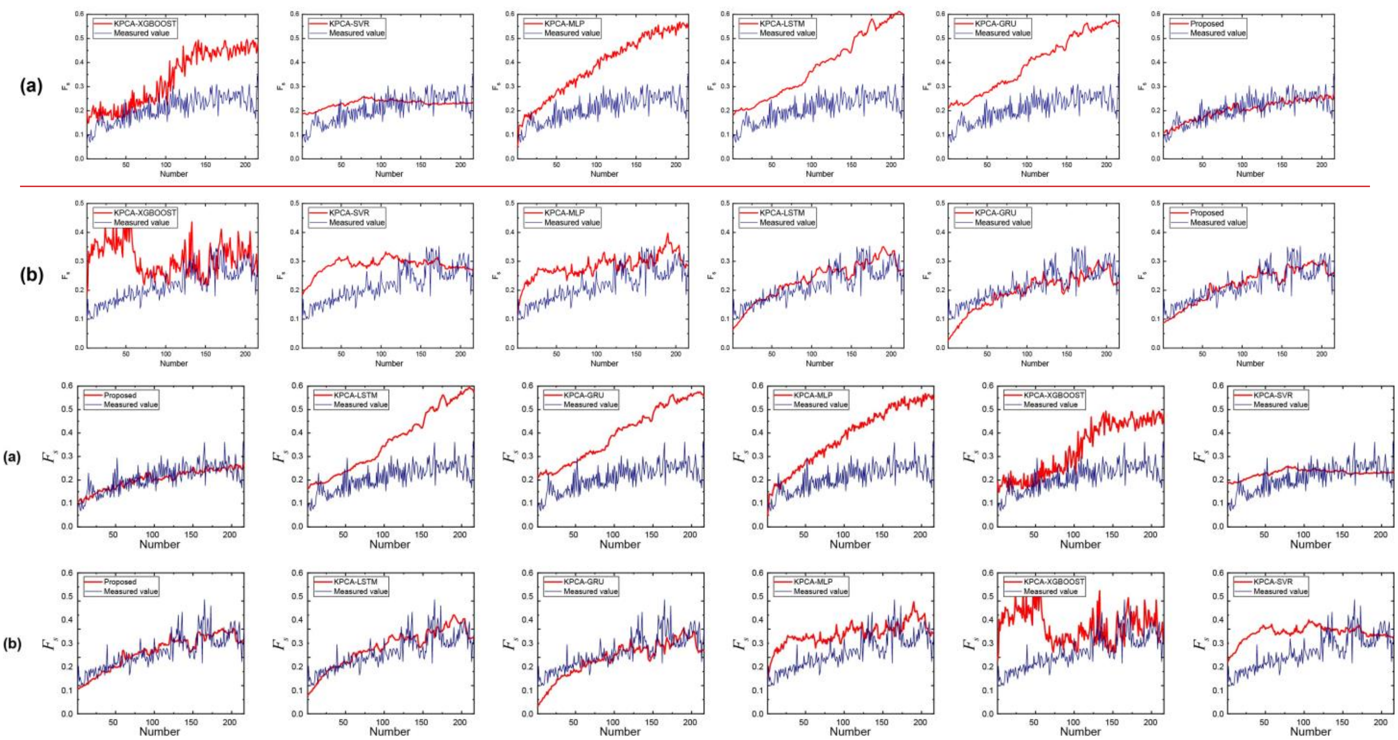


Fig. 10. The drilling quality prediction results of different models: (a) Test no.1, (b) Test no.2

Table 2 Performance comparison of different models under RMSE

Model	Without dimension reduction					Dimension reduction by KPCA					**Proposed Model**
	XGBoost	SVR	MLP	LSTM	GRU	XGBoost	SVR	MLP	LSTM	GRU	
Test no 1	0.0863	0.0745	0.1866	0.1762	0.1634	0.1265	0.0860	0.1576	0.2278	0.2161	**0.0386**
Test no 2	0.0604	0.0782	0.0958	0.1041	0.1099	0.1265	0.0860	0.0789	0.0470	0.0520	**0.0352**

In summary, on the one hand, the SSAEs can extract the features of multi-source data more accurately due to deeper feature extraction. In addition, SSAEs have better feature fusion performance by reducing the dimensionality of force, temperature, and vibration separately. On the other hand, the Bayesian LSTM has more stable point prediction results due to the usage of MC dropout, which averages the multiple prediction results and separates the prediction uncertainties.

