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High-performance manufacturing

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Editorial

High-performance manufacturing

Guo Dongming

State Key Laboratory of High-performance Precision Manufacturing, Dalian, People's Republic of China
School of Mechanical Engineering, Dalian University of Technology, Dalian 116024, People's Republic of China

E-mail: guodm@dlut.edu.cn

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Abstract

The increasing demand for high-end equipment in crucial sectors such as aerospace, aeronautics, energy, power, information and electronics continues growing. However, the manufacturing of such advanced equipment poses significant challenges owing to high-level requirements for loading, transmission, conduction, energy conversion, and stealth. These challenges are amplified by complex structures, hard-to-cut materials, and strict standards for surface integrity and precision. To overcome these barriers in high-end equipment manufacturing, high-performance manufacturing (HPM) has emerged as an essential solution. This paper firstly discusses the key challenges in manufacturing technology and explores the essence of HPM, outlining a quantitative relationship between design and manufacturing. Subsequently, a generalized framework of HPM is proposed, accompanied by an in-depth exploration of the foundational elements and criteria. Ultimately, the feasible approaches and enabling technologies, supported by the analysis of two illustrative case studies are demonstrated. It is concluded that HPM is not just a precision and computational manufacturing framework with a core focus on multiparameter correlation in design, manufacturing, and service environments. It also represents a performance-geometry-integrated manufacturing framework for an accurate guarantee of the optimal performance.

1. Introduction

High-end equipment usually operates at high speed, high precision, high reliability or long life under unconventional working conditions, such as high temperature, high pressure, extreme cold, and radiation exposure. It depends on specific physical capacities, such as kinematic characteristics, loading, energy conversion, transmission, conduction, propulsion, wave penetration, and stealth, which have to be ensured in manufacturing. Therefore, the demands of high-end

equipment manufacturing require special materials, complex structures, and high-performance requirements. The performance of high-end equipment is influenced by the coupling effect of various factors, such as the manufacturing process and service environment. Even slight differences in key parameters, often regarded as constants in conventional design, can lead to remarkable differences in the performance of high-end equipment. Despite advancements in the industry, such as aero-engines achieving worldwide thrust-to-ratio weight ratios of 15–20 and photolithography machines being developed for 2 nm manufacturing processes, a substantial gap remains in the capacity of manufacturing many high-end products. Conventional manufacturing theories and methods that solely rely on geometric size and tolerance are reaching their limits to meet future developmental requirements. This is particularly prominent given the growing demand for improved performance in equipment and products in sectors



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such as aerospace, aeronautics, energy and power, and the military. High scrap rates, low efficiency, extended production cycles, and subpar comprehensive performance have been persistent challenges in the manufacturing industry.

Generally, it is crucial to consider the performance attributes of high-end equipment throughout its life cycle, including its design, manufacturing, and service stages. Design and manufacturing are two key and strongly coupled steps in the development of high-end equipment. Their integration is an effective method to ensure equipment performance, reduce production costs, and shorten the development cycle. However, there is a noticeable lack of connection between design and manufacturing in current mainstream processes, leading to strict upstream and downstream workflows. That is, the design stage mainly focuses on the overall conceptual design, structure design and detailed design of parts in terms of the functional requirements, the manufacturing stage primarily focuses on issues related to geometric shape, tolerance, surface integrity, material performance assurance, and tolerance-driven assembly problems. Moreover, most product designs rely on the experiential analogism, or ideal working conditions owing to various factors, including existing knowledge, foundational understanding, and the need to reduce complexity. This approach often oversimplifies processes that are not directly oriented toward equipment performance during manufacturing, leading to the deterioration in equipment performance. That is also the reason why the performance of ordinary equipment remains up to standards easily, but that of high-end equipment fails to meet the required standards.

These significant changes in conventional manufacturing call for a shift in the manufacturing concept. It needs to move away from a sole focus on geometric requirements and toward a more comprehensive approach that includes performance requirements. This is pertinent in the context of high-end equipment manufacturing, where performance, geometry, and materials are closely interconnected. However, the performance of certain key parts often plays a decisive role in the overall performance of high-end equipment. Examples of such parts include a seeker radome, a hemispherical gyro harmonic oscillator, an aeroengine blade, and a high-performance optical reflection/transmission mirror. Other examples encompass a nuclear main pump thrust bearing, as well as parts with spatial heterogeneous micro/nanostructures, three-dimensional metamaterial stealth structures, and features designed for drag reduction, hydrophobicity, or wear resistance. These high-performance parts could be classified according to their characteristics. Categories might include precision parts with strong performance constraints, complex surface parts with intricate structural constraints, precision parts made from hard-to-process materials, and ultraprecision parts subject to exceptionally high-precision constraints. Other categories may involve parts with complex micro/nano and cross-scale structural features, parts with special functional surface layer structures, and parts with integrated structural material functions [1, 2].

High-performance manufacturing (HPM) is an emerging trend in future manufacturing technologies. It is a critical aspect of the fabrication of high-performance equipment and parts. Numerous studies have reported surface integrity as a key factor in assessing the quality of machined workpiece surfaces [3, 4]. The influence of surface integrity on the wear, corrosion, fatigue resistance, and other properties of parts has been thoroughly investigated. Statistical analysis methods have been used to establish relationships among machining parameters, surface roughness, microhardness, and residual stress. These approaches have successfully addressed the issue of predicting specific requirements for surface integrity based on given process parameters. However, little attention has been dedicated to deriving the inverse modeling of process parameters and initial conditions from a perspective of the product performance. In a previous study, we introduced the remodeling method for precise grinding compensation on the radome based on the correlation between the radome's electrical performance and its material/geometry parameters [5, 6]. Recently, Brinksmeier *et al* [7, 8] proposed a method to solve the inverse problem of surface integrity from a material's internal energy perspective, which altered machining surface integrity. They also established a process signature association between the material's internal load and the part's surface integrity. To meet the HPM requirements, we developed a material-regularized coupling design and a solving method for manufacturing inverse problems. These are intended to determine manufacturing process parameters in coordination with materials, geometry, and structure [1, 3, 5, 9]. Meanwhile, remarkable progress has been made in the fields of machinery, mechanics, materials, computers, information, and electronics. Consequently, it is crucial to improve the level of equipment manufacturing technology, master enabling technologies, and enhance the manufacturing industry's capabilities for independent innovation. This can be achieved by manufacturing high-performance equipment and parts with a primary focus on performance assurance, and advancing the fundamental theory, methods, and technologies for HPM.

2. Connotation of HPM

2.1. Definition of HPM

High-end equipment typically comprises a complex structure with multiple functional component-based units. The fabrication of such equipment necessitates a systematic analysis of the material, structure, geometry, and motion according to their high-performance requirements. At the design stage, the structures of the equipment's functional and sub-functional units should be defined according to the performance requirements. Each subsystem's structure, material parameters, and geometry should be scientifically designed and determined for accuracy. At the manufacturing stage, it is crucial to formulate and optimize the process route, method, and process parameters while considering the cost and cycle time, to realize a performance-oriented manufacturing process.

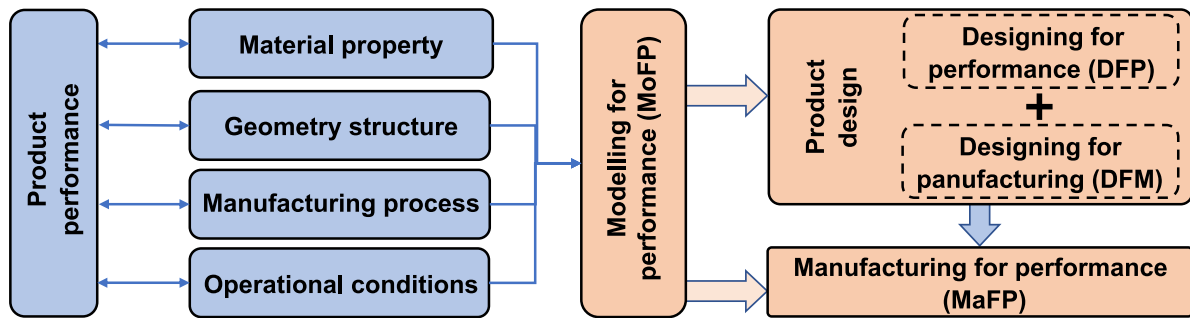


Figure 1. Connotation and the elements involved in high-performance manufacturing (HPM).

HPM refers to the design and manufacturing of high-performance equipment that aims to maintain accurate performance of every element throughout the entire manufacturing process. The geometric parameters and material properties of each unit are determined or optimized by modeling the relationship between the equipment performance and the material, structure, geometry, kinematics, and service parameters of each equipment unit. By doing so, the most suitable manufacturing process route, method, and process parameters can be identified, with the design and manufacturing of high-performance equipment aligning with performance requirements ensured [2]. Therefore, HPM is a kind of technologies with the modelling for performance (MoFP) as its core, and the resolution, analysis, and optimization of parameters as its basis.

HPM encompasses various aspects, including material, structure, geometry, and technology. It emphasizes the performance of the equipment's system, subsystem, or component, fostering an organic connection and coherence among these elements. HPM develops the design and manufacturing methods of equipment by modeling [10, 11], simulations [12, 13], and inverse calculations [14]. The core components of HPM are the following:

- (1) MoFP: it involves establishing a correlation model that describes the correlation between product performance and determining parameters, such as product material properties, geometry, and manufacturing process.
- (2) Product design: it involves a forward design based on the performance correlation model, and consists of two parts: design for performance (DFP) and design for manufacturing (DFM). Generally, design of a product includes conceptual design and scheme design, determines the optimal solution according to the model and product performance requirements. The detailed design encompasses specific materials, structure, and geometric parameters, such as structural design, sensitivity analysis, and precision design. DFP seeks the ideal or theoretical design parameters, such as materials, structures, and motion forms, based on performance requirements. While, DFM determines the most feasible manufacturing process and the reasonable distribution of each link for manufacturing tolerance, and

establishes the geometric parameters of tolerance according to the manufacturing process's capability.

- (3) Manufacturing for performance (MaFP): it involves the modelling of the product manufacturing process (including specific manufacturing process methods and parameters based on the performance model and product design), manufacturing system modeling and the precision manufacturing of products, particularly for key parts with high-performance requirements. This facilitates redesigning and localizing quantitative precision manufacturing. Figure 1 summarizes the connotation of HPM and involved elements.

