A STUDY OF DIGITAL TWINS IN SIMULATING AND IMPROVING MECHANICAL MANUFACTURING PROCESSES

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This paper explores the integration of digital twin technology into the automotive stamping process, aiming to improve production accuracy, efficiency, and sustainability. By building a high-fidelity digital twin model and incorporating intelligent optimization algorithms, the stamping process is simulated and adjusted in a virtual environment. The study demonstrates that the application of digital twin enhances dimensional consistency, optimizes material utilization, and supports decision-making in production systems. The results confirm the potential of digital twin technology in addressing key challenges in mechanical manufacturing and promoting intelligent transformation in the automotive sector.

Keywords: digital twin, automobile body stamping process, multi-objective optimization algorithm, dimensional tolerance, material utilization

1. Introduction

In the context of Industry 4.0, digital twin (DT) technology plays an increasingly important role in monitoring, managing, and improving the entire lifecycle of manufacturing systems. Magalhães et al. [1] demonstrated the creation of a digital twin entity to ensure the coordinated operation of a flexible manufacturing system composed of CNC machines, robotic arms, and pallet conveyors, which highlights DT's potential in achieving intelligent transformation and optimizing resource efficiency. As a key enabler of intelligent manufacturing, digital twin (DT) technology creates virtual replicas of physical systems, enabling lifecycle-wide optimization of design, production, and maintenance. For instance, Polini and Corrado [2] proposed a DT framework for composite assembly manufacturing, demonstrating how simulation-driven decision-making can enhance each phase of the product lifecycle. Recent studies, such as that by Parvanda and Kala [3], emphasize DT's role in improving transparency, resource

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allocation, and real-time monitoring across production systems, particularly when integrated with additive manufacturing and Industry 4.0 platforms. However, challenges remain in standardization, interoperability across domains, and scalable deployment, as outlined by Guivarch et al. [4] in their helicopter dynamic system case. Within the context of stamping processes, Liu and Zhang [5] used a DT-based debugging model to simulate material deformation and optimize die designs, thereby improving formability prediction and tool performance.

This study investigates the application of digital twin technology in mechanical manufacturing process optimization, focusing on parameter modeling, process simulation, and intelligent adjustment in a virtual environment. The objective is to improve efficiency, accuracy, and sustainability through real-world case validation and algorithmic decision support.

2. Literature Review

Mechanical manufacturing process flow, acting as the bridge from digital design to physical realization, is a highly complex systems engineering task, spanning raw material input to finished product output. Böttjer et al. [6] reviewed unit-level DT applications and emphasized the interconnected nature of mechanical process optimization through smart monitoring and control. Traditional optimization methods-such as layout reengineering, tooling upgrades, quality system deployment, and skill training-remain vital. These techniques eliminate inefficiencies, enhance process quality, and ensure product compliance with standards such as ISO 9001. However, they often lack a system-wide perspective. Hartmann et al. [7], through a multiscale DT for laser-directed energy deposition, pointed out that many traditional approaches target isolated processes rather than optimizing across the entire production chain. In addition, Liu et al. [8] highlighted the issue of weak data dependence in legacy manufacturing, where decision-making still heavily relies on human experience rather than on dynamic data-driven analysis, thus limiting accuracy. Lugaresi and Matta [9] further addressed the difficulty of real-time response in conventional systems by comparing automated digital twin generation with static manufacturing flows. Lei and Karimi [10], working on DT models in ironmaking, demonstrated the importance of dynamic 3D simulation in adapting to design variations under changing process parameters, which is difficult to achieve with static legacy approaches.

3. Application of digital twin in mechanical manufacturing technology

In terms of process parameter optimization, digital twin technology combines advanced data analysis and machine learning algorithms to form a closed-loop optimization system [11, 12].

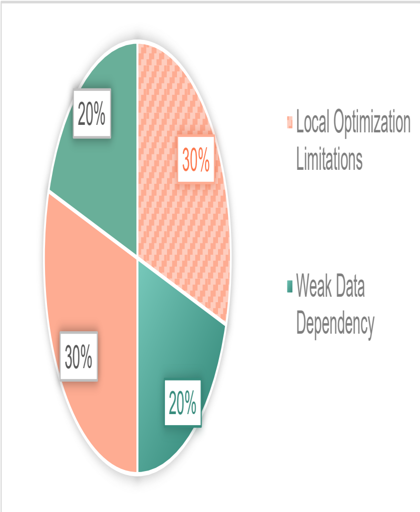

Fig. 1. Mechanical manufacturing process flow

This process is usually subdivided into multiple interrelated stages to ensure accurate execution and efficient coordination of each step. The specific process design flow is shown in Fig. 1.

