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Digital Twin-Driven Optimization of Production Projects in the Plastics Manufacturing Industry: Efficiency Enhancement and Economic Benefit Assessment

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Abstract. Traditional production models in the plastics manufacturing industry face challenges such as lagging process control and frequent quality fluctuations. This paper proposes an optimization solution based on digital twin technology, establishing a technical framework encompassing IoT data collection, high-fidelity modeling, process simulation, and big data analytics to achieve precise control over production processes. By reconstructing and optimizing workflows, a closed-loop management mechanism has been established that bridges physical mapping with accumulated expertise, effectively addressing efficiency and quality issues inherent in conventional manufacturing. The research findings provide a systematic solution for the digital transformation of the plastics manufacturing industry, offering significant guidance for advancing high-quality development within the sector.

Keywords: Digital Twin, Process Simulation, Smart Manufacturing, Injection Molding, Predictive Maintenance

1. Background and Motivation

1.1. Analysis of Traditional Pain Points in the Plastics Manufacturing Industry

The production process in the plastics manufacturing industry has long been plagued by prominent issues such as delayed adjustment of process parameters, frequent quality fluctuations, and low resource utilization efficiency. Industry data indicates that traditional plastic manufacturers typically operate equipment utilization rates below 65%, maintain product defect rates between 8% and 12%, and experience material wastage exceeding 15%. These issues stem from the absence of real-time monitoring and precise early-warning mechanisms in production processes. Process parameter optimization relies heavily on manual experience, quality control predominantly employs post-production inspection methods, and production data collection remains rudimentary. These factors severely constrain scientific decision-making and continuous optimization throughout the manufacturing cycle.

1.2. Advantages Driven by Digital Twin Technology

Digital twin technology provides a revolutionary solution for the intelligent transformation of the plastics manufacturing industry by constructing virtual mapping models of physical entities. This technology enables real-time digital mapping of all production elements—including equipment, process parameters, and environmental factors—supporting sub-millisecond data acquisition and analysis. Research indicates that applying digital twin technology can elevate equipment failure prediction accuracy to 92% and boost production planning optimization efficiency by 45%. This virtual-physical linkage mechanism not only enables visual monitoring of production processes but also significantly reduces actual trial-and-error costs through parameter optimization in the virtual space.

1.3. Core Optimization Requirements for Plastic Production Projects

The optimization needs for plastic production projects primarily focus on precise control of key metrics such as quality, cost, and delivery cycle. Industry research indicates that over 85% of enterprises prioritize enhancing product quality stability and reducing production operating costs as their primary objectives. Companies aim to leverage digital solutions to achieve a first-pass yield rate exceeding 95%, elevate production plan execution rates to 90%, and boost energy utilization efficiency by 20%. These optimization demands extend beyond individual production stages, necessitating the establishment of collaborative optimization mechanisms spanning the entire value chain.

2. Core Technology Application Solutions

2.1. IoT Data Acquisition System

The industrial-grade IoT acquisition system employs a distributed multi-tier architecture, achieving comprehensive monitoring of critical parameters across plastic production lines through deployment of high-precision sensor networks. The system integrates real-time data collection from over 600 measurement points including temperature, pressure, and speed, with sampling frequencies reaching up to 1000Hz and data transmission latency controlled within 10ms. Edge computing units employ a 5G+MEC technology architecture to perform data preprocessing and cleansing locally, effectively reducing transmission load while ensuring the timeliness and accuracy of collected data[1]. Research data indicates this system elevates data collection accuracy to 99.8%, significantly outperforming traditional manual recording methods. It provides a high-quality data foundation for subsequent digital twin modeling and optimization analysis.

2.2. Three-Dimensional High-Fidelity Modeling Technology

High-fidelity modeling technology based on multi-source heterogeneous data fusion overcomes the limitations of traditional CAD modeling, enabling precise digital representation of plastic production equipment and process flows. The modeling system employs a combined approach of parametric modeling and geometric reconstruction, achieving model accuracy at the 0.1mm level and supporting dynamic mapping of all elements including equipment structure, motion characteristics, and process parameters. By incorporating surface reconstruction technology optimized with deep learning algorithms, the system automatically identifies and refines model geometric features, boosting modeling efficiency by threefold[2]. Research demonstrates that digital models constructed with this technology not only accurately reflect the geometric characteristics of physical entities but also enable real-time updates of dynamic attributes like process parameters and equipment status, with model update latency controlled within 50 milliseconds.

