Proceedings of the International Conference on Industrial Engineering and Operations Management

Publisher: IEOM Society International, USA DOI: 10.46254/NA10.20250161
Published: June 17, 2025

Cost Optimization in Mold-Making: Conceptual Industry 4.0 Framework

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Abstract

In the era of Industry 4.0, mold-making firms face increasing pressure to optimize manufacturing costs while maintaining product quality. This research presents a novel integrated framework combining Monte Carlo Simulation (MCS) and Machine Learning (ML) techniques to address the complexities and uncertainties inherent in injection mold tool manufacturing cost estimation. Our approach leverages MCS to model uncertainties in machine performance, downtime, and material cost fluctuations, while ML algorithms analyze historical and real-time production data to predict machine rates and optimize resource allocation. The integration of these techniques with IoT-enabled sensors provides a dynamic, data-driven framework for real-time cost optimization. The conceptual framework demonstrates potential for significant improvements in cost reduction, machine uptime, and process efficiency. This integrated approach offers a scalable solution for mold-making firms seeking to enhance operational efficiency and profitability in an increasingly competitive market.

Keywords
Monte Carlo Simulation, Machine Learning, Cost Optimization, Mold-Making, Industry 4.0

1. Introduction

The manufacturing landscape for mold-making firms is experiencing rapid transformation due to Industry 4.0 technologies, creating both challenges and opportunities for cost optimization. Traditional approaches to manufacturing cost estimation and machine rate modeling often fail to account for the inherent uncertainties and complexities in modern production environments (Koltai et. al. Mourtzis et al.2017). As mold-making firms strive to remain competitive, they must adopt more sophisticated methodologies for cost prediction and resource optimization.

Mold-making operations present unique challenges for cost optimization due to the variability in machine performance, tool wear rates, maintenance requirements, and raw material costs (Wang et al.2018). The custom nature of many mold-making projects further complicates cost estimation and resource allocation. Traditional deterministic cost models typically provide point estimates that fail to capture the probabilistic nature of manufacturing processes, leading to inaccurate budgeting and suboptimal resource allocation (Myrelid & Olhager 2019).

Monte Carlo Simulation (MCS) offers a powerful approach for modeling the stochastic nature of manufacturing processes by running multiple iterations with random variables to generate probability distributions of possible outcomes (Kroese et al. 2013). This technique enables manufacturers to quantify uncertainty in cost estimation and make more informed decisions regarding resource allocation and pricing strategies. However, MCS alone cannot leverage the wealth of historical and real-time data now available through Industry 4.0 technologies.

Machine Learning (ML), on the other hand, excels at identifying patterns in complex datasets and making predictions based on historical trends (Wuest et. al.). ML algorithms can learn from past production data to optimize machine rates, predict maintenance needs, and improve resource allocation (Wang et al. 2017). By combining MCS and ML approaches, manufacturers can develop more robust and adaptable cost optimization frameworks that account for both uncertainty and historical patterns.

The integration of Industry 4.0 technologies such as IoT sensors, cloud computing, and advanced analytics provides the foundation for implementing these computational methods in real-world manufacturing environments (Kagermann et al. 2013). Real-time data collection and processing enable continuous monitoring of machine performance and cost factors, allowing for dynamic adjustments to production parameters and resource allocation (Da Xu et al. 2018).

1.1 Objectives

This research aims to develop a conceptual integrated framework for manufacturing cost optimization in mold-making firms by leveraging Monte Carlo Simulation, Machine Learning, and Industry 4.0 technologies. The specific objectives that this framework is designed to achieve are:

1. Designing a conceptual comprehensive machine rate modeling framework that accurately captures uncertainties in machine performance, material costs, and production schedules using Monte Carlo Simulation.
2. Developing a conceptual approach for ML algorithms that analyze historical and real-time production data to predict machine rates, optimize resource allocation, and identify cost-saving opportunities.
3. Integrating Industry 4.0 technologies, particularly IoT-enabled sensors, to provide real-time data for continuous monitoring and optimization of manufacturing costs.
4. Developing a scalable and adaptable methodology that mold-making firms of varying sizes can implement to enhance operational efficiency and profitability.

