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Review

Management Control and Integration Technology of Intelligent Production Line for Multi-Variety and Complex Aerospace Ring Forgings: A Review

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Abstract: Large and complex ring forgings are key structural parts of the aerospace field, and their quality is closely related to the reliability of aerospace vehicles. However, high-quality production of aerospace ring forgings faces many problems, such as the long process design cycle and impoverished consistency, the difficulties of real-time detection under the severe time-varying state of the deformation process, the complexity of high-quality non-destructive testing under multitudinous defects, and the cumbersome management control of the multi-source and multi-dimensional heterogeneous data. Considering the current situation of multi-variety and multi-batch production for aerospace ring forgings, establishing an intelligent production line is a crucial means to solving the above problems and realizing the standardization and premiumization of key aerospace components. Therefore, management control and integration technology of the intelligent production line play a crucial role. An analysis, including the research progress of the intelligent computer-aided process planning (CAPP) system, the real-time detection and control system, the product quality testing system, and the intelligent management control and integration system, is systematically reviewed in this work. Through intelligently managing and controlling the integrated systems of the production line, the production efficiency of ring forgings can be effectively improved, and the production energy consumption can be remarkably reduced, which is of great significance for enhancing the manufacturing technology level of aerospace products.

Keywords: ring rolling; intelligent manufacturing; intelligent production line control; integrated technology; real-time detection; non-destructive testing

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1. Introduction

With the execution of strategic initiatives such as Industry 4.0 in Germany and re-industrialization in the United States, it proves that the manufacturing industry around the world is developing in the three directions of digitization, networking, and intelligence through information technologies [1]. Intelligent manufacturing is the primary direction of *Made in China 2025*, and it is also the key to the achievement of transformation and upgrading of the manufacturing industry of structural parts in the fields of aerospace [2]. Furthermore, establishing an intelligent production line for aerospace complex forgings is an important guarantee for promoting the intelligent development of the aerospace industry and independent construction.

Figure 1 describes the development of the industry. On the basis of Industry 4.0, Europe began to put forward the concept of Human-centered Industry 5.0 to promote more personalized production, which means that the knowledge-driven intelligent industry can be realized by promoting the integration and interconnection between "Human-Machine-Object-Environment" at the knowledge level [3]. In aerospace ring forging production, larger size ranges, more material choices, and more complex geometric designs are required. Personalized production provides theoretical guidance for the diversified production mode of aerospace ring forgings. Integrated manufacturing and intelligent manufacturing, which are two traits that stand out the most among the many characteristics of modern manufacturing system technology, are widely valued in the manufacturing industry. In reviewing the past, CyberCut was one of the first network-integrated systems to manufacture parts over the Internet in the mid 1990s [4]. Subsequently, Huang et al. [5] proposed a web-based design technology for X (DFX), which provided opportunities to integrate with CAD and computer-aided process planning (CAPP). With the emergence of plant automation based on distributed systems (PABADIS) and holonic manufacturing systems (HMS), the limitations of typical centralized manufacturing execution systems were overcome, and the flexibility of manufacturing systems was enhanced [6,7]. The ARUM and IMD-AESOP projects from the European Commission filled in the gaps in task scheduling and data monitoring for intelligent service-based manufacturing integration systems [8,9]. Following this, Jackson et al. [10] made the cost lower by further optimization. The above shows that in the field of aerospace, building a manufacturing system with an intelligent management control platform as the core not only has a wide range of driving effects and demonstration significance but also contributes to the standardization and high-end, which has been applied to aerospace structural parts and engines [11]. Meanwhile, it can be seen that the continuous updating of industrial concepts and the demand for high-quality equipment in the aerospace industry has promoted the development of manufacturing technology towards intelligent manufacturing and ecological production, which is significant for helping intelligent management control and integration systems further improve productivity and flexibility [12].

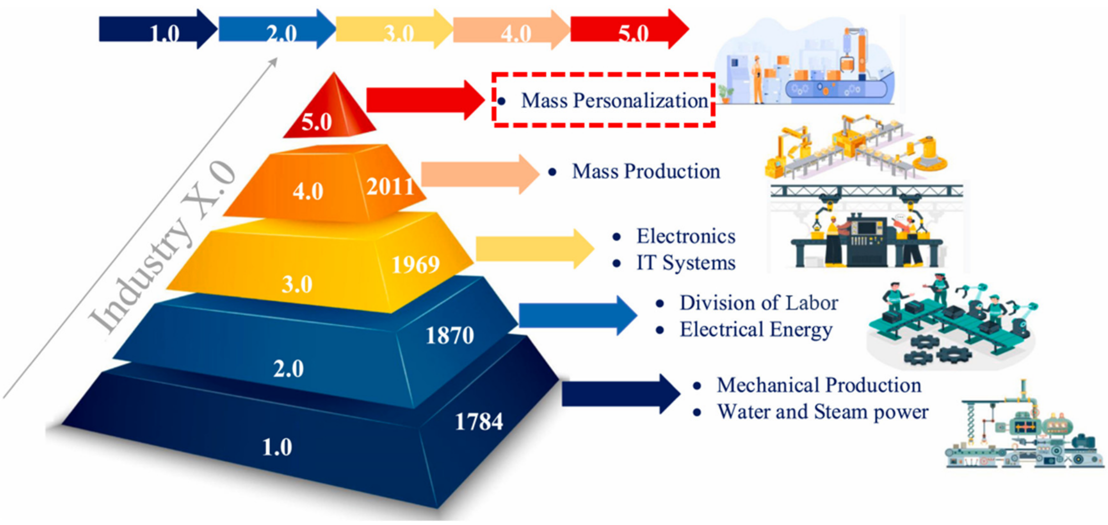


Figure 1. The development of industry from 1784 to the present with permission from [13], 2022, Elsevier.

As an essential basic part, ring forgings have been widely used in the industrial field, especially in aerospace. At the same time, aerospace ring forgings are key components such as aeroengine cases, rocket cabin bodies, satellite shells, missile bodies, and so on, as well as the important guarantee of service performance and reliability of aerospace equipment. The diversification of production varieties and extremely long technological processes put forward higher forming requirements for large and shaped ring forgings. The establishment of intelligent production lines is not only focused on improving production efficiency but also on meeting the aerospace industry's higher requirements in terms of product and process complexity [14]. From the current production level, the following problems need to be considered in the production process of ring forging products:

- There are long process design cycles and inferior consistency under the strong correlation and coupling of multiple factors, such as geometry, material properties, and forming process parameters.
- Real-time detection and control are limited by the large fluctuations caused by random interference sources, such as high temperatures, heavy loads, impacts, and vapor fog.
- It is hard to identify accurately by non-destructive testing techniques under conditions of large detection noise and blind spots.
- The complex establishment of heterogeneous data classification analysis and interaction mechanisms leads to low integration of production lines.

There are two aspects that need to be considered in the construction of an intelligent production line for complex ring forgings. On the one hand, it is important to combine the research status of intelligent management control and integration systems. On the other hand, there are still many problems existing in the production of ring forgings at the present stage. Therefore, we start with four aspects: process design, process detection, quality testing, and intelligent management control and integration.

Nowadays, quite a few studies have put forward targeted optimization or solutions around the multi-variety and multi-batch production mode of large ring forgings and the above-mentioned problems in the manufacturing process, but no one has systematically classified them. The content of our study proposes the new concept of the intelligent CAPP system, the real-time detection and control system, the product quality testing system, and the intelligent management control and integration system, which are appropriate for the ring forging process. It is believed that a systematic review will provide guidance for researchers who require in-depth research on the intelligent production line management and control of ring forgings, especially the production line integration technology.

2. Intelligent CAPP Systems for Complex Ring Forgings

The intelligent CAPP system is an important beginning to build an intelligent production line for complex ring forgings. Compared to the traditional process design, the intelligent CAPP system has more advantages in reducing personnel involvement, providing optimized process planning, and reducing the time to develop a new product or design/develop of an optimized production process. In addition, the combination with artificial intelligence technology effectively solves the limitations of the first-generation CAPP system. Intelligent CAPP promotes the realization of ring forgings intelligent design and manufacturing as a platform that integrates design development systems such as CAD, CAM, CAE, and PLM (Product Lifecycle Management) and production manufacturing systems such as ERP (Enterprise Resource Planning) and MES (Manufacturing Execution System).

