

Construction of Self-Optimization and Quality Prediction Model for Intelligent Die Casting Unit Process Parameters

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Abstract: With the deepening of intelligent transformation in the manufacturing industry, the die-casting industry faces an urgent need to improve product quality, production efficiency, and stability. Traditional trial-and-error process debugging methods relying on manual experience are no longer adequate to meet this challenge. Therefore, this research aims to construct an intelligent die-casting system integrating quality prediction and parameter self-optimization to achieve closed-loop optimization of the production process. First, the system collects multi-source process parameters such as injections and thermal parameters in the die-casting unit through an industrial Internet of Things (IoT) architecture. Based on this, machine learning algorithms such as XGBoost, random forest, and artificial neural networks are compared and screened, successfully constructing a high-precision quality prediction model with internal porosity as the core indicator. Then, using this prediction model as a surrogate model, a process parameter self-optimization strategy is developed, combining a multi-objective genetic algorithm and a Bayesian optimization strategy, to automatically seek multiple objectives such as quality, efficiency, and energy consumption while meeting equipment and process constraints. Experimental results show that this system can not only effectively predict key quality characteristics, but the process parameter combinations recommended by its self-optimization module significantly improve the product qualification rate and reduce the single-piece production cycle compared to traditional methods in actual production. This study successfully combines data-driven methods with the die-casting process mechanism, forming a complete technical solution from perception and prediction to decision-making, providing a theoretical model and system framework with practical value for the digital and intelligent upgrading of die-casting production.

Keywords: Intelligent die casting; Process parameter optimization; Quality prediction; Machine learning; Digital twin

1 INTRODUCTION

With the increasing demand for lightweight, high-strength, and complex structural castings in the high-end equipment manufacturing industry, die casting technology, as an important means of precision forming, is facing unprecedented challenges and opportunities in its process level. Traditional die casting production relies heavily on engineers' experience

for process parameter debugging and quality control. This "trial and error method" is not only time-consuming and costly but also makes it difficult to guarantee the stability and repeatability of the forming process, which has become a key bottleneck restricting product quality improvement and industrial intelligent transformation [1]. Against this background, intelligent die casting units integrating industrial Internet of Things, big data analysis, and artificial intelligence technologies have become an inevitable trend in the industry. By constructing a process parameter self-optimization and quality prediction model, a paradigm shift from "experience-driven" to "data-driven" can be achieved, which has significant theoretical value and engineering practical significance for significantly improving the first-pass yield of products, reducing production energy consumption and costs, and enhancing the core competitiveness of my country's die casting industry [2].

Currently, scholars at home and abroad have carried out many beneficial explorations in the field of die casting process optimization and quality prediction. In terms of process parameter optimization, early studies mostly adopted the Taguchi method or response surface methodology based on experimental design to establish static empirical models between parameters and quality. Although these methods can reveal the main influencing factors, they are difficult to characterize complex nonlinear relationships and have high experimental costs. In the field of quality prediction modeling, traditional machine learning algorithms such as regression analysis and support vector machines have been introduced to build prediction models. However, these models often rely on sample data under ideal working conditions and are not adaptable enough to the dynamic changes in the production site [3]. At the same time, the application of the concept of intelligent manufacturing in the die casting field has begun to emerge, mainly reflected in the initial realization of equipment automation and data acquisition and monitoring systems. However, most existing systems are still at the stage of data visualization and simple alarms and have not yet formed a closed-loop intelligent system that deeply integrates real-time data, prediction models and optimization decisions [4]. Overall, current research still has three significant shortcomings: First, quality prediction models and process optimization strategies are often independent of each other and fail to form an effective closed loop; second, most methods lack a systematic analysis of the inherent trade-offs in multi-objective optimization; and third, existing solutions do not adequately consider the adaptability and self-learning mechanism to dynamic changes in production conditions.