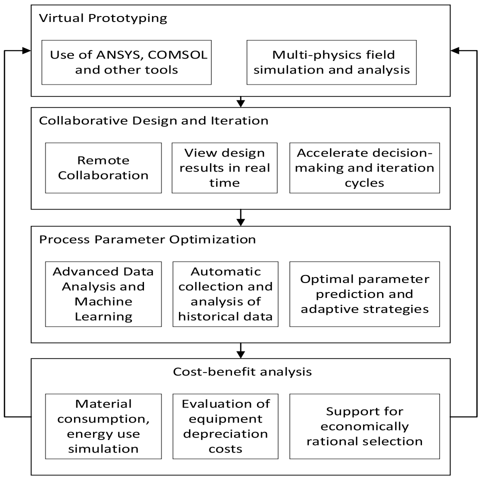

Fig. 2. Application of digital twins in mechanical manufacturing technology

The system automatically collects historical processing data, analyzes processing results under different parameter combinations, identifies optimal parameter intervals, and predicts optimal processing strategies under new materials and designs. Through deep learning algorithms, the system learns from past successes and failures and gradually improves the accuracy and applicability of the recommended parameters, providing customized strategies for efficient and high-quality machining of complex parts. This is shown in Fig. 2.

4. Mechanical manufacturing process simulation based on digital twin

4.1 Application frame of digital twin in mechanical manufacturing

The application framework of digital twin technology in mechanical manufacturing usually includes four core links: data acquisition of physical entities, data processing and model building, real-time simulation and optimization analysis, feedback control and decision support. At the heart of this framework is the full lifecycle management of physical devices by integrating technologies such as the Internet of Things (IoT), big data, cloud computing and artificial intelligence. The specific framework is shown in Fig. 3.

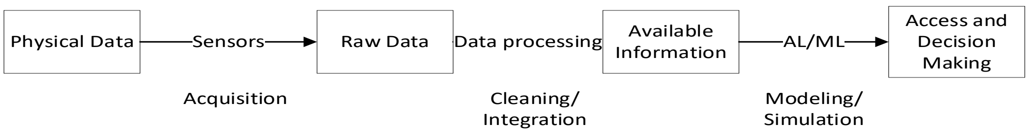

Fig. 3. Framework process

4.2. Process modeling and simulation

In the process of mechanical manufacturing simulation based on digital twinning technology, CAD model and virtual prototype construction, simulation analysis of material characteristics and dynamic simulation analysis are three core components, which together constitute a solid foundation for process simulation and optimization.

In sophisticated CAD environments, designers use parametric or nonparametric techniques to build part models, where parametric design gives models the ability to dynamically adjust through flexible mathematical expressions. A typical parametric design expression is the Bézier curve equation, as shown in Equation 1.

$$P(t) = \sum_{i=0}^{n} B_i^n(t) \cdot P_i \tag{1}$$

where *P(t)* represents the point on the curve at parameter *t*, $B_u^n(t)$ is the i the Bernstein basis polynomial of degree *n*, and P_i denotes the ith control point. The degree *n* determines the smoothness of the curve. This formulation allows the geometric shape of the model to be flexibly adjusted, which is responsible for controlling the shape of the curve, and is the control point, which determines the key turning position of the curve, and n defines the smoothness of the curve. This design method not only improves the flexibility of model modification, but also provides a solid foundation for subsequent virtual prototype verification and optimization

Material mechanics simulation relies on finite element method (FEM) to predict and analyze material behavior during machining by solving complex physical field problems. Equilibrium equation is a core equation in FEM, which describes the equilibrium state of internal force in continuous medium: in this equation, represents stress tensor, describes the action state of force on each point inside the object; F is volume force density, reflecting the influence of external force. By solving these equations, one can gain insight into the material's response to stress and predict possible deformation and fracture conditions [13, 14].