2.1. Key Technologies of Intelligent Process Design

2.1.1. Feature Technology

Due to the fact that CAPP systems usually store the corresponding data according to the characteristics of part structure [15], the technologies of design by feature (DBF) and feature recognition (FR) have spontaneously become important technologies to facilitate the integration of CAPP systems.

In the technology of DBF, predefined feature information is often stored in the data structure of the CAD module, thereby simplifying the model establishment process [16,17]. The encoding system mainly describes parts through the above information, so it becomes a primary part of the CAPP system. In the study of encoding systems, Wang et al. [18] adopted a mixed coding structure of nine-digit codes to represent seven common aircraft structural parts, providing a foundation for subsequent feature extraction. In order to give the basic characteristics of parts better information descriptions, Ma et al. [19] added four accuracy classes to the “Part Code + Shape Processing Code + Aided Code” encoding system. By inputting the feature code of the part, the process contents, which were similar and stored in the process file database, could be called up. Eventually, the corresponding process file could be obtained after modifying the relevant procedures of the part.

In regard to FR, it can be found that identification techniques for slots and steps are no longer able to effectively identify target parts with complex features [20]. Therefore, Ueno et al. [21,22] divided the entire complex target part into several manufacturing elements and arranged the processing sequence for each of them to accomplish the part's processing characteristics identification. Zhang et al. [23] developed a method based on deep 3D convolutional neural networks (3D-CNNs) to learn processing features from CAD models as shown in Figure 2. While successfully completing the automatic recognition of complex parts, the method proposed above also created the first application of deep learning in machining feature recognition. Furthermore, the feature recognition method based on multi-section views, which was proposed by Shi et al. [24], was more efficient in recognizing single features and had more advantages in multi-feature recognition.

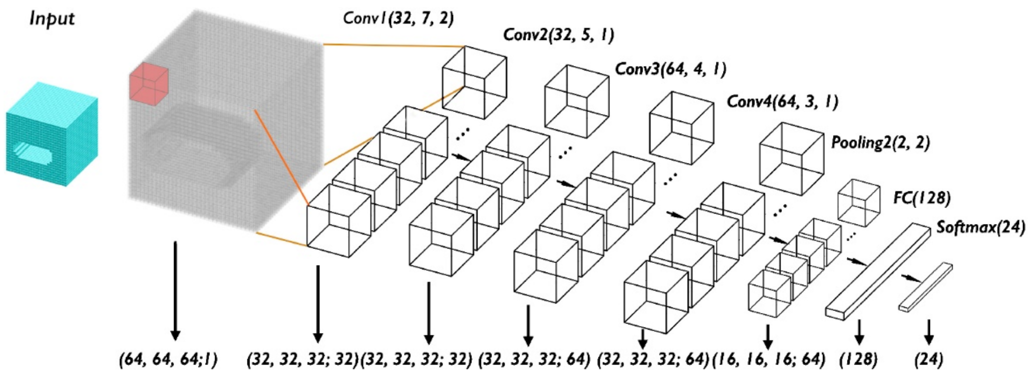


Figure 2. The proposed architecture of the CNN network trained to recognize machining features on 3D CAD models with permission from [23], 2018, Elsevier.

2.1.2. Knowledge-Based System (KBS)

The knowledge-based system (KBS) based on knowledge-based engineering (KBE) can solve the problems of process reasoning through storing expert knowledge design rules. Additionally, KBS not only realizes process automation planning but also makes the process design of parts more reasonable and standardized [25–27].

Singh et al. [28] designed corresponding rules to realize the function of process automation planning by uploading information such as manufacturing characteristics of parts to KBS. Chang et al. [29] performed process reasoning on the Java platform using process simulation and the Taguchi method, making the system knowledge base scalable by combining web ontology language (OWL) ontology and semantic web rule language (SWRL) rules.

At the same time, the process reasoning of KBS is realized by the coupling effect of a variety of mixed rules. The technique for order preference by similarity to the ideal solution (TOPSIS), which has been widely used, is a compromise scheme of referring to relevant theories to select the scheme closest to the optimal solution and farthest from the inferior solution [30]. However, traditional TOPSIS is not suitable for sorting machining processes, workpiece material and shape characteristics, etc. [31]. Azaryoon et al. [32] completed the evaluation of the quantitative and qualitative performance indicators of the workpiece material and shape characteristics using decision-making trial and evaluation laboratory (DEMATEL), analytic network process (ANP), and multi-criteria optimization and compromise solution (MOCS).

2.2. Intelligent CAPP Systems

The intelligent CAPP system is the key to solving the problems of complex aerospace ring forgings, such as the numerous types of materials, large structural differences, and complex forming process knowledge. It is mostly composed of information databases, web-based user interfaces, and functional requirements of the CAPP system.

AutoCAD, Visual Basic 6.0, and other software have been used in the research of intelligent CAPP system development by Naranje [33] and Jiang et al. [34]. Besides, the former used the AutoLISP language to program 27 modules that made up the system in the design and realized the automation of the process design by combining with KBS. Del Pozo et al. [35] completed the simulation and verification of the process using 3D CAE and output the key parameters to the process periodic table, including press layout, materials of required parts, operation times, and so on. Gao et al. [36] developed a CAPP system for MES-integrated, focusing on completing the automated filling of the process card and the summary output of process data. In the meantime, it could satisfy the needs of intelligent manufacturing and intelligent workshops to some extent by developing the process design terminal and shop browsing terminal of the CAPP system.

The development of an intelligent CAPP system is used to solve the technical problems of intelligent process reasoning under the collaborative effect of shape and property and concurrently provides support for the research on the real-time detection and feedback control of the deformation process of complex ring forgings.

3. Real-Time Detection and Feedback Control of Deformation Process

The manufacturing of ring forgings is carried out after the completion of the process design, including blanking, heating, forging, rolling, heat treatment, and machining. There is no doubt that the real-time detection of dynamic data as constantly changed data in manufacturing processes is a key method to realize the stability and reliability of intelligent production lines. Therefore, the rolling process must be detected in real time to meet the requirements of large ring forgings in the rolling process, including geometric shape, movement posture, microstructure, and so on.

3.1. Key Technologies of Real-Time Detection

3.1.1. Critical Dimensional Parameter Detection

The section line refers to the curve reflecting diameter change and position deviation formed by the axial scanning of ring forgings from top to bottom by the measuring system. Researchers have paid close attention to the section line because it affects the accuracy, quality, and performance of ring forgings [37,38]. Zhang et al. [39] proposed an optimization algorithm for the section line based on L_1-median and normal vector, namely "Algorithm from Zhang et al." in Figure 3. The algorithms compared with the algorithm proposed by Zhang et al. are the moving least squares (MLS) method and the rotational symmetry axis (ROSA) algorithm, respectively. The better anti-noise performance of the algorithm can be seen from Figure 3. The simulation results showed that the six axial height errors of the ring forgings were all within 0.6 mm, which was in superb agreement with the actual size. Fu et al. [40] optimized the laser scanning data of the radial section size by combining the gradient descent method and the uniform isomorphism factor, which provided an approach to solve the undetermined coefficient. Quantitative results revealed the average diameter error of standard ring forgings was reduced by approximately 0.26 mm and for non-standard ring forgings was reduced by about 0.39 mm, which effectively improved the detection accuracy. Škulj et al. [41] combined temperature and geometric data with machine operator commands using a variety of machine learning (ML) algorithms. The decision-making algorithm created by this technology successfully completed automatic detection.