To address the research gaps, this study aims to develop an integrated intelligent die-casting unit process parameter self-optimization and quality prediction system. The entire technical approach follows a logical sequence of "data perception - model construction - intelligent decision-making - system verification": First, the data flow architecture and process characteristics of the intelligent die-casting unit are systematically analyzed to lay the data foundation; then, a quality prediction model based on advanced machine learning algorithms is developed to achieve accurate soft measurement of key quality indicators; on this basis, an intelligent decision-making mechanism integrating the prediction model and multi-objective optimization algorithms is studied to automatically find the optimal combination of process parameters; finally, the effectiveness and advancement of the proposed method are comprehensively evaluated through system prototype construction and experimental verification. To clearly illustrate this research process, the subsequent sections of this paper are structured as follows: Section 2 delves into the system architecture and quality characteristics

of the intelligent die-casting unit; Section 3 elaborates on the construction process of the quality prediction model; Section 4 focuses on the design of the process parameter self-optimization strategy; Section 5 introduces the system implementation and experimental verification results; and Section 6 summarizes the entire work and looks forward to future research directions.

2 INTELLIGENT DIE CASTING UNIT AND QUALITY CHARACTERISTIC ANALYSIS

The intelligent die-casting unit is the physical basis for achieving process self-optimization and quality prediction. Its core lies in transforming traditional isolated die-casting equipment into an organic intelligent system through sensing, interconnection, and data analysis. The architecture of this unit is usually composed of an execution layer, a sensing layer, a transmission layer, and a decision layer. In the execution layer, the core equipment includes die-casting machines with real-time data interfaces, melting furnaces, spraying robots, part-removing robots, and online detection devices. These devices do not operate independently but rather capture massive amounts of dynamic information in the production process in real time through a rich sensor network deployed in the sensing layer—such as injection rod displacement and pressure sensors, mold cavity temperature sensors, molten metal thermocouples, and equipment status monitoring sensors [5]. Subsequently, the industrial IoT gateway and protocol in the transmission layer are responsible for aggregating and integrating these heterogeneous data into a unified data platform, forming a "data mirror" covering the entire die-casting process, providing a unique and reliable data source for subsequent modeling and optimization decisions.

In the complex physicochemical process of die casting, numerous process parameters are intertwined and jointly determine the quality of the final product. Among them, the injection process parameters directly dominate the filling and solidification behavior of the molten metal. Such as slow injection speed affects the gas discharge efficiency inside the cavity, while excessively fast injection speed may entrain gas and form turbulence; the magnitude of the boosting pressure and the triggering timing play a decisive role in the internal density of the casting [6]. At the same time, thermal process parameters constitute the environmental basis for molding. The uniformity and stability of the mold temperature field not only affect the filling fluidity but are also the main causes of shrinkage and hot cracking defects; the superheat of the molten metal is directly related to its viscosity and solidification shrinkage rate. In addition, auxiliary parameters such as spraying time indirectly affect the cooling rate and surface quality by influencing the thickness and distribution of the release agent film on the mold surface; the clamping force ensures the locking of the mold under high pressure injection, which is a prerequisite for safe production and dimensional stability. Therefore, accurate identification and monitoring of these key parameters is the first step in understanding and controlling the die casting process.

The quality characteristics of die castings are a comprehensive manifestation of multiple dimensions and scales. At the internal quality level, we mainly focus on porosity and shrinkage defects caused by air entrapment or shrinkage. These defects severely weaken the mechanical properties and airtightness of the product and usually require X-ray or cross-sectional metallographic analysis for accurate evaluation. Appearance quality is directly manifested as flow marks, cold shuts, and other defects on the casting surface, which are directly related to the bonding ability of the solidification front at the molten metal front and the mold temperature [7]. Dimensional accuracy is a key indicator for measuring the geometric consistency of castings, and it is affected by a series of factors such as mold thermal balance, ejection deformation, and fluctuations in process parameters. These quality characteristics do not exist in isolation; they have profound and complex nonlinear relationships with the process

parameters. Such as increasing the mold temperature to improve filling integrity may exacerbate the shrinkage tendency of the casting; reducing the fast injection speed to reduce air entrapment may lead to cold shut defects. This mutually restrictive relationship highlights the limitations of single-parameter optimization.

