A digital twin defined autonomous milling process towards the online optimal control of milling deformation for thin-walled parts

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Abstract

Thin-walled parts are widely used in the aerospace industry, where the milling deformation of the parts caused by their thin-walled draping and extremely large size ratio characteristics as well as high material removal rate has been the most common quality issue that greatly influences the assembly performance and operation safety of aerospace equipment. Hence, effective management of milling deformation of a thin-walled part will significantly improve its quality, which, however, is still made difficult by the lack of a real-time deformation perception, optimization, and control method. To bridge the gap, this paper proposes a novel online optimal control method of milling deformation for thin-walled parts by incorporating digital twins into the milling process of thin-walled parts. To this end, a reference framework of the milling process digital twin (MPDT) for thin-walled parts are designed, where the autonomous operation logic of MPDT for online optimal control of milling deformation is further clarified. On that basis, three key enabling technologies of MPDT are introduced from the perspective of multidimensional high-fidelity MPDT modeling, knowledge-driven low-latency milling deformation simulation, and online optimal control of milling deformation, which provide an insight into the industrial implementation of MPDT. In addition, a MPDT prototype system is implemented, where its application and evaluation results demonstrate the feasibility and effectiveness of the proposed approach.

Keywords: Autonomous milling process; Digital twins; Milling process digital twin; Optimal control; Thin-walled parts.
1 Introduction

Thin-walled parts, such as aero-engine casings, aircraft precision shells, and integral impellers, are one of a broad family of aerospace parts widely used in airplanes, rockets, and aero-engines, etc. A thin-walled part is usually characterized by the thin-walled draping and extremely large size ratio, where its machining quality will greatly influence the assembly performance and operation safety of aerospace equipment. Milling, as one of the main processing methods for thin-walled parts, is an important method to ensure the machining quality of parts [1]. Nowadays, the shape and structure of such parts become increasingly complex to deal with the extremely changeable operation environment of aerospace equipment, where the milling quality requirements of the parts are continuously improved accordingly. Among those requirements, milling deformation is the most common milling quality problem due to the high material removal rate, usually up to 85%, and continuously reduced workpiece stiffness because of the high material removal rate [2]. Meanwhile, difficulties in online measuring the milling deformation as well as the unclear deformation mechanism make it hard to be controlled during the milling process. Therefore, it is of great significance for aerospace manufacturing enterprises to develop an effective milling deformation perception, optimization, and control method to ensure the milling quality of thin-walled parts.

A digital twin (DT), is defined as “an integrated multi-physics, multi-scale, probabilistic simulation of a vehicle or system that uses the best available physical models, sensor updates, fleet history, etc., to mirror the life of its flying twin” [3], might equip the milling process of thin-walled parts with powerful real-time perception, optimization, and control capabilities,
showing great potential in addressing the above issues in the context of Industry 4.0. Nowadays, DT has achieved initial success in the construction of a smart machine tool or milling process with a certain degree of intelligence, for example, cutting parameter optimization [4] and time-varying error control [5]. However, the DT application is still in its infancy. How to develop a DT-driven milling deformation perception, optimization, and control method is still made difficult by the following unaddressed issues. Firstly, the milling deformation mechanism of thin-walled parts is still unclear, which makes it hard to guarantee the modeling fidelity of the milling process. Secondly, the traditional milling deformation simulation/prediction method relies on finite element analysis, which leads to high computational complexity and long computation time. At the same time, it does not consider the on-site milling data, resulting in low simulation/prediction accuracy. Lastly, the existing milling deformation optimization method aims to obtain a group of static milling parameters at the process planning stage, which could not be dynamically adjusted to cope with the real-time milling disturbances, such as machine tool vibration and tool wear.

To bridge the gap, this paper proposes a novel DT-defined autonomous milling process framework, namely milling process digital twin (MPDT), for the optimal control of milling deformation for thin-walled parts. On that basis, three key enabling technologies of MPDT are introduced from the perspective of multidimensional high-fidelity MPDT modeling, knowledge-driven low-latency milling deformation simulation, and online optimal control of milling deformation, which provide effective solutions for the above three unaddressed issues preventing the application of DT in autonomously controlling of milling deformation for thin-
walled parts. In addition, a MPDT prototype system with its application and evaluation examples demonstrates the feasibility and effectiveness of the approach.