HPM represents an improvement in the manufacturing concept, transitioning from prioritizing accurate geometry to emphasizing the accurate guarantee of product performance. It also extends beyond advanced manufacturing by shifting focus away from advancements in technology towards optimization in design and economic efficiency in manufacturing, all centered around product performance. As a scientific and accurate manufacturing technology, the design and manufacturing parameters in HPM are derived by solving, analyzing, and optimizing performance. At present, establishing an organic relationship between equipment performance and design and manufacturing parameters for high-end equipment is challenging, owing to the complexity of understanding regularities in error/energy transfer, surface/interface effect, dynamic behavior, and performance evolution. Concurrently, the selection range for crucial parts of high-end equipment is constantly expanding, introducing increasingly complex shapes and structures. This, in turn, further increases the complexity of selecting factors to consider and laws to follow during the manufacturing process. Therefore, without systematic analysis, modeling, decoupling, and optimization, the design schemes for equipment products with the best performance will be hardly achieved, and the difficulty in manufacturing will also be further compounded, even exceeding the capabilities of existing technology. Based on the performance requirements of equipment or parts, HPM models the relationship between performance and material, structure, geometry, manufacturing process, service conditions, and other parameters. Consequently, the appropriate precision

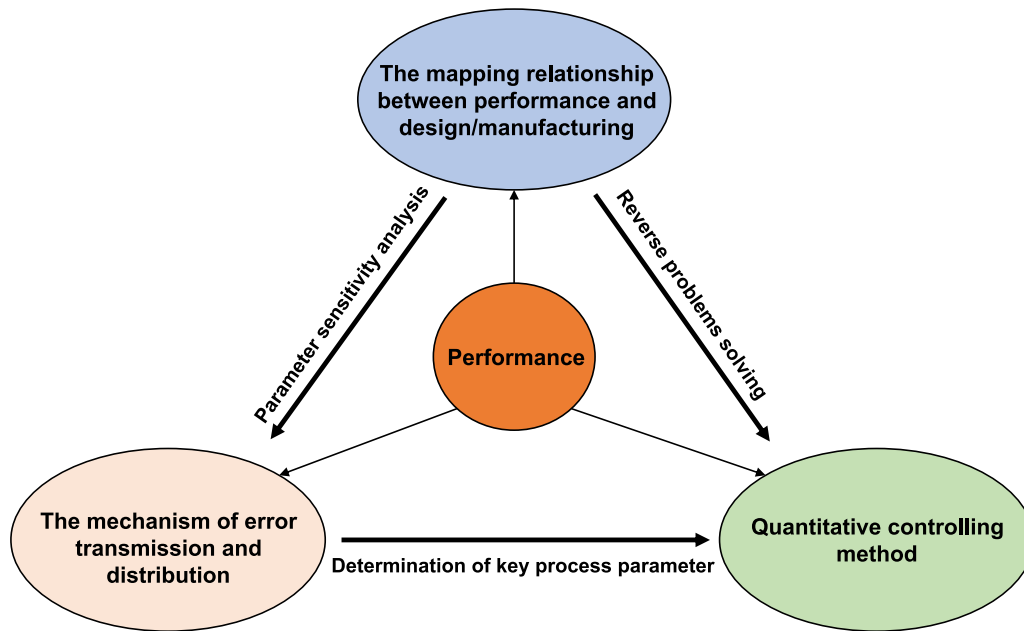


Figure 2. Fundamental issues of HPM.

distribution, error correction, compensation strategy, and manufacturing process can be deduced accordingly. This approach can effectively reduce both the difficulty and cost of manufacturing. Therefore, HPM is an inevitable trend for advancing manufacturing technology and integrating disciplines such as materials, mechanics, and information technology, signifying a shift from traditional manufacturing based on geometric size requirements to high-end manufacturing based on high-performance requirements.

2.2. Basic issues of HPM

High-end equipment typically exhibits characteristics such as electro-hydraulic integration, operation under complex or extreme conditions, diverse and rigorous performance requirements. Additionally, a firm or weak coupling relationship between the precision and performance requirements of each function makes it harder to fully understand their collective impact on the overall equipment performance. Therefore, the manufacturing process involves a multitude of factors within a continually expanding scope, making the governing rules difficult to decipher. To address these challenges, HPM develops a prediction model for performance evolution and solves the algorithm for the entire process under simulated conditions. This is achieved through interdisciplinary explorations in machinery, materials science, mechanics, and information technology, using new physicochemical effects, materials, structures, machine tools, and advanced techniques in modeling, simulation, and testing. It formulates strategies for customizing materials, structures, manufacturing routes, and parameters, thereby ensuring and enhancing equipment performance.

When implementing HPM, it is crucial to consider factors such as performance, efficiency, precision, and cost. HPM should adhere to the principle of compatibility and the best match between service performance and material, structure, geometry, and process. Moreover, HPM is expected to follow an innovative path for discovering new phenomena, exploring new laws, and proposing new methods. HPM should also select the most effective design and manufacturing process strategy and method. This decision should be based on establishing parameter detection, service performance characterization, and a comprehensive evaluation system. HPM presents a design and manufacturing approach based on scientific modeling, optimal calculation and design, and precise control of the manufacturing process. It proposes novel manufacturing principles and flows, considering the systematic, comprehensive, and accurate performance modeling of the entire process or key links of manufacturing. To promote breakthroughs in manufacturing technology, HPM is guided by solid scientific principles and innovation in interdisciplinary cross-field system modeling simulations and integration. As shown in figure 2, the fundamental issues to be explored in HPM include the following:

- (1) The mapping relationship between performance and material, structure, process, and other parameters
In essence, MoFP for high-end equipment is intended to construct a mathematical model expressing the correlation between the comprehensive performance of the equipment and parameters such as material, design (including geometry, structure, and movement), manufacturing (including process parameters and methods), and operating conditions. This is achieved by reasonably abstracting and processing a real physical system during the equipment design and service process. However, the MoFP for high-end equipment often

involves multi-condition, multiscale, and multifield coupling, along with high-dimensional uncertainty. This complexity makes it particularly challenging to describe and quantify some parameters, resulting in highly complex relationships between parameters. Moreover, the existing performance-oriented computational modeling technology lacks the strong support of unified modeling theory and efficient computing capabilities of multi-disciplines and multi-physics such as mechanical and electrical hydraulic control, fluid–solid magnetic and electric heating, making it particularly difficult to solve the MoFP for complex systems of entire machine [15]. Therefore, constructing efficient and accurate models and algorithms represents not only the first premise but also one of the main challenges of MoFP for high-end equipment. On one hand, simulating the equipment MoFP and analyzing the interaction mechanism of each element allow for feedback into the design process. This helps realize DFP and DFM, obtaining the best performance matching to meet actual requirements considering manufacturing and service under actual conditions. On the other hand, establishing the relationship between manufacturing process parameters and running state parameters ensures consistency between actual, service, and target performance after manufacturing while setting up the optimal process.

The manufacturing process significantly influences the reliability and service performance of equipment, especially in the case of high-end computer numerical control machine tools and aircraft engines with increasing complexity and difficulty of assembly and commissioning under external loads, the multifield coupling, and complex service conditions, the physical and mechanical characteristics of the connecting interface, dynamic and static characteristics, and service performance undergo dynamic spatiotemporal nonlinear changes. For example, the dynamic characteristics of a spindle system such as the contact stiffness of the spindle–holder–tool joint surface, the electromechanical coupling characteristics of the feed system, and the creep phenomenon during service, etc can directly affect the comprehensive performance of the equipment. Therefore, it is necessary to thoroughly understand the mechanism of equipment performance evolution and degradation from the macro and micro levels, and clarify its influence on equipment performance. Many existing modeling methods and performance evaluation models can be used in HPM, such as analytical models, mechanism and data-driven hybrid models [16], as well as fully digital virtual models [17–19]. The key to their selection hinges on the accuracy of models, efficiency of their solution, and the constructability of a calculation model used to obtain manufacturing process parameters.

(2) Comprehensive performance characterization, error transmission, and distribution mechanism of the system

The performance of high-end equipment is subject to high-level requirements, numerous constraints, and complex restrictive relationships. Therefore, HPM should establish a

quantitative characterization model of the system's comprehensive performance. This model will analyze parameter sensitivity and clarify the mechanisms of conflict coordination and error accumulation. High-end equipment development should consider strong constraints such as material, structure, and geometric size, and also meet many requirements for accuracy, strength, stiffness, service performance and among others. However, the development of high-end equipment still faces significant challenges. These challenges include how to rely on existing conditions and foundations to balance and select among various performance indicators, find innovative ways to overcome key difficulties, and propose innovative design ideas and methods; how to advance breakthroughs in manufacturing high-end equipment with outstanding key performance without any shortcomings when the performance indicators of each component are average; how to coordinate the performance of equipment and break conventional paradigms to achieve disruptive innovation of technology with assurance in their relationship with reference examples and design/process inheritances. Effectively response to these above challenges hinges on the development of a comprehensive performance characterization system, which plays an enormously important role in establishing guidelines for the design and manufacturing processes, formulating the optimal design scheme and developing process routes.

In the HPM process, exploring the causes behind various errors, revealing the error transfer mechanism for various performances for a range of system performance parameters, shedding light on the sensitivity rule of variable groups to performance at different scales, and tracing cross-level error variation from system to unit, would help track the evolution of equipment's comprehensive performance and aids in developing optimal error allocation criteria. These criteria not only guide the performance and manufacturing design in high-end equipment development but also address inherent challenges in traditional manufacturing methods, including high requirements for material property parameters and structure, and increasingly stringent tolerance allocation. For example, when designing precise high-end equipment, the comprehensive performance requirements should focus on the top–down calculation inverse problem of precision distribution from the entire machine to its parts. However, existing methods based on the dimension chain of equal precision, tolerance, and comparative distribution are hard to meet these requirements. Although hierarchical analysis method *et al* can consider the weighting of precision allocation for each functional part, they are limited when establishing the internal relationship between performance and tolerance, as the influence of tolerance on the performance of the entire machine or a part is often not well understood. Therefore, it is important to clarify the significance of factors such as material, structure, tolerance, and other vital parameters on performance and process constraints. By conducting a scientific analysis and accurately determining relevant factors influencing the premanufacturing design and manufacturing redesign, the precise performance with minimal degradation can be ensured.

(3) Process parameter inversion and localized quantitative regulation of MaFP

In HPM, the manufacturing methods, processing accuracy, and surface integrity considerably influence the performance of the end product. As new materials and structures, extreme processing conditions, as well as optical, electric, magnetic and other energy fields, chemical reactions, and physical effects are continuously introduced, the accuracy range in HPM extends from precision to ultraprecision and even close-to-atomic removal. Given these factors, it is necessary to deeply explore the interaction mechanism of materials, structure, load, and energy field, as well as the interpretation of the manufacturing mechanism. This investigation is crucial to understanding the laws governing the manufacturing mechanism and service process of high-end equipment. For example, we need to consider issues like the material yielding behavior under dynamic cutting loads, deformation and fracture propagation laws, surface damage generation mechanisms [20], and time-varying dynamic behavior of weakly rigid complex thin-walled component processing [21]. Additionally, we need to consider adaptive feed rate customization methods [22], mechanisms for eliminating and releasing internal stresses in high-end equipment components, and the impact of high-speed start–stop on the dynamic characteristics of the feed system and methods for vibration suppression. All of these aspects fall within the category of intrinsic relationships among material, structure, process, and performance in the space–time domain. Such problems generally exhibit high-dimensional nonlinear characteristics and sometimes include mesoscale parameters, which are key to achieving optimal matching of materials, structures, and manufacturing processes.

The formulation of an HPM process using MoFP should define a method for determining performance-oriented manufacturing process and a strategy for inversely setting its process parameters, grounded in understanding the principles of material, structure, and process matching. To meet the performance needs of high-end equipment and parts, it is important to describe machining process imprint that determine the performance of equipment and parts under the thermodynamic principles of energy and material flow transfer, transformation and dissipation during manufacturing. This completes the HPM process modeling based on the performance correlation model and design. Therefore, it is necessary to propose a coupling solution strategy for design and machining during specific optimization processes. By following the associated process signature, the ill-posed inverse problem of geometry, material, structure, and the highly nonlinear multivariable process are transformed into a well-posed relationship between the energy of the manufacturing process and the characteristic value of material flow. Manufacturing methods are often determined based on their energy and material flow characteristics. The optimization of these manufacturing process methods and procedures is primarily guided by factors such as efficiency and cost. An important part of this optimization process involves conducting a sensitivity analysis of the machining process imprint. This helps to identify the eigenvalue solution

conditions determined by aspects such as surface integrity. Then, the machining process parameters and manufacturing tolerance with high sensitivity characteristics are optimized.