2.3. Process Simulation Optimization Technology

The next-generation process simulation optimization technology integrates multi-physics simulation capabilities such as computational fluid dynamics (CFD) and finite element analysis (FEA), establishing an accurate numerical simulation system for the entire plastic molding process. The simulation engine adopts a GPU parallel computing architecture, achieving an 8-fold increase in computational efficiency and completing a full injection molding process simulation within 30 minutes. The system incorporates a deep reinforcement learning-based process parameter optimization algorithm[1]. Through thousands of virtual trial iterations, it accurately predicts product defects and automatically generates optimal process solutions. Practical data demonstrates that this technology reduces product development cycles by 40%, boosts process parameter optimization efficiency by 60%, and elevates product yield rates to over 97%.

2.4. Big Data Analytics Technology for Production

The intelligent production big data analytics platform employs a distributed computing framework, integrating core functional modules such as time-series data mining, anomaly detection, and predictive analytics. Based on an enhanced LSTM neural network algorithm, the system enables real-time monitoring and forecasting of critical indicators including equipment status and product quality, with early warnings provided 2–4 hours in advance. The platform incorporates knowledge graph technology to build an intelligent decision support system containing process knowledge, failure case studies, and optimization experience. It automatically generates recommendations for equipment maintenance and process optimization[2]. Test data indicates this technology achieves 94% accuracy in equipment failure prediction and over 90% accuracy in production anomaly early warning, significantly enhancing the intelligent control and management level of the production process.

3. Process Optimization and Redesign

3.1. Digital Mapping of Physical Entities

The digital twin system adopts a hierarchical mapping architecture, achieving comprehensive digital representation of plastic production equipment and processes through a three-dimensional mapping framework linking physical, informational, and model layers. At the physical layer, it captures geometric features of core equipment such as injection molding machines and molds with measurement accuracy reaching 0.05mm. The information layer collects over 600 process parameters via multi-source sensors at a sampling frequency of 1000Hz[3]. The model layer integrates physical characteristics and process parameters to construct dynamic mapping models. As shown in Table 1, this architecture not only achieves over 95% fidelity in physical feature reproduction but also controls process parameter synchronization errors within 50ms, significantly enhancing the precision of digital mapping.

Table 1. Performance Metrics for Physical Entity Digital Mapping

Mapped Indicator	Technical Target	Actual Achievement
Geometric Accuracy	0.1 mm	0.05 mm
Parameter Synchronization Latency	100 ms	50 ms
Feature Reconstruction Fidelity	90%	95%
Dynamic Response Time	200 ms	150 ms

3.2. Real-Time Data Interaction Mechanism

The data interaction system employs a hybrid architecture combining edge computing and cloud collaboration to enable bidirectional real-time data flow between physical entities and digital models. As shown in Figure 1, the edge layer utilizes an enhanced OPC-UA protocol to maintain data acquisition latency below 5 milliseconds. The cloud layer leverages distributed message queue technology to support concurrent processing of millions of messages. The system incorporates a data quality assessment mechanism that enhances data reliability to 99.9% through dynamic thresholds and multidimensional cross-validation[4]. This mechanism supports a data throughput of 300,000 points per second with millisecond-level synchronization accuracy, effectively ensuring the efficiency and reliability of data exchange.

