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A high-fidelity digital twin approach for the optimisation of fluid jet polishing process

Chao Liu[a,*], Chunjin Wang[b], Zili Zhang[b], Pin Lyu[c,b], Chi Fai Cheung[b]

[a]*College of Engineering and Physical Sciences, Aston University, Birmingham B47ET, UK*
[b]*State Key Laboratory of Ultra-Precision Machining Technology, Department of Industrial and Systems Engineering, The Hong Kong Polytechnic University, Hong Kong, China*
[c]*School of Electronic Information Engineering, Shanghai Dianji University, 300 Shuihua Road, Shanghai 201306, China*

* Corresponding author. Tel.: +44-7551223073. *E-mail address:* c.liu16@aston.ac.uk

Abstract

Fluid Jet Polishing (FJP) is an Ultra-Precision Machining (UPM) technology for super-fine finishing of small and complex components. FJP has distinctive advantages compared to other polishing methods, including high polishing accuracy, no heat generation, no tool wear, applicability for various types of materials, and suitability for various freeform surfaces. Nevertheless, previous research work on FJP focuses mainly on theoretical modelling and simulation of the polishing mechanisms with experimental validations, a large amount of process uncertainties happened during the polishing process have been overlooked. These uncertainties could cause variations of the surface quality of workpieces in terms of material removal rate and surface roughness. Recent advancements of Digital Twin (DT) technology have shown great potential in addressing this issue. However, high-fidelity DT for FJP has not been investigated to date. In this paper, we propose a novel high-fidelity DT approach for the optimisation of FJP process. First, related research on FJP and DT is reviewed to identify the limitations of the existing approaches. Second, we propose a conceptual framework of the high-fidelity DT for FJP process. Third, the key enabling technologies and major challenges for the development of the high-fidelity DT are identified and discussed. Finally, a conceptual application scenario of the in-process control optimisation for FJP of freeform surfaces is presented. This work attempts to integrate smart manufacturing technologies into FJP process and will contribute to the theoretical development of high-fidelity DT for various UPM technologies.

Keywords: fluid jet polishing; digital twin; ultra-precision machining; smart manufacturing

1. Introduction

Fluid Jet Polishing (FJP) is an Ultra-Precision Machining (UPM) technology for super-fine finishing of small and complex components that was first introduced in 1998 [1]. In the FJP process, a mixed slurry of water and abrasive particles is pressurised and delivered through a nozzle of small outlet diameter as a slurry jet that impinges the surface of the workpiece to generate a small polishing area [2]. As a non-contact processing technology, FJP has distinctive advantages compared to other polishing methods, including high polishing accuracy, no temperature rise of the workpiece, no tool wear, applicability for various types of materials, and suitability for various kinds of freeform surfaces.

Despite these advantages, FJP still has some limitations due to its relatively short development history. One of the major limitations of FJP is the inaccurate and inefficient process optimisation. Previous research work on FJP process optimisation mostly applies the traditional approach that combines theoretical modelling and simulation of the polishing mechanisms with experimental validations [3–5]. A large amount of process uncertainties happened during the polishing process (such as unexpected variations in slurry concentration and fluid pressure) have been overlooked. These uncertainties could cause variations of the surface quality of workpieces in terms of material removal rate and surface roughness. In

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addition, most FJP systems are controlled in an open-loop manner without considering feedback from the polishing process, and hence cannot adapt to those process uncertainties.

Fortunately, recent advancements in smart manufacturing, especially the Digital Twin (DT) technology, have shown a great potential in addressing these issues. DT represents “an integrated multi-physics, multi-scale, probabilistic simulation of a complex product that uses the best available physical models, sensor updates, etc., to mirror the life of its corresponding twin” [6]. In the domain of manufacturing, DT has been widely investigated and applied in different areas such as product development and lifecycle management [7], CNC machine tools and machining processes [8], manufacturing systems [9], and prognostics and health management [10]. DT has demonstrated a great potential for realising accurate and efficient optimisation, real-time monitoring, and closed-loop control of various manufacturing processes. Nevertheless, in the field of UPM, there has been very little work on the application of DT technology to date. For FJP process, the DT technology could be potentially utilised to improve the accuracy and efficiency of process simulation, optimisation, and control by integrating various real-time sensor feedback into the simulation models and data analysis processes. Nevertheless, the complex multi-physics and multi-scale polishing mechanisms of FJP also raise great challenges for developing its DT applications.