In the automobile body stamping process, the workpiece material used is DP980 dual-phase steel, with a yield strength of 600 MPa, a tensile strength of 980 MPa, and an elongation of 12%. The geometric shape of the stamping parts is complex, including multiple curved surfaces with different curvature radii. For example, the maximum curvature radius of the door stamping part is 300 mm, the minimum curvature radius is 50 mm, and there are multiple mounting holes of different sizes and positions distributed on it, with hole diameters ranging from 8 mm to 20 mm.

The stamping technology used in this study is multi-station progressive stamping technology. This technology sets multiple stations on the same mold, so that the workpiece can complete multiple stamping processes in one stamping stroke, which greatly improves production efficiency. Its working principle is to use the reciprocating motion of the press to send the sheet into each station for stamping processing in turn, and each station completes specific stamping operations, such as blanking, punching, bending, etc. Compared with traditional stamping technology, multi-station progressive stamping technology has the advantages of high precision, high efficiency, and high degree of automation, which can meet the needs of high-quality and large-scale production of automobile body stamping parts. In actual production, this technology can control the dimensional accuracy of stamping parts within ± 0.15 mm, and the production efficiency is increased by more than 30% compared with traditional stamping [15, 16].

The model of the stamping machine used in this process is JH21-250, and the equipment code is CN2023005. Its nominal pressure is 2500 kN, which can meet the pressure requirements of different stamping processes; the slide stroke is 250 mm, which can ensure the forming depth of the stamping parts; the stamping speed is 40 times/minute, which ensures production efficiency. In the long-term operation test, the stamping machine worked continuously for 1000 hours at the rated pressure, the equipment stability was good, and the failure rate was less than 1% [17, 18].

This study adopts a stamping simulation model based on the finite element method, which can simulate the flow of materials, stress and strain distribution, and the force of the mold during the stamping process. When establishing the simulation model, the stamping parts and molds are firstly three-dimensionally modeled and imported into the finite element analysis software ABAQUS. Then the model is meshed and the model is meshed using C3D8R eight-node linear hexahedral unit with a unit size of 2 mm is used to ensure calculation accuracy and efficiency. Material properties are set. The elastic modulus of DP980 dual-phase steel is 207 GPa, the Poisson's ratio is 0.3, and the yield criterion adopts the above-mentioned Hill yield criterion. At the same time, the stamping process parameters are defined, such as the stamping speed of 500 mm/s and the friction coefficient of 0.12. Through simulation calculation, the distribution of various physical quantities in the stamping process, such as equivalent stress, equivalent plastic strain, etc., can be obtained to provide data support for process optimization. Compared with the metallographic structure analysis of the actual stamping parts, the deviation of the simulated equivalent strain distribution from the actual situation is within 5%.

5. Technology Improvement Strategy of Digital Twin Drive

5.1 Optimization of process parameters based on simulation results

In the actual production scenario, process parameter optimization is faced with a multi-objective optimization problem, the core of which lies in how to achieve the optimal balance among multiple mutually restrictive objectives such as cost, quality and energy consumption. This process is made more efficient and accurate by digital twinning techniques, which integrate advanced multi-objective optimization algorithms such as Genetic Algorithm (GA, Particle Swarm Optimization (PSO), and Fuzzy Logic to search for a series of compromise solutions in a wide parameter space, known as Pareto Frontier, rather than a single optimal solution. The application of these algorithms on digital twin platforms provides powerful decision support systems for complex manufacturing processes.

Taking the stamping process of automobile body as an example, the optimization objectives include not only improving the size accuracy of stamping parts (measured by tolerance range, where and are the maximum and minimum values of size respectively), but also reducing material waste (expressed by scrap ratio) and prolonging the service life of dies (die wear rate). In the framework of multi-objective optimization, we can define the objective function as follows. In pursuit of the ultimate optimization of the manufacturing process, three core objectives are clearly stated: quality maximization, aimed at reducing the size tolerance range, expressed by the formula minimize (), to ensure product accuracy; cost minimization, focusing on efficient use of materials, striving to reduce the proportion of scrap, expressed by the formula minimize (); and energy consumption reduction, aimed at extending mold life, achieved by minimizing mold wear rate minimize (), thereby reducing maintenance costs. Genetic algorithms play a key role in achieving these multi-objective optimizations. The algorithm advances the population evolution to a better solution through an iterative process, including population initialization, fitness based selection, crossover and mutation operations of genetic operators, where t is an intergenerational marker indicating the sequence of operations. This series of carefully designed steps, supported by the digital twin platform, find the best balance point between size accuracy, material utilization rate and energy consumption for complex manufacturing processes such as automobile body stamping, showing the powerful power and unlimited potential of intelligent optimization technology in modern manufacturing industry. Particle swarm optimization, on the other hand, simulates the foraging behavior of birds, each particle represents a potential solution, and by updating the individual optimal solution, individual optimal solution and global optimal solution, the flight direction and speed are continuously adjusted to approach the optimal solution set. The update formula can be expressed as Equations 2-3.