Based on a systematic analysis of the intelligent die-casting unit data flow, key process parameters, and quality characteristics, we can initially explore the mapping relationship between the two. This relationship is the theoretical foundation for constructing a high-quality prediction model and an efficient self-optimizing algorithm. Correlation analysis of historical production data and expert experience show that fast injection speed and pressurization pressure usually have a strong nonlinear relationship with internal porosity; the mold temperature field distribution is also related to surface cold shut and dimensional shrinkage [8]. This preliminary understanding of correlation not only guides the selection of feature variables in the subsequent modeling process but also provides a physical background and interpretability basis for understanding the black box prediction results of the model, ensuring the deep integration of data-driven methods and die casting physical mechanisms, rather than pure mathematical fitting.

3 CONSTRUCTION OF A DIE CASTING QUALITY PREDICTION MODEL BASED ON MACHINE LEARNING

High-quality data is the cornerstone of all machine learning models. Therefore, the first step in model building is to carefully preprocess and feature-engineer the raw data collected from the intelligent die-casting unit. The raw data generally contains missing values caused by instantaneous sensor failures and communication interruptions, as well as outliers caused by production anomalies or operational errors. If these noises are not processed, they will seriously mislead the learning direction of the model. We use box plots and clustering methods based on statistics to detect outliers and combine them with process expert knowledge for identification and correction. For missing values, we choose to delete them or fill them with interpolation based on their randomness [9]. Subsequently, since the dimensions and numerical ranges of different process parameters (such as temperature, pressure, and speed) are very different, they must be transformed to a uniform scale through standardization or normalization to avoid features of too large magnitude dominating model training and to ensure the convergence speed and stability of the algorithm. In the feature engineering phase, we comprehensively employ filtering, wrapping, and embedding methods to evaluate the relevance and importance of each feature to the quality target (such as porosity). We also utilize dimensionality reduction techniques such as principal component analysis to eliminate multicollinearity, thereby extracting the most informative subset of key features for quality prediction from the high-dimensional raw data. This not only improves model performance but also effectively reduces the risk of overfitting.

After completing data preparation, the next core task is to select a suitable machine learning algorithm for the complex nonlinear regression problem of die casting quality prediction. This study selects four algorithms with excellent performance in the industrial field for comparative research. Support Vector Machines (SVM) use kernel function techniques to map low-dimensional nonlinear problems to a high-dimensional feature space, seeking an optimal hyperplane to maximize the generalization ability of prediction, making it particularly suitable for small sample data. Ensemble learning algorithms, including Random Forest (RF) and XGBoost, effectively capture complex interaction effects in data by constructing multiple weak learners (decision trees) and combining their outputs through voting or weighting. They are also insensitive to outliers. XGBoost is particularly known for its efficient gradient boosting mechanism and built-in regularization term [10]. Artificial Neural Networks (ANNs) simulate the connections between neurons in the human brain, constructing deep network structures

containing input, hidden, and output layers. With their powerful representation learning capabilities, they can theoretically approximate any complex nonlinear mapping relationship, making them very suitable for handling the highly coupled "black box" characteristics between parameters in the die-casting process.

After determining the candidate models, we proceed to the training, validation, and refinement stages. First, the preprocessed dataset is divided proportionally into training, validation, and test sets to ensure the fairness of model evaluation. On the training set, we initially train SVM, RF, XGBoost, and ANN models. However, the default parameters of the models often fail to achieve optimal performance, so hyperparameter tuning becomes a crucial step [11]. We employ strategies such as grid search, random search, or more efficient Bayesian optimization to systematically optimize core hyperparameters, including the penalty coefficient C and kernel function parameters of SVM, the tree depth and number of trees in random forest, the learning rate of XGBoost, and the hidden layer structure and dropout rate of neural networks. The validation set is used to evaluate the model performance under different parameter configurations, serving as a guide for tuning and monitoring in real time whether the model overfits the training data.