High-end equipment often comes with particularly stringent requirements for product performance. With the limitations of the existing materials and manufacturing processes, the performance of products directly manufactured based on design parameters often fails to meet the requirements of high-end equipment products. Therefore, it becomes necessary to perform reverse design (also known as re-design) of some design and manufacturing parameters according to the performance deviations identified due to the manufacturing. This reverse design process can be achieved directly through detection approaches or indirectly through parameters such as geometric dimensions and surface integrity. The initial performance deviations of the product are inversely calculated to determine localized quantitative precision machining parameters. Subsequently, precision machining control generates a specific performance deviation, ensuring that the product's performance after initial manufacturing or remanufacturing meets the required specifications. In essence, precision machining regulation is used to generate a small performance deviation, enabling the quantitative control of specific performance requirements [2]. The successful inversion of corresponding design and manufacturing process parameters for high-end equipment relies heavily on several key factors such as establishing performance correlations and manufacturing process models, using efficient problem-solving algorithms, obtaining accurate test data, and precisely measuring and characterizing multiple uncertainty factors. Simultaneously, there are various localized quantitative processing control methods available, including subtractive, equal-material, and additive manufacturing methods. However, the choice of method should be situation-specific. For example, precise quantitative localized grinding can be used to improve the electrical performance of radomes and the performance of hemispherical gyroharmonic oscillators; a localized quantitative directional additive manufacturing method for composite materials can be employed to change the structural elasticity (mode) of an aircraft flutter model; and a surface-localized quantitative modification method can be used to improve the fatigue strength of blades. Localized quantitative machining is the optimally controlled manufacturing technology under multiple performance constraints. Its difficulties lie in correcting specific performance deviations while preventing other performance aspects from exceeding allowed ranges.

2.3. Coordination of design and manufacturing in HPM

The primary objective of HPM is to meet the comprehensive performance requirements of a product by optimally matching a series of processes and parameters, such as material, structure, precision, and technology, through robust modeling. It ensures that the performance realizes the expected design objectives while considering constraints such as existing manufacturing capacity, cost, and production cycle. Therefore, HPM is essentially a collaborative process of designing and

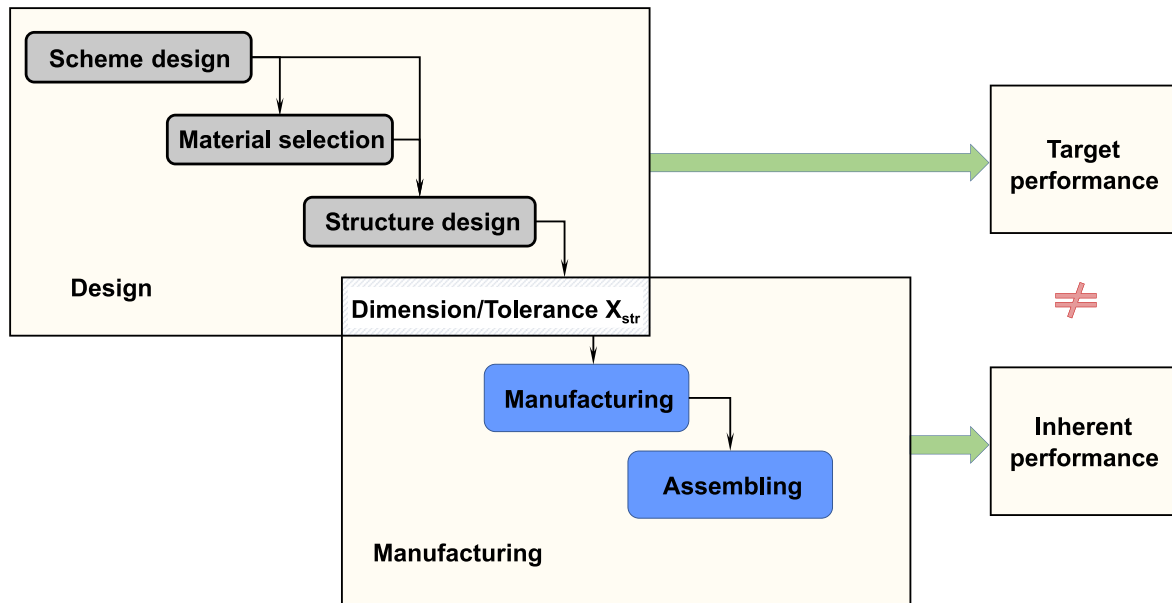


Figure 3. Traditional serial design manufacturing paradigm.

manufacturing [23–25]. High-end equipment and its key components often have wide functional requirements for different applications, including force, heat, sound, light, electricity, wear and corrosion resistance, superhydrophobicity, fatigue resistance, and kinematic characteristics. The characteristics of these parts are intrinsically linked to materials, surface/sub-surface layers and structures, covering the size, geometric accuracy, material property, surface integrity, and surface texture. The process parameters of the parts, such as processing amount, heat treatment parameter, process load, and energy field, assist in realizing optimization and quantitative control of the manufacturing process. At the equipment level, the collaboration between design and manufacturing is most apparent in the assembly process, which requires assembling the parts according to design requirements and meeting the indicated requirements for equipment performance. To achieve this, HPM should delineate the independent cross-design and manufacturing factors. It should understand the boundaries of manufacturing capacity for the product design process and establish correlations between equipment function, feature, and process parameter sets. This information is crucial in formulating valid principles of structural design, material determination, tolerance allocation, and process screening. The ultimate aim is the fine regulation and optimization of parameters in each link.

Traditional manufacturing connects to design through material properties and dimensional tolerances, as shown in figure 3. Design and manufacturing have interactions and overlaps from a hierarchical perspective, but there is no feedback loop, thus artificially separating the deep-coupling mechanism of design and manufacturing [26]. For example, although the existing design processes are performance-oriented, they often miss considering the manufacturing link; besides, the design

is often analogical rather than schematic, with design parameters obtained through MoFP calculation and optimization. Ultimately, these approaches fail to fully address uncertainties in the material properties, geometric tolerance distribution, surface integrity, assembly accuracy, and material property changes caused by the manufacturing process. However, when materials are selected, the only goal in the manufacturing process is usually to ensure accuracy instead of performance. It becomes challenging to adjust the process strategy in a localized, quantitative, and fixed processing way according to the accuracy and performance deviation of equipment or parts. Moreover, it is difficult to determine the removed/added amount of precision machining and realize dynamic online optimization of design and manufacturing. Therefore, the relationship between design and manufacturing needs to be re-evaluated to optimize the HPM process effectively.

Thus, in the HPM process, although the design and manufacturing have different focuses and manufacturing approaches are diverse, it is essential to change the traditional single-discipline and single-system serial mode of design and manufacturing, and adopt an innovative paradigm and modelling and simulation methods that embrace multidisciplinary, cross-field and whole-process considerations at the system level [27, 28]. The first step is to identify elements belonging to either the design or manufacturing category while also considering the coupling elements within these two categories. Second, it is important to distinguish between the performance-sensitive factors from the manufacturing-sensitive factors, understanding how the latter should be incorporated into the design process. Third, currently overlooked factors in the design process should be identified, and determine whether their corresponding deviations in performance could be corrected during the manufacturing; if applicable,

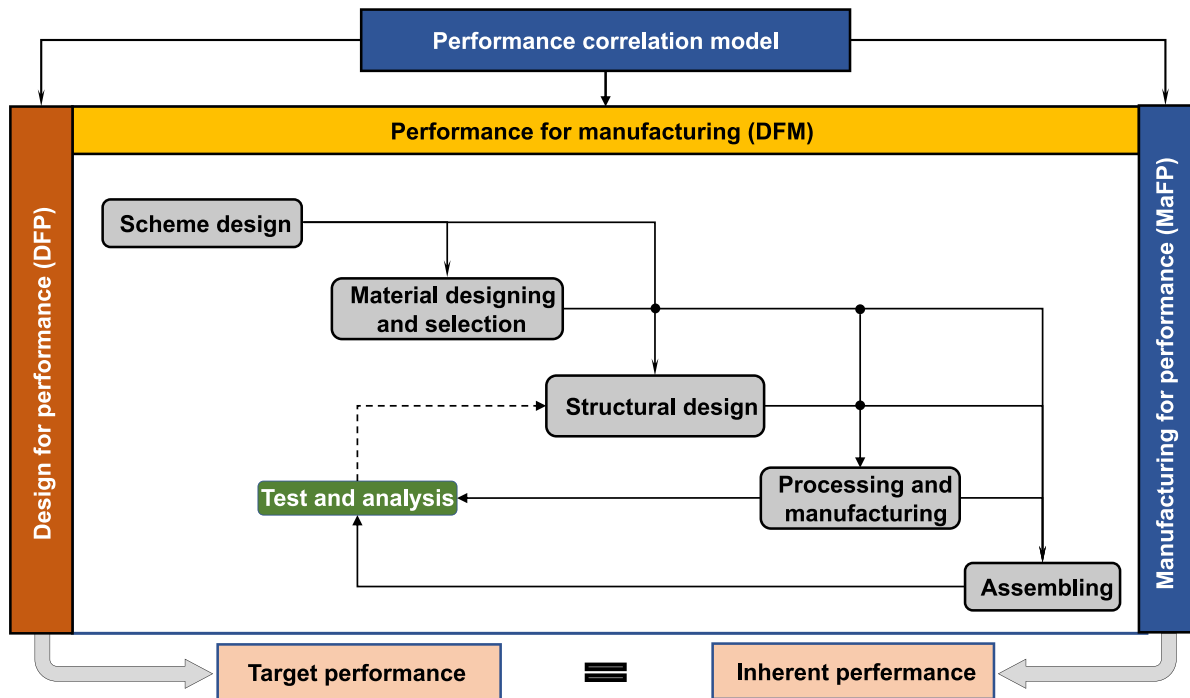


Figure 4. Design and manufacturing paradigm for performance.

potential compensation and correction forms should be specified. For example, improving the accuracy retention of processing equipment requires collaboration between design and manufacturing links. The impacts of increasing temperature, centrifugal and preload forces, and configuration mode under working conditions should be considered in designing bearing clearance. Additionally, internal stress control, assembly stress, and abnormal wear prevention should be considered during manufacturing and service processes. Another example is the manufacturing of optical imaging systems where the impact of the surface shape error on wave aberration and other properties differs across different areas of the optical surface, but it still follows certain predictable patterns. It is worth exploring whether the surface shape could be used for localized, quantitative and accurate creation, and surface integrity control to improve imaging quality or reduce manufacturing difficulty. In HPM, key factors sensitive to manufacturing should be systematically considered in both design and manufacturing processes.

As shown in figure 4, design and manufacturing in HPM should constitute a collaborative unity of DFP, DFM, and MaFP. This collaborative manufacturing approach, with MaFP at its core, facilitates deep integration of design and manufacturing. It combines effectively with new theories and methods to optimize the process. Specifically, this approach considers the comprehensive performance of equipment or parts as the system-level objective. It leverages the internal correlation among parameters such as material, structure, geometry, and process, as well as integrated multidisciplinary and multifield co-simulation as the means to achieving this objective. By processing and utilizing static and dynamic manufacturing

data flows, information can be returned from manufacturing to design. Parameters can then be customized, adjusted, or redesigned to minimize performance deviations and meet the HPM requirements.

