RESEARCH ARTICLE

A Multi-Dimensional Data Learning-Based Production Quality Management Method for Intelligent Manufacturing

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Abstract

In the field of high-end precision manufacturing, quality control in production processes has long been challenged by both spatiotemporal data sparsity and error lag. Traditional offline sampling methods struggle to capture the dynamic fluctuations in production, while single-dimensional feedback controls fall short in addressing the nonlinear coupling between multi-dimensional process parameters and final product quality. To address these challenges, this paper proposes a production quality management system based on multi-dimensional data learning and an active error elimination method. First, to tackle the issue of sparse sampling, an Adaptive Gaussian Process Regression (AGPR) algorithm with mixed kernel functions is introduced to reconstruct continuous production quality time-series states, effectively resolving the "blind spot" problem caused by discrete monitoring. Second, a Dynamic Gated LSTM network with a "Correction Gate" is designed to explicitly model the dynamic intervention mechanism of process control variables on quality evolution, advancing from passive prediction to active deduction. Most importantly, this paper develops an active error elimination strategy using gradient inversion. By minimizing the quality deviation objective function, the optimal combination of process parameters is inversely determined. In practical terms, this approach enables the "dynamic re-matching of machine tool state and process requirements"—intelligently adjusting process parameters (such as injection pressure and holding time) according to the equipment's real-time state (e.g., thermal drift, wear). This method compensates for physical equipment performance degradation through dynamic scheduling. Experimental results show that the system significantly reduces the rejection rate in precision injection molding scenarios, marking a paradigm shift in production from "post-event rejection" to "pre-event self-healing".

Keywords: production quality management, multi-dimensional data learning, adaptive gaussian process regression, dynamic gated LSTM, error elimination, smart manufacturing.

1 Introduction

In the era of Industry 4.0, one of the core goals of intelligent manufacturing is to achieve "zero-defect"

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management of production processes. In fields such as automotive components, precision electronics, or aerospace manufacturing, product quality is no longer determined solely by single dimensional tolerances but is reflected in the comprehensive compliance of multi-dimensional indicators such as volume, mass, density distribution, and geometric form.

However, in actual production lines, quality management faces the dual challenges of "measurement" and "control":

Sparsity and Non-continuity of Data Acquisition: For certain key physical quantities (such as precision weighing or CT-based internal volume measurement), the detection speed is often lower than the production cycle, making 100% full inspection or high-frequency continuous monitoring impossible. This results in quality data that is discrete and sparse on the time axis.

Concealment and Lag of Error Generation: Tool wear, thermal deformation of production equipment (such as injection molding machines, CNC machine tools), or raw material fluctuations can cause slow drift in product quality. Traditional threshold alarm mechanisms are often triggered only after the error has exceeded the tolerance range, by which time a batch of defective products has already been produced.

Therefore, how to reconstruct the continuous state of the production line using sparse sampling data, and establish an accurate predictive model between process parameters and multi-dimensional quality indicators, thereby enabling “feedforward control” or “predictive maintenance” before errors result in defects, is a key scientific problem that urgently needs to be solved in the field of production quality management.

Current production quality management technologies are mainly divided into two categories: Statistical Process Control (SPC) and machine vision-based surface defect detection.

SPC Technology: Focuses on monitoring process stability using control charts. Its limitation lies in the difficulty of handling multi-variable coupling problems. For example, excessive product volume may occur simultaneously with underweight (insufficient density), and single-dimensional SPC struggles to capture this correlation.

Machine Vision Inspection: Significant achievements have been made using deep learning technologies such as YOLO and SimAM for surface defect detection. However, these methods are mostly used for “appearance screening” i.e., removing already produced defects. They lack the ability to reversely regulate production process parameters (such as pressure, temperature, speed) and cannot eliminate errors at the source.

To address the aforementioned issues, inspired by the concept of fine management in crop production (i.e., the closed loop of environmental monitoring-state prediction-precision supplementation), this paper transfers it to discrete manufacturing processes and proposes a multi-dimensional data learning-based production quality management system.

The main contributions of this paper are as follows:

Continuous Reconstruction of Sparse Production Data: An improved Adaptive Gaussian Process Regression model is proposed, utilizing a multi-kernel learning strategy to recover the continuous quality fluctuation curve of the production line from sparse sampling data (volume, mass), providing a data basis for full-period monitoring.