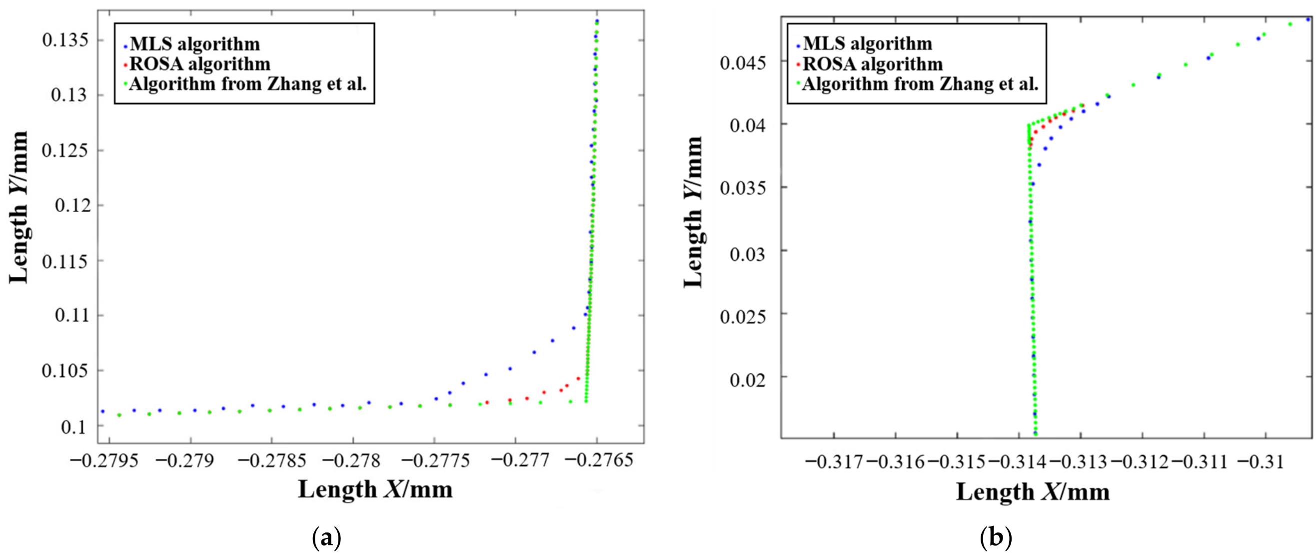


Figure 3. Magnified angle diagram of ring forging section line extracted by three algorithms in (**a**) second order and (**b**) third order with permission from [39], 2021, Elsevier.

3.1.2. Detection Data Processing and Optimization

However, the following problems still exist in the actual detection process:

- There are many interference factors such as high temperature, heavy load, impact, and vapor mist.
- The amount of scanned data is huge.

These lead to inefficient real-time detection and large errors in detection results [42].

Considering that the coupling effect of various interference factors leads to massive noise data in 3D detection, Zhang et al. [43,44] proposed an improved quadratic error metric (QEM) point cloud data reduction algorithm based on the artificial immune algorithm (AIA), which reduces point cloud data under strong noise by simulating the specific response of the biological immune system. Compared with the traditional simplified algorithm, this algorithm based on the above characteristics could effectively resist the interference of noise data. Zaman et al. [45] used particle swarm optimization (PSO) and mean-shift based clustering techniques to eliminate most point noise, while the method of bilateral mesh filtering eliminated the rest. The proposed method showed excellent robustness when dealing with high-noise data sets.

On the other hand, for a large number of point clouds in the scanning area, Herraez et al. [46] accurately extracted the part of the point cloud with higher feature resolution, and the optimized point cloud was reduced by up to 99%. Tao et al. [47] fitted point data in reverse engineering by an online extraction method based on bi-Akima spline interpolation as shown in Figure 4, which could obtain a smaller data reduction ratio and a smoother machined surface than conventional methods.

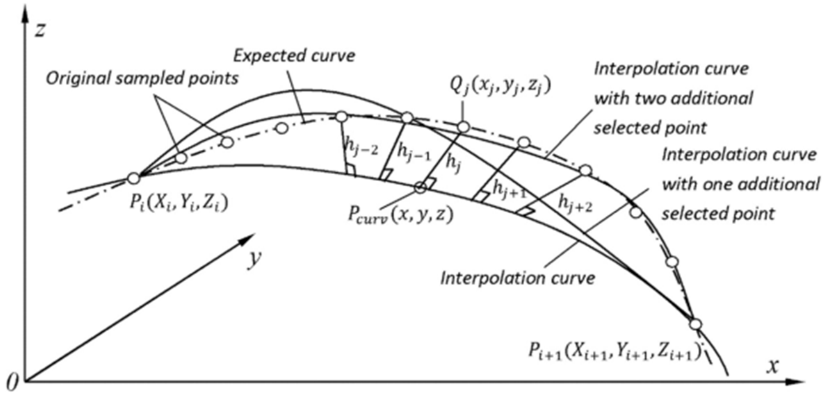


Figure 4. Schematic diagram of point cloud data extraction method with permission from [47], 2016, Elsevier.

3.2. Key Technologies of Deformation Process Control

The rolling of large ring forgings has many characteristics, such as the following:

- The axial and radial motion of the roller-driven ring forging motion is complex.
- The geometry changes significantly at large sizes.
- The state of deformation is unpredictable during the rolling process.
- The initial microstructure of the material is unsatisfactory.

Hence, in the rolling process, there are three noticeable points that need to be valued, including geometrical shape, movement posture, and the microstructure of materials.

3.2.1. Geometrical Shape

In terms of geometrical shape, Deng et al. [48] designed a trapezoidal section blank to solve the problem of uneven distribution of materials, which showed on the upper and lower steps of the rectangular section blank during the rolling process. Figure 5 supported the conclusion that the trapezoidal section blank was found to be about 1.4 mm more accurate than the rectangle in the finite element analysis, and the advanced nature of the design could be certified convincingly.

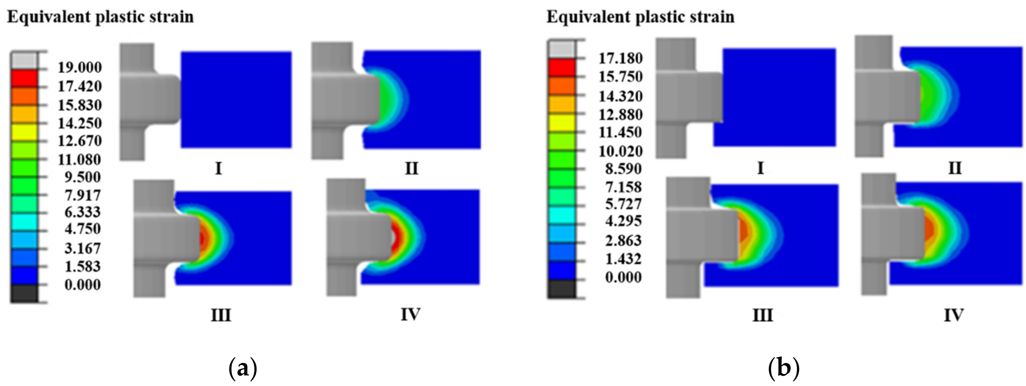


Figure 5. Section shape in three-roll cross-rolling process: (**a**) rectangular cross-section blank; (**b**) trapezoid cross-section blank with permission from [48], 2015, Elsevier.

Considering that the size ratio and the thinning of ring forgings had a strong influence on the free curvature change, Cleaver et al. [49] established an analytical model of free curvature change based on force balance and coordination to reveal the influence of roll size on the variation of ring rolling curvature. At the same time, by repeatedly searching for mandrel size, the model could yield the ideal size change of ring forgings during the rolling process.

3.2.2. Movement Posture

In the field of movement posture, Merayo et al. [50] accurately predicted the UTS (ultimate tensile strength) in the mechanical properties of materials through machine learning so as to judge whether the product would suffer from plastic instability. Hua et al. [51] established an analytical model based on the relationship between rolling power, torque, and force in the rolling process and found that the revised analytical model was in good agreement with the finite element analysis results, which provided a design basis for the key force parameters. Jenkouk et al. [52] constructed an integrated finite element model through sensors, actuators, and industrial control algorithms, as shown in Figure 6, and successfully achieved full control over constraints such as force, torque, and power in finite element analysis. This closed-loop control method not only assisted in setting key parameter thresholds, but it also reduced uncertainty in the performance and quality of ring forging products during rolling.