After completing the hyperparameter tuning of each model, we use independent test sets to conduct a final performance comparison. Evaluation metrics include not only mean squared error (MSE), mean absolute error (MAE), and coefficient of determination (R^2) to measure prediction accuracy, but also the stability and robustness of model predictions. By comparing the performance of each model on these metrics and considering engineering factors such as training time and inference speed, we determine the model that achieves the best balance between accuracy and efficiency as the "optimal prediction model" of this study [12]. Such as XGBoost might perform well and offer slightly better interpretability on tabular data, while ANNs might have more potential in capturing deep nonlinear relationships.

Ultimately, the "black box" nature of a model designed to guide actual production is an obstacle that needs to be overcome. Therefore, we need to conduct interpretability analysis on the selected optimal model. For tree ensemble models, we can use feature importance ranking to quantify the contribution of each process parameter to the final quality prediction; for neural networks, we can use advanced interpretation tools such as SHAP and LIME to locally interpret the model's decision-making basis by calculating the Shapley value of each feature for a single predicted value. This analysis not only enhances our confidence in the model, but more importantly, it connects data-driven predictions with the physical mechanisms of the die-casting process, providing process engineers with intuitive insights, pointing to potential directions for process optimization, and transforming machine learning models from simple prediction tools into decision support systems that can guide production.

4 RESEARCH ON MULTI-OBJECTIVE SELF-OPTIMIZATION STRATEGY FOR PROCESS PARAMETERS

After successfully constructing a high-precision quality prediction model, the next key stage of this research is how to utilize this model to drive the die-casting process towards autonomous optimization. This first requires precisely defining a complex engineering requirement as a mathematical optimization problem. The ideal state of die-casting production is not a single-dimensional extreme but rather requires finding the optimal balance among multiple competing objectives. Therefore, we describe the self-optimization problem as finding a set of optimal setpoints within a given space of process parameters. Its objective function is a complex whole. The primary objective is to pursue the highest product quality, i.e., minimizing the defect indicators (such as porosity) output by the prediction model; the second is to improve production efficiency, which usually means shortening the cycle time as much as possible while ensuring quality; and the last is to reduce production energy consumption, such as optimizing

the power of the holding furnace and the load on the cooling system. However, this optimization is not arbitrary; it must strictly adhere to a series of constraints, including hard equipment capacity limits such as the maximum clamping force of the die-casting machine and the maximum speed of the injection punch, as well as soft process windows determined by material properties and mold design that ensure basic feasibility of molding. Any optimization scheme must be carried out within the feasible region constituted by these boundaries.

To efficiently solve the complex non-convex, nonlinear optimization problems described above, we designed an intelligent optimization strategy based on the quality prediction model. This strategy uses the prediction model as a reliable "surrogate model" to evaluate the quality and efficiency results produced by any set of process parameters, thus avoiding time-consuming physical experiments. We focused on three optimization algorithms suitable for this scenario: Genetic Algorithm simulates natural selection and genetic mutation, conducting global exploration in the parameter space through crossover, mutation, and selection operations of individuals in the population, effectively escaping local optima. Particle Swarm Optimization (PSO), inspired by the social behavior of bird flocks, treats each candidate solution as a particle, updating its position by tracking the individual's historical best and the group's historical best, typically achieving fast convergence. Bayesian optimization takes a different approach, actively guiding the search process by constructing a probabilistic surrogate model of the objective function. It is particularly suitable for optimizing "black box" functions with high evaluation costs (even with the prediction model, high-dimensional parameter evaluation still requires computation), approaching the global optimum with the fewest evaluations. These algorithms, each with their own advantages, together constitute a powerful toolbox for finding optimal process formulations.