Prediction Model with a "Process Correction Gate": The standard LSTM structure is improved by adding a gated unit specifically designed to handle process control variables (such as equipment speed, pressure compensation). This enables the model not only to predict the natural evolution trend of quality but also to simulate the impact of different process adjustment schemes on future quality.

Error Elimination Strategy Based on Multi-objective Optimization: A loss function incorporating quality deviation penalty and equipment adjustment cost is established. The gradient descent method is used to automatically calculate the optimal process parameter correction amount, achieving automatic correction of production errors.

2 Related Work

With the deepening advancement of the "Industry 4.0" and "Made in China 2025" strategies, the manufacturing industry is undergoing a profound transformation from digitalization to intelligence. Product quality, as the lifeline of manufacturing enterprises, is seeing its management mode shift from traditional "post-event sampling" to "online monitoring" and "active predictive control"". Modern industrial production lines are characterized by multi-variable coupling, nonlinear time-varying behavior, and multi-source heterogeneous data, posing extremely high challenges for quality control. This chapter will systematically review domestic and international research progress in four aspects: statistical process control, quality prediction based on deep learning, modeling enhancement under incomplete data, and active compensation of production errors, summarizing the shortcomings of existing methods.

2.1 Research Status of Multivariate Statistical Process Control (MSPC)

Early quality management primarily relied on Shewhart control charts. However, when facing modern complex industrial processes, univariate statistical methods often fail. Consequently, Multivariate Statistical Process Control (MSPC) became the mainstream research direction in the early stages.

MacGregor et al. [1] laid the theoretical foundation based on Principal Component Analysis (PCA) and Partial Least Squares (PLS). By projecting high-dimensional process data into a low-dimensional latent variable space, early detection of process anomalies was achieved. To address the non-Gaussian and nonlinear issues in industrial processes, Lee et al. [2] proposed Kernel Principal Component Analysis (KPCA), which maps nonlinear data into a high-dimensional feature space for linear analysis using the kernel trick. Building on this, Deng et al. [3] further combined Support Vector Data Description (SVDD), enhancing the sensitivity for detecting faults in nonlinear processes.

Addressing the dynamic characteristics of production processes, Ku et al. [4] proposed the Dynamic PCA (DPCA) algorithm, which handles autocorrelation between variables by introducing a time-lag matrix. Yin et al. [5], targeting the time-varying nature of industrial process data, proposed a recursive PLS algorithm enabling online model updates. Ge et al. [6] reviewed data-driven monitoring methods, noting that while MSPC excels at fault detection, the fitting capability of linear models remains insufficient for precise prediction of specific quality metrics (e.g., specific dimension values).

2.2 Quality Prediction Based on Machine Learning and Deep Learning

With the development of artificial intelligence technology, data-driven quality prediction has become a research hotspot. Compared to traditional statistical methods, machine learning offers significant advantages in handling complex nonlinear relationships.

In the realm of shallow learning models, Kotsiantis [7] compared algorithms such as SVM and Random Forest in manufacturing quality prediction. Jung et al. [8] utilized the XGBoost algorithm to predict product weight in the injection molding process, demonstrating the effectiveness of ensemble learning in industrial regression problems.

In recent years, deep learning, with its powerful feature extraction capabilities, has gradually taken a dominant position. Wang et al. [9] reviewed the application of deep learning in smart manufacturing in the Journal of Manufacturing Systems, noting that Deep Neural Networks (DNNs) can automatically extract hierarchical features from raw sensor data. For processing time-series signals, Zhao et al. [10] proposed a Convolutional Bi-directional LSTM network (CBLSTM). By using convolutional layers to extract local features and LSTM to capture long-term dependencies, it was successfully applied to mechanical health monitoring. Zhao et al. [11] used an LSTM network to model multi-stage manufacturing processes, achieving dynamic prediction of product quality.