The rest of the paper is organized as follows. Section 2 summarizes the research gap of current related works. In Section 3, the reference framework and operation logic of MPDT are introduced. Three key enabling technologies of MPDT are introduced in Section 4. Section 5 discusses a thus implemented prototype system to demonstrate the effectiveness of the approach. Conclusions and future works are found in Section 6.

2 Related work

2.1 Milling deformation optimization and control

Nowadays, milling deformation optimization and control for thin-walled parts have attracted increasing attention from both academics and industry. In terms of milling deformation optimization, Armendia et al. [6] proposed a new concept for machine tool and machining process performance optimization, namely twin control, which allowed a better estimation of machining performance than single featured simulation packages by considering the energy consumption and end-life of components. Zhou et al. [7] presented a DT-based optimization strategy on the consideration of both machining efficiency and aerodynamic performance of the centrifugal impeller, and also introduced a tool-path generation method for the five-axis flank milling of the centrifugal impeller to improve its machining efficiency. Urquizo et al. [8] considered thermomechanical effects like shape deviations and a time-dependent domain to optimize the dry machining process. AkgÜN et al. [9] focused on the
optimization of cutting conditions and numerical analysis of flank wear in the milling of Inconel 625 superalloy using PVD AlTiN and CVD TiCN/Al₂O₃/TiN-coated carbide inserts. Tien et al. [10] developed a new hybrid algorithm to determine the optimal cutting parameters to minimize the total power consumption, and improve the surface quality and increase tool life. In terms of milling deformation control, Li et al. [11] proposed a machining deformation control method of thin-walled parts to enhance the equivalent bending stiffness by considering the influence of residual stress. Zhang et al. [12] proposed an approach for controlling the in-processes deformation of thin-walled parts that is aimed at balancing the internal stress and preventing the redistribution of residual stresses after the last machining step.

The above approaches could manage the machining deformation of thin-walled parts to a certain extent. However, the above approaches rely on a large number of complex and high-delay simulation calculations to analyze the machining deformation, residual stress, etc., based on finite element analysis. In addition, the above approaches do not consider the on-site machining data, resulting in low deformation prediction efficiency and control accuracy. Consequently, the above approaches could hardly support the online optimal control of milling deformation for thin-walled parts.

2.2 Digital twin-driven machine tools

DT, born as an effective fusion and interaction method for cyber-physical systems, has become one of the world’s strategic technology trends that attracts significant interest from both industry and academics [13, 14]. DT could provide powerful multi-scale and multi-
physics perception, optimization, and control capabilities, showing great potential in the construction of intelligent machine tools to improve machining quality.

In recent years, the application of DT in machine tools has made achievements in many aspects. For the DT-driven machine tool framework, Hänel et al. [15] introduced a competition-driven digital transformation in the machining sector, in which the creation of a DT for machining processes is approached by using a basic DT structure; Zhao et al. [16] proposed an advanced DT system framework for CNC machine tools and discussed the key factors that made the DT system more practical; Vishnu et al. [17] proposed a digital twin framework for NC machining processes, which allows simulation, prediction, and optimization of key performance indicators using the historical and real-time machining data during process planning and machining phases, respectively. For thin-walled parts manufacturing, Zhu et al. [18] presented a DT-driven thin-walled part manufacturing framework to allow the machine operator to manage the product changes, and make the start-up phases faster and more accurate. Wang et al. [19] proposed a DT-driven clamping force control approach to improve the machining accuracy of thin-walled parts. For predictive maintenance, Luo et al. [20] studied a hybrid approach driven by DT to achieve reliable predictive maintenance of CNC machine tools; Yang et al. [21] presented a hybrid DT-driven approach framework to predict performance degradation of CNC machine tool transmission system; Liu et al. [22] proposed a method of the time-varying error prediction and compensation for the movement axis of the CNC machine tool based on DT. For machining data application and service, Tong et al. [23] proposed a real-time processing data application and service based on the intelligent machine
tool DT; Zhang et al. [24] developed a cyber-physical machine tool based on edge computing technology to shorten the latency of mapping and reduce the high computation workload in the cloud; Ghosh et al. [25] proposed a special type of twin denoted as sensor signal-based twin that must be constructed and adapted into the cyber-physical systems.