2. Literature Review

2.1 Cost Optimization in Manufacturing

Cost optimization in manufacturing has evolved significantly with the advent of computational methods and Industry 4.0 technologies. Early work by Spedding and Sun established the foundation for using simulation-based approaches to manufacturing cost estimation, demonstrating improvements over traditional accounting methods. More recently, Mourtzis et al. highlighted the importance of accurate cost estimation in competitive manufacturing environments, particularly for custom production like mold-making.

2.2 Monte Carlo Simulation in Manufacturing

Monte Carlo Simulation has proven effective for modeling uncertainties in manufacturing processes. Hoffman and Hammonds demonstrated the application of MCS for uncertainty analysis in engineering systems, while Hammersley and Handscomb provided the mathematical foundation for modern Monte Carlo methods. In manufacturing specifically, Marseguerra and Zio applied MCS to model equipment reliability and maintenance costs, showing that the probabilistic approach improved decision-making regarding maintenance scheduling and resource allocation.

Recent work by Ghadge et al. utilized MCS to quantify supply chain risks in manufacturing, demonstrating its value for modeling material cost fluctuations. Similarly, Ben-Daya et al. employed MCS to optimize inventory management in manufacturing environments with uncertain demand, achieving significant cost reductions.

2.3 Machine Learning Applications in Manufacturing

Machine Learning applications in manufacturing have expanded rapidly with the increasing availability of production data. Wuest et al. provided a comprehensive review of ML applications in manufacturing, highlighting opportunities for quality prediction, process optimization, and predictive maintenance. Specifically for cost optimization, Ning et al. demonstrated the application of supervised learning algorithms for predicting manufacturing costs based on historical production data.

Recent advances include the work of Wang et. al., who developed neural network models for predicting tool wear and optimizing replacement schedules in machining operations. Similarly, Ogunfowora and Homayoun employed reinforcement learning algorithms to optimize production scheduling and resource allocation, achieving significant improvements in operational efficiency.

2.4 IoT in Manufacturing

The emergence of Industry 4.0 has transformed data collection and processing capabilities in manufacturing environments. Zhong et al.2017 examined the integration of IoT technologies in smart manufacturing, highlighting opportunities for real-time monitoring and optimization. Frank et al. further explored the technological foundations of Industry 4.0, identifying key enablers for data-driven manufacturing.

For mold-making specifically, Kuo et al.2017 demonstrated the implementation of IoT sensors for monitoring injection molding processes, enabling real-time quality control and cost optimization. Similarly, Mourtzis et al.2014 developed cloud-based platforms for collecting and analyzing manufacturing data, facilitating the implementation of advanced analytics in traditional manufacturing environments.

2.5 Integration of Computational Methods in Manufacturing

The integration of multiple computational methods for manufacturing optimization represents an emerging research area. Wuest et al. explored the combination of data mining and simulation for manufacturing process optimization, demonstrating synergistic benefits. Similarly, Zheng et al. combined optimization algorithms with ML techniques for production scheduling, achieving improvements in both efficiency and cost reduction.

However, few studies have specifically addressed the integration of MCS and ML for manufacturing cost optimization, particularly in the context of mold-making firms. This research aims to fill this gap by developing an integrated conceptual framework that leverages the strengths of both approaches, enhanced by real-time data from Industry 4.0 technologies.

3. Methods

Our integrated methodology combines stochastic modeling through Monte Carlo Simulation with predictive analytics via Machine Learning algorithms, enhanced by real-time data collection through Industry 4.0 technologies. This section details the mathematical foundation and implementation approach for each component of the framework.