The design and manufacturing processes in HPM should be continuously advanced across 'macro, micro, novel, and intelligent' level. To move towards the 'macro', HPM should keep pushing the boundaries of scale and load for extremely large and heavy equipment like carriers; to move toward the 'micro', it is essential to meet the performance requirements of super-hard and super-slippery surfaces and interfaces based on a deeper understanding of microscopic mechanism of multi-physics field coupling; to move towards the 'new', the design and manufacturing processes in HPM should explore the applicability of new scientific principles in the manufacturing field, and to understand the evolution of uncertain factors in new materials throughout processing and assembly cycles, preventing performance degradation and instability failures from unanticipated interactions; and moving towards the 'intelligent', HPM should integrate intelligent control [29] and analysis and evaluation of performance into the manufacturing process, adapt to the complex requirements of multiscale and multi-material manufacturing [30], as well as multiple working conditions and tasks in intelligent control.

3. Overall framework and characteristics of HPM

3.1. Overall framework for HPM

HPM is currently in its infancy stage, with various interpretations of its goals, connotations, and theoretical frameworks

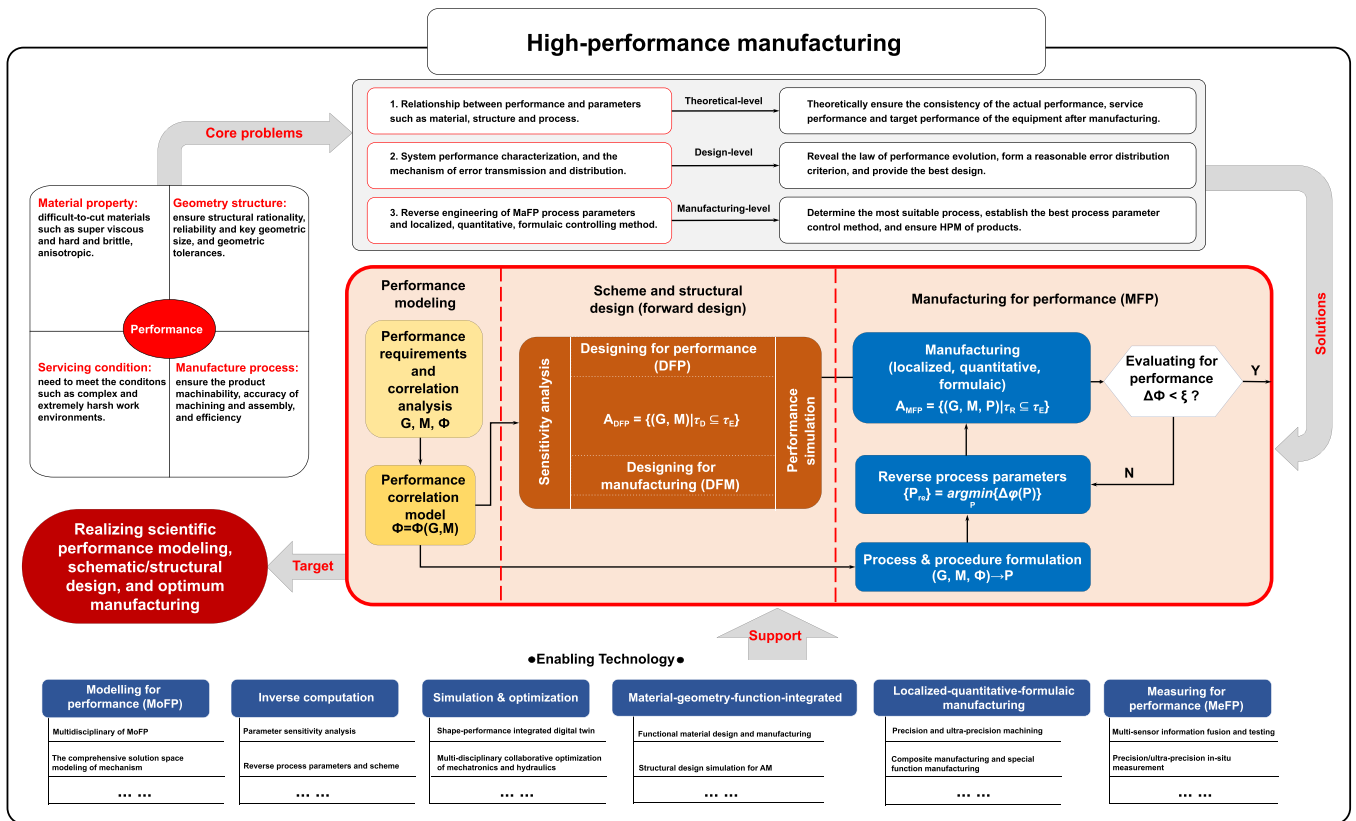


Figure 5. Overall framework of HPM theory and technology.

coexisting. To mature this concept, it is essential to invest in fundamental research and shift the manufacturing paradigms and goal orientations. Based on extensive theoretical explorations and engineering practices, we propose a general framework for HPM. As illustrated in figure 5, this framework consists of four main parts: HPM objectives, key scientific issues, solutions and processes, and key supporting technologies.

The goal of HPM is to consider the comprehensive interplay between material properties, geometric structures, manufacturing processes, and service conditions, achieving scientific MoFP and scheme/structure design. It also aims to achieve computable and optimal manufacturing methods for high-performance equipment or parts in the most economical, convenient and efficient way, given existing conditions and technologies. The foundation of HPM is formed by three interconnected scientific issues: theoretical, design, and manufacturing issues. These aspects work together to ensure consistency between actual, service, and target performances of manufactured equipment; reveal performance evolution laws and establish reasonable error distribution criteria for optimal scientific design; determine the most suitable manufacturing process and develop the best process parameter control methods for ensuring the HPM of products. HPM solutions mainly include the following. (i) MoFP, which involves analyzing performance requirements and building models to determine correlations between performance, structure, material, and other parameters. (ii) Scheme and structure design, also

known as forward design, which includes parameter sensitivity analysis, DFP, DFM, and performance simulation, with the core on MoFP and geometric structure parameter optimization. (iii) MaFP, which includes formulating process specifications, inversely calculating processing parameters and correcting key parameters based on performance deviations. Enabling technologies in HPM draw from different fields and perspectives, such as modeling, design, and manufacturing. These include MoFP, computational inverse, simulation optimization, material–structure–function integration, localized quantitative manufacturing, and testing for performance (TFP) technologies.

Conventional manufacturing usually comprises a unidirectional serial manufacturing mode. While the primary goal is to ensure accuracy, tracing performance errors becomes challenging when the performance of equipment or parts falls short of the expected standards. Even when manufacturing feedback is obtained under error tracing, it is usually a direct correction of geometric errors. By contrast, HPM focuses on the traceability and reverse correction of performance errors. This approach underscores the interplay between these two types of errors through the coordination of some vital elements in the design and manufacturing processes. Therefore, HPM relies heavily on the detection or evaluation of relevant parameters. This process is guided by an inverse model and the correlation between performance deviations and factors such as material characteristics and geometric properties. By understanding the

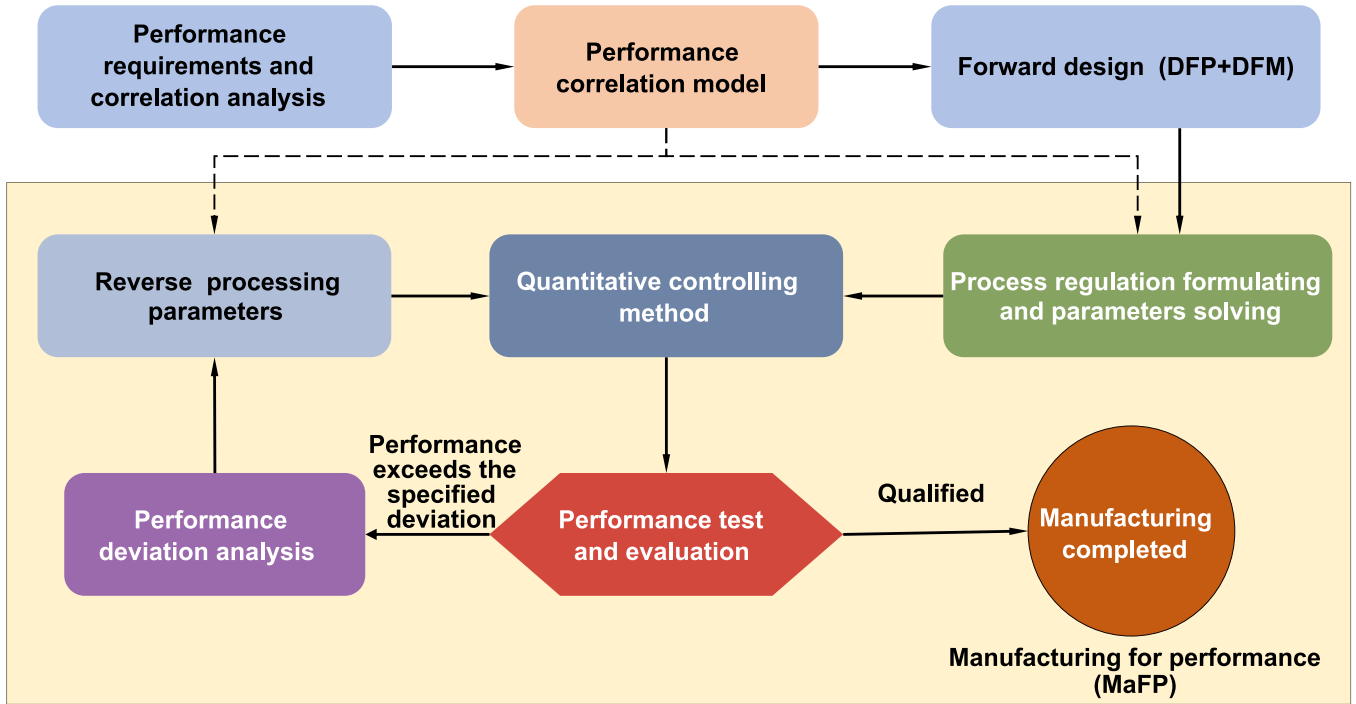


Figure 6. MaFP process flow.

influence of the manufacturing process on equipment performance, as well as error transmission and formation mechanisms, the formation and evolution laws of performance deviation over time and space can be revealed, allowing to guarantee and enhance the performance of equipment through performance-oriented manufacturing.

Considering the difficulty in controlling geometric errors affected by manufacturing and assembly, the challenge in making accurate predictions of surface integrity owing to the impact of manufacturing processes, and predictions of performance owing to the heavy dependence on idealized assumptions in conventional design, manufacturing high-end equipment and their vital parts require an inverse method of manufacturing process and quantitative localized manufacturing methods. As shown in figure 6, the MaFP in HPM represents a closed-loop manufacturing mode that relies on the integration of design and manufacturing. This mode acknowledges key factors that pose challenges to achieving precise performance. The precise performance of parts can be achieved through the reverse manufacturing of the process specifications and parameter solving under the constraint of MoFP. This includes the correction machining method of quantitative localization, which is based on the performance deviation test and process parameter inversion.