In this context, this paper proposes a novel high-fidelity DT approach for the optimisation of FJP process, aiming to provide a theoretical foundation for integrating smart manufacturing technologies into FJP system. The rest of this paper is organised as follows. Section 2 reviews related research work on FJP and DT and identifies the research gaps. Section 3 introduces a novel conceptual framework of the high-fidelity DT for FJP process. The key enabling technologies and major challenges are identified and discussed in Section 4. Section 5 presents a conceptual application scenarios of the high-fidelity DT. Finally, Section 6 concludes the paper.

2. Literature review

2.1. Process optimisation and control of FJP

Research on the optimisation of FJP process using the traditional approach that combines theoretical modelling and simulation with experimental validations has been extensively studied in the past two decades. In general, the workflow of the traditional approach for FJP process optimisation can be briefly summarised as shown in Fig. 1.

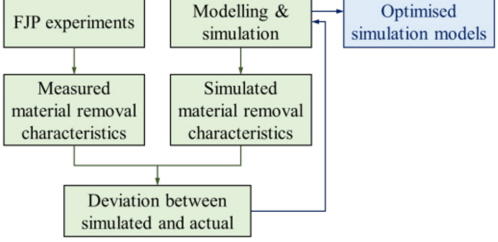

Fig. 1. Traditional approach for FJP process optimisation

Computational Fluid Dynamics (CFD) is the most widely used modelling and simulation method for FJP process [11,12]. To investigate the material removal mechanism of FJP, Beaucamp et al. [12] proposed a CFD model based on multiphase turbulent flow computational methods that could dynamically simulate the interface between fluid and air. The model was used to optimize surface texture performance of FJP process. Cao and Cheung [13] developed an integrated CFD-based erosion model to predict the material removal characteristics in FJP. Their experimental results showed a good agreement between the simulated and actual polishing quality, although random deviations still existed. Based on CFD, Wang et al. [14] further developed a universal three-dimensional numerical model to simulate FJP process in both vertical and oblique impinging modes. Corresponding experiments demonstrated high robustness of the model under various conditions.

Currently, closed-loop control of FJP process has not been widely studied. Beaucamp et al. [12] developed a closed-loop FJP process optimisation method with a focus on the slurry delivery system. A pressure sensor and a bypass were installed in the slurry delivery system to monitor and control the inlet pressure, such that the fluid pressure can be stabilised during the polishing process. However, feedback from the polishing process was not considered in this system.

Previous research on the optimisation and control of FJP process indicates that the traditional approach lacks accuracy and efficiency since it overlooked the uncertainties happened during the polishing process which could result in variations of polishing quality. A high-fidelity DT approach that takes advantages of smart manufacturing technologies needs to be developed for the optimisation and control of FJP process.

2.2. Digital Twin modelling methods

In the domain of smart manufacturing, research on DT has proliferated in the past few years [15–17]. Recently, multi-dimensional DT that integrates both model-based simulation and data-driven methods has attracted much attention. To achieve prognostics and health management of complex equipment, Tao et al. [10] proposed a five-dimension DT modelling method integrating physical entity, virtual model, data, services, and connections of the equipment. A case study of fault cause prediction for a wind turbine was presented to validate the modelling method. Wang et al. [18] introduced a DT reference model for fault diagnosis of rotating machinery. The DT model integrates the design parameters, dynamics simulation model, finite element analysis model, and vibration signals during operation to mirror the actual status of the physical system and perform quantitative fault diagnosis. Experimental results showed that DT-based approach outperforms traditional fault diagnosis methods.

One of the distinct advantages of DT is its ability to enable the optimisation, real-time monitoring, as well as closed-loop control of various manufacturing processes [19,20]. Inspired by biomimicry principles, Liu et al. [21] proposed a DT modelling method that can adaptively construct a multi-physics DT for machining process. The DT comprises several sub-models such as geometry model, behaviour model, and process model that interact with each other to accurately represent the physical machining process. To achieve optimised machining process, Botkina et al. [22] developed a standard-based DT modelling method for cutting tools that allows the cutting tool DT to be continuously updated during machining, and hence enabling precise process simulation, control, and analysis.