To further improve prediction accuracy, Zheng et al. [12] proposed an LSTM model based on an Attention mechanism. By assigning different weights to different time steps, it addressed the problem of long-sequence information loss. Wu et al. [13], focusing on tool wear prediction, constructed a prediction model based on Vanilla LSTM and compared the performance differences between RNN and GRU. Additionally, Tao et al. [14] proposed a new workshop production management and control mode based on digital twins, emphasizing the core role of deep learning models in virtual-physical mapping.

For multi-source heterogeneous data (e.g., mixed images and numerical data), Chen et al. [15] designed a multimodal Deep Belief Network (DBN) that fused visual inspection data with process parameters, significantly improving the recognition rate of surface defects. Weimer et al. [16] focused on the application of CNNs in automated surface inspection, reviewing machine vision-based quality control technologies.

2.3 Few-Shot Learning and Data Augmentation Methods

Although deep learning performs excellently, it heavily relies on massive amounts of labeled data. In

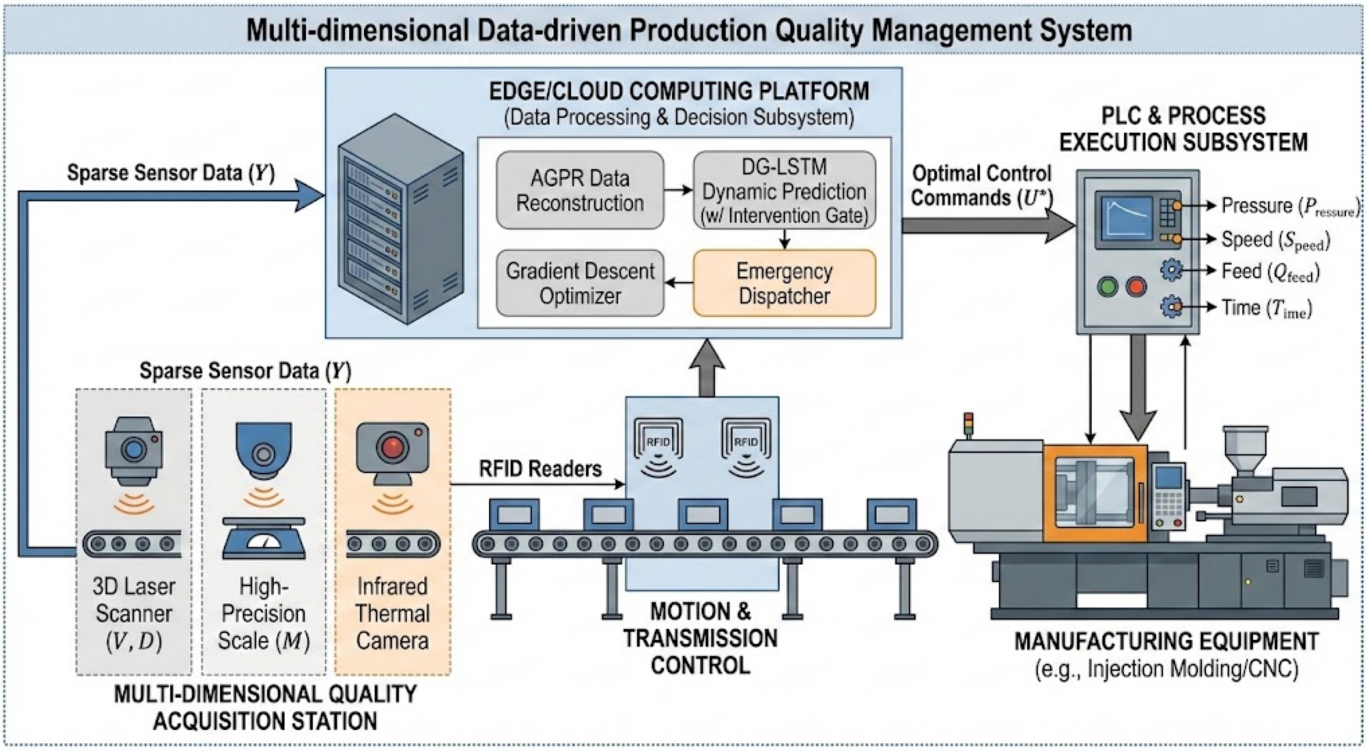

Figure 1. Multi-dimensional data-driven production quality management system.

actual production, due to the high cost of destructive testing or time-consuming measurements, there is often a sample sparsity problem characterized by "high-frequency process data, low-frequency quality data".