3.1 Stochastic Model Development and Monte Carlo Simulation

We developed a stochastic model to represent the manufacturing cost structure in mold-making operations, incorporating the following key components:

1. Machine hourly rate (MHR) calculation: $MHR = \frac{OC+MC+EC+LC}{AHY}$
   Where:
   - OC = Ownership costs (depreciation, interest)
   - MC = Maintenance costs
   - EC = Energy consumption costs
   - LC = Labor costs
   - AHY = Available hours per year

2. Tool cost (TC) calculation: $TC = TPC \times \frac{PT}{TL}$
   Where:
   - TPC = Tool purchase cost
   - PT = Processing time
   - TL = Tool life

3. Material cost (MatC) calculation: $MatC = MU \times MUC$
   Where:
   - MU = Material usage
   - MUC = Material unit cost

4. Total manufacturing cost (TMC) for a complete mold :

$TMC = \sum_{i=1}^{n}(MHR_i \times PT_i) + \sum_{j=1}^{n} TC_j + MatC + OC + DC$

Where:

- n = Number of machining operations
- m = Number of cutting tools used
- MHRi = Machine hourly rate for operation i
- PTi = Processing time for operation i
- OC = Overhead costs
- DC = Design and engineering costs

For the Monte Carlo Simulation, we identified probability distributions for key uncertain variables based on historical data analysis:

- Maintenance costs: Gamma distribution (shape parameter $\alpha = 2.3$, scale parameter $\beta = 4{,}500$)
- Tool life: Weibull distribution (shape parameter $k = 2.1$, scale parameter $\lambda = 350$)
- Material unit cost: Normal distribution ($\mu = 25.4$, $\sigma = 3.2$)
- Processing time: Log-normal distribution ($\mu = 4.2$, $\sigma = 0.35$)
- Design and engineering hours: Triangular distribution (min = 120, mode = 180, max = 250)

The expected total manufacturing cost was then calculated using Monte Carlo Simulation:

$$E(TMC) = \frac{1}{N}\sum_{i=1}^{N} TMC_i$$

Where:

- N = Number of simulation iterations (typically 10,000 for our implementation)
- TMCi = Total manufacturing cost calculated in iteration i

The variance in total manufacturing cost provides a measure of uncertainty:

$$Var(TMC) = \frac{1}{N}\sum_{i=1}^{N}\left(TMC_i - E(TMC)\right)^2$$

3.2 Machine Learning Integration for Cost Estimation and Optimization

We implemented multiple ML algorithms to address different aspects of cost optimization:

1. **Cost Prediction Models**: We developed supervised learning models to predict manufacturing costs based on historical production data. The general form of the model is:

$$TMC' = f(X) + \varepsilon$$

   Where:
   - TMC' = Predicted total manufacturing cost
   - f(X) = ML model function (e.g., regression, neural network)
   - X = Feature vector (machine parameters, material properties, production specifications)
   - ε = Error term

We evaluated multiple algorithms including Random Forest Regression, Support Vector Regression, and Neural Networks, selecting the best-performing model based on cross-validation results.

2. **Predictive Maintenance Models**: We implemented classification algorithms to predict machine failures and optimize maintenance scheduling. The probability of machine failure is modeled as:

$$P(F \mid X) = g(X)$$

   Where:
   - P(F|X) = Probability of failure given feature vector X
   - g(X) = ML classification model (e.g., Random Forest, Gradient Boosting)
   - X = Feature vector (vibration data, temperature, energy consumption, operating hours)

3. **Optimization Models**: We employed reinforcement learning (RL) to optimize resource allocation and machine parameter settings. The RL agent learns to maximize the reward function:

$$R = w_1 \times TCR + w_2 \times MPE - w_3 \times MD$$

Where:
   - R = Reward
   - TCR = Total cost reduction
   - MPE = Manufacturing process efficiency
   - MD = Machine downtime
   - w_1, w_2, w_3 = Weighting factors

3.3 Sensitivity Analysis for Cost Drivers
We conducted global sensitivity analysis to identify the most significant cost drivers using the Sobol method [27]. The Sobol sensitivity index for each input variable is calculated as:

$$Si = \frac{Var(E[TMC \mid X_i])}{Var(TMC)}$$

Where:
- $Var(E[TMC \mid Xi])$= Variance of the expected cost conditioned on input Xi
- $Var(TMC)$= Total variance of cost

The total-effect sensitivity index, which accounts for interactions between variables, is calculated as:

$$STi = 1 - \frac{Var(E[TMC \mid X_{-i}])}{Var(TMC)}$$

Where:
- X-i = All input variables except Xi

3.4 IoT Integration and Real-Time Data Collection
We implemented an IoT-based data collection system with the following components:

1. **Sensor Deployment**: Temperature sensors, vibration sensors, power meters, and production counters were installed on key equipment.