Although various DT applications for the optimisation and control of machining process have been developed, application of DT for UPM systems have not been presented to date. How to develop a high-fidelity DT that can accurately represent and predict the FJP process remains a great challenge.

3. High-fidelity Digital Twin for FJP process

FJP is an UPM technology that involves complex multi-physics and multi-scale interactions between water, abrasive particles, and the surface of the workpiece. To accurately simulate the FJP process and predict the polishing quality, a high-fidelity DT that deeply integrates both model-based simulations and data-driven methods needs to be developed. Furthermore, to systematically and comprehensively represent the FJP process, all the part design data, process parameters, in-process feedback from sensors, experimental knowledge, and data analytics methods should also be included in the high-fidelity DT. Based on these requirements and previous work on DT modelling methods for machining processes, we propose a conceptual framework of high-fidelity DT for FJP process as depicted in Fig. 2. The main functions of each model are explained in this section.

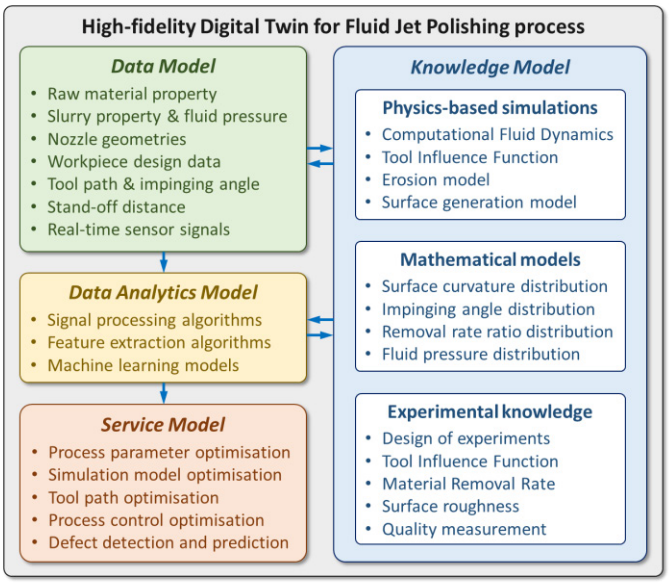

Fig. 2. Conceptual framework of the high-fidelity DT for FJP process

The conceptual framework represents a multidimensional DT for FJP process that contains four main models, i.e., 1) data model, 2) knowledge model, 3) data analytics model, and 4) service model. Identifying the specific items contained in each model is a prerequisite as well as a critical task for modelling the high-fidelity DT.

The data model represents all the data and parameters in FJP process that influence the polishing quality and efficiency and can be used for simulations and experiments. It contains mainly three types of data, including design data (raw material properties, part shape, required accuracy, etc.), process parameters (fluid pressure, tool path, nozzle size, stand-off distance, impinging angle, slurry property, etc.), and in-process feedback data (polishing force signals, vibration signals, etc.). Note that in-process sensor feedback is essential since they reflect the uncertainties happened during the FJP process which need to be analysed with advanced data analytics methods.

Due to the high complexity of the FJP process, a pure data-driven approach as used in many other DT applications could not achieve accurate process simulation and quality prediction. To thoroughly analyse the complex relationships among various process parameters, in-process sensor feedback, and final polishing quality, a vast amount of domain knowledge must also be included in the DT. The proposed knowledge model contains mainly three types of knowledge, i.e., 1) physics-based simulations, 2) mathematic models, and 3) experimental knowledge. Physics-based simulations represent all the multi-physics and multi-scale simulation models involved in the FJP process simulation, including CFD models, erosion models, surface generation model, etc. These models are usually developed with specialised software such as ANSYS Fluent. Mathematical models include various mathematical functions related to the FJP process such as workpiece surface curvature distribution, jet impinging angle distribution, fluid pressure distribution, etc. Experimental knowledge refers to the knowledge accumulated through experiments such as the design of experiments and the Tool Influence Function (TIF), Material Removal Rate (MRR), workpiece surface characteristics, etc. which are usually measured after the FJP process. The knowledge model is continuously accumulated and updated with more and more experiments conducted to record various polishing conditions and the up-to-date machine status in the high-fidelity DT.