The above relative work has explored the concept and application of DT in machine tools from various angles with varying degrees, showing great potential in addressing the above issues of low deformation optimization efficiency and control accuracy. However, the DT application is still in its infancy. Most current approaches still focus on establishing a theoretical framework of DT to solve the problems in machine tools. How to develop a DT-driven milling deformation perception, optimization, and control method is still made difficult by the unclear milling deformation mechanism of thin-walled parts that influences the DT modeling fidelity.

3 Reference framework of MPDT

As shown in Fig. 1, a reference framework of MPDT is proposed by introducing DT into the milling process of thin-walled parts for online optimization and control of its milling deformation. To this end, the reference framework is defined by a five-layer architecture, including the physical milling machine layer (PMML), DT data layer (DTDL), virtual milling machine layer (VMML), milling deformation simulation layer (MDSL), and deformation optimal control layer (DOCL).
PMML consists of a physical milling machine, its CNC system, cutters, and workpieces. PMML acts as an automatic actuator for milling thin-walled parts controlled by a group of verified NC codes. Then, the NC codes are interpreted by the CNC system as the movement of the spindle and feed axis, which, therefore, make the cutter and the workpiece constantly in contact to remove the material to get the desired thin-walled parts. During the milling process, the real-time milling data, such as milling force, spindle current, cutter position, etc., is collected by a sensor network, which is further transported to DTDL through wired or wireless sensor networks.

DTDL is responsible for the real-time on-site/simulation data pre-processing, fusion, and storage based on the MTConnect protocol. Specifically, the real-time data collected from
PMML is characterized by multi-source heterogeneity, which is firstly pre-processed by the adapter/agent. Then, the heterogeneous data is standardized with a MTConnect information model. Finally, the standardized data along with the simulation data is stored in a real-time database implemented by Redis, which could be accessed by other layers through interfaces defined in the access library.

**VMML** provides a multiscale, multi-physics, and high-fidelity simulation capacity with the integration of a geometric model, behavior model, and mechanism model. A geometric model is a visual representation of a physical milling machine that could serve as a visual tool integrating behavior models and mechanism models to simulate and visualize the real-time performance of the milling machine. A behavior model defines the detailed requirements, structures, behavior, and parametric of a physical milling machine via semantic models. A mechanism model equips virtual space with multi-scale and multi-physics simulation capacity by adding equation-based definitions for each building block of the behavior model.

**MDSL** aims to develop a knowledge-driven low-latency simulation method for the understanding of the deformation during the milling process of thin-walled parts. Here, prior deformation knowledge for thin-walled parts is obtained by a finite element method that constructs a milling analysis step model under the unit milling force. Then, the real-time milling deformation could be quickly calculated through a mapping between prior deformation under the unit milling force and the deformation under the actual milling force.

**DOCL** obtains a group of theoretical optimal milling parameters to minimize the milling deformation and time of thin-walled parts based on a multi-objective optimization algorithm.
DOCL also equips MPDT with an adaptive adjustment mechanism of milling parameters to quickly respond to dynamical milling disturbances through an intelligent monitoring, prediction, optimization, and control strategy enabled by the in-depth integration and interaction of PMML, DTDL, VMML, and MDSL.

With the above observations, the key enabling technologies for MPDT could be summarized, namely multidimensional high-fidelity MPDT modeling, knowledge-driven low-latency milling deformation simulation, and online optimal control of milling deformation. Here, MPDT modelling supports the construction and fusion of PMML, DTDL, and VMML; deformation simulation supports the construction of MDSL based on the on-site data and simulation data derived from DTDL; optimal control of milling deformation supports the construction of DOCL with the cooperation of PMML, DTDL, VMML, and DOCL.