$$v_{i,d}^{t+1} = w \cdot v_{i,d}^{t} + c_1 \cdot r_1 \cdot (p_{i,d}^{t} - x_{i,d}^{t}) + c_2 \cdot r_2 \cdot (g_d^{t} - x_{i,d}^{t}) \tag{2}$$

$$x_{i,d}^{t+1} = x_{i,d}^{t} + v_{i,d}^{t+1} \tag{3}$$

where v_i^t is the velocity of particle *i* at iteration *t*, x_i^t is the current position, *w* is the inertia weight, c_1 and c_2 are the cognitive and social learning coefficients respectively, r_1 and r_2 are random values uniformly distributed in [0, 1], p_i^t is the personal best position of particle iii, and z^t is the global best position found by the swarm so far.

Fuzzy logic provides a flexible way to deal with complex and nonlinear relations by establishing rule base to deal with the transformation from qualitative to quantitative, and helps decision makers to make reasonable trade-offs among multiple objectives. Through the parallel implementation of the above algorithm on the digital twin platform, the automobile body stamping process can realize accurate parameter optimization, for example, while maintaining the size accuracy within the range of ± 0.1 mm, the scrap ratio can be reduced to less than 5%, and the die wear rate can be reduced by 10% annually, so that the double improvement of production efficiency and economic benefit can be realized while ensuring high-quality products, which perfectly reflects the great potential and value of digital twin and multi-objective optimization algorithm in modern manufacturing process improvement.

5.2. Virtual debugging and verification

The use of digital twinning technology significantly reduces the need for physical prototypes, and designs that previously required physical trials can now be completed in highly simulated virtual environments. That means expensive physical testing costs are drastically reduced, research and development cycles are shortened, and innovation speeds up. For example, in the aerospace field, thermodynamic cycle simulation of engines through digital twins can verify the effectiveness and reliability of design solutions without the need to manufacture actual prototypes, greatly saving development costs and time.

5.3. Predictive maintenance and health management

A core advantage of digital twins is their ability to monitor and predict the status of equipment in real time. By integrating IoT sensor data, digital twins can continuously track the operating state of critical equipment, such as vibration, temperature, pressure, etc., and build predictive models using machine learning algorithms. These models can identify impending failure modes of equipment in advance and provide early warning signals to maintenance teams, making maintenance activities more proactive and efficient. For example, in the maintenance of wind turbines, through the analysis of gearbox vibration data, the digital twin model can predict bearing failures weeks in advance, ensuring timely maintenance and avoiding sudden downtime losses.

In the process of in-depth exploration of the application of digital twin technology in stamping process, many cutting-edge research results have provided valuable references for this article. For example, Zhou et al., conducted research on the incremental bending stamping system based on digital twin in the literature [19]. They elaborated in detail how the system uses digital twin technology to optimize the stamping process, achieve precise control of complex stamping processes, and significantly improve the forming quality and process stability of stamping parts. In the literature [20], Zhao et al. focused on the application of digital twin-driven information-physical systems in the autonomous control of micro-punching systems. By building advanced information-physical models, they realized real-time monitoring and intelligent control of the micro-punching process, effectively improving the processing accuracy and production efficiency of the micro-punching system. These studies have demonstrated the great potential of digital twin technology in the stamping field from different dimensions, providing an important theoretical and practical basis for this article to deeply integrate digital twin technology into the automobile body stamping process, and inspiring this article to further explore the application possibilities of digital twin technology in optimizing stamping process parameters, improving product quality and production efficiency.

5.4 Case studies and application practices

In today's global automobile manufacturing arena, the competitive situation is increasingly white-hot, technological innovation has become the core driving force for major manufacturers to seek competitive advantage. With the diversification of consumer preferences and the continuous improvement of automobile quality requirements, not only the appearance design and driving experience have become the focus of attention, but also the safety, durability and fuel efficiency of vehicles have become important criteria for evaluating a car. Under this background, a well-known automobile manufacturing enterprise, facing the fierce competition of domestic and foreign competitors and the industry transformation brought by the new energy automobile wave, deeply realized that the traditional production mode has been difficult to meet the new demand of the market.