The data analytics model represents different types of advanced data analytics methods such as signal processing algorithms, feature extraction algorithms, and machine learning models. These methods are specifically developed for analysing the complex relationships among various process parameters, in-process sensor feedback, and final polishing quality. The data analytics model is the key to integrate the domain knowledge with the in-process sensor feedback which distinguishes the high-fidelity DT approach from the traditional modelling and simulation-based approach.

The service model represents various types of applications that can be provided by the high-fidelity DT such as optimisation of the process parameters, simulation models, tool path, process control, and defect detection and prediction tasks. The service model defines all the required data and parameters, knowledge models, and data analytics methods for each application and should allow end users to flexibly customise the applications through user-friendly software interfaces.

Overall, the high-fidelity DT deeply integrates these four models in a hybrid data-knowledge-driven approach and interacts with the physical FJP system to realise higher polishing accuracy and efficiency. Note that the proposed conceptual framework represents a generic and high-level approach. Specific application scenarios may only require some specific models and functions in the high-fidelity DT.

4. key enabling technologies and major challenges

Development of the high-fidelity DT is naturally a complex multi-disciplinary task that involves a lot of concepts, methods, standards, and techniques from different research areas. This section discusses the key enabling technologies and related major challenges that need to be addressed in future research. Note that the discussions in this section mainly focus on the smart manufacturing technologies rather than the traditional modelling and simulation methods of FJP process which have been extensively studied.

Development of the data model is not a challenging task, but it requires a comprehensive understanding of all the data involved in the FJP process. The data need to be logically categorised into a hierarchical structure corresponding to different aspects of the FJP process. To realise interoperable and efficient data storage, communication, and sharing, standardised data modelling methods such as MTConnect and OPC UA [23] can be applied. Furthermore, since the in-process sensor signals also need to be included in the data model, time-serious databases such as InfluxDB [24] can be used to enable efficient and cloud-based data management.

Knowledge modelling of the FJP process is a critical and challenging task. Firstly, a comprehensive and systematic analysis of the existing knowledge on the modelling and simulation methods and the experimental results of FJP process need to be conducted to establish a logical structure for the knowledge model. Identifying the complex relationships among the complicated simulation models and experimental results represents a great challenge. Secondly, new knowledge about the influence of in-process sensor feedback on the polishing quality and efficiency of FJP process also needs to be included in the knowledge model. Different types of sensors such as dynamometers, accelerometers, acoustic emission sensors, etc. need to be implemented and tested to investigate the level of influence caused by different factors (polishing forces, vibrations, acoustic emissions, etc.). This requires extensive FJP experiments as well as various types of advanced data analytics methods which need a vast amount of costs and manpower. Furthermore, efficient knowledge accumulation, update, reasoning, reuse, and sharing are critical requirements that ensure the high fidelity of the DT. To achieve these goals, recent advancements in knowledge engineering such as ontology and knowledge graph [25] need to be deeply studied and practically applied. Developing an ontology or knowledge graph for FJP process also represents a great challenge since little work has been done in this area.

The data analytics model plays a vital role in the high-fidelity DT. Although various advanced data analytics methods have been developed to analyse machining processes such as milling and turning [26], the ultra-precision requirement of FJP process raises some critical challenges that have not been considered in previous studies. First, since the slurry jet impacted on the workpiece is a mixed slurry of water and abrasive particles, the resulting sensor signals such as cutting forces and vibrations may contain a considerable amount of noise. Specialised signal processing algorithms for data cleansing and denoising need to be developed to extract more useful information from the raw sensor signals. Another feasible solution is to develop deep learning models (e.g. deep belief networks) that can perform automatic noise reduction functions [27]. Second, machine learning and deep learning methods usually require a large amount of balanced data for model training. Apart from the time- and cost-consuming experiments, it is also a challenge to collect sufficient defect data during the FJP process. To address the data imbalance issue, not only should the experiments be carefully designed to include enough defective conditions, but the advanced data augmentation techniques such as additional Gaussian noise and amplitude shifting [28] should also be applied.

The service model allows the required data, knowledge, and data analytics methods to be combined as integrated solutions. Modularised service templates for typical optimisation and prediction tasks should be designed to enable customisable options for users who have different requirements (higher accuracy, less polishing time, less cost, etc.). Cloud-based data communication architecture should also be applied to allow distributed decision-making tasks and efficient service updating, reuse, and sharing.