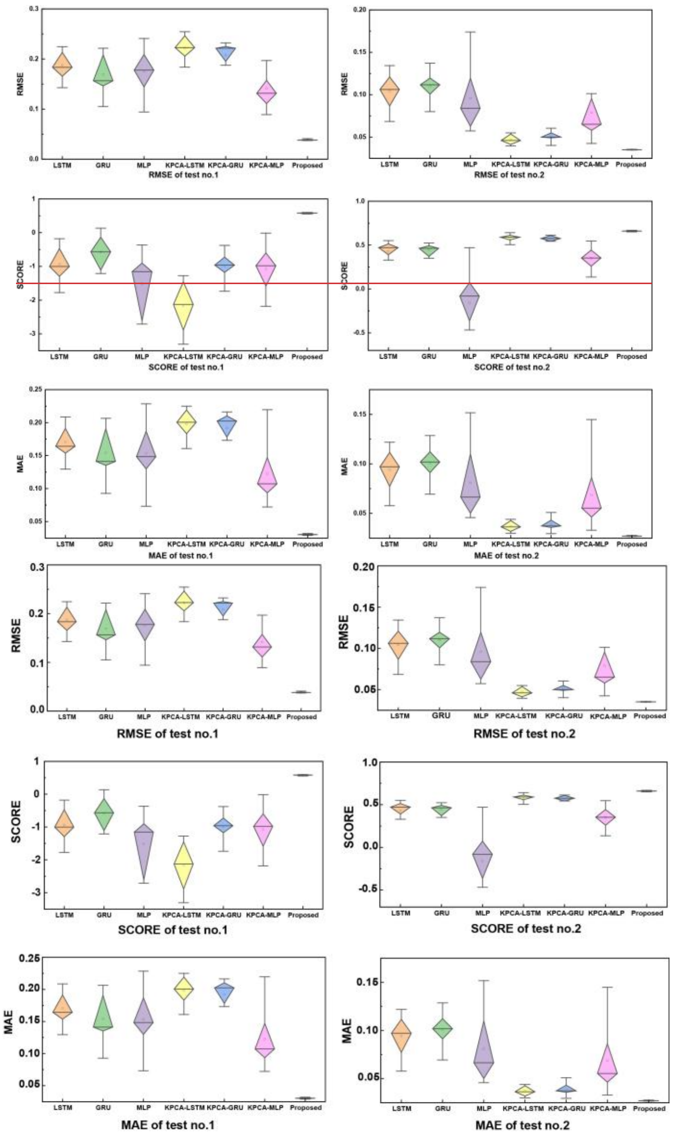


Fig. 11. Performance estimation results

Feature Selection analysis

To further validate the performance of the proposed method and to analyze the influence of sensor selection and fusion method on the final prediction results, validation experiments are designed. In this section, five main cases are discussed. The model prediction errors are shown in Fig. 12, and the prediction results are shown in Fig. 13. F , V and T represent the thrust force, vibration, and temperature respectively. E.g., $F+T$ means that only force and temperature signals are used for prediction. "Mixed features" means that all the eigenvalues of the signals are input to the proposed model for prediction mixed, instead of inputting each signal into the model separately.