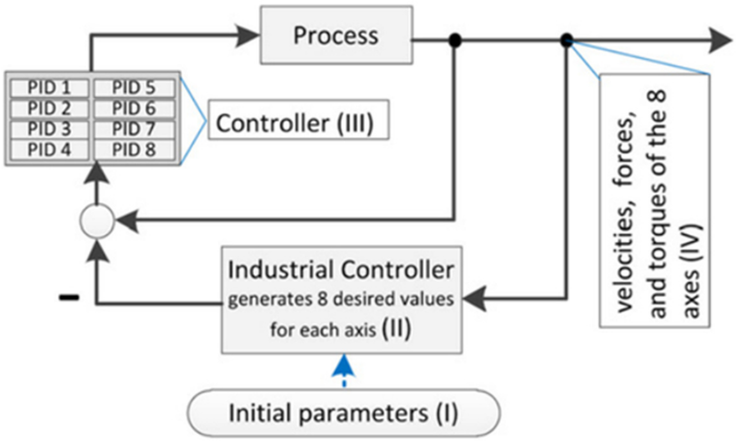
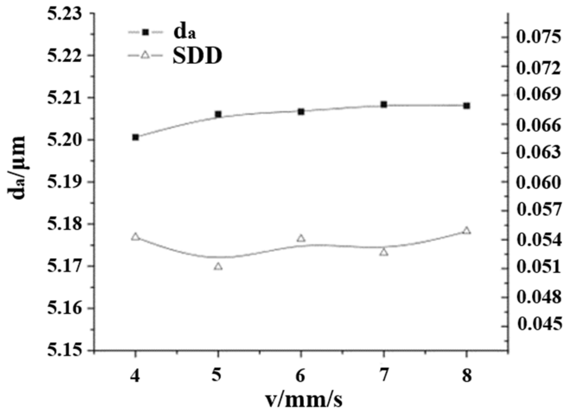


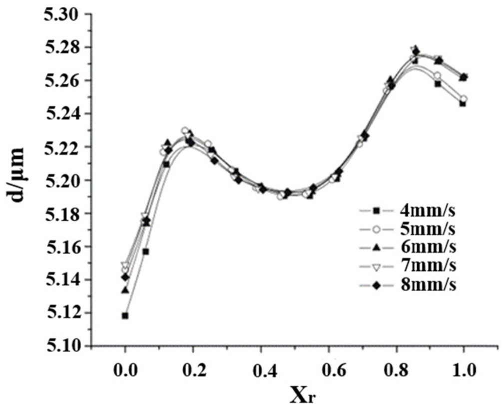
Figure 6. Feedback control of ring rolling process with permission from [52], 2012, Elsevier.

3.2.3. Microstructure of Materials

For the microstructure of large ring forgings, the raw materials are mostly large ingots, and the cast structure is coarse and unevenly distributed. By studying the effect of the rolling curve on the roundness and microstructure of ring forgings, Guo et al. [53] found that the use of the downward concave rolling curve was the most favorable for the improvement of the roundness, while the upward convex rolling curves gave the best uniformity to the microstructure of ring forgings. Based on this finding, the authors designed an S-shaped rolling curve that allowed both to be taken into account at the same time. In the study of the microstructure evolution model and rate-/temperature-/microstructure-dependent constitutive model of titanium alloy, Wang et al. [54] found that decreasing the rotational velocity of the drive roll n_1 or increasing the feed rate of the idle roll v or the initial temperature of the ring T_0 contributed to more distributions of β phase and its grain size, as shown in Figure 7. This finding provided a theoretical basis for the microstructure control and performance improvement of the hot rolling process.



(**a**)



(**b**)

Figure 7. Variation of β grain size with feed rate of idle roll: (**a**) average grain size d_a and uniformity of β grain size distribution SDD; (**b**) d distribution along radial direction of ring with permission from [54], 2013, Springer.

The research of real-time detection and feedback control methods for the deformation process solved the technical challenges of online detection and control of workpiece state in a dynamic environment and provided support for non-destructive testing and evaluation of the quality.

4. Reliable Non-Destructive Testing of the Quality of Complex Ring Forgings

The quality testing described in this chapter is a technology based on the finished ring forgings that is used for intelligent identification and quantitative characterization of defects in large-sized and complex ring forgings. This is also different from real-time detection in the intelligent production process.

In the practical production process, the process is extremely complicated and restricted by various factors such as the quality of blanks, the original defects of materials, and fluctuations in process parameters. Manufacturing defects are easily generated in the internal area and the surface layer during processing, such as holes, cracks, and folds [55]. In the research of rolling forming defects of large aluminum alloy rings, Zhou et al. [56] indicated that the heterogeneous distribution of equivalent plastic strain, temperature, and stress is the main reason for the above defects. These defects could seriously affect the fatigue life of ring forgings and cause problems such as spalling, pitting, and fatigue failure.

4.1. Key Technologies of Quality Testing

Ring forgings must undergo strict quality testing before actual use in order to ensure the product quality, reliability, and structural safety. As we can see, non-destructive testing technology (NDT) is a testing process that characterizes materials and evaluates defects without damaging the object. NDT has been widely used in internal and external structural component defect testing due to its high testing sensitivity and efficiency [57].

4.1.1. Ultrasonic Testing (UT)

UT, as one of the commonly used non-destructive testing techniques, has the advantages of simple operation, strong applicability, fast testing speed, and a large testing range. Therefore, it has become one of the most widely used detection technologies in the industry at present [58].

Among the practical applications, UT is widely used in industrial equipment weld quality testing, especially for nuclear power plant pipeline welds, cylinder welds, pipe welds, and so on [59–61]. For large ring forgings, Dong et al. [62] combined with the bottom wave monitoring method to effectively solve the problem that defects parallel to the sound beam were not easily detected by conventional ultrasonic C-scan. With regard to the testing of aerospace composite defects, Grondin et al. [63] proposed an array ultrasonic testing technology based on adaptive focusing. This method could deal with the change of the array ultrasonic focusing law caused by the variation of the geometric shape of the part and improve the testing accuracy. Guan et al. [64] made use of signal processing and statistical techniques to represent near-surface defect information, providing an important technology for automatic full-coverage non-destructive testing of large ring forgings. Additionally, ultrasound could reduce the coarse second phase in the aluminum alloy ingot, which was beneficial for improving the mechanical properties and elongation [65].

4.1.2. Radiographic Testing (RT)

RT is a novel technology for computer real-time imaging using array detectors and image acquisition cards, which has the advantages of high sensitivity, fast real-time imaging, and long service life. This has attracted extensive attention from researchers.

Gong et al. [66] proposed a transfer learning target testing model based on DA-Faster for the structural components of aerospace equipment, which not only facilitated the localization of small-sized defects by X-ray but also improved the limitation that traditional testing was easily influenced by operators. With the continuous penetration of deep learning in the field of the aerospace industry, Ferguson [67] and Wu et al. [68] improved the architecture to accurately identify casting defects in X-ray images and overcame the shortcomings of artificial defect identification methods such as misidentification, heavy workload, and low identification efficiency. Based on X-ray testing, our research project proposed an integration scheme combining ultrasonic phased array technology, as shown in Figure 8. The combination of ultrasonic and X-ray could ensure the testing of small defects and high-density inclusions. In addition, the ultrasonic testing signal and the radiographic testing image were used for precise positioning and quantity analysis, which further improved the accuracy of the testing results.

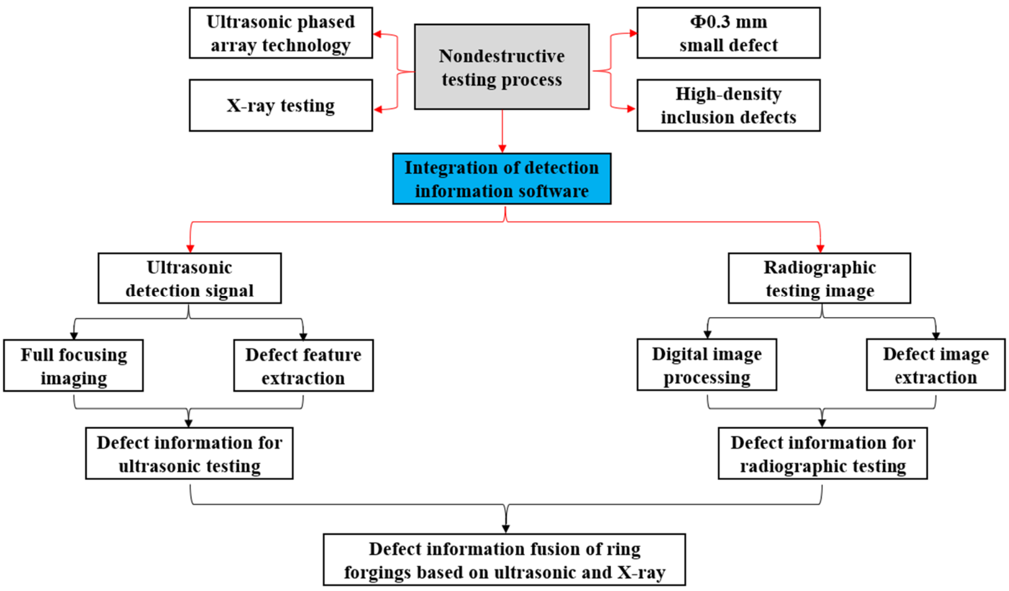


Figure 8. Integrated testing scheme based on ultrasound and X-ray.