5. A conceptual application scenario

Based on the proposed conceptual framework and the discussed key enabling technologies, this section presents a conceptual application scenario for the high-fidelity DT, i.e., in-process control optimisation for FJP of freeform surfaces. The overall system architecture of the conceptual application scenario is demonstrated in Fig. 3.

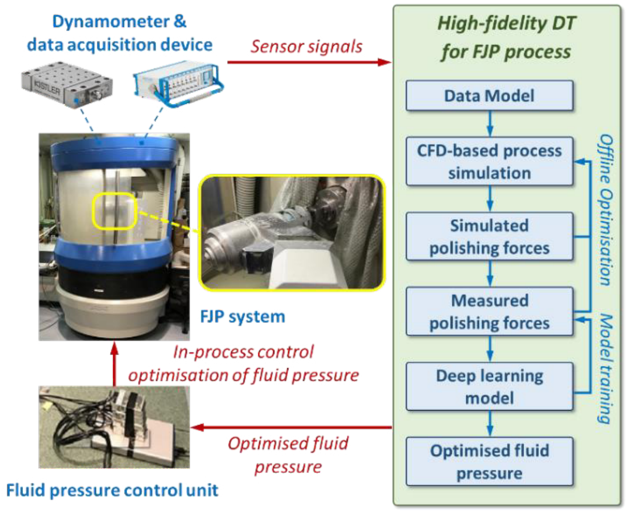

Fig. 3. High-fidelity DT-enabled in-process control optimisation for FJP

In this application, a dynamometer is implemented at the bottom of the workpiece to collect in-process sensor signals that reflect the polishing forces. This is the key difference between the proposed high-fidelity DT approach and traditional simulation-based approach. Overall, the application can be divided into two phases: 1) offline optimisation of simulation models, and 2) in-process control optimisation.

5.1. Offline optimisation of simulation models

Firstly, CFD-based FJP process simulations are conducted using the Ansys Fluent software to calculate the theoretical polishing forces resulted from the FJP process under different combinations of fluid pressure, surface curvature, and impinging angle. Geometrical modelling should be performed first to model the geometrical structure of the FJP process. The Eulerian-Lagrangian approach can be applied to simulate the slurry jet as a multi-phase flow comprising the continuous phase (liquid water) and the discrete phase (abrasive particles). Hydrodynamic modelling with consideration of the spatial distribution of abrasive particles also needs to be conducted to simulate the impact of the slurry jet on the target surface. Combining the hydrodynamic model with the calculated kinetic energy of the abrasive particles, the polishing force generated by the slurry jet can then be simulated. In addition, the Oka's erosion model can be applied to simulate the material removal mechanism, and hence the theoretical MRR and TIF can be calculated. Finally, results from the CFD-based simulations can be generalised and expressed as:

$$MRR_S = f(F_S, p, \alpha, k) \tag{1}$$

where MRR_S is the simulated MRR distribution, F_S is the simulated polishing force distribution, p is the fluid pressure distribution, α is the impinging angle distribution, k is the surface curvature distribution, and f is the function representing the relationship among those parameters.

Secondly, experiments on FJP of freeform surfaces with the same parameter settings used in the simulation models need to be conducted using the FJP system. Real-time polishing force signals during the FJP process must be collected. Different signal processing and feature extraction algorithms (fast Fourier transform, wavelet packet transform, etc.) can be applied to analyse the force signals and calculate the actual polishing force distribution F_A. The actual MRR distribution of the machined workpiece, MRR_A, will also be calculated by measuring the surface form error using a Coordinate Measuring Machine. Then advanced data analytics models such as deep belief networks can be trained and developed to analyse the relationship among F_S, F_A, MRR_S, and MRR_A, to improve the accuracy of the simulation models and eventually establish a high-accuracy prediction model that can be expressed as:

$$MRR_T = g(F_T, p, \alpha, k) \tag{2}$$

where MRR_T is the theoretical MRR distribution, F_T is the theoretical polishing force distribution, and g is the function representing the relationship among those parameters.

In this way, a high-fidelity simulation model considering the actual in-process uncertainties reflected by polishing forces can be developed for the FJP process. The simulation model will be eventually integrated into the knowledge model of the DT.