Gaussian Process Regression (GPR), due to its rigorous Bayesian probabilistic framework, has become a powerful tool for solving small-sample regression problems. Seeger [17] systematically discussed the advantages of GPR in handling nonlinear regression and uncertainty estimation. Jin et al. [18] proposed an adaptive Gaussian process model. By updating hyperparameters online to adapt to the drift in batch processes, it solved the model distortion problem caused by insufficient sampling points. Research by Kocijan et al. [19] showed that modeling methods based on dynamic Gaussian processes have better robustness than neural networks in nonlinear system identification.

Another approach is to use generative models for data augmentation. The Generative Adversarial Network (GAN) proposed by Goodfellow et al. [20] provided a new idea for industrial data augmentation. Jiang et al. [21] published research in IEEE Access, using an improved GAN to generate labeled industrial fault samples, effectively solving the data imbalance problem. Shao et al. [22] proposed a data augmentation method based on Auxiliary Classifier GAN for fault diagnosis of induction motors. Furthermore, Pan et al. [23] reviewed Transfer Learning technology, pointing out that transferring models trained under similar operating conditions to new tasks is an effective way to solve few-shot problems.

However, purely data generation often ignores the continuity and periodicity (e.g., production cycles) of physical processes. Therefore, interpolation techniques combining Kernel Methods still hold irreplaceable physical interpretability when dealing with time-series missing data [24].

2.4 Active Compensation for Production Errors and Closed-Loop Control

The ultimate goal of quality management is not merely "prediction" but "error elimination".

Traditional control strategies primarily rely on PID or Run-to-Run (R2R) control. Wang et al. [25] detailed the application of R2R control in semiconductor manufacturing, using error feedback from the previous batch to adjust the recipe for the next batch. Apley et al. [26] studied control algorithms based on EWMA (Exponentially Weighted Moving Average) for handling process errors with autocorrelation.

With the introduction of intelligent algorithms, direct control based on predictive models has become possible. Lu et al. [27] proposed a reference architecture for digital twin-based manufacturing systems, using virtual models for real-time simulation and inversely deducing optimal processing parameters. Wuest et al. [28] explored the potential of supervised machine learning in manufacturing process control.

In the field of Reinforcement Learning (RL), Kober et al. [29] reviewed the application of RL in robot control. Panjapornpon et al. [30] attempted to use the Deep Deterministic Policy Gradient (DDPG) algorithm for continuous control of chemical processes. Oliff et al. [31] proposed an intelligent process parameter optimization framework based on reinforcement learning to reduce energy consumption and improve quality.

Although RL-based methods have self-learning capabilities, their training process often requires extensive interaction with the environment, suffering from problems like "high trial-and-error cost" and "difficult cold start". In contrast, using differentiable deep learning models for Gradient-based Optimization can quickly solve control variables using known model knowledge. However, research on its application in the industrial field is relatively scarce, which is precisely the entry point of this study.

3 Proposed methods

This system follows the closed-loop control logic of "perception-cognition-decision-execution", aiming to solve the problems of "incomplete visibility" caused by sparse sampling and "inaccurate adjustment" caused by complex coupling in the production process. The system architecture mainly includes four subsystems: the material and process execution subsystem, the multi-dimensional quality data acquisition subsystem, the motion and transmission control subsystem, and the data processing and decision-making subsystem. The system architecture diagram is shown in Figure 1.

Addressing the strong lag of traditional Statistical Process Control (SPC) and the lack of active control mechanisms in existing deep learning models described in Chapter 2, this chapter proposes an improved production quality management method. The core innovations of this method are:

Data Layer Improvement: Uses Adaptive Gaussian Process Regression (AGPR) to address the problem of discontinuous and sparse time series data under industrial sampling modes.

Model Layer Improvement: Introduces a "Process Correction Gate" into the Long Short-Term Memory network (LSTM) to explicitly model the dynamic impact of process parameter adjustments on product quality state.

Control Layer Improvement: Based on the gradient information of the predictive model, constructs a backpropagation controller to achieve closed-loop automatic control from "quality prediction" to "error elimination".