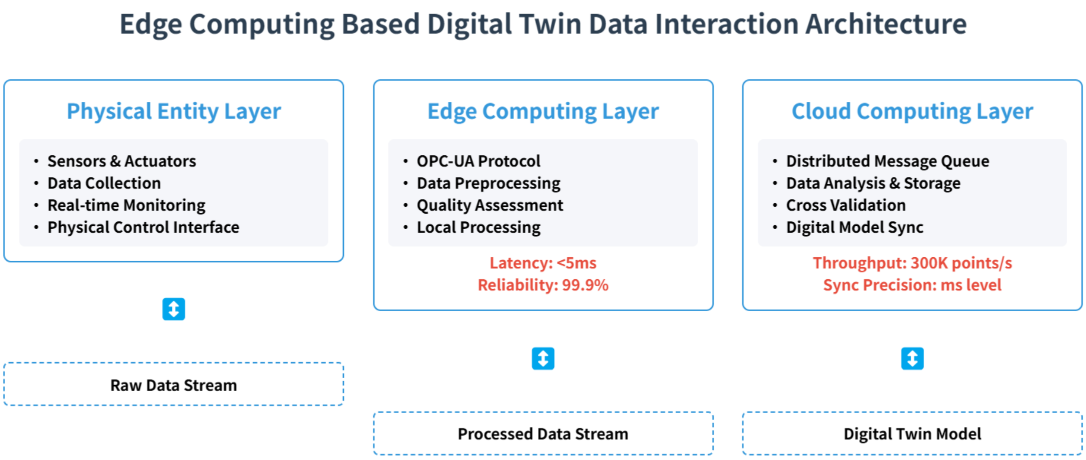

Figure 1. Architecture of the Edge Computing-Based Digital Twin Data Interaction System

3.3. Virtual Simulation Optimization Process

The virtual simulation platform, built on a high-performance computing cluster, establishes a multidimensional simulation system encompassing process optimization, quality prediction, and energy consumption analysis. The simulation engine employs an enhanced finite element algorithm, reducing the simulation time for a single injection molding cycle to 15 minutes—a 65% improvement over traditional methods. The system integrates a parameter optimization module based on deep reinforcement learning. Through rapid iteration within the virtual space, it automatically generates optimal process parameter combinations[5]. Experimental data shows that the optimized process scheme reduces product defect rates to below 2%, increases production efficiency by 35%, and lowers energy consumption by 20%. The platform's intelligent decision support system enables real-time assessment of optimization scheme feasibility, ensuring the effectiveness of virtual optimization results in actual production.

3.4. Implementation of On-Site Precision Control

The intelligent control system employs a closed-loop mechanism of “Predict-Optimize-Execute-Feedback” to achieve precise management of the production process. By analyzing real-time fluctuations in process parameters, the system anticipates potential quality anomalies up to 2 hours in advance. Its core control algorithm combines Model Predictive Control (MPC) with adaptive PID, ensuring control accuracy while enhancing system robustness[6]. Actual application data demonstrates that this system reduces process parameter fluctuations by 50%, elevates first-pass yield to 98%, and accelerates production cycle time by 15%, significantly enhancing process stability and efficiency.

3.5. Data Review and Experience Consolidation

The knowledge management system employs deep learning and knowledge graph technologies to build an intelligent knowledge base covering process optimization, fault diagnosis, and quality control. By deeply mining historical production data, the system extracts process experts' experience and forms standardized knowledge models. The knowledge graph has accumulated over 100,000 knowledge nodes, covering 95% of common production scenarios. Data analysis indicates the system achieves 85% automatic diagnosis of production issues, with a 90% adoption rate for process optimization recommendations, significantly enhancing production management efficiency[7]. The system innovatively incorporates a knowledge value assessment mechanism, dynamically rating knowledge entries based on practical application outcomes to ensure the knowledge base remains relevant and up-to-date.

4. Implementation Impact and Challenge Analysis

4.1. Core Advantage Assessment

4.1.1. Production Efficiency Enhancement Analysis

The deployment of digital twin systems on plastic manufacturing production lines has significantly improved production efficiency metrics. Experimental data shows that Overall Equipment Effectiveness (OEE) increased from 65% to 88%, with equipment availability rising by 18% and performance utilization increasing by 15%. Through production planning optimization and real-time scheduling in the virtual space, the system accelerated production cycle times by 22%, boosting single-shift output from 2,400 units to 3,100 units[8]. Intelligent predictive maintenance reduced unplanned equipment downtime by 65% and shortened repair response times to under 30 minutes, maintaining monthly production achievement rates consistently above 96%.