2. **Data Preprocessing**: The raw sensor data underwent cleaning, normalization, and feature extraction using a sliding window approach: $X_{processed} = h(X_{raw})$
   Where:
   - h() = Preprocessing function
   - X_{raw} = Raw sensor data
   - $X_{processed}$ = Processed features for ML models

3. **Real-Time Integration**: The processed data was fed into the ML models for continuous updating and prediction: $TMC_t' = f_t(X_t)$
   Where:
   - TMC_t'= Predicted cost at time t
   - f_t = ML model at time t
   - X_t = Feature vector at time t

3.5 Implementation Framework
The proposed integrated framework involves the following implementation steps:
- Historical data collection for model development and training.
- Stochastic cost model development with probability distributions.
- Monte Carlo Simulation (MCS) for probabilistic cost estimation.

- Machine Learning (ML) model development for prediction and optimization.
- IoT sensor deployment for real-time data acquisition.
- Integrated software platform development for data integration and system operation.

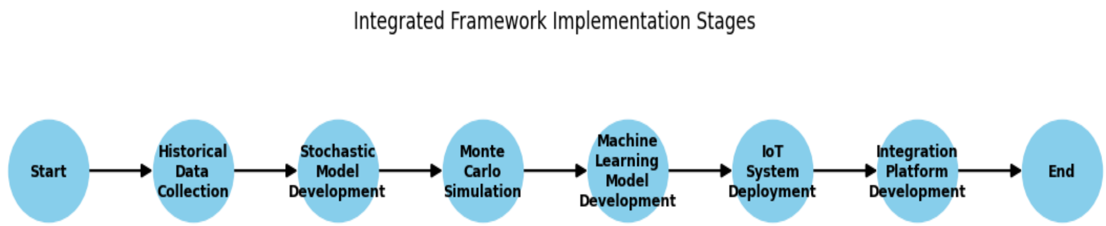

Figure 1. Integrated Framework Implementation Stages

4. Conceptual Framework for Injection Mold Manufacturing

4.1 Cost Structure for Injection Mold Manufacturing

Injection mold manufacturing has unique cost characteristics that make it well-suited to our integrated approach. First, it relies on specialized cutting tools with variable lifespans, significantly impacting total manufacturing costs. Second, the production process involves complex machining operations with multiple stages and varying precision requirements. Third, material costs for mold production can fluctuate considerably based on market conditions. Finally, the design and engineering phase represents a substantial portion of total costs, varying in complexity and cost depending on the mold's intricacy. These factors create significant challenges for traditional cost estimation methods, underscoring the need for a tailored, integrative framework for effective cost management in this sector.

For a typical injection mold, the cost structure might be represented as shown in Table 1.

Table 1. Representative Cost Structure for Injection Mold Manufacturing

Cost Component	Percentage of Total Cost	Uncertainty Level
Machine Operations	32%	Medium
Tool Costs	10%	High
Material Costs	18%	Medium
Design & Engineering	28%	High
Overhead	12%	Low