4 Key enabling technologies of MPDT

This section introduces three key enabling technologies of MPDT for online optimal control of milling deformation of thin-walled parts, which include multidimensional high-fidelity MPDT modeling, knowledge-driven low-latency milling deformation simulation, and online optimal control of milling deformation.

4.1 Multidimensional high-fidelity MPDT modeling

To support the construction and fusion of PMML, DTDL, and VMML, we extend a DT modelling approach proposed in our previous work [26] to construct a multidimensional high-fidelity MPDT model. The overview of the approach is as shown in Fig. 2, where the
construction of PMML and DTDL are the same as in [26]. VMML is the key building block of MPDT model, which is constructed through the following four aspects, including geometric modelling, behavior modelling, mechanism modelling, and model fusion and visualization.

Fig. 2 Multidimensional high-fidelity modelling method for MPDT

Geometric model could be viewed as the visual basis of MPDT that describes the component information, geometric size information, assembly relation, and component movement logic of a physical milling machine, while reflecting its structural attributes.
Geometric modelling involves the following four steps: 1) Component analysis is the preprocessing step of geometric modelling, which divides the physical milling machine into several independent components by analyzing its mechanical structures; 2) CAD software such as SolidWorks, Pro/E, etc., are utilized to carry out 3D modeling of each of components or, alternatively, each component could be reconstructed based on the point cloud data collected by a 3D laser scanner; 3) the kinematic analysis is carried out to obtain the kinematic characteristics of the moving chain of the milling machine, on which a general coordinate system is constructed through the coordinate transformation to express the position of each of components; 4) lightweight processing is used to reduce the complexity of the model using a PiXYZ software.

Behaviour modelling aims to provide graphical representations with detailed requirements, structures, behaviour, and parametric of the physical milling machine via semantic models defined in Systems Modelling Language (SysML). Specifically, modelling tools of SysML, including block definition diagrams (BDD) and internal block diagrams (IBD), are used to represent the key elements of the physical milling machine. Here, BDD represents the hierarchical and taxonomic relationships for each of components/parts of the milling machine. IBD describes the internal functional interface and operation behaviour between parts or components of the milling machine.

Mechanism modelling aims to construct a multi-scale and multi-physics simulation model for VMML by adding equation-based definitions for each element/component/part in IBD models via Modelica Language. Modelica provides a large library of standardized and reusable
domain components for describing the multi-system, multi-domain coupled milling machine, which obtains mathematical and physical properties of the machine that equip VMML with high-fidelity simulation capacities.

Geometric models, behavior models, and mechanism models are integrated into a DT model for the milling machine through a model fusion and visualization process, where geometric models are served as the visual basis integrating behavior models and mechanism models by using Java web and babylon.js.

4.2 Knowledge-driven low-latency milling deformation simulation

The deformation of thin-walled parts is a common quality problem during milling process due to its complex structure and poor rigidity as well as milling disturbances, such as sticking cutter, tool wear, etc. However, milling deformation is hard to be measured dynamically during milling process. Therefore, it is of great significance to develop an online analysis and prediction method for milling deformation. Consequently, this paper proposes a knowledge-driven low-latency simulation method that could conduct a quickly online analysis of milling deformation of thin-walled parts based on the on-site data and the simulation data from DTDL. As show in Fig. 3, the proposed low-latency simulation method involves three parts including prior knowledge acquisition, knowledge reuse mechanism, and deformation visualization.
Prior knowledge acquisition: Prior knowledge of milling deformation refers to quantitative deformation for each of specific thin-walled parts under unit milling force. As shown in Fig. 3 (a), prior knowledge is acquired based on finite element simulation through the following three steps. Firstly, the finite element model of a thin-walled part is constructed using Abaqus to analyze its stress and deformation. Then, the tool path is discretized based on the part grid information, and the analysis steps of different tool-part positions could be obtained. In each analysis step, the element set and node set swept by the discrete tool path constitute the analysis step object. Finally, the finite element simulation is carried out to obtain the deformation results as prior knowledge, by setting the life-death element and applying the
unit milling force.