4.1.3. Machine Vision Testing

In the actual testing work, UT and RT are usually used to detect internal defects in large ring forgings. For external defects, machine vision testing is more practical compared with magnetic particle testing, liquid penetrant testing, and other external testing methods. This has become an important technology to promote the intelligent factory.

Considering the image processing technology of canny edge detection and histogram analysis, Manish et al. [69] realized the testing of surface defects through the device based on machine vision, as shown in Figure 9. Wang et al. [70] proposed a new machine vision testing method based on deep learning to identify and classify defective products without losing accuracy. Wu et al. [71] used the region division method based on texture information to accurately detect the defects on the surface of aluminum alloy, such as cracks, pits, rust, scratches, and other defects. The robustness and effectiveness of the aluminum alloy casting process were enhanced effectively. Li et al. [72] completed the discrimination and classification of defects from the inner and outer surfaces of ring forgings using supporting vector machines (SVM). The experimental result was satisfactory.

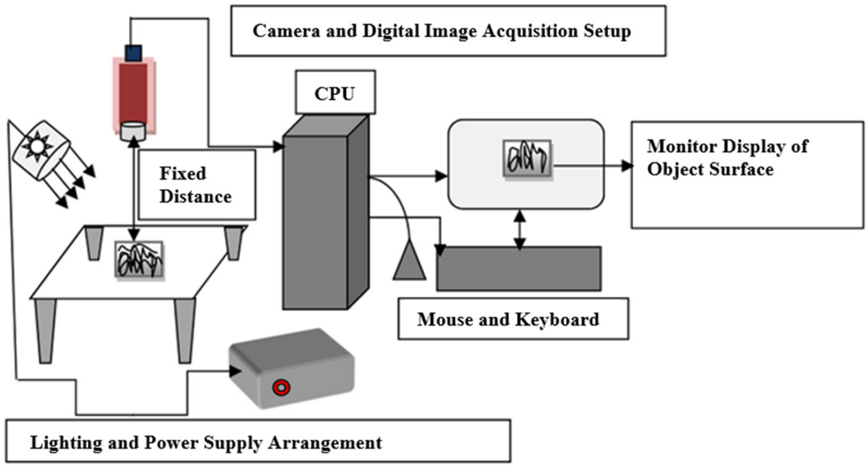


Figure 9. The testing device based on machine vision with permission from [69], 2018, Elsevier.

4.2. Intelligent Automatic Testing System

At the present stage, traditional manual testing has gradually revealed its limitations in the quality testing of large ring forgings, and automated, digitized, and intelligent ultrasonic testing equipment has aroused the great interest of researchers. Schmitte et al. [73] developed an ultrasonic phased array automatic equipment for testing surface and internal defects of nuclear waste storage tanks, which could operate 13 transducers simultaneously to achieve sector scan imaging. Among them, the automatic scanning in this equipment was completed by the axial motion of the ultrasonic phased array transducer group driven by the portal scanning mechanism and the rotational motion of the storage tank driven by the clamping mechanism. Zhou et al. [74] established an automated testing system for large medium-thick metal plates, which controlled the work of the automatic scanning by setting the zero point and angle of the probe. The corresponding images of B-scan and C-scan can be calculated by combining the workpiece information, defect data, and A-scan waveform data recorded during the testing process.

However, the testing accuracy of UT was often difficult to control because of various factors. Water immersion ultrasonic testing technology could effectively overcome this deficiency. Jiang et al. [75] experimentally confirmed that UT based on water immersion technology could shorten the time by 6–7 times. Zhou et al. [76] developed a phased array ultrasonic water immersion C-scan automatic testing system based on water distance control and a delayed focusing method to obtain the best testing scheme. At the same time, the efficiency could be increased by 49 times through the scanning path shown in Figure 10, and the ability to detect thick-walled workpieces could be improved by changing the size of the aperture and adjusting the focal depth of the transducer.

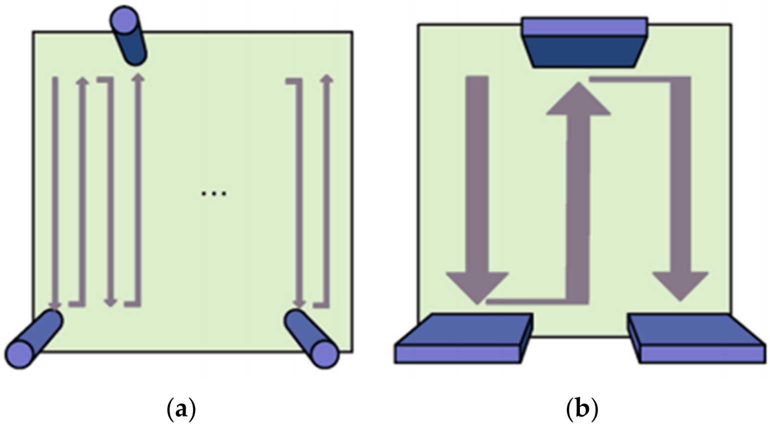


Figure 10. Comparison between conventional C-scan and phased array C-scan: (**a**) conventional ultrasound probe scanning path; (**b**) phased array ultrasonic probe scanning path with permission from [76], 2017, Journal of Mechanical Engineering.

Considering that it was difficult for a conventional single-frequency probe to cover the internal defects of the entire ring forging, Li et al. [77] solved this problem by using a high-frequency probe to detect near-surface defects and a low-frequency probe to detect deep defects, as shown in Figure 11. The interference between high- and low-frequency signals was eliminated by adjusting the pulse emission timing. The full-coverage testing of defects was achieved in the depth direction.

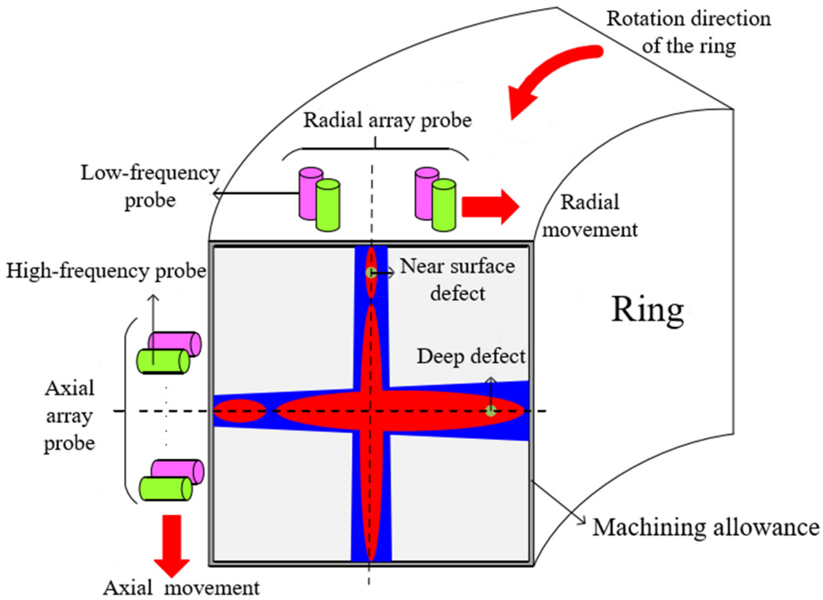


Figure 11. Schematic diagram of ultrasonic testing of large thick-wall ring array with permission from [77], 2019, Wuhan Univ. Technol.

Through research of the high-quality, non-destructive testing and evaluation methods of complex ring forgings, the technical problems of reliable identification and quantitative characterization were solved. Moreover, the multi-stage closed loop, which consists of the intelligent CAPP system, the real-time testing system, and the quality testing system, plays an indispensable role in constructing intelligent management control and integration systems.

5. Intelligent Management Control and Integration Systems in an Industrial Network Environment

As next-generation information technologies, such as the Internet of things (IoT), digital twins, edge computing, and blockchain technology, gain popularity, many researchers are combining them with traditional manufacturing, particularly in research on the development of intelligent management control and integration systems. Table 1 summarizes these technologies and their opportunities and challenges.