5.2. In-process control optimisation

Upon the development of the high-fidelity simulation model, in-process fluid pressure control optimisation for FJP of freeform surfaces can be further achieved. As mentioned previously, a large amount of unexpected process uncertainties happened during the FJP process could not be modelled in the simulation models due to certain assumptions and constraints needed for the simulation process. However, the variations in polishing quality caused by those uncertainties can be reflected by the deviation of the detected in-process polishing forces compared with the theoretical polishing forces. Since the polishing force is affected by the fluid pressure which can be controlled automatically, it is possible to compensate for the deviation of polishing force during the FJP process by optimising the control of fluid pressure in real-time.

Additional experiments must be conducted to investigate the relationship between fluid pressure and polishing force. Based on the experimental data, deep learning methods can be used to develop a real-time fluid pressure control optimisation algorithm. A generalised expression of the optimisation algorithm can be expressed as:

$$\Delta P = \rho(\Delta F, \alpha, k) \tag{3}$$

where ΔP is the change of fluid pressure, $\Delta F = F_A - F_T$ is the difference between measured actual polishing force and theoretical polishing force, and ρ is the function representing the relationship among those parameters. A simplified workflow of the real-time fluid pressure control optimisation for FJP of freeform surfaces is depicted in Fig. 4.

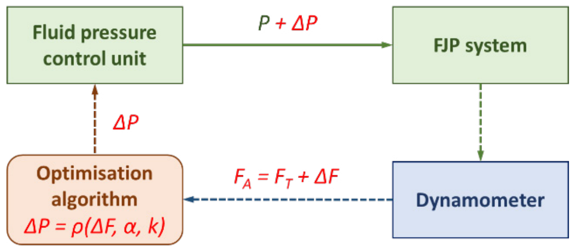

Fig. 4. Simplified workflow of the in-process control optimisation for FJP

The inlet fluid pressure of the FJP system is controlled by the fluid pressure control unit. Originally, the pressure is set as a constant value P. During the FJP process, the real-time actual polishing force F_A is collected and measured by the dynamometer. Based on the developed polishing force simulation model, $\Delta F = F_A - F_T$ is calculated and fed to the optimisation algorithm. The optimisation algorithm calculates the change of pressure ΔP needed for the polishing force compensation and sends the control commands back to the fluid pressure control unit. Then the inlet fluid pressure is adjusted as $P + \Delta P$ to keep the actual polishing force consistent with the theoretical polishing force.

In this way, a real-time feedback control loop can be established to improve the accuracy and efficiency of the FJP process. From a systematic perspective, this application is achieved through the deep integration of various data, knowledge, and advanced data analytics methods provided by the high-fidelity DT and is eventually represented as one of the various types of services in the service model.

6. Conclusions and future work

As a promising UPM technology that enables super-fine finishing of small and complex components, FJP has attracted significant attention in both academia and industry. However, the traditional approach for the optimisation and control of FJP process suffer from low accuracy and efficiency due to the neglect of unexpected process uncertainties.

To address this critical issue, this paper proposes a novel high-fidelity DT approach for the optimisation of FJP process. A conceptual framework of the high-fidelity DT is developed based on various emerging smart manufacturing technologies. The key enabling technologies and related challenges are identified and discussed in detail from the perspective of smart manufacturing. Furthermore, a conceptual application scenario of the high-fidelity DT which allows in-process control optimisation for FJP of freeform surfaces is presented. The specific data, simulation models, and data analytics methods for both offline optimisation of simulation models and in-process control optimisation are explained. Overall, the high-fidelity DT approach demonstrates a great potential in improving the polishing accuracy and efficient of FJP process.

Our future work will focus on the practical development of the proposed high-fidelity DT. The high-fidelity simulation model that integrates in-process polishing forces with CFD-based models will be investigated. Different types of deep learning methods will be developed to tackle the challenges caused by the noisy and imbalanced raw sensor signals. Extensive experiments will also be conducted to establish the experimental knowledge model and to validate feasibility of the proposed high-fidelity DT approach.

As a preliminary conceptual study, this work provides a visionary approach to deeply integrating various emerging smart manufacturing technologies into the FJP process. It is expected that this work could contribute to the theoretical development of the high-fidelity DT for FJP process. Moreover, the authors believe that, with the rapid advancement of Industry 4.0, it is an inevitable trend for more and more UPM technologies to adopt the emerging concepts, methods, techniques, and applications of smart manufacturing. The merge between UPM and smart manufacturing technologies will bring enormous advantages, great opportunities, as well as significant challenges.

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