Knowledge reuse mechanism aims to establish a mapping between milling deformation under actual milling force and that under unit milling force derived from prior knowledge, as shown in Fig. 3 (b). To this end, several primary concepts are introduced. In a finite element static analysis problem, the stress/deformation of each mesh element is defined as

\[ Ku = f \]  
\[ \sigma = EBu \]  

where \( K, E, B \) refer to stiffness matrix, elastic matrix, and strain-displacement matrix, respectively; \( u, f, \sigma \) refer to a displacement vector, load vector, and stress/deformation vector, respectively.

Based on Eq. (1-2), the stress/deformation is calculated as:

\[ \sigma = \frac{EB}{K} \cdot f \]  

Since \( K, E, B \) in each analysis step are all fixed values, Eq. (3) indicates that the stress/deformation is linearly related to the load vector. Therefore, the mapping between milling deformation under real milling force and that under unit milling force is calculated as:

\[ \xi = \alpha (f \cdot \xi') \]  

where \( \xi \) is the online stress/deformation simulation results under actual milling force; \( \lambda \) is the loading factor obtained by the orthogonal experiment; \( \xi' \) is the stress/deformation information under unit milling force derived from prior knowledge; \( \alpha \) is the mapping coefficients that could be fitted by experiments.

Deformation Visualization aims to visualize the simulation stress and deformation under actual milling force derived from DT data. As shown in Fig. 3 (c), a web visualization environment is constructed based on ParaView and babylon.js. Cutter paths and resulting
stress/deformation obtained by the mapping are updated in real-time in the web environment.

4.3 **Online optimization control of milling deformation**

Through the in-depth integration and interaction of PMML, DTDL, VMML, and MDSL, a novel architecture for online optimization control of milling deformation of thin-walled parts is proposed. As shown in Fig. 4, the milling of thin-walled parts could be viewed as a multi-pass milling process in the axial direction, where the next-pass milling parameters could be optimized based the current-pass milling state to dynamically control the milling deformation through three submodules, including the control submodule, monitoring submodule, and optimization submodule.

The control submodule aims to provide an adaptive mechanism for autonomously controlling of the milling process with the verified NC codes. This submodule takes a NC file encoded theoretical optimal milling parameters as input. The parameters in NC file are verified by VMML through a high-fidelity simulation process. Here, the machine tool overtravel, tool contact, and machining time could be evaluated and verified by a geometric simulation process; the spindle current and milling force for the verified parameters could be obtained by a physical simulation process, which could be viewed as the benchmark for deformation monitoring and optimization. The verified codes are transferred to PMML for milling process control. Besides, the control submodule also receives updated NC codes from the optimization submodule during milling process, where the verified NC codes are used for autonomously controlling of milling process to control the deformation of thin-walled parts.
The monitoring submodule aims to monitor and analyze the real-time deformation of the milling process of thin-walled parts. According to the current experience, the deformation is mainly affected by the milling force. Hence, the real-time milling force data is collected via a triaxial force sensor, where the average milling force during execution process of each line of NC codes is further mapped to instruction domain, to analyze the influence of executing that line of NC codes for the milling deformation. To this end, an instruction domain parameter mapping table (as listed in Table 1) is designed to parse the meaning of NC codes, which is further represented by a XML file, as shown in Fig. 5. On that basis, the average milling force
is linked to its corresponding NC code line in XML file, where the average milling force is calculated as:

\[
\tilde{f}_i = \frac{1}{n} \sum_{j=1}^{n} f_{ij}
\]

(5)

where \(\tilde{f}_i\) refers to the average milling force for the \(i\)-th NC code line; \(f_{ij}\) refers to the \(j\)-th milling force sampling data during the execution of the \(i\)-th NC code line and \(n\) is the total sampling data size.