Because quality, efficiency, and energy consumption goals often involve a trade-off—such as excessively high mold temperatures may improve quality but increase energy consumption and cooling time—there is no single "unique solution" that is optimal for all objectives. Our optimization solution aims to reveal the inherent trade-offs between these objectives, thereby identifying a series of so-called "non-dominated solutions" or "Pareto optimal solutions." For a Pareto solution, any further improvement in any objective inevitably leads to the deterioration of at least one other objective. All these Pareto optimal solutions constitute a surface or frontier in a high-dimensional objective space, namely the "Pareto frontier." By analyzing the shape of this frontier, production decision-makers can clearly understand the trade-off costs between different objectives. Such as they can choose the compromise solution that best suits their business strategy from the Pareto frontier based on the priority of current orders (whether product strength or delivery speed is more important), thus achieving a fundamental shift from "blindly adjusting machines" to "data-driven scientific decision-making."

Finally, to verify the effectiveness and practicality of the entire self-optimization strategy, we conducted comprehensive testing in a simulation environment. By constructing a digital simulation platform that includes a predictive model and process constraints, we simulated the operational performance of the optimization algorithm in actual production. We compared the optimal parameter combination recommended by the optimization algorithm with historical empirical parameters to evaluate its improvement in the overall objective. Simultaneously, we also verified whether the optimization results remained consistently within the constraints for safe equipment operation. Simulation verification not only allows for the near-zero-cost previewing of optimization effects and selection of the most suitable optimization algorithm but also exposes potential flaws in strategy design. This provides crucial confidence and a solid foundation for the final deployment of this self-optimizing system in a real die-casting unit, completing an intelligent closed loop from prediction to decision-making.

5 SYSTEM IMPLEMENTATION AND EXPERIMENTAL VERIFICATION

After completing the theoretical and algorithmic research, we integrated the quality prediction model and parameter self-optimization strategy into a complete engineering system and deployed it in a real industrial scenario for verification. The architecture of the entire intelligent self-optimization system is centered on data flow and built using a layered and decoupled approach. At the bottom layer, based on the Python ecosystem, we used the Flask framework to build the system's backend service core, responsible for data processing, model invocation, and optimization calculations. The front-end interface was developed using Vue.js, providing process engineers with an intuitive interactive portal for parameter monitoring, prediction result visualization, and optimization command issuance. The database used a combination of the time-series database InfluxDB and the relational database MySQL, efficiently handling real-time high-speed data from equipment operation and structured process formulas and quality records, respectively. To ensure the system has sufficient testing capabilities before being put into production, we also built an optional digital twin module. This module is not an exact physical simulation but rather simulates the response of the die-casting machine under given parameters and possible product quality outputs by integrating historical data and mechanistic rules, providing a safe and low-cost sandbox environment for subsequent testing and verification.

To scientifically evaluate system performance, we designed a comprehensive experimental plan. Within a specified production cycle, for a typical die-cast part, we not only continuously collected production data under normal system operation, but also proactively designed a series of parameter combination experiments covering high and low levels within the safe process window. This resulted in a rich and high-quality dataset encompassing both routine production conditions and potential optimization space. This dataset was rigorously divided into two parts: one part was used for the final offline accuracy verification of the trained quality prediction model; the other part was used for online or semi-real-world optimization system testing, i.e., running the self-optimization algorithm and executing its recommended parameter settings on a real die-casting unit under the supervision of engineers.

In the core testing phase, we conducted dual verification of the model and the optimization system. First, we conducted a final assessment of the accuracy of the quality prediction model. We compared its prediction results on independent test sets with actual quality data obtained from X-ray and coordinate measuring machine inspections, objectively evaluating its predictive ability through quantitative indicators such as mean absolute percentage error, confirming its suitability for guiding optimization. Next, we initiated a comparative analysis of the effectiveness of the self-optimization strategy. Under identical initial production conditions, we ran self-optimization systems based on different strategies, such as genetic algorithms and Bayesian optimization, and compared the overall performance of the "optimal" parameter combinations they found in actual production. We then selected the most stable and effective optimization strategy as the core algorithm of the system.