3.2. Model expression and solution form of HPM

Equipment design is primarily driven by the desired performance of the final product. During the design process, elements such as the material, structure, geometric dimensions, tolerance, and associated design performance are defined using

a theoretical model. The actual performance of equipment, however, relies heavily on how its parts are processed and assembled. For any given piece of equipment and its components, there are often multiple performance criteria. Let the performance be $\Phi = \{\phi_1, \phi_2, \phi_3, \dots, \phi_n\}$. The expected design and actual performance are represented by Φ_E , Φ_D , and Φ_R , respectively. Depending on epistemic uncertainty and variances in user expectations, an acceptable Φ_E is often described as a numerical interval. Moreover, the geometry, motion characteristics $G = \{g_1, g_2, g_3, \dots, g_n\}$, and material property parameters $M = \{m_1, m_2, m_3, \dots, m_n\}$ affect equipment performance. This relationship can be expressed as follows:

$$\Phi = \Phi(G, M). \tag{1}$$

The primary objective of designing and producing equipment is to ensure that the actual performance under given conditions meets the expected performance. This alignment can be described as follows:

$$\Phi_R \subseteq \Phi_E. \tag{2}$$

Similarly, in the DFP stage, it is necessary to ensure that the design performance meets the expected performance while considering safety margins. This requirement necessitates the establishment of design parameters for the kinematic system, material, and construction in several ways. Although the multi-objective and multi-constraint optimization approach can often be complex and challenging, it is advantageous for achieving optimal performance. By using weighting or norm

operations, a multi-objective optimization issue can be simplified to a single-objective problem. As a result, the design performance of the product can be transformed into a scalar ϕ_D ; moreover, ϕ_E and ϕ_R represent the expected and actual performances. Performance can be expressed in various ways. For example, the wear resistance of a bearing can be expressed in terms of wear rate or as service life to achieve a specific wear rate. From a safety margin perspective, the interval τ_D of design performance parameters should be a subset of the feasible interval τ_E of expected performance parameters. Therefore, the design model at the DFP stage can be expressed as follows:

$$A_{DFP} = \{(\mathbf{G}, \mathbf{M}) | \tau_D \subseteq \tau_E\} \quad (3)$$

where A_{DFP} is a solution set of geometric and kinetic parameters \mathbf{G} and material property parameters \mathbf{M} . Given the limitations of available materials, processing capabilities, and economic considerations, achieving ideal geometries and material properties can be challenging. This underscores the need for DFM, a necessary step to ensure that the actual performance matches the requirements. To achieve this alignment, it is vital to consider currently available materials and mature processes. Additionally, changes in material characteristics, geometric tolerance distribution, surface integrity, assembly precision, and other aspects induced during processing should be factored into the equation. Consequently, the final geometric parameter \mathbf{G}_0 and material property parameter \mathbf{M}_0 should be computed in line with the performance criteria.

The manufacturing process often involves the application of load or energy fields, which will alter the size and material characteristics after manufacturing. These changes can be expressed as follows:

$$\mathbf{G}_R(\mathbf{P}) = \mathbf{G}_0 + \Delta\mathbf{G}_P(\mathbf{P}) \quad (4)$$

$$\mathbf{M}_R(\mathbf{P}) = \mathbf{M}_0 + \Delta\mathbf{M}_P(\mathbf{P}) \quad (5)$$

where \mathbf{G}_R and \mathbf{M}_R represent the actual geometric parameters and material feature vectors after machining, respectively. \mathbf{G}_P and \mathbf{M}_P represent variations in geometric parameters and material characteristics caused by the machining process \mathbf{P} . Therefore, the actual performance of the product after processing and manufacturing can be described as follows:

$$\phi_R = \phi(\mathbf{G}_0, \mathbf{M}_0, \mathbf{P}). \quad (6)$$

In the MaFP stage, precise performance simulation is crucial, as is the integration of design and production. This ensures that the final product satisfies the performance requirements. Equation (3) can be further written as follows:

$$A_{MFP} = \{(\mathbf{G}, \mathbf{M}, \mathbf{P}) | \tau_R \subseteq \tau_E\}. \quad (7)$$

For products with particularly high-performance requirements, their geometry and performance parameters can be measured during manufacturing. This allows for obtaining the corresponding modified processing parameter \mathbf{P}_{re} according

to the performance deviation. This is often a fine redesign parameter, allowing the product performance to meet the target requirements. In essence, obtaining the process parameters involves an inverse process that aims to minimize the deviation between the actual and target performance of the product. This is expressed as follows:

$$\{\mathbf{P}_{re}\} = \operatorname{argmin}_{\mathbf{P}} \{\Delta\phi(\mathbf{P})\} \quad (8)$$

where $\Delta\phi(\mathbf{P})$ can be obtained according to actual measurements based on MoFP.

For complex products, various parameters can affect the performance deviation, which is often nonlinear. Therefore, determining process parameters often falls in the category of complex inverse problems involving multiparameter composite functions. Direct solutions to these problems frequently present multiple or ill-posed solutions. Feasible methods for addressing this complexity include constrained-based solutions, regularization [31], or sensitivity analysis [32]. Correction sensitivity for the performance $\Delta\phi$ to the j th processing parameter p_j can be expressed as follows:

$$S_{p_j}^{\Delta\phi} = \frac{\partial\Delta\phi}{\partial p_j} \frac{p_j}{\Delta\phi}. \quad (9)$$

Key process parameters are then optimized using sensitivity analysis, significantly reducing the solution complexity. In the actual solving process, reasonable constraints, based on expert knowledge, can be added to better meet the requirements of HPM performance.

3.3. Characteristics of HPM

HPM is centered on the precise guarantee of performance. It is not only the forward design (also the reverse design that obtains the design parameters from performance) and reverse manufacturing based on the performance model, but also the localized quantitative precision manufacturing, characterized by MoFP and inverse computing. In essence, guaranteeing high-performance precision does not necessarily rely on the highest-end materials, highest-level requirements for precision, or most advanced manufacturing processes. Instead, it relies on the synergy of scientific calculation, analysis, and optimization with commonly available materials, the most reasonable requirements for precision, and the most viable manufacturing process. Specifically, HPM is grounded in the modeling of the coupling relationship between the performance parameters of equipment/parts and parameters of geometry, material characteristics, and manufacturing process. Based on the solution and analysis of the performance model, existing manufacturing technology and capabilities are fully considered to realize the scientific and precise design of products, as well as the scientific, economical, convenient, efficient, and optimal manufacturing. For instances where performance requirements are exceptionally high, it becomes necessary to further analyze the control strategy of manufacturing process parameters according to the measured performance deviation based on the performance model. This analysis

helps obtain the optimal control value of key geometric and process parameters for equipment/parts in the manufacturing process from the performance deviation and perform precision machining to compensate for the performance deviation. Therefore, HPM tends to have the following characteristics:

- (1) The first step in HPM is establishing the performance correlation model for equipment or parts, which expresses the relationship between performance and various factors, such as material characteristics, motion, geometry, structure, and service condition parameters.
- (2) The design and manufacturing parameters are derived from the optimization calculations and analyses of performance models, namely DFP and MaFP. Leveraging the performance correlation model, HPM enables performance analysis of equipment or parts, and compatibility and sensitivity analyses of material and geometric property parameters. Subsequently, HPM aids in obtaining the optimal design scheme, including material selection, ideal geometric structure parameters, the most appropriate manufacturing processing, and input conditions of process load. These encompass the process method, process route, and specific process parameters.
- (3) HPM typically integrates the measurement and processing, and material structure and function are also integrated sometimes. Accurate control of the processing state is essential, guided by the correlation between previous data and the characteristic quantity of performance and manufacturing process parameters.
- (4) Customized precision manufacturing models are frequently adopted, particularly for high-end equipment with stringent performance requirements for their components. There may be instances where, despite meeting geometric accuracy requirements, performance parameters fall short. In such cases, it becomes necessary to replace the trial-and-error method based on experimental iteration with a scientific approach based on experience. This approach enables precise, quantitative, and localized precision machining according to each product's performance deviation.
- (5) With the performance model as the foundation, digital twinning of equipment or parts can be easily achieved. This allows for accurate prediction of performance and simulation of manufacturing processes.
- (6) The manufacturing of high-end equipment or components reflects the trinity of performance parameters, structural features, and process parameter sets. This reflects performance-driven multidisciplinary integrated computing and intelligent manufacturing.

4. Methods to realize HPM and its enabling technologies

4.1. Methods to realize HPM

The performance of high-end equipment and its vital parts often exhibits considerable customized features. Owing to the

involvement of diverse scientific principles and specific manufacturing processes, these characteristics cannot be generalized. Different types of equipment have varying functional requirements and performance levels. The development of their respective design theories, predictability of process methods, and completeness of detection technology also differs, leading to variations in the HPM implementation. Based on the HPM's concept, it is necessary to systematically research the fundamental theory of design and manufacturing, manufacturing process technology, and testing methods. These investigations cater to the development and production requirements of various high-end equipment. Regarding the design and manufacturing theory, improving the accuracy of performance design and prediction is a priority. Besides, the development of multidisciplinary optimization design methods and techniques should consider process constraints and uncertainties. In the manufacturing process, principles such as manufacturing thermodynamics and process imprinting become crucial. These principles are based on the transfer, transformation, and dissipation of energy and material flow during the manufacturing process. The performance correlation model aids in solving the manufacturing inverse problem, optimizing the manufacturing process and process parameters. Furthermore, it is essential to advance the simulation analysis method of process flow and assembly process under the interaction of multifield coupling. This development leads to highly stable, predictable, and evaluable manufacturing and assembly technology. In terms of testing, the development of efficient on-spot detection techniques for various performance parameters and manufacturing-related geometry and material key characteristics is needed. Concurrently, the theoretical and technical HPM frameworks are constantly enriched using systematic analysis methods. Therefore, the implementation of HPM can be generally outlined as follows.

- (1) The MoFP of the product forms a correlation model between performance and material, motion, geometry and structure, manufacturing process, and service conditions. Moreover, it establishes a set of performance, characteristics, and process parameters according to the comprehensive performance requirements.
- (2) The product design scheme, including kinematics design, is solved and optimized using the performance correlation model. Design parameters are optimized, completing the DFP process.
- (3) Building upon the performance correlation model and DFP, the sensitivity of relevant characteristic parameters is analyzed, and then DFM is completed based on available manufacturing technology.
- (4) A forward model of the manufacturing process is established. This model outlines the correlation among performance and material, structure, process, and other characteristic quantities. The process route and process regulations are determined, which include the process parameters, vital process parameters to be adjusted, and input conditions of the process load.

- (5) Performance-based manufacturing, as well as testing and evaluation of performance and related parameters are conducted.
- (6) For precision machining and manufacturing with performance deviation correction and compensation, the optimal process parameter set is determined using the inverse problem-solving model of the performance deviation. The number of parameters requiring adjustment is determined, leading to the realization of controllable and localized quantitative precision manufacturing.

4.2. Enabling technologies of HPM

As high-end equipment rapidly evolves toward diversified materials, extreme scales, cross-scale structure, ultrahigh precision, extreme service performance, complex surface shape, and controllable surface integrity, it also gradually evolves from digital manufacturing [33, 34] to intelligent manufacturing. The essence of digital manufacturing is to model, simulate, and optimize geometric and complex physical behaviors in a manufacturing process, along with their evolution laws. This is achieved through simulation and experimental testing, enabling the analysis and evaluation of equipment features, such as productivity, producibility and predictability (3P). As shown in figure 5, HPM should incorporate more advanced manufacturing concepts, methods, and tools. The enabling technologies involved in these advancements are the following.

4.2.1. MoFP technique. In recent years, this technique has evolved from a single-mechanism modeling to a comprehensive ‘function–configuration–structure’ generalized function modeling. This considers aspects such as the speed, accuracy, stiffness, and dynamic performance of the mechanism [35]. The MoFP technology is advancing from computer-aided design–focused geometric design to computer-aided engineering–focused physical performance modeling. It is progressing from steady-state statics modeling to transient, time-varying dynamics modeling; from single-part modeling to rigid–flexible coupling multibody dynamics modeling; from single-physical field modeling of structural stress to fluid–solid thermal multifield coupling modeling; from macro single-scale modeling to macro and micro multiscale modeling; from homogeneous continuous modeling to heterogeneous discrete and continuous mixing modeling; and from all digital virtual modeling to virtual and real integration of semi-physical modeling. The rapid development of the MoFP technology undeniably forms the theoretical foundation for HPM and offers some software support.