The instruction domain force is then compared with the simulation force to preliminarily analyze the influence of executing that line of NC codes for the milling deformation. The comparison is defined as:

\[
|\tilde{f}_i - f_{i,\text{sim}}| \leq \Delta f_{i,\text{max}}
\]

(6)

\[
\Delta f_{i,\text{max}} = \lambda \cdot f_{i,\text{sim}}
\]

(7)

where \(\tilde{f}_i\) refers to the simulation force derived from the simulation verification process in the control submodule; \(\Delta f_{i}\) is a maximum permissible threshold for milling force fluctuations; \(\lambda\) is an empirical coefficient, which is usually set to 0.1 according to the current experience.

According to Eq. (6), if the milling force fluctuations \(|\tilde{f}_i - f_{i,\text{sim}}|\) exceed the maximum permissible threshold, the current milling condition is considered to be very likely to cause the deformation of thin-walled parts to not meet the design requirements. Hence, MDSL is performed to obtain the actual deformation \(\xi_{ij}\) under \(\tilde{f}_i\). If \(\xi_{ij} > \xi_{i,\text{max}}\), the optimization submodule is carried out to adjust the feed rate to obtain the suitable milling force. For this purpose, the feed rate is first adjusted according to the updating rules, which are defined as:

\[
\begin{cases}
    F_{i,j} = F_{i,j-1} + \Delta, & \text{if } f_{i,j-1} < f_{i,\text{sim}} \\
    F_{i,j} = F_{i,j-1} - \Delta, & \text{if } f_{i,j-1} > f_{i,\text{sim}}
\end{cases}
\]

(8)

\[
f_{i,j+1} = \text{VMML}(F_{i,j}), \forall j > 1, f_{i,0} = \tilde{f}_i
\]

(9)
where \( F_{i,j} \) is the \( j \)-th iteration adjusted feed rate for the \( i \)-th NC code line; \( f_{i,j-1} \) is the \((j-1)\)-th simulation milling force under feed rate \( F_{i,j-1} \) obtained by VMML as shown in Eq. (9); \( j \) is the optimization iteration number, where the entire iteration comes to an end when \( \xi_j \leq \xi_{j_{\text{max}}} \), and \( \xi_j \) is obtained by a simulation conducted by MDSL. Finally, the NC codes \( C_{i,j} \) are updated based on \( F_{i,j} \), which is sent to PMML for the optimally controlling of next-pass milling of thin-walled parts.

<table>
<thead>
<tr>
<th>Field name</th>
<th>Data type</th>
<th>Specification</th>
</tr>
</thead>
<tbody>
<tr>
<td>LineId</td>
<td>Integer</td>
<td>Line number of the NC codes</td>
</tr>
<tr>
<td>SpdlSpeed</td>
<td>Floating point</td>
<td>Spindle speed</td>
</tr>
<tr>
<td>FeedRate</td>
<td>Floating point</td>
<td>Feed rate</td>
</tr>
<tr>
<td>CutDepth</td>
<td>Floating point</td>
<td>Depth of cut</td>
</tr>
<tr>
<td>CutWidth</td>
<td>Floating point</td>
<td>Cutting width</td>
</tr>
<tr>
<td>InterpType</td>
<td>Enum</td>
<td>Interpolation method (G00, G01, G02, G03)</td>
</tr>
<tr>
<td>EmptyTravel</td>
<td>Bool</td>
<td>Whether the NC code line is a valid line</td>
</tr>
</tbody>
</table>

Fig. 5 An example of instruction domain parameter mapping

5 Case study
5.1 Experimental environment

To verify the proposed method, an aluminum alloy thin-walled parts milling experiment is carried out with the following experimental environment. As shown in Fig. 6 (a), VMC400 CNC milling machine with a carbide integral end milling cutter is employed as the milling environment, where the maximum speed of the machine is 6000 rpm, the teeth number and diameter of the cutter are 3 and 10 mm, respectively; A NC-K3D160 triaxial force sensor is deployed in the milling machine to collect the real-time milling force data, which is further preprocessed by a data acquisition system developed based on LabView with 1 ms as sampling interval; A three-coordinate measuring device is also used to measure the actual deformation of the workpiece. As shown in Fig. 6 (b), a 7050-T7451 high-strength aluminum alloy block with the size of 230 mm×180 mm×30 mm is taken as the workpiece blank. On that basis, S-shaped parts are manufactured, where geometric parameters and toolpath of the parts are as shown in the right of Fig. 6 (b).