Table 1. Opportunities and challenges of key technologies in intelligent management control and integration system.

Technology	Opportunities	Challenges
MES [78–81]	Realizes the interaction of data between devices, which is helpful for the scheduling and maintenance of production tasks.	Commands depend on the operator and have certain limitations.
CPS [82–85]	The integration of computing, communication, and physical systems makes the system more reliable, efficient, and real-time collaborative.	The information that needs to be processed is variable, and the amount is very large.
5G-IoT [86–91]	More excellent performance, such as speed, delay, coverage, and reliability.	Most research tasks are still in the preliminary stage.
Blockchain [92–97]	Strong coordination in the face of many devices, which is conducive to eliminating single points of failure.	In the initial stage of development, mature products are yet to be developed.
Edge Computing [98–103]	Lower latency and power consumption; higher reliability.	The research results are still in the theoretical and experimental stages.
Digital Twins [104–109]	The design cycle is short, the reliability is high, and the maintenance costs are low.	It is difficult for collecting data and modeling in multidimensional data.

5.1. Key Technologies of Intelligent Management Control and Integration System

5.1.1. Manufacturing Execution System (MES)

With the development of artificial intelligence technology, researchers combine it with MES for productivity estimation, quality failure detection, job scheduling, manufacturing process control, etc. Some scholars have reviewed this aspect [78] and summarized the development situation and the technology trend of MES.

In the research content, it was found that most MES worked together with ERP to realize intelligent manufacturing. Aiming at the limitation that some popular MES software is mainly designed for specific industries, Shojaeinasab et al. [78] developed the IMES conceptual framework shown in Figure 12. It utilized a proven cloud architecture that supports edge devices [79] to upload critical information to the MES. This method could perform predictive and highly adaptable MES tasks while achieving higher data security. Wang et al. [80] integrated physical objects and products with information systems to propose an intelligent factory framework, which included a supervisory layer, a cloud layer, an industrial network layer, and a physical resource layer. The physical resource layer interacted with the industrial network through resources such as equipment and products. Then the cloud layer collected a large amount of data from the physical resource layer and interacted with the operation staff through monitoring terminals. Thus, a double closed-loop system could be formed.

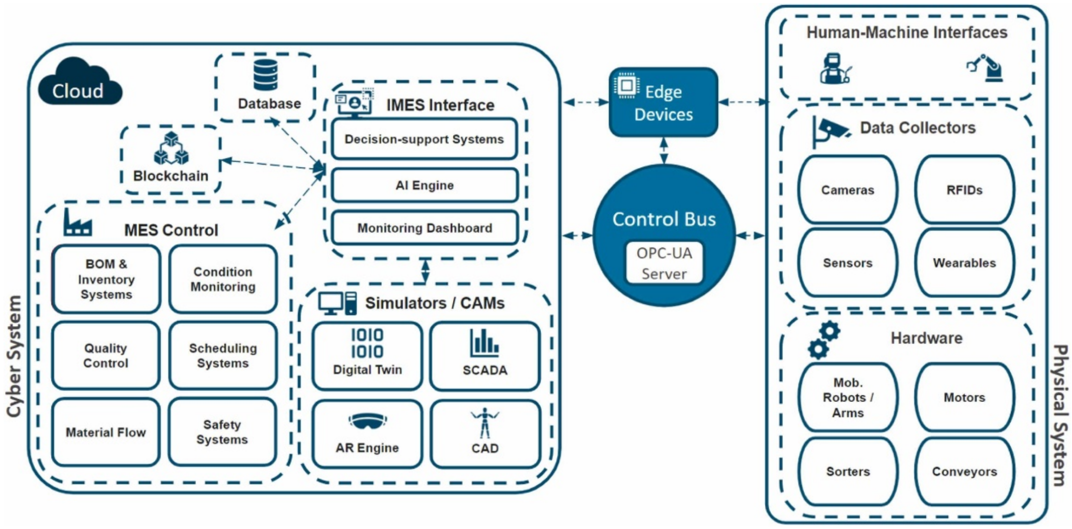


Figure 12. Components of the IMES conceptual model with permission from [78], 2022, Elsevier.

5.1.2. Cyber Physical Systems (CPS)

Compared with MES, CPS is more flexible in realizing the organic integration of "human-machine-material". A CPS-based intelligent factory is the essence of Industry 4.0. The reason is that it connects virtual space with physical reality and operates reliably and efficiently.

A CPS is a complex system composed of many heterogeneous elements and requires specific system structures in different application scenarios. Considering the capability of self-monitoring and self-diagnosis of CPS, Schneider et al. [82] constructed a CPS-based cyber-physical fault management system. Through the direct integration of CPS and IT systems, faults in operation could be automatically detected and relevant information could be provided to maintenance personnel. In the research on the further development of CPS, Yao et al. [83] added considerations of social networking in CPS-based smart manufacturing and proposed an extended definition called Social-CPS (SCPS). It further promoted innovation and sustainability in manufacturing with its prominent features, such as social computing, community, and crowdsourcing.

5.1.3. 5G-Internet of Things (5G-IoT)

Looking at the development trend of CPS, one of the key topics for discussion is the IoT, which has the characteristics of automation, intelligent connection, real-time monitoring, and collaborative control. However, with the continuous application of advanced technology in manufacturing, a large amount of data is generated. Communication technologies such as 3G and 4G have been unable to meet the requirements of CPS for high data rate, high reliability, high coverage, and low latency. As an advanced wireless transmission technology in the future, 5G can provide richer service capabilities. The performance of speed, delay, and coverage obtained a significant improvement compared with the previous generation and has great potential in promoting IoT and CPS [86,87].

Cheng et al. [88] proposed a 5G-based Industrial Internet of Things (IIoT) architecture by analyzing 5G application scenarios and the basic architecture of CPS, as shown in Figure 13. This architecture could not only realize large-scale intelligent interconnection of end-to-end heterogeneous devices but also accomplish industrial automation monitoring and collaborative control. Moreover, with the multi-beamforming directional transmission technology of 5G, low energy consumption and low cost could be achieved even with a large number of communication nodes. Wang et al. [89] pointed out that the ultra-low transmission delay was strongly needed for human–machine cooperation, machine equipment cooperation, and remote control in intelligent workshops. 5G wireless communication technology was a strong guarantee for IoT construction.