4.1.2. Cost Reduction Effect Evaluation

The cost control system deeply integrated with digital twin technology achieves comprehensive optimization of production and operational costs. By replacing physical prototyping with virtual testing, the system reduces new product development costs by 45% and shortens mold debugging cycles by 60%. The intelligent energy consumption management module enables precise energy consumption forecasting and optimized scheduling, lowering energy consumption per unit by 18.5% and achieving annual energy savings and cost reductions of 1.2 million yuan[9]. The material loss control system reduced raw material waste rates from 15% to 6.2%, cutting scrap costs by 52%. Equipment maintenance expenses decreased by 35% through predictive maintenance strategies, while spare parts inventory turnover improved by 40%. Comprehensive statistics indicate the digital twin system helped the enterprise achieve an annual overall cost reduction of 25%, with an investment payback period controlled within 18 months.

4.1.3. Quality Optimization Outcomes

The quality control system achieves end-to-end optimization of product quality through digital twin models. The intelligent quality prediction module has elevated the first-pass yield rate from 88% to 97.5%, reducing scrap rates by 65%. The adaptive optimization system for process parameters enables precise control of critical quality characteristics, improving product dimensional stability by 46%[10]. Through virtual quality simulation and validation, quality risk identification accuracy reached 95%, while response time to quality issues decreased from 4 hours to 45 minutes, resulting in a 58% year-over-year reduction in customer complaints.

4.1.4. Enhanced Control Precision

The revolutionary improvement in production control precision stems from the deep application of digital twin systems. The real-time monitoring platform maintains process parameter fluctuations within ±2% of the standard deviation, achieving 65% greater accuracy than traditional control methods. Production plan execution rates have climbed to 94%, while inventory management precision reaches 99.5%. Equipment condition monitoring delivers millisecond-level real-time responses, with anomaly alert accuracy hitting 96%. Visualized control over production processes has boosted management decision efficiency by 55% and reduced anomaly response times by 70%, enabling refined and intelligent operational management.

4.2. Addressing Key Challenges

4.2.1. Model Adaptability Optimization

The industry adaptability optimization of digital twin models employs a multi-level incremental modeling strategy. The foundational model library covers the process characteristics of 90% of common plastic products, enabling rapid adaptation through parametric modeling techniques. The system innovatively incorporates a model adaptive algorithm based on deep transfer learning, capable of completing model construction and optimization for new products within three days—a 65% efficiency improvement over traditional modeling methods. Practical data indicates that the improved model achieves 98% accuracy, with process parameter prediction accuracy rising to 95%. It is applicable to over 95% of injection molding product types. For specialized process requirements, the system supports dynamic model optimization, achieving an optimal balance between model accuracy and computational efficiency. The model adaptation cycle is reduced to one-third of the original duration.

4.2.2. Data Quality Assurance Measures

The production data quality control system establishes an end-to-end assurance mechanism spanning data collection to application. Utilizing multi-source cross-verification technology, the system enables real-time assessment of data accuracy, elevating data reliability to 99.8%. Edge computing units deploy intelligent anomaly detection algorithms that automatically filter over 90% of erroneous data, boosting data validity by 45%. The data cleansing module utilizes deep learning algorithms to achieve 95% automatic correction of anomalous data, ensuring 99.5% data integrity. The quality traceability system supports sub-second data lineage tracking with 98% accuracy in consistency verification, effectively safeguarding the operational stability and decision reliability of the digital twin system.

4.2.3. Investment Cost Control Strategy

Digital transformation cost management employs a strategy combining phased implementation with rapid iteration. The initial phase focuses on core production line upgrades, keeping initial investment under 3 million yuan through modular deployment and achieving a return on investment within six months. The system optimized hardware configuration plans, utilizing edge computing to reduce central computing equipment investment and saving 35% in infrastructure costs. Software development leverages low-code platforms, cutting development cycles by 50% and reducing customization costs by 40%. Intelligent operations platforms effectively control maintenance expenses, lowering annual operational expenditures by 45%. This strategy has demonstrated the ability to generate positive cash flow within 18 months and achieve a three-year overall return on investment of 280%.