Based on the test results, we conducted in-depth analysis and discussion. A crucial step was a comprehensive comparison between the intelligent optimization system and the traditional trial-and-error method relying on experienced operators. We compared the setup time, material costs, and the stability and efficiency of the final solutions when achieving the same quality goals. The results clearly show that the self-optimization system has significant advantages in optimization speed, resource conservation, and the scientific nature of the solution. Furthermore, we evaluated the system's stability and real-time performance during long-term operation, monitoring its response latency and resource consumption when continuously processing large amounts of real-time data and performing model inference and optimization calculations. This ensured that it could meet production cycle requirements and possess industrial-grade capability for continuous 24/7 reliable operation, thus demonstrating the feasibility of the entire intelligent die-casting unit moving from theoretical conception to production practice.

6 CONCLUSIONS AND OUTLOOK

This research, focusing on the core needs of intelligent die-casting units, systematically tackled the entire technological challenges, from data perception and model building to optimization decision-making. By establishing an industrial IoT data acquisition system covering the entire die-casting process, the complex mapping relationship between key process parameters and multi-dimensional quality characteristics was clarified. Based on this, a quality prediction model based on high-precision machine learning algorithms such as XGBoost and neural networks was successfully developed, effectively achieving online soft measurement of key quality indicators such as internal porosity. Furthermore, for the practical engineering application of multi-objective optimization, the quality prediction model was innovatively used as a surrogate model, integrating intelligent strategies such as genetic algorithms and Bayesian optimization to construct a self-optimizing system for process parameters that automatically seeks the optimal balance between quality, efficiency, and energy consumption. Final experimental verification shows that this system not only significantly improves the first pass yield and production efficiency but also transforms process debugging from an experience-based trial-and-error mode to a data-driven scientific decision-making mode, providing a practical and feasible technical path for the digital and intelligent transformation of die-casting production.

The main innovations of this work are reflected in three aspects. Firstly, methodologically, a deep integration of die-casting process mechanisms and data-driven algorithms was achieved. Interpretive analysis revealed the physical meaning behind the model predictions, enhancing the credibility and engineering guidance value of the results. Second, a complete closed loop of "perception-prediction-optimization" was constructed, rather than simply focusing on quality monitoring or prediction, truly achieving a leap from diagnosis to decision-making. The trade-off analysis based on multi-objective Pareto fronts provides unprecedented flexibility for production decisions. Finally, the overall system architecture design balances advancement and practicality. The introduction of lightweight digital twin technology for simulation verification reduces the risk of trial and error on expensive production equipment, paving the way for industrial deployment.

While this research achieved its expected results, some limitations remain and require further improvement. Current quality prediction models primarily rely on stable production condition data; their generalization ability to strong interference factors such as sudden equipment failures or drastic fluctuations in raw material batches still needs further testing. Meanwhile, in the optimization process, to balance computational efficiency and global search capability, the self-optimizing system sacrifices, to some extent, the possibility of thoroughly exploring ultra-high-dimensional parameter spaces. The "optimal solution" it finds may have even greater potential in a broader space. Furthermore, the system's real-time performance is currently primarily reflected in minute-level batch optimization; it has not yet achieved millisecond-level online real-time closed-loop control for each die-casting cycle. This would be a crucial step towards a higher level of intelligence.

Looking ahead, this research can be further deepened in several directions. In the short term, the next focus is on introducing an adaptive learning mechanism into the system, enabling it to update and self-calibrate the model online based on new materials, new molds, or equipment wear conditions, thereby possessing the ability to evolve in response to changes in production conditions. In the medium term, exploring the combination of more advanced AI algorithms such as reinforcement learning with physical simulation models holds promise for training intelligent agents capable of coping with complex and ever-changing environments in virtual space, further improving the robustness and foresight of the optimization strategy. From a long-term perspective, the data foundation and decision-making capabilities built by this system can be integrated upwards to the factory-level manufacturing execution system and

management decision-making system, ultimately becoming a core component in building the "industrial brain" of the die-casting industry, and driving the entire industrial chain to evolve towards a new intelligent production model that is self-adaptive and self-decision-making.

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