At present, the theoretical system for equipment spatial geometric error modeling, dynamic characteristic analysis, and assembly scheme evaluation is comparatively complete. However, there is still a deficiency in multidisciplinary modeling technology, which is mainly attributed to the following challenges: (i) characterizing uncertainty in load and design

boundary conditions of high-performance equipment, nonlinear attribute parameters of materials, and multiple performance parameters poses difficulty. (ii) Establishing a complex correlation and coupling modeling among multidisciplinary and multilevel parameters is challenging, as is variable information transfer between different physical fields. As a result, MoFP is often hierarchically decomposed into various disciplines and fields. Bidirectional unsteady and strong coupling models are often simplified into unidirectional progressive steady and weak coupling models, where the coupling mechanism cannot be accurately revealed. (iii) High-performance equipment often has multiple performance requirements, such as load bearing, conduction, and many other parameters. These performances may not only have implicit nonlinear correlations but also conflict with each other, making it tough to balance and coordinate various performance aspects of high-performance equipment. (iv) Solving a model with large-scale nodes and elements efficiently and accurately is challenging. (v) Software with autonomous, reliable, and advanced modeling tools are lacking. Therefore, developing high-efficiency and excellent-fidelity MoFP techniques and software tools is crucial.

4.2.2. Computational inverse technique. Computational inverse technology plays a crucial role in obtaining design schemes, structural design parameters, and manufacturing process parameters. It has been applied in areas such as design of equipment kinematics scheme and structural optimization, modification of machining adjustment parameters, identification of manufacturing system model parameters, inversion of load and other boundary conditions, identification of work-piece material attributes, solution of machining allowance distribution, and determination of localized quantitative manufacturing parameters. However, as performance requirements become more complex, the number of interconnected parameters, including those related to materials, structures, and technology, has sharply increased. This increase has led to a more intricate and nonlinear performance correlation model. Computational inverse technology for performance faces its challenges, including difficulties with ill-posed inverse solutions, the absence of forward analytical solutions for inverse solutions, and efficiency concerns. HPM demands strict control over the sufficiency of performance test data and control of noise to prevent the ill-conditioned system matrix, which could destabilize inverse solutions. Additionally, high-confidence inverse calculations are closely linked to the analysis of the forward problem and the iterative optimization process, further complicating inverse calculations involving high-dimensional parameters.

To overcome these challenges, it is essential to leverage advanced mathematical tools tailored to HPM’s unique requirements. For example, integrating high-precision sensor testing technology with data filtering and mining technology can effectively eliminate noise during measurement. Sensitivity analysis methods can be used to assess both localized and overall sensitivities of various parameters. By

utilizing sensitivity analysis and ranking, we can identify a precise set of inverse parameters and their reasonable intervals. The regularization method can be used to introduce strong constraint conditions, improve the ill-conditioning of the system matrix, and ensure the stability of the inverse solution. A practical example of the aforementioned approaches is the use of surrogate model technology. This technology constructs a black-box model of geometric structure parameters, process parameters, and product performance, thereby improving the efficiency of calling massive functions for high-dimensional problems.

4.2.3. Simulation-based optimization technology. Building a multidomain and multiscale simulation-based optimization technology is a significant advancement in manufacturing. The technology enables precise and efficient simulations of manufacturing processes, thereby informing and improving real-world processes. The shift from single-part to component or system-level simulation optimization is vital for achieving HPM [36]. However, mainstream manufacturing simulation technology still focuses on structural simulations, leaving a gap in multidisciplinary joint simulations. For instance, there is a lack of comprehensive simulations that incorporate electromechanical hydraulic control. Existing technologies mainly concentrate on topology optimization, size optimization, and comparatively simpler multi-objective coupling optimization for enhancing equipment performance. Emerging technologies such as digital twins [37, 38] facilitate real-time mapping and control of physical entities in a virtual space through interactive feedback between the virtual and real worlds, data fusion, and iterative optimization. Mainly used for system status monitoring, prediction, maintenance, and control [39], digital twins can timely identify bottlenecks in design and manufacturing processes, thereby improving understanding, control, and prediction capabilities across the processes. The application of the digital twin technology in HPM spans five key areas: (i) theoretical and data modeling technologies for the manufacturing process, (ii) real-time data acquisition, (iii) multisource data fusion, (iv) real-time dynamic simulation of the manufacturing process, and (v) model and data-driven real-time prediction and decision making of the manufacturing process. Despite its potential, the application of digital twin technology in HPM presents several challenges including integrating, analyzing, and predicting multisource heterogeneous big data [40]. For example, in high-performance metal additive manufacturing, several crucial issues need to be addressed: how to efficiently store and transmit multisource and multimode data, such as images, temperature readings, stress and strain measurements, and phase transformations? How to integrate and process real-time monitoring and historical data for developing an HPM information base? How to mine the embedded manufacturing knowledge from manufacturing information to understand defect mechanisms, modes, and timings, and establish a correlation between performance parameters and manufacturing process parameters? Finally,

how to achieve the fusion of physical and virtual information of manufacturing equipment?

4.2.4. Localized quantitative manufacturing technology. HPM significantly differs from traditional manufacturing, particularly in its use of localized quantitative manufacturing technology during the precision machining stage of finishing. Various methods can be employed to implement this technology, including precision and ultraprecision machining technology at micro, submicro, nano, and even subnano levels; five-axis machining technology for microlevel precision; 3D printing; controlled growth of surface layers in 3D; surface modification; and controlled strengthening of surface layers. The primary objective is to establish a performance-driven, point-by-point, controllable correction model. This model is paired with a micro or submicro reduction or additive manufacturing technology that can be controlled in the same manner and is based on performance prediction or data detection. Essentially, manufacturing parameters such as removal or additive processing at each point are not static but vary according to performance requirements. For example, a radome requires precise grinding based on the measured internal profile and other geometric data. Initially, performance parameter errors after semi-finishing are calculated, and the distribution of machining removal allowance that can correct the performance deviation is determined. Subsequently, a radome that meets the electrical performance requirements is processed using a point-by-point controllable grinding method. This localized quantitative removal technology offers greater precision and control than conventional manufacturing methods. However, it requires determining the target surface for correction, correction methods, and process input parameters for each point. These should be based on the surface of the target shape, taking into account the specific machining requirements and performance deviations of parts. The goal is to correct the product's performance deviations through a quantitative control of manufacturing behavior, ensuring the high performance and yield of products. It is worth noting that understanding the interaction mechanism between performance and the manufacturing process is crucial. The development of automated processes for decision-making models and precision manufacturing process equipment with point-by-point controllable correction capabilities will greatly support the future advancement of localized quantitative manufacturing technology.

4.2.5. Performance test and analysis technique. Ensuring performance in HPM can be complex owing to various uncertain factors. To bridge the gap between design and manufacturing, integrating measurement and processing technologies is crucial in connecting the upstream and downstream sections. This integration proves particularly beneficial for HPM, which heavily relies on the performance testing and assessing key geometric and material property parameters. Namely, the precision of performance testing and the capacity to quantitatively adjust based on performance deviations greatly influence the

ultimate performance of equipment or parts. The HPM generally typically involves TFP, geometric measurements, and material property parameter testing. Geometric detection is mainly used to measure factors related to process parameters, including surface topography, geometric shape, size, and position deviation. For example, in some high-performance parts, an adjustable parameter, such as the wall thickness of the machining part, would need to be measured in advance. In addition to detecting internal defects and evaluating consistency for material structures, measuring for performance is vital. This primarily focuses on detecting machining surface layer property parameters affected by processing technology, such as surface damage, residual stress, hardness, and wear resistance. Traditional manufacturing processes usually conduct TFP and part evaluations after production, using specialized testing equipment. However, this approach does not align well with the evolving requirements of measurement and processing integration technology and HPM equipment, especially for the precise and high-efficiency measurements in extreme environments, such as extreme temperatures or amid significant noise interference. Therefore, a deeper exploration into the fundamental TFP principles, technologies, and multi-sensor fusion instruments in performance testing becomes necessary, as well as the development of new *in-situ* and online testing technologies.

4.2.6. Integrated technology of material structure and function. The ultimate goal of future on-demand manufacturing is to create ideal material parts with integrated structures and functions [41]. Achieving this goal relies heavily on technology that can seamlessly integrate these aspects. This innovative manufacturing approach promises to substantially expand the possibilities for equipment or part design and performance improvement while also fostering parallel design and manufacturing of material structures. Nonetheless, integrating material structure and function presents three key challenges: (i) establishing a clear mapping relationship between material, structure, process, and performance; (ii) designing materials, structures, and functions that harmonize under process constraints; and (iii) executing precision manufacturing processes for multimaterial, multiscale, or multifunctional structures. High-performance components, engineered for use under extreme conditions, often come with strict requirements for the materials used, such as strength, stiffness, and fatigue characteristics. Additional characteristics may include lightweight, heat insulation, noise reduction, vibration reduction, stealth, and unique composite functional requirements such as electrical light, magnetic, hydrophobic, dustproof, and icing resistance. To ensure optimal performance, structural configurations for these parts are typically achieved using topological optimization. Complex configurations, encompassing multimaterial composites, gradient materials, and multilevel macro, fine, or microstructures, escalate manufacturing complexity. This demands the rapid development and adoption of new manufacturing methods and technologies. While 3D printing, additive, and subtractive composite manufacturing

technologies provide strong support for fabricating complex structures with internal cavities, there are still many limitations concerning molding material types, microstructure sizes, and multimaterial structures. Alongside topology optimization and other advanced design methods, it is highly desired to actively explore new manufacturing technologies and processes. These should facilitate the integration of material structure and function, adapt to various materials, suppress manufacturing defects effectively, achieve high forming accuracy of macrostructures and microstructures, and demonstrate the good forming performance of multimaterial composites. These elements are crucial for the widespread application of ideal material parts in the near future.

5. Application of HPM

The principles and methods of HPM have been successfully applied to the design and manufacturing of several high-end equipment and components. Noteworthy examples include a scaled model for an aircraft flutter wind tunnel test and the main engine of a reactor coolant pump (RCP).

5.1. Scaled model of aircraft for the flutter test in the wind tunnel

Aircraft flutter, a dangerous self-excited oscillation phenomenon, can lead to fatal aircraft crash and fatalities in an instant. Therefore, conducting flutter wind tunnel tests on scaled aircraft models is a critical aspect of aircraft design and flight safety. These aero-elastically scaled aircraft models (hereinafter referred to as flutter scaled models) are very important for flutter wind tunnel tests. They should accurately represent the original aircraft in terms of structure, shape, mass distribution, and frequencies [42]. However, designing and manufacturing these scaled models is a remarkably difficult task. The key procedures in creating a flutter scaled model involve the following:

- (1) Aircraft performance modeling and performance-oriented flutter scaled model design: this step is based on the modeling and aeroelastic design of the aircraft structure. Through the performance-oriented design and scaling relationship between the scaled model and aircraft [43], the governing equation of an ideal flutter scaled model is developed (equation (10)):

$$(\lambda^2 C + \lambda D_0 + D + qQ_A(k, Ma))x_0 = 0 \quad (10)$$

where λ represents the eigenvalue; C , D_0 , G , and Q_A denote the inertia, damping, elasticity, and aerodynamic terms, respectively; and q , k , and Ma represent the velocity pressure, reduced frequency, and Mach number, respectively. According to the Rayleigh principle, the frequency of the ideal flutter scaled model can be expressed as follows:

$$\omega^2 = \frac{\int \epsilon_0^T \mathbf{D} \epsilon_0 dV}{\int \rho (u^2 + v^2 + w^2) dV}. \quad (11)$$

In the formula, \mathbf{D} is the elastic coefficient matrix; ε_0 is the strain; ρ represents the material density, and u , v , and w represent the displacement along the three directions.