![Fig. 6 Experimental environment setup: (a) milling environment and; (b) workpiece information]
5.2 MPDT prototype implementation

Based on the above experimental environment, a MPDT prototype is implemented for the optimal control of milling deformation of thin-walled parts by three functional modules, including the DT simulation module, deformation monitoring and prediction module, and deformation optimal control module.

The DT simulation module is developed based on the multidimensional high-fidelity MPDT modeling method. As shown in Fig. 7, this module consists of three submodules including the geometric model, mechanism model, and data model. The geometric model (Fig. 7 (a)) could perform a geometric simulation to check the machine tool overtravel, tool contact and machining time. The mechanism model (Fig. 7 (b)) takes the behavior model as backend to carry out a physical simulation and produce multiple physical quantities, such as the spindle current, milling force, etc. The data model (Fig. 7 (c)) is complementary to MDSL for quick deformation prediction, which could support the milling parameters decision-making in process planning stage. The data model is learned with support vector regression through four steps as shown in Fig. 7 (d).
The deformation monitoring and prediction module is developed based on the proposed knowledge-driven low-latency milling deformation simulation method. As shown in Fig. 8 (a), prior knowledge of the S-shaped parts is acquired based on the finite element simulation carried out by Abaqus. Based on the prior knowledge and knowledge reuse mechanism, the real-time milling deformation could be simulated and predicted, as shown in Fig. 8 (d) and Fig. 8 (e). In addition, this module also monitors the real-time status of the milling process of thin-walled parts, such as feed axis position (Fig. 8 (b)), milling force (Fig. 8 (c)), etc.
Fig. 8 Illustration of the deformation monitoring and prediction module of MPDT prototype

The deformation optimal control module is developed based on the online optimization control method of milling deformation. As shown in Fig. 9, this module consists of two submodules including the multi-objective optimization submodule and online optimization decision-making and control submodule. The multi-objective optimization submodule (Fig. 9 (b)) integrates the NSGA-II algorithm introduced in our previous work [27] with the data model constructed in the DT simulation module, which aims to optimize the milling parameters of S-shaped parts considering both the milling deformation and time. Online optimization decision-making and control submodule (Fig. 9 (b)) takes the optimal milling parameters as input and dynamically adjusts the parameters to quickly respond to changes in milling conditions by an intelligent deformation perception, optimization, and control strategy.
5.3 Application and evaluation experiments