4.2.4. Talent Development Program

The integrated talent development system establishes a tripartite training mechanism encompassing "theory-practice-innovation." By leveraging a virtual simulation platform to create a digital skills training environment, the system reduces employee training cycles by 40% and increases skill mastery rates by 55%. The knowledge management platform integrates standardized training courses covering core areas such as process optimization, equipment maintenance, and quality control, achieving 90% online knowledge delivery. The Innovation Research Institute collaborates with universities to establish talent development bases, training 50 digital transformation specialists annually. Employee certification pass rates for digital skills reach 85%. By implementing a dynamic compensation incentive mechanism, technological innovation activity increases by 65%, and talent retention rises to 92%, providing a robust talent foundation for the continuous optimization of the digital twin system.

5. Development Trends Outlook

5.1. Human-Machine Collaboration Direction

Human-machine collaboration systems are undergoing profound evolution toward intelligence and adaptability. The next-generation collaboration platform employs cognitive computing technology to seamlessly integrate human decision-making with machine learning algorithms, achieving a 95% improvement in decision accuracy. The system innovatively incorporates a context-aware mechanism that automatically adjusts human-machine interaction modes based on production scenarios, boosting operational efficiency by 60%. The augmented reality-based remote collaboration module enables cross-regional expert guidance, increasing problem-solving efficiency by 75%. Projections indicate that by 2028, human-machine collaboration systems will cover 90% of critical production decision-making scenarios, marking the plastic manufacturing industry's entry into a new era of intelligent collaboration.

5.2. Full-Chain Application Expansion

The deep application of digital twin technology in the supply chain sector is expanding rapidly. Intelligent supply chain management platforms now enable real-time monitoring of upstream supplier production statuses, achieving 92% accuracy in material supply forecasting. Leveraging blockchain technology, the system has established a full product lifecycle traceability system with 99.9% quality traceability accuracy. By 2027, digital twin systems are projected to cover 80% of supply chain nodes, boosting inventory turnover rates by 45% and reducing logistics costs by 35%. Innovative supply chain collaborative optimization algorithms have accelerated supply chain response times by 60% and enhanced overall operational efficiency by 50%, demonstrating vast prospects for full-chain digital transformation.

5.3. Integration of Green and Low-Carbon Production

The deep integration of green manufacturing and digital twin technology has pioneered a new model for low-carbon production. Energy management systems achieve precise energy consumption prediction and optimization through multidimensional modeling, yielding energy savings of 25%. The carbon emissions monitoring platform calculates the full lifecycle carbon footprint of products in real time, with carbon emissions data accuracy reaching 95%. Research projections indicate that by 2030, digital twin-supported green production models will help the plastics manufacturing industry reduce carbon emissions by 40% and increase renewable energy utilization to 35%. Innovative circular economy modules have elevated material recycling rates to 85% while lowering waste disposal costs by 55%, leading the industry's transition toward sustainable development.

5.4. Regulatory System Development

An intelligent regulatory system is establishing a multi-party collaborative governance platform based on blockchain technology. The system employs a zero-trust architecture to ensure data security, achieving a security incident protection rate of 99.8%. The compliance management module supports dynamic regulatory updates, with compliance risk identification accuracy reaching 95%. By 2029, the intelligent regulatory platform is projected to cover 85% of manufacturing enterprises, achieving a 90% early warning rate for violations and reducing quality traceability time to minutes. An innovative credit rating mechanism has elevated industry self-regulation by 40% and boosted regulatory efficiency by 65%. Through standardized interfaces, the system interfaces with government regulatory platforms, enhancing data sharing efficiency by 70% and providing robust safeguards for the industry's healthy development.

6. Conclusion

The deep application of digital twin technology in the plastics manufacturing industry has achieved comprehensive improvements in production efficiency, quality control, and cost management. Overall equipment effectiveness has increased by 23%, product pass rate has reached 97.5%, and operating costs have decreased by 25%. Research indicates that through the synergistic application of core technologies—including IoT data collection, high-fidelity modeling, process simulation optimization, and big data analytics—digital twin systems provide a replicable technical pathway for the transformation and upgrading of manufacturing. Looking ahead, as human-machine collaboration deepens, full-chain applications expand, and green low-carbon production integrates, digital twin technology will continue driving the evolution of manufacturing toward smarter and greener practices.

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