To accurately capture the flutter characteristics of an original aircraft, equation (11) suggests that the elasticity, density, geometric shape, and structure of the scaled model should be position-wise equivalent to those of the original aircraft. This is in line with the similarity requirements of multiple frequencies and modes. Essentially, an ideal flutter scaled model should be a heterogeneous continuous scaled model. Its material and structure should be constructed point-by-point according to the original aircraft performance. However, owing to the complex topological configuration, the large number of components, various connection forms, and the use of multiple materials in the original aircraft structure, it is practically impossible to continuously control the construction of materials and structures of the scaled model point-by-point. This, coupled with the limitations of available materials and manufacturing processes, makes the overall manufacturing of the ideal scaled model extremely difficult. Therefore, it is necessary to adopt a DFM approach to perform equivalent processing.

- (2) Manufacturing-oriented flutter scaled model design: by adopting the manufacturing-oriented design approach, the flutter scaled model is designed and manufactured using fiber-reinforced composite materials, leveraging their excellent designability, suitability for additive manufacturing, and ease of forming composite materials. Through modeling, analysis, and considering manufacturing characteristics, we obtain a flutter scaled model design that closely mirrors the performance of the original aircraft across various domains. Typically, the flutter scaled model should ensure the accuracy of the first N frequencies. By introducing material parameters \mathbf{M} and geometric parameters \mathbf{G} and determining the stiffness $\mathbf{K}_j(\mathbf{M}, \mathbf{G})$ and mass $\mathbf{B}_j(\mathbf{M}, \mathbf{G})$ in each region of all design domains, we can establish the design formulation of the first N frequencies as follows:

$$\{\mathbf{M}_0, \mathbf{G}_0\} = \arg \min_{\mathbf{M}, \mathbf{G}} \left\{ \left\| \mathbf{w}_D \left(\sum_{i=1}^Q \mathbf{K}_i(\mathbf{M}, \mathbf{G}), \sum_{i=1}^Q \mathbf{B}_i(\mathbf{M}, \mathbf{G}) \right) - \mathbf{w}_E \right\| \right\} \quad (12)$$

where the stiffness $\mathbf{K}_j(\mathbf{M}, \mathbf{G})$ and mass $\mathbf{B}_j(\mathbf{M}, \mathbf{G})$ of each domain are calculated separately. In the formula, $\omega_D = \{\omega_1, \omega_2, \dots, \omega_N\}^T$ represents the first N frequencies of the developed model and $\omega_E = \{\omega_1^*, \omega_2^*, \dots, \omega_N^*\}^T$ represents the first N expected frequencies. Given the challenges inherent in forming and manufacturing composite materials, alongside limitations in our current manufacturing methods, achieving precise control over fiber distribution and orientation, as well as accurately regulating material interface properties, poses a significant complexity. To address this, a segmented and layered approach

is employed for the approximation, resulting in a model that closely mirrors the performance of the original aircraft. Consequently, composite material scale models have emerged as pivotal tools in overcoming the manufacturing bottlenecks associated with flutter scale models.

- (3) The manufacturing of the flutter scaled model, a performance-oriented process, encompasses several stages: forming, error analysis, modal measurement, precision correction, and interface strengthening. The model is constructed using composite additive manufacturing. However, owing to the influence of process parameters such as forming temperature t_p , pressure f_p , and assembly connection a_p on the development of the composite flutter scaled model, manufacturing errors $\Delta \mathbf{G}_P$ and $\Delta \mathbf{M}_P$ of geometric parameters \mathbf{G}_R and material parameters $\Delta \mathbf{M}_R$ are inevitable in comparison with the target values,

$$\begin{aligned} \mathbf{G}_R(t_p, f_p, a_p) &= \mathbf{G}_0 + \Delta \mathbf{G}_P(t_p, f_p, a_p) \\ \mathbf{M}_R(t_p, f_p, a_p) &= \mathbf{M}_0 + \Delta \mathbf{M}_P(t_p, f_p, a_p) \end{aligned} \quad (13)$$

Therefore, these manufacturing errors result in a deviation $\Delta \omega$ of multi-order frequencies of the model after manufacturing.

Achieving the specified accuracy requirements of frequencies for the scaled flutter model through adjusting and controlling process parameters alone is challenging. Alternatively, precise control of geometric and material error ranges necessitates upgraded forming equipment and processes, which significantly increases costs and reduces the economic viability of manufacturing flutter margin models. Therefore, we adopt a performance-oriented manufacturing approach. This method is based on the relationship between the multimodal frequencies of the flutter scaled model and the design parameters of model geometry, material, and connection. We conduct frequency measurement and error analysis for the developed scaled model and construct a multiparameter optimization formulation for the topology–material–geometry with manufacturing constraints, as shown in equation (14). In this equation, minimizing the maximum frequency error is defined as the design objective. By solving this optimization problem, we determine the number, topology, and location of correction subdomains subjected to additive correction processing. Simultaneously, we estimate the material selection, layer thickness, and fiber-laying angle of each correction subdomain. This process allows us to achieve precise quantitative correction of the flutter scaled model with the specified subdomain and fiber orientation, as shown in figure 7,

$$\begin{aligned} &\min_{\rho^i, d^i, \theta^i} \max |\Delta \omega| \\ \text{s.t. } &\rho_i^l \in (1, 2, \dots, n^{\text{Mat}}), i = 1, 2, \dots, m, \\ &d_i^l \in (0, t, 2t, \dots, n^* t), i = 1, 2, \dots, m, \\ &0^\circ \leq \theta_i^l \leq 180^\circ, i = 1, 2, \dots, m. \end{aligned} \quad (14)$$

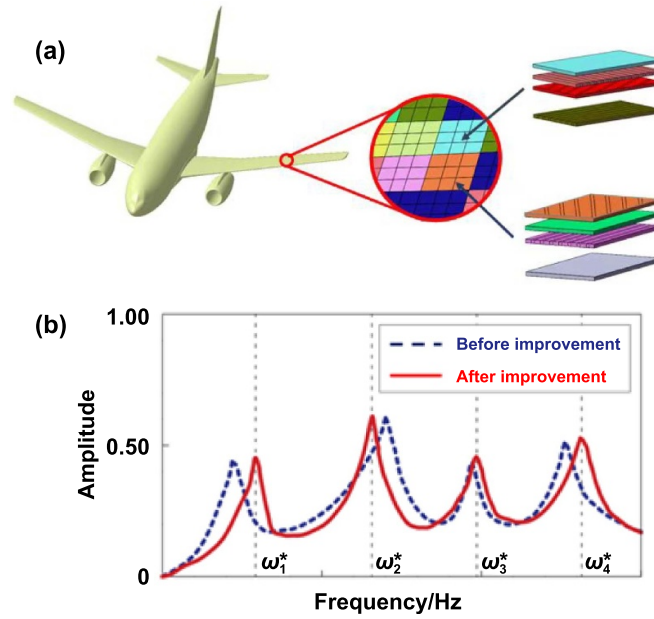


Figure 7. Multimodal frequency correction of an aircraft flutter scaled model. (a) Schematic diagram of precisely quantitative correction of the flutter scaled model with specified subdomain and fiber orientation. (b) Frequency comparison before and after improvement.

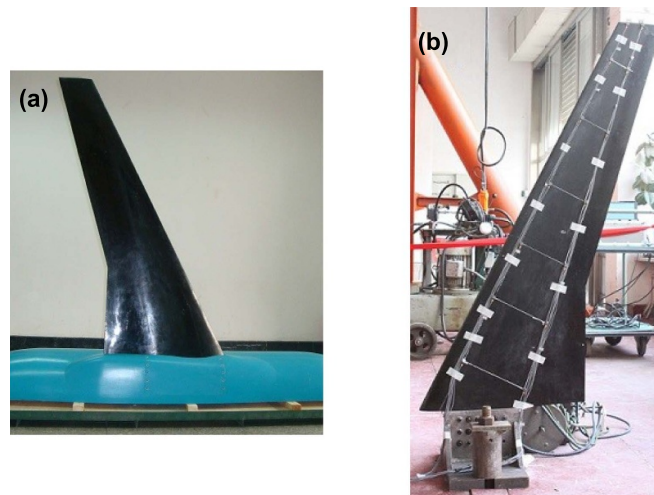


Figure 8. A flutter scaled model of an aircraft wing. (a) The model. (b) Modal test.

where ρ^l , d^l , and θ^l represent the material selection, layer thickness, and fiber orientation in the correction subdomain, respectively. t is the single-layer thickness of the composite. Considering the geometric and technological constraints, the number of layers in the correction subdomain cannot exceed n^* . As a result, the layer thickness is a discrete variable with an allowable range of $(0, t, 2t, \dots, n^*t)$. The fiber orientation is a continuous variable varying between 0° and 180° . Beyond ensuring the frequency and modes, it is necessary to meet the strength requirements of the model for wind tunnel testing. To improve the interference performance while maintaining stiffness, we employ a short fiber toughening process in forming the interface of the correction subdomain.

According to the requirements of the wind tunnel test on the flutter scaled model for an aircraft, its HPM is completed using the aforementioned manufacturing procedures. As an example, figure 8 shows that the first five modes of the completed flutter scaled model including wing bending and twisting, all meet the requirements of the flutter wind tunnel test. The measured error for the first three frequencies is $<5\%$ in comparison with the target values.