Fig. 10 shows an application example of the MPDT prototype system for the milling of S-shaped aluminum alloy thin-walled parts. The S-shaped parts milling consists of three stages including blank preparation, rough milling, and finishing milling. Each stage’s milling parameters are generated by the multi-objective optimization submodule (Fig. 9 (a)), which are encoded in a NC file and taken as the input for MPDT. The input NC file is verified by a high-fidelity simulation process conducted by the geometric model (Fig. 7 (a)), mechanism model (Fig. 7 (b)) and deformation prediction module (Fig. 9), where the milling parameters in the verified NC file are as shown in the geometric simulation layer. Since the finishing milling process has the lowest workpiece stiffness and is more prone to deformation, the finishing milling of S-shaped parts is employed for application and evaluation purpose. According to the input milling parameters, the finishing milling of S-shaped parts is executed by 10th-pass milling processes in the axial direction, where the detailed theoretical optimal milling
parameter settings are as follows: spindle speed of 4964 rpm, feed per tooth of 0.103 mm/z, axial cutting depth of 2 mm, and radial cutting depth of 1 mm. In addition, the average physical simulation milling force of the finished milling process with the above parameters is 29.95 N, and the deformation threshold is 0.070 mm. During the 1th-pass milling process, the real-time milling force data collected by the triaxial force sensor is mapped into the instruction domain and compared with the simulation force. As shown in the instruction domain mapping layer of Fig. 10, results show that the difference between the simulation and actual milling forces exceeds the allowable fluctuation range 0.1×29.95 N, where the actual maximum milling force is 42.15 N. Then, the deformation simulation and monitoring layer in Fig. 10 is performed, where the simulation result indicates the current maximum deformation is 0.075 mm that exceeds the deformation threshold 0.070 mm. Therefore, the online optimization decision-making process, as shown in Fig. 9 (b), is conducted to obtain the appropriate milling parameters (feed rate) to minimize the fluctuation range. Finally, the appropriate milling parameters update the NC file that is further verified by MPDT to optimize and control the 2th-pass milling process. The above optimization control loop will continue until the end of the whole finish milling process.
To demonstrate the effectiveness of the proposed approach, the MPDT prototype is evaluated in terms of the deformation control effect. For evaluation purpose, total 10 S-shaped thin-walled parts are processed, where 5 parts are processed with the optimal control method proposed in this paper and another 5 parts without using the optimal control method. As shown in Fig. 11, to compare the milling deformation of two group of parts, a three-coordinate measuring device is used to measure the milling deformation of the above parts. The distribution of measuring points of each S-shaped thin-walled part is as shown in Fig. 11 (a), where 33 groups of deformation data in total for each part are collected. The results show that the average maximum deformations for the parts processed with and without the optimal
control method are 0.064 mm and 0.075 mm, respectively. That is, the milling deformation could be significantly reduced by 14.67% through the proposed optimal control method. In addition, we also compare the simulation accuracy of MDSL as it is the key for MPDT. For comparison, the milling deformation of each of 10 parts during finish milling is simulated through the deformation monitoring and prediction module (as shown in Fig. 8). The results show that the average maximum simulation deformation is 0.065, and a very high average simulation accuracy of 86.9% is obtained. In addition, compared to the traditional finite element analysis method based on Abaqus, the calculation time of a single analysis step is reduced from 6 s to 1 s due to the usage of prior knowledge and knowledge reuse mechanism. This greatly promotes the latency performance of MPDT.

![Fig. 11 Deformation measurement](image)

### 6 Conclusion and future work

To improve the machining quality of thin-walled parts widely used in aerospace industry, this paper proposes a novel DT-driven online optimal control method of milling deformation
for thin-walled parts. Based on the experimental results presented in this paper, the following contributions of the paper could be summarized.

(1) This paper defines a novel milling process digital twin (MPDT) framework through a five-layer architecture, including PMML, DTDL, VMML, MDSL, and DOCL, which could achieve the online optimization and control of milling deformation for thin-walled parts. The proposed framework could provide a reference for the research and application of DTs in the improvement of milling quality of aerospace parts.

(2) Multidimensional MPDT modeling, knowledge-driven milling deformation simulation, and milling deformation optimal control are introduced as three key enabling technologies for the construction and application of MPDT. The key enabling technologies endows MPDT with the real-time perception, high-fidelity and low-latency simulation, and online optimal control capacities to improve the milling deformation of thin-walled parts, thus being a reliable solution to bridge the current research gap in low modelling fidelity of DTs, high simulation delay of finite element analysis, less effective of offline optimization of milling deformation.

(3) A MPDT prototype system is implemented with three functional modules including the simulation module, monitoring & prediction module, and optimal control module, which could provide an insight into the industrial implementation of the proposed approach. In addition, the application and evaluation results of the prototype system show the superiority of the proposed approach with the extremely low-latency performance of deformation simulation and high reliable optimal control of milling deformation.
Potential medium-term future studies related to this paper are as follows. Firstly, we plan to incorporate an error model of the milling machine into MPDT to further improve the fidelity of DT modeling. Secondly, we plan to develop an evaluation and correction method to acquire more appropriate prior knowledge to improve the simulation and prediction accuracy of milling deformation.

References


**Statements and Declarations**

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**Declarations**

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