As the backbone of the industry, the company has long been committed to innovation and optimization of automobile manufacturing processes. However, the stamping workshop, as the first key process of automobile parts production, faces several challenges: firstly, the size tolerance control of stamping parts is unstable, which leads to frequent matching problems in subsequent assembly links, which affects the assembly quality and production efficiency of the whole vehicle; secondly, the material waste is serious, and the high raw material cost is lost in the processing process, which directly affects the profit space of the enterprise; Third, frequent replacement of molds not only increases maintenance costs, but also affects the continuity and stability of production lines.

Table 1 shows the specific layout of sensors in key parts of the press, as well as the types and frequencies of data they collect. Through the pressure sensor, we can monitor the pressure change of the working surface of the stamping machine in real time, with a frequency of up to 100 Hz, which provides an important basis for accurate control of the stamping process. Temperature sensors are deployed inside the mold to monitor temperature changes at a frequency of 5 Hz, which is essential to prevent mold damage due to excessive temperatures. The vibration sensor is installed on the drive shaft and monitors the vibration amplitude at a frequency of 20 Hz, which helps to detect equipment abnormalities in advance and prevent sudden failures.

In the digital twin-assisted optimization process described in this section, the use of Bézier-based parametric modeling (as in Equation 1) enabled dynamic shape adjustments for parts with complex geometries during CAD-based prototyping. Additionally, the particle swarm optimization strategy (Equations 3 and 4) was deployed to iteratively refine stamping speed and die parameters, effectively identifying configurations that minimized deviation in part accuracy and material loss.

Table 1

Overview of sensor layouts and data types

Sensor type	Installation position	Measurement parameters	Data acquisition frequency (Hz)
Pressure sensor	Punch face	Pressure (Pa)	100
Temperature sensor	Mold interior	Temperature (°C)	5
Vibration sensor	On the transmission shaft	Vibration amplitude (mm)	20

Table 2

Architecture composition of digital twin

Component category	Component name	Description	Correlated with
Physical model	3D model of stamping machine	A high-precision simulation of the physical structure and operational principles of the stamping machine, providing an intuitive visual representation for digital twins.	Data model
Data model	Real-time data processing module	Responsible for cleaning, integrating, and storing collected data to support algorithmic models with high-quality data.	Physical model, algorithm model
Algorithm model	Genetic algorithm optimization module	Utilizes intelligent algorithms to automatically optimize stamping parameters, thereby enhancing overall process performance.	Data model

Table 2 describes the three core components of the digital twin architecture: physical model, data model, and algorithm model. The physical model is a high-precision 3D model of the stamping machine, which simulates the physical structure and working principle of the equipment and provides an intuitive visual representation for the digital twin; the real-time data processing module in the data model is responsible for cleaning, integrating, and storing data collected from machine sensors to ensure high-quality data support for the algorithm model; and the algorithm model uses an intelligent algorithm to automatically optimize stamping parameters through the genetic algorithm optimization module to improve the overall process performance.

Table 3

Comparison of virtual debugging and actual measurement results

Indicators	Virtual debugging results	Actual production results	Difference analysis
Production efficiency (pieces/h)	2000	197	±3% fluctuation due to factors like equipment wear, manual operation, etc.
Pass rate (%)	98.5	97.8	±0.7% difference, indicating high prediction accuracy of the digital twin model

Table 3 compares the results of virtual commissioning and actual production, showing the differences in production efficiency and qualified rate. Virtual commissioning shows that 2,000 pieces can be produced per hour, while the actual production number is 197 pieces/hour, with a fluctuation of ± 3%, which may be due to interference factors in actual production such as equipment wear and manual operation. As for the qualified rate, virtual commissioning reached 98.5%, while actual production was 97.8%, with a difference of ± 0.7%, indicating that the digital twin model has high prediction accuracy and can provide effective guidance for actual production.