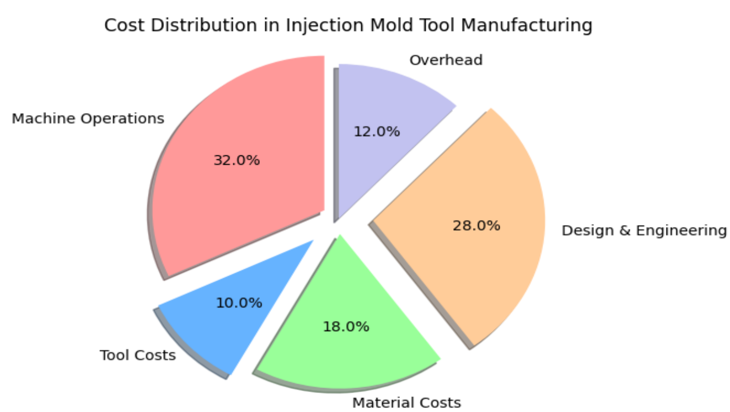

Figure 2. Cost Structure for Injection Mold Manufacturing

4.2 Monte Carlo Simulation for Injection Mold Cost Modeling

To address inherent uncertainties in injection mold manufacturing, the Monte Carlo Simulation component of our framework proceeds methodically. First, for each uncertain parameter, such as tool life or processing time, we identify the most appropriate probability distribution through historical data analysis. Next, the framework considers correlations between parameters, including the relationship between material complexity and processing time, to ensure nuanced modeling. Then, by sampling from these distributions, we generate multiple cost scenarios, creating a comprehensive view of possible outcomes. Finally, the simulation results produce probability distributions for total manufacturing costs, quantifying potential financial exposures to facilitate risk-based decision-making.
For injection mold manufacturing, MCS is particularly valuable for modeling the uncertainty in tool life and processing time, which can significantly impact overall costs.

4.3 Machine Learning Models for Injection Mold Manufacturing

The ML component of our framework incorporates specialized models tailored for injection mold manufacturing, leveraging historical production data to enhance accuracy. These models include a tool wear prediction model, where regression techniques forecast tool wear rates based on material properties, cutting parameters, and historical wear patterns, enabling proactive tool replacement and minimizing defects. Additionally, machine learning algorithms are employed to optimize machine parameters to minimize processing time while adhering to quality requirements, increasing production throughput. For design time estimation, given specific mold specifications, ML models estimate the required design and engineering hours, reducing uncertainty in this substantial cost component and improving project planning. Lastly, material usage optimization models utilize mold design specifications to minimize waste and material costs, streamlining the manufacturing process and reducing material expenses.

4.4 IoT Sensor Implementation for Injection Mold Manufacturing

The IoT component of our framework employs an array of sensors and IoT systems to collect real-time data critical to injection mold manufacturing. To monitor machine performance, sensors track key indicators for CNC machines, including spindle load, vibration levels, and energy consumption. Advanced sensors monitor tool wear in real time, enabling proactive tool replacement and preventing quality issues. IoT systems also monitor material flow, tracking material usage and waste generation for optimization. Environmental monitoring is integrated through sensors that record ambient conditions like temperature and humidity, which influence material properties and machine performance. This real-time data enables dynamic adjustments to machine parameters and maintenance schedules, enhancing manufacturing efficiency and reducing costs.

4.5 Integrated Optimization for Injection Mold Manufacturing

The integrated framework delivers several tailored optimization capabilities for injection mold manufacturing. Predictive analytics enable dynamic resource allocation across machines and operations, minimizing manufacturing time and costs. Adaptive maintenance scheduling uses predicted failure probabilities to optimize maintenance timing, reducing downtime and extending equipment life. Real-time cost tracking monitors manufacturing costs, allowing for timely intervention when deviations from forecasts occur. Furthermore, ML models enhance design optimization by suggesting modifications that maintain functionality while reducing manufacturing complexity and cost. This integration of Monte Carlo Simulation (MCS), Machine Learning (ML), and the Internet of Things (IoT) provides a comprehensive solution that advances cost optimization and operational efficiency in injection mold manufacturing.