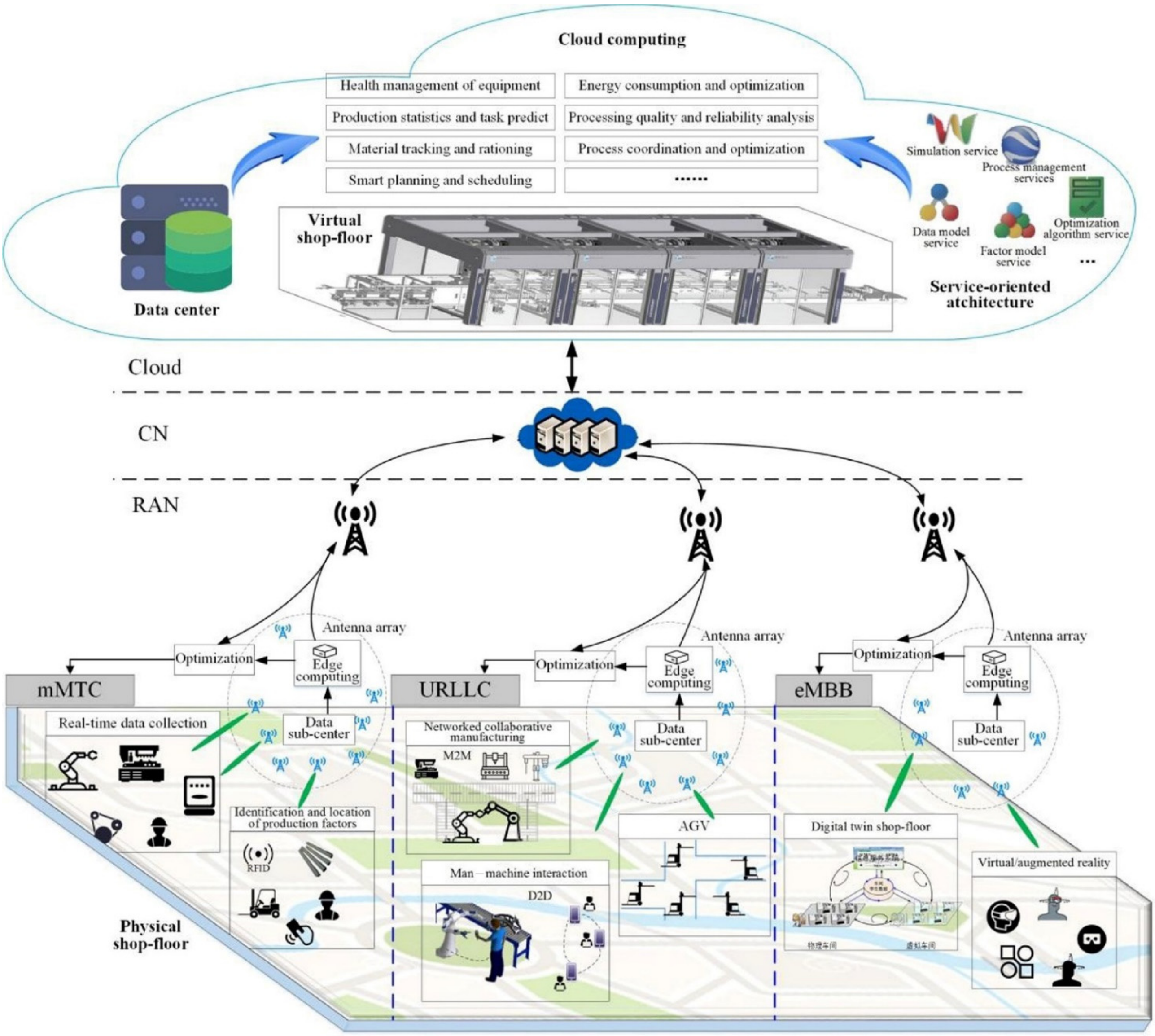


Figure 13. Intelligent manufacturing IIoT architecture based on 5G with permission from [88], 2019, IEEE.

5.1.4. Blockchain

As we know, the IoT is playing a crucial role in the development of intelligent factories. However, existing IoT systems are prone to single points of failure and cannot provide stable service. As node scale and network number increase, so does the risk of data privacy disclosure and maintenance costs. However, these problems can be effectively solved by the advantages of blockchain [92].

In the problem of high pressure on data storage space, Li et al. [93] lowered the network pressure in the system by reducing the cross-link communication data, which helped improve the communication efficiency of the system. In order to overcome the shortcomings of the single point of failure of the IoT system, Xu et al. [94] combined with concurrent Merkle–Patricia tree (CMPT) and proposed a blockchain-based intelligent manufacturing security model to enhance the performance in high data volume scenarios. In terms of multi-technology integration, Shahbazi et al. [95] considered the integration of blockchain, edge computing, and machine learning methods and designed an overall architecture of intelligent manufacturing based on an integrated system. Blockchain technology could reduce data transmission risks, making distributed system architectures more adaptable.

5.1.5. Digital Twins

The intelligent management control and integration system is a physical system involving multiple fields and has complex coupling relationships between the components. Due to the limited knowledge used to design subsystems, it is very challenging to develop a unified model to effectively simulate every interaction behavior in the manufacturing process [104]. Digital twins, as a cutting-edge technology, effectively reduce the time and cost of physical debugging and reconfiguration by virtualizing and optimizing physical objects [105].

Qi et al. [106] developed an intelligent manufacturing flexible production line system based on digital twins, which could realize seamless integration and model management of dynamic capacity planning, production line design, and local product lifecycle management. Yu et al. [107] pointed out that reconfigurability was the distinctive feature of multi-variety and multi-batch production lines. That is, the corresponding virtual production line, which was formed through the process rules and manufacturing resources, was simulated and optimized in the intelligent production control system and finally formed the intelligent production line entity. This method provides powerful theoretical guidance for actual production and saves the trial-and-error cost that should be spent.

5.2. The Architecture of Intelligent Management Control and Integration System

Currently, aerospace parts manufacturing enterprises are exploring the construction of intelligent production based on digital production. In the fierce international competitive environment, the innovation of production technology and management is helpful in occupying the commanding heights in the new round of industrial competition. The architecture design is the most critical part in the construction of an intelligent management control and integration system and has come into widespread notice from scientific researchers.

In the process of ring forging, the consistency and the production efficiency are usually affected by uncertain factors, such as material attributes, boundary conditions, and environmental temperature and humidity. By collecting real-time disturbance parameters, Zhou et al. [110] built an authentic mapping system of disturbing factor information. The action law of the corresponding disturbance factors could be obtained by digitally defining the quality influencing factors in the forming process. Moreover, when combined with MES, the intelligent management control system based on the above mechanism could guarantee production efficiency and quality consistency.

Referring to the integration model defined by the ANSI/ISA-95.00.01—2000 standard, Sun et al. [111] proposed an integration architecture for multi-level closed-loop intelligent control systems. While realizing the interaction of various subsystems through MES, the extensible markup language (XML) technology was used to collect and store multi-source heterogeneous data from the detecting device. In addition, the data interaction and integration between the intelligent management platform and subsystems were realized through ESB. Eventually, the systems at all levels had established a multi-level closed-loop control mode for four aspects at different time granularities so that the process parameters, production efficiency, product quality, and production line energy consumption could be continuously optimized.

Aiming at the distributed and highly flexible production mode of aerospace ring forgings as well as the complex characteristics of multi-link information coupling and collaborative operation, our research group also conducted in-depth research and proposed the architecture for intelligent management control and integration systems, as shown in Figure 14. Overall, there are four main aspects of our research, including intelligent process design, intelligent process detection, intelligent quality testing, and intelligent management control and integration. Through the above four aspects, intelligent decisions can be made in the process of ring forging to control product quality. At the same time, it is very important to collect, process, and interact with the data and information from each subsystem, which is related to the normal operation of an intelligent management control and integration system. Furthermore, proper allocation of equipment and facilities can effectively reduce production efficiency and cost. The establishment of an intelligent security system can ensure that the work of intelligent management control and integration systems can be reliably monitored and prevent interference from external factors.

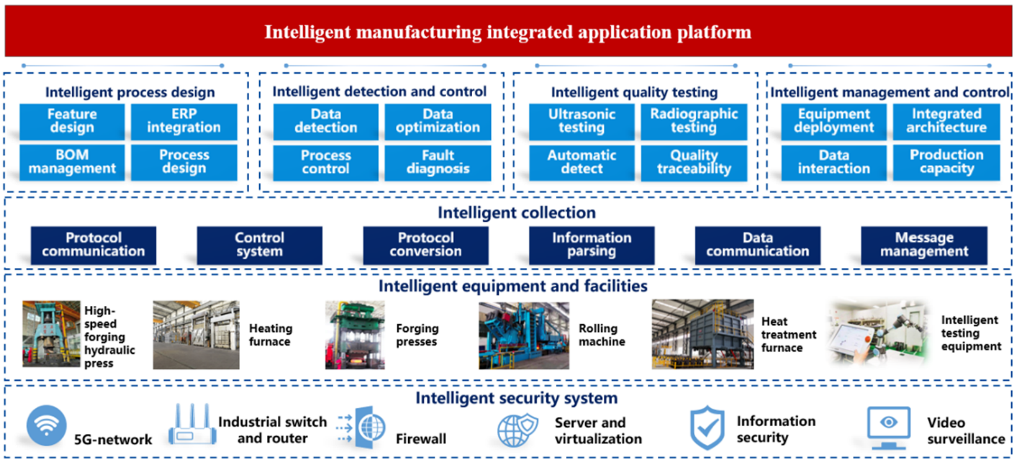


Figure 14. Architecture design of intelligent manufacturing integrated application platform based on enterprise network environment.

In the aspect of the local network architecture design, the application layer, the platform layer, the resource layer, and the edge layer constitute a multi-level structure. The application layer mainly uses the data analysis technology to form a complex ring forging production line management platform, which is composed of an intelligent CAPP system, energy management system, and equipment online management system. Through Internet technology, remote control technology, and remote resource storage technology, the platform layer integrates the equipment information, material information, and personnel information to form the integrated management and application platform of the Internet of Things. The resource layer is responsible for resource planning and management for all systems. The edge layer is mainly to intelligently collect process data, production data, equipment data, energy data, etc. In the meantime, the data of an intelligent production line can be collected and processed accurately in real time by using advanced methods, including configuration communication technology, edge processing technology, and sensor middleware technology.