Table 4

Summary of economic benefits

Benefit indicators	Initial value	Optimized value	Percentage improvement (%)	Description
Total cost savings (ten thousand yuan)	1000	85	15	Including materials, maintenance, etc.
Productivity improvement (%)	80	95	18.75	Increase yield per unit time
Payback period (months)	18	6	66.67	Faster cost recovery
Waste emission reduction (tons)	50	40	20	Environmental contribution

Note: The percentage changes are calculated as follows:
Cost reduction = (1000 - 850)/1000 × 100% = 15%
Productivity increase = (95 - 80)/80 × 100% = 18.75%
Payback period shortening = (18 - 6)/18 × 100% = 66.67%

Waste emission reduction = (50 - 40)/50 × 100% = 20%

The final row indicates a 20% reduction in monthly scrap emissions, which reflects a direct contribution to environmental sustainability.

Table 4 summarizes the economics of optimization. The total cost savings reached 15%, or 850,000 yuan, due to the reduction of materials, maintenance and other costs. Production efficiency increased by 18.75%, from 80% to 95%, which means a significant increase in production per unit time.

Table 5

Comparison of Dimensional Accuracy Before and After Optimization

Indicator	Before optimization	After optimization	Improvement (%)
Tolerance (mm)	±0.5	±0.1	80
Occurrence rate of fitting issues (%)	20	5	75
Assembly quality rating	3/5	4.5/5	-

Table 5 shows the changes in dimensional accuracy of stamped parts before and after implementing digital twin technology. After optimization, the tolerance was reduced from ± 0.5 mm to ± 0.1 mm, an 80% reduction; the occurrence rate of fitting issues dropped from 20% to 5%, improving by 75%. Additionally, the assembly quality rating increased from 3 to 4.5 out of 5, indicating a significant improvement in product quality.

Table 6

Comparison of die change frequency and maintenance costs

Indicator	Before optimization	After optimization	Improvement (%)
Die changes per year	12	6	50
Annual maintenance cost (ten thousand yuan)	50	30	40

Table 6 illustrates the impact of optimization measures on die change frequency and maintenance costs. By adopting more efficient process parameters and better monitoring methods, the number of die changes was halved, and annual maintenance costs were reduced by 40%, effectively controlling operating costs while enhancing the continuity and stability of production lines.

Table 7 reflects changes in material utilization rates and scrap emissions. Through optimized processes, material utilization improved by 15 percentage points to reach 90%, while scrap emissions decreased by 40%, with only 3 tons produced monthly.

Table 7

Material utilization rate and waste emission comparison

Indicator	Before optimization	After optimization	Improvement (%)
Material utilization rate (%)	75	90	20
Scrap emissions (tons/month)	5	3	40

This not only reduces raw material waste but also contributes to environmental protection.

6. Conclusion

This study demonstrated the effective integration of digital twin technology into the optimization of automotive stamping processes. The results provide both theoretical insights and practical validation, leading to several key conclusions: Digital twins enable intelligent, closed-loop manufacturing optimization by virtually modeling physical systems, integrating real-time sensor feedback, and applying machine learning-based decision-making. This significantly enhances design flexibility, process accuracy, and adaptability in mechanical manufacturing.

Multi-objective optimization algorithms, such as genetic algorithms and particle swarm optimization, when deployed within digital twin frameworks, provide actionable strategies to balance cost, quality, and energy usage. This supports dynamic parameter adjustment and production system responsiveness to design changes.

The digital twin approach significantly improves predictive maintenance and operational stability, reducing the frequency of unplanned downtime and extending equipment service life through early fault detection and virtual testing environments.

The application of digital twin technology in real-world industrial scenarios validates its transformative role in intelligent manufacturing, offering measurable improvements in sustainability, efficiency, and quality assurance, and establishing a viable path for scalable industrial deployment.

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REFERENCES

[1] *L.C. Magalhaes, J.B. Ramos, L.R. Moura, R.E.N. de Moraes, J.B. Gonçalves, et al.,* Conceiving a digital twin for a flexible manufacturing system, Applied Sciences-Basel, Vol. **12**, Iss. 19, 2022, 18.