5. Discussion and Theoretical Implications

The proposed framework significantly contributes to the theoretical understanding and practical application of cost optimization in manufacturing. By integrating uncertainty modeling (MCS) with machine learning (ML) for pattern recognition and prediction, it represents a novel approach that leverages both statistical modeling and data-driven learning. Unlike traditional static cost models, which provide a fixed view, this framework adopts a dynamic approach; it adjusts cost predictions and optimization strategies continuously as new data becomes available and conditions change. This adaptability is crucial in the dynamic manufacturing environment. Furthermore, it demonstrates how computational methods can be tailored to meet the unique challenges of injection mold manufacturing, providing a template for industry-specific adaptations and promoting a collaborative model where computational intelligence augments human decision-making.

From a practical standpoint, the framework offers multiple benefits to mold-making firms. It enhances cost estimation accuracy, supporting better pricing strategies and improved profitability. Predictive maintenance capabilities incorporated into the framework reduce unplanned downtime and extend equipment life, while machine learning algorithms optimize resource allocation to minimize waste and enhance efficiency. The framework also supports risk management by quantifying uncertainties. For example, by providing a range of likely cost outcomes, it allows businesses to better prepare for potential cost overruns. Finally, the framework adapts continuously to changing manufacturing conditions, helping it remain relevant over time.

However, the framework has limitations, which open avenues for future research. It relies heavily on substantial historical data; this could pose a challenge for smaller manufacturers that have limited data collection capabilities. The integration of multiple computational methods also introduces complexity, potentially creating implementation challenges for firms with limited technical expertise. Currently focused on injection mold manufacturing, the framework's applicability to other sectors needs further validation. Future research should aim to develop more streamlined implementation models for less technically resourced manufacturers, explore transfer learning to reduce data requirements, test the framework across different manufacturing environments to confirm its broad applicability, and enhance the explainability of model predictions and recommendations to better support manufacturing personnel

6. Conclusion

This research presented an integrated conceptual framework for manufacturing cost optimization in mold-making firms, combining Monte Carlo Simulation, Machine Learning, and Industry 4.0 technologies. The framework addresses the limitations of traditional cost estimation approaches by incorporating uncertainty modeling, predictive analytics, and real-time data processing. The key contributions of this work include a comprehensive methodology for integrating stochastic modeling and machine learning techniques for manufacturing cost optimization, specifically tailored to mold-making operations. Furthermore, it outlines a practical implementation approach that leverages Industry 4.0 technologies for real-time data collection and processing, enabling dynamic cost optimization. Finally, it includes the identification of key cost drivers in mold-making operations through sensitivity analysis, providing insights for targeted optimization efforts. This integrated approach offers mold-making firms a powerful tool for enhancing operational efficiency and profitability in an increasingly competitive market, representing a significant advancement in manufacturing cost optimization for the Industry 4.0 era.

References

.Ben-Daya, M., Hassini, E., and Bahroun, Z., Internet of things and supply chain management: a literature review, *International Journal of Production Research*, vol. 57, no. 15-16, pp. 4719-4742, 2017.

Da Xu, L., Xu, E. L., and Li, L., Industry 4.0: state of the art and future trends, *International Journal of Production Research*, vol. 56, no. 8, pp. 2941-2962, 2018.

Frank, A. G., Dalenogare, L. S., and Ayala, N. F., Industry 4.0 technologies: Implementation patterns in manufacturing companies, *International Journal of Production Economics*, vol. 210, pp. 15-26, 2019.

Ghadge, A., Dani, S., Chester, M., and Kalawsky, R., A systems approach for modelling supply chain risks, *Supply Chain Management: An International Journal*, vol. 18, no. 5, pp. 523-538, 2013.

Hammersley, J. M. and Handscomb, D. C., *Monte Carlo Methods*, Methuen, 1964.

Hoffman, F. O. and Hammonds, J. S., Propagation of uncertainty in risk assessments: the need to distinguish between uncertainty due to lack of knowledge and uncertainty due to variability, *Risk Analysis*, vol. 14, no. 5, pp. 707-712, 1994.

Kagermann, H., Wahlster, W., and Helbig, J., Recommendations for Implementing the Strategic Initiative Industrie 4.0, Final Report of the Industrie 4.0 Working Group, 2013.