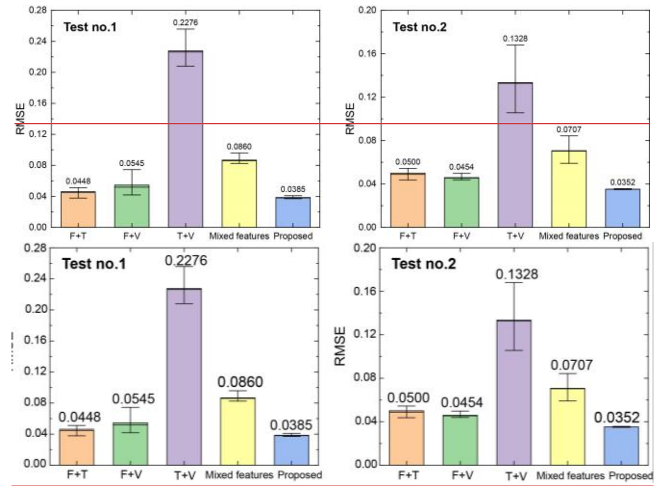
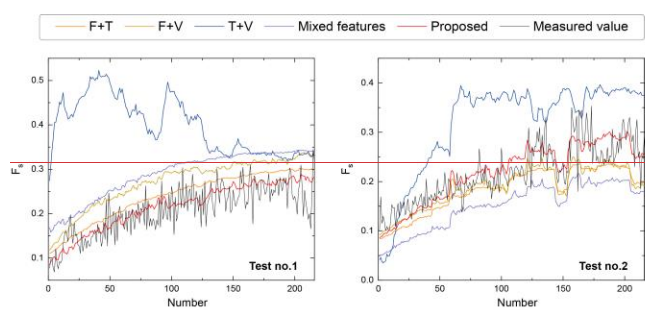


Fig. 12. The model prediction errors with different features

As can be seen from the figures, the thrust is the key to accurate prediction of drilling quality, which is demonstrated by the fact that $F+T$ and $F+V$ show good prediction results, while $T+V$ has a very large error. In addition to this, accurate prediction results cannot be obtained if the "Mixed features" is used. The proposed method uses data from three sensors and the RMSE is reduced by more than 20% compared to $F+T$ and $F+V$. The effect of different sensor signals on the prediction results of drilling quality can also be further analyzed from the comparison of the predicted value and the measured value. The force and temperature signals can complement each other to predict the smoothed trend of drilling quality. The introduction of vibration signals on the one hand improved the accuracy of the drilling quality prediction results, and on the other hand adds volatility to the prediction results.

In summary, the three physical quantities selected for monitoring all play a key role int quality prediction. Based on the multi-sensor fusion measurements, the proposed method can effectively fuse the heterogeneous data from multiple sources, which can eventually achieve accurate prediction of the drilling quality.