[2] *W. Polini, A. Corrado,* Digital twin of composite assembly manufacturing process. International Journal of Production Research, Vol. **58**, Iss. 17, 2020, 5238-52.
[3] *R. Parvanda, P. Kala,* Trends, opportunities, and challenges in the integration of the additive manufacturing with Industry 4.0. Progress in Additive Manufacturing, Vol. **8,** 2023.
[4] *D. Guivarch, E. Mermoz, Y. Marino, M. Sartor,* Creation of helicopter dynamic systems digital twin using multibody simulations. Cirp Annals-Manufacturing Technology, Vol. **68**, Iss. 1, 2019, 133-6.
[5] *J.Y. Liu, K. Zhang,* Design and simulation debugging of automobile connecting rod production line based on the digital twin. Applied Sciences-Basel, Vol. **13**, Iss. 8, 2023, 22.
[6] *T. Böttjer, D. Tola, F. Kakavandi, C.R. Wewer, D. Ramanujan, C. Gomes, et al.,* A review of unit level digital twin applications in the manufacturing industry. Cirp Journal of Manufacturing Science and Technology, Vol. **45**, 2023, 162-89.
[7] *S. Hartmann, O. Murua, J.I. Arrizubieta, A. Lamikiz, P. Mayr,* Digital Twin of the laser-DED process based on a multiscale approach. Simulation Modelling Practice and Theory, Vol. **132**, 2024, 18.
[8] *J.F. Liu, X.W. Cao, H.G. Zhou, L. Li, X.J. Liu, P. Zhao, J.W. Dong,* A digital twin-driven approach towards traceability and dynamic control for processing quality. Advanced Engineering Informatics, Vol. **50**, 2021, 17.
[9] *G. Lugaresi, A. Matta,* Automated digital twin generation of manufacturing systems with complex material flows: graph model completion. Computers in Industry, Vol. **151**, 2023, 14.
[10] *Y.X. Lei, H.R. Karimi,* A Digital Twin Model of Three-Dimensional Shading for Simulation of the Ironmaking Process. Machines, Vol. **10**, Iss. 12, 2022, 19.
[11] *C.H. Hu, Q. Yi, C.B. Li, Y.S. Luo, S.P. Yi,* Digital twin-based dynamic prediction and simulation model of carbon efficiency in gear hobbing process. International Journal of Advanced Manufacturing Technology, Vol. **126**, Iss. 9-10, 2023, 3959-80.
[12] *Y.B. Guo, A. Klink, P. Bartolo, W.G. Guo,* Digital twins for electro-physical, chemical, and photonic processes. Cirp Annals-Manufacturing Technology, Vol. **72**, Iss. 2, 2023, 593-619.
[13] *H.C. Mu, F.Y. He, L. Yuan, P. Commins, H.M. Wang, Z.X. Pan,* Toward a smart wire arc additive manufacturing system: A review on current developments and a framework of digital twin. Journal of Manufacturing Systems, Vol. **67**, 2023, 174-89.
[14] *J.Z. Sheng, Q.Y. Zhang, H. Li, S.N. Shen, R.J. Ming, J. Jiang, et al.,* Digital twin driven intelligent manufacturing for FPCB etching production line. Computers & Industrial Engineering, Vol. **186**, 2023, 11.
[15] *A.K. Ramasubramanian, R. Mathew, M. Kelly, V. Hargaden, N. Papakostas,* Digital twin for human-robot collaboration in manufacturing: review and outlook. Applied Sciences-Basel, Vol. **12**, Iss. 10, 2022, 35.
[16] *T.W. Heo, S.A. Khairallah, R.P. Shi, J. Berry, A. Perron, N.P. Calta, et al.,* A mesoscopic digital twin that bridges length and time scales for control of additively manufactured metal microstructures. Journal of Physics-Materials, Vol. **4**, Iss. 3, 2021, 24.
[17] *H.R. Li, X.C. Shi, B.T. Wu, D.R. Corradi, Z.X. Pan, H.J. Li,* Wire arc additive manufacturing: A review on digital twinning and visualization process. Journal of Manufacturing Processes, Vol. **116**, 2024, 293-305.
[18] *P. Stavropoulos, A. Papacharalampopoulos, C.K. Michail, G. Chryssolouris,* Robust additive manufacturing performance through a control oriented digital twin. Metals, Vol. **11**, Iss. 5, 2021, 19.
[19] *C.H. Zhou, F.F. Zhang, B. Wei, Y.J. Lin, K. He, R.X. Du,* Digital twin-based stamping system for incremental bending. International Journal of Advanced Manufacturing Technology, Vol. **116**, 2021, 389-401.
[20] *R.L. Zhao, D.X. Yan, Q. Liu, J.W. Leng, J.F. Wan, X. Chen,* Digital twin-driven cyber-physical system for autonomously controlling of micro punching system, IEEE Access, vol. **7**, 2019, 9459-9469.