Koltai, T. and Gallina, V., Formulation of workforce skill constraints in assembly line balancing models, *Optimization and Engineering*, vol. 14, 2013.

Kroese, D. P., Taimre, T., and Botev, Z. I., *Handbook of Monte Carlo Methods*, John Wiley & Sons, 2013.

Kuo, C. F. J., Su, T. L., Jhang, P. R., Huang, C. Y., and Chiu, C. H., Using the Taguchi method and grey relational analysis to optimize the flat-plate collector process with multiple quality characteristics in solar energy collector manufacturing, *Energy*, vol. 118, pp. 1243-1253, 2017.

Marseguerra, M. and Zio, E., Optimizing Maintenance and Repair Policies via a Combination of Genetic Algorithms and Monte Carlo Simulation, *Reliability Engineering & System Safety*, vol. 68, no. 1, pp. 69-83, 2000.

Mourtzis, D., Doukas, M., and Bernidaki, D., Simulation in Manufacturing: Review and Challenges, *Procedia CIRP*, vol. 25, pp. 213-229, 2014.

Mourtzis, D., Doukas, M., and Vandera, C., Smart mobile apps for supporting product design and decision-making in the era of mass customisation, *International Journal of Computer Integrated Manufacturing*, vol. 30, no. 7, pp. 690-707, 2017.

Mourtzis, D., Vlachou, K., and Zogopoulos, V., Cloud-based augmented reality remote maintenance through shop-floor monitoring: A product-service system approach, *Journal of Manufacturing Science and Engineering*, vol. 139, no. 6, 061011, 2017.

Myrelid, A. and Olhager, J., Hybrid manufacturing accounting in mixed process environments: A methodology and a case study, *International Journal of Production Economics*, vol. 210, pp. 137-144, 2019.

Ning, F., Shi, Y., Cai, M., Xu, W., and Zhang, X., Manufacturing cost estimation based on the machining process and deep-learning method, *Journal of Manufacturing Systems*, vol. 56, pp. 11-22, 2020.

Ogunfowora, O. and Najjaran, H., Reinforcement and Deep Reinforcement Learning-Based Solutions for Machine Maintenance Planning, Scheduling Policies, and Optimization, *Journal of Manufacturing Systems*, vol. 70, pp. 244-263, 2023.

Sobol, I. M., Global sensitivity indices for nonlinear mathematical models and their Monte Carlo estimates, *Mathematics and Computers in Simulation*, vol. 55, no. 1-3, pp. 271-280, 2001.

Spedding, T. A. and Sun, G. Q., Application of discrete event simulation to the activity based costing of manufacturing systems, *International Journal of Production Economics*, vol. 58, no. 3, pp. 289-301, 1999.

Wang, J., Ma, Y., Zhang, L., Gao, R. X., and Wu, D., Deep learning for smart manufacturing: Methods and applications, *Journal of Manufacturing Systems*, vol. 48, pp. 144-156, 2018.

Wang, X. V., Wang, L., Mohammed, A., and Givehchi, M., Ubiquitous manufacturing system based on Cloud: A robotics application, *Robotics and Computer-Integrated Manufacturing*, vol. 45, pp. 116-127, 2017.

Wuest, T., Weimer, D., Irgens, C., and Thoben, K. D., Machine learning in manufacturing: advantages, challenges, and applications, *Production & Manufacturing Research*, vol. 4, no. 1, pp. 23-45, 2016.

Zheng, P., Wang, H., Sang, Z., Zhong, R. Y., Liu, Y., Liu, C., Mubarok, K., Yu, S., and Xu, X., Smart manufacturing systems for Industry 4.0: Conceptual framework, scenarios, and future perspectives, *Frontiers of Mechanical Engineering*, vol. 13, no. 2, pp. 137-150, 2018.

Zhong, R. Y., Xu, X., Klotz, E., and Newman, S. T., Intelligent Manufacturing in the Context of Industry 4.0: A Review, *Engineering*, vol. 3, no. 5, pp. 616-630, 2017.

Biography

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