6. Discussion

By studying intelligent technology in the application of process design-forming detection-quality testing-system integration of aerospace ring forgings, it is believed that the construction of an intelligent production line responsible for the production process and an intelligent integrated system responsible for management and control is the main direction of the future development for the industry. Integration and application of intelligent production line is not only the necessary way to realize industrial transformation and upgrading under the influence of digital technology but also the development trend of the international manufacturing industry [112]. For instance, SMS SIEMAG and RWTH Aachen University have developed automatic production lines for the ring forgings. The traditional manufacturing industry has undergone a qualitative revolution with the continuous penetration of digital technologies in the industry. Under the digital transformation, the European iron and steel industry takes innovation guided by digital technology as the foundation to establish competitive advantages, which is advantageous to the future development of the transformation and upgrading of enterprises and brings more scientific and technological achievements [113,114]. GPV (an electronics manufacturing service company) rolled out a digital tractability tool and used elements from Industry 4.0 and IIoT to track products in the production process, which makes contributions to intelligent manufacturing transformation [115]. However, with the further application of the IIoT, big data, and artificial intelligence (AI) technologies, new digitization has emerged. After the decision mechanism is modeled by the system or equipment, the execution unit can directly be commanded and then automatically execute. Making decisions driven by expert knowledge diminishes the role of professionals in the production of products, which not only reduces the difficulty for managers to make decisions but also improves the production efficiency of the industry. Therefore, the new generation of digitization is intelligentization. With regard to the discussions about the intelligent production line of aerospace ring forgings, intelligent management and control could extremely reduce manual intervention in the production process of ring forgings. Besides, intelligent decisions are made through data interaction and information analysis between all levels of systems, thus realizing intelligent process design, intelligent process detection, intelligent quality testing, and intelligent management control and integration in the intelligent production line of ring forgings.

As for the intelligent process design, feature technology is the basis for the CAPP system to identify product features and promote the integration between the CAPP system and CAD/CAE software. When the information on various product characteristics is collected, KBS arranges the appropriate process combination. Moreover, the intelligent CAPP system also needs to consider the material and process requirements of ring forgings. In general, the typical material of ring forgings includes stainless steel, high-temperature alloys, aluminum alloy, titanium alloy, magnesium alloy, and so on. For each material, the design methods of forging forming size, ring billet size, baiting size, and heat treatment planning in the rolling process need to be further improved, and the process requirements and combination modes of ring forgings, such as heating, cogging, rolling, bulging, and heat treatment, need to be further analyzed, which is beneficial for an intelligent CAPP system to make more reasonable decisions.

Regarding the intelligent process detection, the section line of a ring forging is the key parameter to characterize the state of forming process. To improve the detection accuracy, an effective optimization algorithm is absolutely necessary. Moreover, the non-contact machine vision testing method, which adapts to the outline of ring forgings, can also effectively improve the detection accuracy. However, it is not enough to conclude the forming state of ring forgings only by section line, and the parameters, such as temperature, size, motion state, and force energy, are also needed. Since the three aspects of geometrical shape, movement posture, and microstructure are the key factors affecting the quality of ring forging, the control system should be driven to control the above three aspects of the ring forging forming process through the on-line measurement of these parameters.

In terms of intelligent quality testing, the improvement in the detection accuracy of large ring forgings is remarkable through reliable NDT. Considering the combination of UT, RT, and machine vision testing, the internal and external defects of large ring forgings can be detected effectively. Meanwhile, water immersion technology can avoid the interference of the ultrasonic beam by external factors, but limitations exist in the detection of large ring forgings. In addition, we think that there are two other points worth paying attention to: on one hand, it should ensure that the detection technology adopted can effectively deal with the ring forgings of various material types; on the other hand, compared to simple rectangular rings, shaped rings have more blind detection areas, so the detection of defects in blind areas should be further improved.

With regarding to intelligent management control and integration, digital technology provides strong support at the technical level. MES and CPS enable systems at all levels to collaborate more reliably, efficiently, and in real time, and they realize data interaction between equipment, which is conducive to scheduling and maintenance of production tasks. 5G-IoT enables the information transmission more outstanding in terms of delay, coverage, as well as reliability. Blockchain enhances the ability of intelligent production lines to coordinate multiple devices. Digital twins provide theoretical guidance for the actual production of ring forgings and can reduce the trial-and-error cost in the production process, which was also confirmed by the specific industrial case mentioned by Zambrano et al. [116].

Combining with digital technology, a scheduling control decision technology based on multi-objective information fusion can be developed to effectively reduce energy consumption. Low energy consumption is a key concern for most enterprises, and Miśkiewicz [117] and Gajdzik et al. [118] also draw a similar viewpoint through their work. We believe that the architecture design of the intelligent manufacturing integrated application platform can be further improved by using the above digital technologies, and based on this, the intelligent production line and management control system for aerospace ring forgings can be established.

Aerospace ring forgings are key components of the aeroengine cases, rocket cabin bodies, satellite shells, missile bodies, etc.; thus, improving the production level through intelligent manufacturing technology is conducive to promoting industrial transformation and upgrading. Currently, the intelligent manufacturing of aerospace structural parts is still in the exploratory stage. Only a few enterprises can have the ability to develop a complete intelligent production line and control system, and there are still technical barriers for most enterprises. Therefore, we believe that this review can play a significant guiding role for establishing and improving the intelligent production line and enhancing the intelligent manufacturing technology level of multi-variety and complex products for aerospace ring forgings.

7. Conclusions

With the deep integration of information technology and industrialization, establishing an intelligent production line for management control and integration of complex aerospace ring forgings not only helps to realize the standardization and high-end of key aerospace components but also promotes intelligent upgrading of the industry. The research progress of the intelligent CAPP system, the real-time detection and control system, the product quality testing system, and the intelligent management control and integration system are systematically reviewed in this work. The conclusions can be drawn as follows:

1. In terms of intelligent process design, the intelligent CAPP system integrates design development systems such as CAD, CAM, CAE, and PLM and production manufacturing systems such as ERP and MES. Through feature technology and knowledge-based systems, the recognition of part structures and the automatic deduction and optimization of processes are realized. As the demands for larger sizes, various materials, and complex structures grow, the intelligent CAPP system, which can design the most appropriate process method by considering multiple factors at the same time, will be more widely used.
2. In the field of real-time detection and control systems for deformation processes, the section line optimization algorithm makes the real-time detection more accurate. On the other hand, the data point cloud optimization algorithm decreases the interference of noisy data and simplifies the huge number of point clouds. To ensure product accuracy for ring forgings with huge size, the two optimization algorithms will be even more important. At the same time, by establishing the corresponding analytical/constitutive model, the real-time control, which involves the three aspects of geometrical shape, movement posture, and microstructure of materials, is successfully accomplished. The online closed-loop control based on the deformation state of ring forgings can automatically make the control decision according to the detection information. Strong robustness and high stability are of great significance to the production of aerospace parts.
3. Comprehensive testing of large ring forgings is critical due to the need for structural safety and high reliability. Advanced non-destructive testing techniques of product quality, such as ultrasonic testing, X-ray testing, and machine vision testing, are used to reliably identify internal and external defects of large ring forgings. With dependable and stable testing capabilities, NDT will continue to be the primary choice for forming aerospace parts in the future. Automatic detection equipment, when combined with water immersion technology, can significantly improve detection

accuracy, and the problems caused by near-surface blind zones and limited coverage have also been resolved. Concurrently, it provides a new and reliable method for the defect testing of ring forging products.

4. With the further application of new-generation information technologies, such as MES, CPS, 5G-IoT, blockchain, and digital twins in the manufacturing industry, the functions of intelligent production lines have gradually improved. The production line of complex ring forgings universally integrates the intelligent CAPP system, the production process real-time detection and control system, the quality testing system, and the intelligent management control and integration system. In network collaboration, system integration plays a motivating role in the application of intelligent production lines. Meanwhile, the intelligent production line realizes the stable production of aerospace ring forgings with better performance and efficiency. The research on the intelligent management control and integration systems of the manufacturing process integrates each single common technology together efficiently, which provides a transformation approach for enhancing the intelligent manufacturing technology level of multi-variety and complex aerospace ring forgings.

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