5.2. HPM of the RCP

RCP, the central equipment in nuclear power plants, is a sophisticated machine responsible for driving the circulation of a high-radiation, high-temperature, and high-pressure

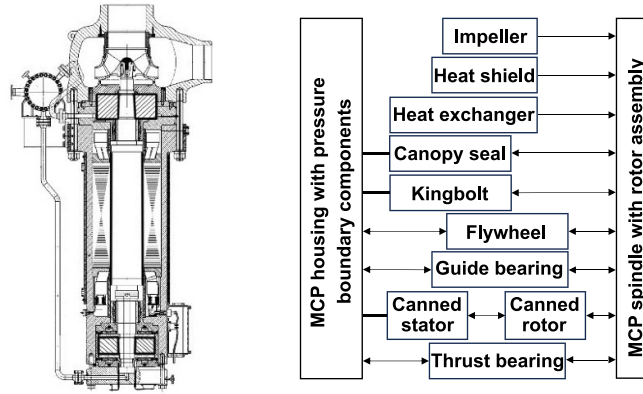


Figure 9. A schematic structure of a canned MCP and the illustration of interactions between multiple components for the HPM model with a system–component hierarchical architecture.

heat-carrying medium in a nuclear island. It transfers the heat generated from nuclear fission in the reactor core to a steam generator, subsequently producing steam to drive the turbine and generate electricity. The RCP is composed of multiple components, including a pump shell, pump shaft, impeller, heat screen, idle rotary flywheel, drive motor, shield sleeve or shaft seal, and axial/radial–thrust bearing. As the only continuously operating high-speed and heavy-duty rotating equipment in the nuclear island, the RCP is a vital part of the pressure boundary of the primary circuit. It is the core equipment of nuclear safety level 1, seismic grade I, and quality assurance level QA1. Ensuring the stability of large flow and high-efficiency transmission of the heat-carrying medium, especially the high reliability over 60 years of ultralong service, poses great challenges to the design and manufacturing of high-power RCPs. However, after more than 10 years of research, our team has successfully realized the HPM of the nuclear main pump, with key steps outline below:

(1) Performance modeling for the HPM of RCP

For the target performance requirements Φ_E of the RCP, such as large flow Φ_h , high-efficiency Φ_e , and high reliability Φ_r , we constructed a physical model of the fluid–solid thermal and electromagnetic interaction of the RCP based on the system dynamics and manufacturing thermodynamic principles of the multisource coupling constraints of the RCP geometry G , material M , and structure S . The typical structure of the high-power shielded RCP and the interaction of each component are shown in figure 9. By analyzing the dynamic performance of the RCP system under full working conditions, we developed a load distribution plan for the components and determined a part design according to the thermodynamic calculations of the parts manufacturing under the action of the distributed load. We then updated the dynamic design conditions of the system to optimize the RCP performance. This led us to obtain a correlation model satisfying the RCP Φ_E and design performance Φ_D :

$$\Phi_E \{ \Phi_h, \Phi_e, \Phi_r \} = \Phi_D + \Delta \Phi_D \quad (15)$$

(2) DFP

In the DFP stage of the RCP, the design of Φ_E , which is the independent correlation between the RCP G , M , S , and the manufacturing process chain P is considered. The design performance is determined based on the principles of system dynamics and reversible thermodynamics Φ_D

$$\Phi_E(G, M, S) = \Phi_D(G, M, S, P) + \Delta \Phi_D(\Delta G, \Delta M, \Delta S). \quad (16)$$

A sensitivity analysis $S_D = [S_{LB} | \Phi_D]$ is carried out, focusing on the surface integrity LB of parts manufacturing, which plays a decisive role on Φ_D , G , M , and S . The tolerance distribution principle of vital parts G , M , and S is determined using the characteristic value of LB with high-sensitivity to complete the initial design of the RCP G_0 , M_0 , and S_0 satisfying Φ_E .

(3) DFM

Based on the DFP in the RCP, the deviation in the manufacturing performance Φ_P caused by the P constraint of the manufacturing process chain, is considered. The $\Phi_D(G, M, S, P)$ influenced by P is determined based on the principle of irreversible thermodynamics of system dynamics and manufacturing. This establishes the coupling relationship between Φ_P and Φ_D .

$$\begin{aligned} \Phi_D \{ \Phi_h, \Phi_e, \Phi_r \} (G, M, S, P) \\ = \Phi_P(G, M, S, P) + \Delta \Phi_P(\Delta G, \Delta M, \Delta S, \Delta P). \end{aligned} \quad (17)$$

On the right side of the aforementioned equation, the manufacturing performance term employs thermodynamic parameters such as mechanical energy ΔE_{me} , thermal energy ΔE_{th} , and interface energy ΔE_a . These determine the relationship between the process imprinting $\Delta LB(\Delta E_{me}, \Delta E_{th}, \Delta E_a)$, quantitative and localized P , part performance ΔB_n , and system performance Φ_P of G_P , M_P , and S_P manufactured by the RCP.

$$\Phi_P(G_P, M_P, S_P) = \Delta \Phi_P[\Delta LB(\Delta E_{me}, \Delta E_{th}, \Delta E_a)]. \quad (18)$$

According to the effect of manufacturing process chain P on LB , the sensitivity analysis of process parameters $S_P = [S_{\Delta E}|_{LB}]$ is performed, and the core processing and assembly process chain P that determines LB is selected. For the design performance item on the left side of equation (18), under the action of various loads such as impeller hydraulics, bearing force, flywheel clearance circulation force, rotor eccentric magnetic tension, and the thermal stress of each component, the system mass matrix W , damping matrix D , and stiffness matrix K are determined by LB of parts manufacturing. This data is used to calculate the performance of the nuclear main pump Φ_D through the multiphysical field analysis of component interaction

$$\Phi_D(G_P, M_P, S_P) = \Phi_D[W, D, K(\Delta LB)]. \quad (19)$$

Therefore, the LB of key components of the RCP is taken as the hub, and the DFM of the RCP is completed using equation (17). The result shows that G_P , M_P , and S_P satisfy the equivalent relation of Φ_D and Φ_P

$$\Phi_D\{\Phi_h, \Phi_e, \Phi_r\}(G_P, M_P, S_P) = \Phi_P(G_P, M_P, S_P) \quad (20)$$

(4) MaFP of RCP

To derive the design parameters G , M , and S and manufacturing parameters P of the RCP Φ_E , a material-oriented regularization (MOR) method is proposed. This method, based on surface integrity, effectively transforms the complex multi-source coupling constraints of the nuclear main pump manufacturing into a solvable relationship between G , M , S , and P . This approach addresses the inverse problem of achieving RCP in HPM [44]. By extracting surface integrity eigenvalues $LB\{LB_j\}$, which determine the system performance Φ_P and part performance B_n , and corresponding energy eigenvalues $\Delta E\{\Delta E_j\}$ from the part LB and P , the MOR high-sensitivity matrix S_{MOR} for the inverse problem-solving is constructed,

$$S_{MOR} = [S_{LB_j}] [S_{E_i}] (i, j = 1, 2, 3 \dots). \quad (21)$$

Using equations (18)–(20), we can obtain the cooperative optimal design and manufacturing parameters satisfying the target performance Φ_E of the RCP:

$$\{G, M, S, P\} = \arg \min_{G, M, S, P} \|\Phi_E - \Phi_P(G_P, M_P, S_P)\|. \quad (22)$$

During the performance testing of the RCP parts, if the performance fails to meet the design requirements based on the high-sensitivity of LB and P , a reverse optimization and precision correction of performance deviations will be conducted to ensure that its performance meets the standard. Subsequent system performance testing of the nuclear main pump involves assessing whether design reverse correction and solution optimization of design and manufacturing coupling are necessary based on its comprehensive performance index, as well as the necessary precision correction processing. This process continues until the RCP performance reaches the standard and passes the comprehensive performance test.

For example, the shielded RCP thrust bearing, which is a high-performance component composed of a tilting thrust pad, thrust disk, pump shaft sleeve, positioning mechanism, and supporting mechanism, is a typical highly nonlinear dynamic system with critical component performance requirements. These include the use of self-lubricating composites, integrated structural design of the thrust tile, application of a super-hard carbide coating, and structural integration of the positioning mechanism. With a thrust diameter ranging from 1.2 m to 1.5 m and a rotational speed of $1500 \text{ r} \cdot \text{min}^{-1}$, water is used as a lubricant, forming a $10\text{--}50 \mu\text{m}$ thick film on the surface of the graphite thrust tile. The vertical support rotor, which weighs 16 000 kg, meets high load bearing requirements and ensures stable, even loading, and wear-resistant self-lubricating performance. However, there is an inherent design contradiction between the mixed lubrication state at start–stop and idle rotation and the normal hydrodynamic lubrication state under full working conditions. This causes the thrust pad and thrust disk to be prone to wear and failure, reducing the service life of thrust bearings significantly. Therefore, the RCP thrust bearings represent one of the most challenging key parts in nuclear power equipment manufacturing.

In the context of the RCP performance modeling and design, we further delve into modeling and analysis of the RCP parameters G , M , and S , as well as the processing and assembly process P . Initially, we establish procedures and parameters. These include the molding process P_1 for the carbon fiber-reinforced resin matrix composite M_1 on wedge surface G_1 , the thermal spraying process P_2 for the cemented carbide coating M_2 on cylinder surface G_2 , and the ion injection process P_3 of the stainless steel M_3 needle roller cylinder G_3 of the supporting mechanism. We also consider the preloading assembly process P_4 of the thrust bearing, among other process specifications and parameters. Next, we develop a series of new technologies that encompass the manufacturing of carbon fiber-reinforced resin-based composite tile surfaces through molding, positioning mechanisms for hard alloy buffer coatings, and strengthening manufacturing technologies of stainless steel wear-resisting and corrosion-resisting ion impregnation composites. The LB characteristic values of the thrust bearing, uniform load, wear resistance, and effect resistance are extracted. A collaborative optimization of manufacturing process parameters is then performed. This includes the thrust tile residual stress $LB_1(G_1, M_1, P_1, P_4)$, surface topography $LB_2(G_1, M_1, P_1, P_4)$, positioning mechanism microhardness $LB_3(G_2, M_2, P_2, P_4)$, residual stress $LB_1(G_2, M_2, P_2, P_4)$, elastic deformation of the supporting mechanism $LB_4(G_3, M_3, P_3, P_4)$, residual stress $LB_1(G_3, M_3, P_3, P_4)$, and energy characteristic values such as the maximum heat, plastic strain, and storage elastic strain energy for machining and assembly processes. The outcome of all aforementioned actions enables us to meet high-performance requirements for thrust bearing. For instance, when the molding temperature is $385 \text{ }^\circ\text{C}$ and pressure is 30 MPa, the maximum offset load of the thrust pad's load balancing performance B_1 is less than 10 kN. The vibration performance B_2 has an axial amplitude of less than

100 μm , while the thermal spraying positioning mechanism of the buffer coating achieves a wear resistance depth for wear resistance B_3 of less than 100 μm . Moreover, it can resist 6000 cycles of 5 kN heavy dynamic load for impact resistance B_4 , among other performance standards.

The HPM methodology has been pivotal in developing manufacturing processes for high-power canned RCPs with axial/radial-thrust bearings. The successful production and testing of a prototype have confirmed the efficiency of these processes. Comprehensive full-flow tests of the RCP reveal that the thrust bearing exhibits high dynamic lubrication under heavy loads and high speeds under full working conditions. Simultaneously, the thrust bearing demonstrates adaptive adjustment capabilities for dynamic structural deviations arising from various working conditions, ensuring excellent load sharing performance. It also maintains excellent self-lubrication and wearing resistance under transient and extreme working conditions such as start-stop and water loss.

Addressing the HPM of the RCP involves tackling several technical challenges inherent in the manufacturing process. These obstacles have been overcome through extensive research into performance modeling, design analysis, materials, and manufacturing processes.

6. Conclusions

The increasing demand for high-end equipment has elevated HPM of equipment and parts to a transformative role in industrial and economic sectors, signifying future development directions. While significant breakthroughs have been made in the manufacturing process and equipment for specific high-performance components, fundamental research on HPM is still lacking. So far, comprehensive theoretical and technical systems for HPM are still in their infancy, with a lack of significant breakthroughs in many singular research points and technologies. This lack is evident in the development of innovative manufacturing concepts and processing methods. There are profound distinctions between conventional manufacturing and manufacturing of high-end equipment and their critical components. These differences encompass aspects such as material, structure, shape, surface integrity, precision and performance. Therefore, the exploration of an approach suitable for HPM is crucial to improving the manufacturing capacity and standard of high-end equipment.

Looking ahead, research and development in this field should be firmly grounded in practical applications, seeking to identify unique technical benefits and striving to establish innovative MoFP theories, design methodologies and technologies. Emphasis should be placed on the synergy between design and manufacturing, along with research and development of processes and equipment for systematic solutions. In summary, HPM is a scientific manufacturing approach centered around precise performance goals and theoretical modeling. It is a quantitative, localized, and formulaic digitized manufacturing method driven by performance. Achieving HPM necessitates long-term, systematic, in-depth research to

establish a solid, feasible, and systematic HPM theoretical and technological system.

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