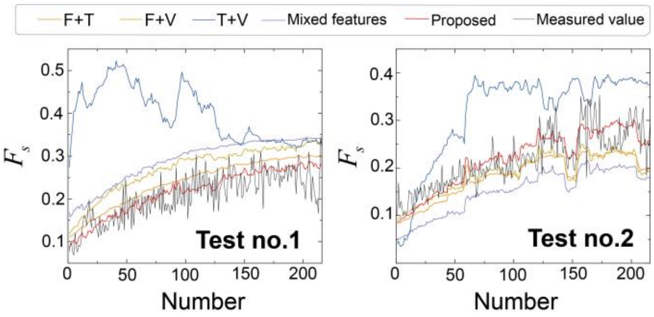


Fig. 13. The prediction results with different features

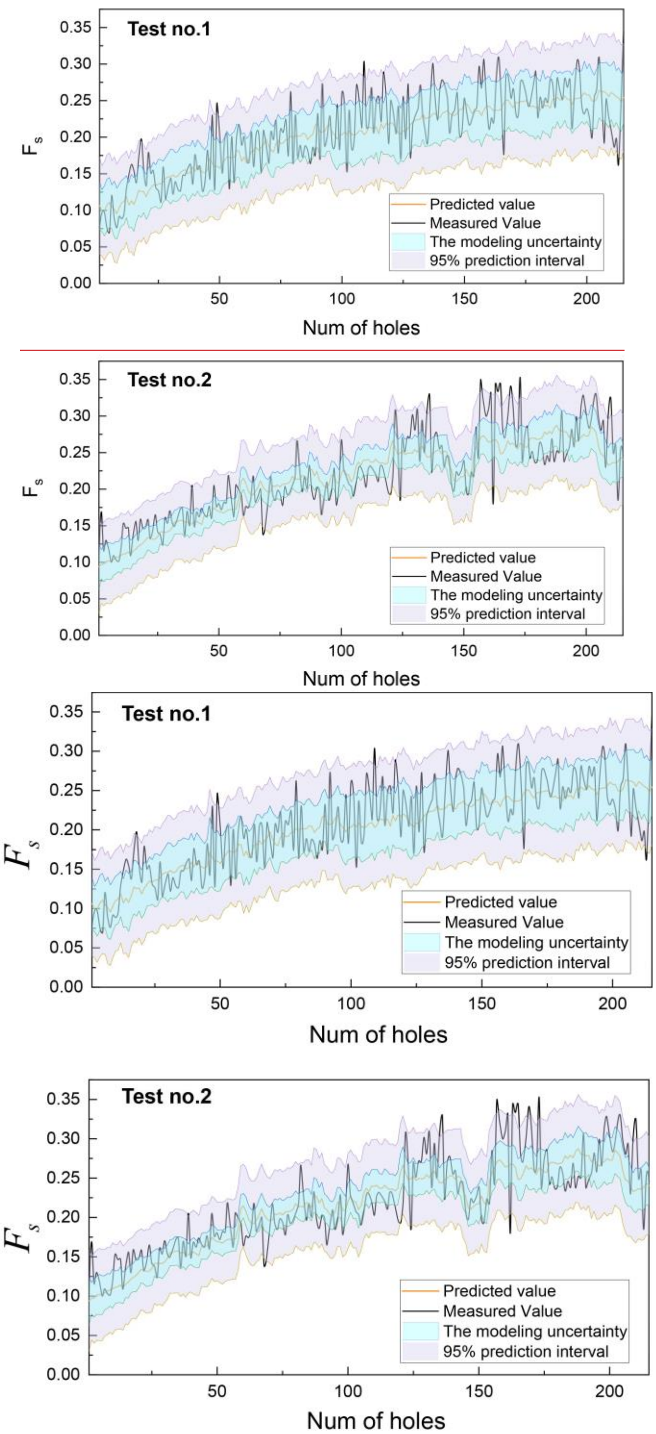


Fig. 14. Drilling quality prediction results with 95% PI

Interval Forecast Results

By measuring the uncertainty, the drilling quality can be predicted with an α-level PI according to (~~24)~~ ~~(27~~28). The forecasting results are visualized in Fig. 14. The blue area in the figure represents model uncertainty, and the purple area represents the overall uncertainty of model uncertainty and inherent noise together. When the confidence is 95%, only a few points are not with in the PI, and these points are near the confidence upper bound.

In the drilling process, different strategies can be adopted according to production need, which offers the possibility of flexible manufacturing. If it is necessary to ensure that no damage out of tolerance occurs for any processed hole, a larger confidence coefficient can be selected. If the quality requirement is not strict and more holes need to be drilled, a smaller confidence coefficient can also be selected.

Comparison with similar research

To further highlight the advantages of the proposed method, a comparison was conducted with other quality prediction methods, as shown in Table 3. Currently, most other methods focus on predicting the machining quality of a small batch of holes under multi-parameter conditions, where the input is machining parameters and the output is machining quality, without incorporating sensor data from the machining process. Only a few studies (Choi et al., 2024) have integrated multi-sensor data for machining quality prediction. Compared to these methods, the proposed approach significantly increases the number of predicted instances. Moreover, it is the first to achieve predictive capabilities for the holes yet to be processed, and it provides uncertainty assessments, which are critical for ensuring a 100% success rate in composite material machining.

Software Integration and Application

Based on the principles and algorithms, a machining quality control software was developed, as shown in Fig.15. The software is designed according to three layers: data acquisition, quality prediction, and frontend display. The data acquisition layer acquires sensor data via REST APIs, with sensors connected to the software system through the TCP/IP network communication protocol. The quality prediction layer, developed using the Spring Boot framework, is responsible for fetching, processing, and analyzing data from the data acquisition layer. Data is stored and managed using the MySQL database management system. The frontend display layer, built on the Vue framework, provides a human-machine interface, enabling interactive real-time display of machine tool processing status and sensor data. ~~The~~

As shown in Fig. 15, the front-end interface of the software is mainly composed of the following parts. First, the left side of the software is reserved for the selection and input interface of machining tools, materials, and parameters. The interface, when expanded, is shown in Fig. 16. In existing research, the focus has primarily been on the combination of a single tool and material, a limitation that is also discussed in the final conclusion. On the right side of the software, an interactive display interface for force, temperature, and vibration during the machining process is provided, and it can display the predicted damage value after the machining is completed. The damage tolerance value can be determined by the user based on different machining quality requirements. Because of the lag due to data transmission, the time from the end of processing to the result of damage prediction is within 1s, but it is still quite efficient. If the predicted damage value for the next hole exceeds the damage tolerance value during the machining process, an alarm program will be triggered, as shown in Fig. 17. The user can then decide whether the tool replacement process needs to be initiated based on this result.

In summary, the software can be deployed during the machining process to provide warnings for machining damage out of tolerance and manage process data, thereby laying the foundation for continuous process optimization.

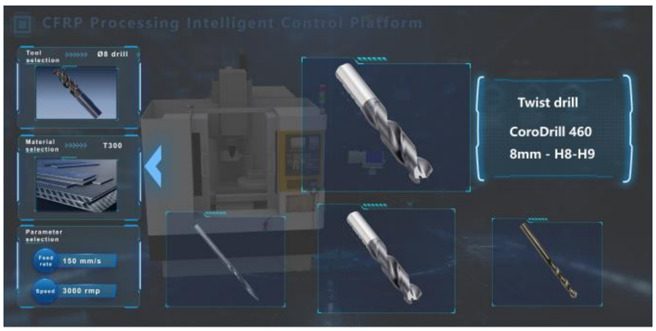


Fig. 16. Processing conditions and parameter configuration interface

Fig. 17. Alarm interface when damage exceeds tolerance limits

CONCLUSIONS

This paper presents a novel online prediction method for the quality of composite material drilling based on multi-sensor fusion. Compared to traditional TCM methods, the proposed method has the advantage of directly predicting the quality of the product. The findings from the analysis include:

(1) The proposed framework, through the extraction and quantification of composite drilling damage, allows for the development of control strategies based on prediction results directly.

(2) The integration of multiple sensor data can significantly reduce prediction error. The three types of signals chosen all play an important role, and he thrust is the most crucial factor.

(3) Experimental results demonstrate that the proposed MFLSTM model can provide stable point prediction results with a 25% reduction in prediction error and interval prediction results, effectively overcoming the impact of damage stochasticity.

The proposed method has the potential to enhance the intelligence of composite component manufacturing~~,~~ and has enabled industrial deployment through the developed software. ~~Future research should focus on multi-sensor integration and adaptive adjustment strategies for processing parameters, as well as expanding the application of the proposed methods to other composite material processing quality predictions.~~

Although the effectiveness of this method has been fully validated experimentally, there are still some limitations to the proposed approach. Firstly, there is an urgent need to develop an intelligent measurement system that integrates multiple measurement functions such as feed force, temperature, and vibration. This can significantly reduce the complexity of deploying the measurement system and expands the applicability of the proposed method. Additionally, the method is suitable for positive quality prediction under different processing parameters for a single type of material, but it exhibits poor extrapolation in different composite materials. In the future, it may be beneficial to explore optimal drilling parameter prediction in reverse using experimental data, or to combine transfer learning to quickly develop processing quality prediction models for different composite materials.

Table 3 Related work on the quality prediction of CFRP drilling

Reference	Method	Utilization of multiple sensors	Number of consecutively machined holes	utilization of multiple machining parameters	Prediction of the machining quality of the next hole	Uncertainty assessment
Soepangkat et al., 2020	BPNN-PSO	-	single	✓	-	-
Wang et al., 2020	ANN, NSGAII and fuzzy C-means	-	10	✓	-	-
Jiao et al., 2020	BP Neural Network	-	20	✓	-	-
Zhang et al., 2021	Gaussian process regression	-	single	✓	-	-
Romoli et al., 2021	Fuzzy logic algorithm	-	4	✓	-	-
Choi et al., 2024	Multimodal 1D CNN	✓	100	-	-	-
Ours	MFLSTM	✓	220	✓	✓	✓

Fig. 15. Intelligent management and control software for CFRP processing

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