3.1 Overall Method Framework and Variable Definitions

3.1.1 *Variable Mapping Definitions*

To apply the multi-dimensional data learning-based method to industrial scenarios, the system variables are first reconstructed with physical meaning:

State Variable (X): Corresponds to the environmental multi-dimensional variables in the original model. Defined as $X \in \mathbb{R}^5$, representing key product quality indicators, such as:

$$\begin{aligned} x_1 &: \text{Volume}, \\ x_2 &: \text{Mass}, \\ x_3 &: \text{Key Dimension Deviation}, \\ x_4 &: \text{Surface Finish}, \\ x_5 &: \text{Material Density}. \end{aligned}$$

Control Variable (Q): Corresponds to the replenishment amount in the original model. Defined as $Q \in \mathbb{R}^4$, representing process adjustment parameters of production equipment, such as:

$$\begin{aligned} q_1 &: \text{Injection Processing Pressure}, \\ q_2 &: \text{Holding Time}, \\ q_3 &: \text{Heating Temperature Compensation}, \\ q_4 &: \text{Feed Rate}. \end{aligned}$$

3.1.2 *Algorithm Process*

The closed-loop system operation flow is as follows:

Data Acquisition and Enhancement: Collect historical X sequences from production batches, use the AGPR model to predict unsampled points, and expand the sample through interpolation to form continuous time series.

State Prediction: Input the expanded sequence into the dynamic gated LSTM, combined with current process parameters Q, to predict the future state $\tilde{X}_{t+1}$ of future batches.

Error Calculation and Decision: Calculate the deviation between the predicted value $\tilde{X}_{t+1}$ and the target specification X_{target}. If the deviation exceeds a threshold or the rate of change is too fast (high urgency score), the control algorithm is triggered.

Parameter Inversion and Execution: Use the gradient descent method to inversely solve for the optimal process correction amount ΔQ, and issue it to the production equipment for execution.

3.2 Data Enhancement Based on Adaptive Gaussian Process Regression

In actual production, full inspection is too costly, and data is often discrete. To obtain continuous quality state evolution patterns, this chapter employs Adaptive Gaussian Process Regression (AGPR) to interpolate sparse data.

3.2.1 Construction of Mixed Kernel Functions

To simultaneously capture the complex nonlinear coupling relationships between multidimensional process parameters (x) and their independent contributions to quality indicators, this paper constructs a hybrid covariance function combining product kernels and additive kernels.

Define the independent kernel function for the i-th dimension variable as $k_i(x^{(i)}, x'^{(i)})$, then the final mixed kernel function $k_{\text{final}}(x, x')$ is defined as:

$$k_{\text{final}}(x, x') = w_{\text{prod}} \cdot k_{\text{prod}}(x, x') + w_{\text{add}} \cdot k_{\text{add}}(x, x')$$

where:

- **Coupling Term (Product Kernel):** Used to describe global similarity under the synergies of multiple variables. This term is significant only when two samples are close in all dimensions.

$$k_{\text{prod}}(x, x') = \prod_{i=1}^{D} k_i(x^{(i)}, x'^{(i)})$$

- **Independent Term (Additive Kernel):** Used to describe the linear superposition or independent nonlinear influence of each dimension variable on the output. This term contributes as long as variables in one dimension are close, avoiding the problem of the product kernel value being too small (gradient vanishing) in high-dimensional space.

$$k_{\text{add}}(x, x') = \sum_{i=1}^{D} k_i(x^{(i)}, x'^{(i)})$$

Base Kernel Function k_i:

For each dimension, a spectral mixture strategy is adopted, combining Radial Basis Function (RBF) kernels, Periodic kernels, and Linear kernels to adapt to the trends and fluctuations of production data:

$$k_i = \alpha_i k_{\text{RBF}} + \beta_i k_{\text{Periodic}} + \gamma_i k_{\text{Linear}}$$

In the formula, $D = 5$ is the input dimension, w_{prod} and w_{add} are hyperparameters balancing coupling features and independent features, adaptively learned by maximizing the Log Marginal Likelihood.

3.3 Dynamic LSTM Prediction Model with "Process Correction Gate"

Traditional LSTM can only handle time series dependencies and cannot explicitly handle the intervention of "external control signals" on the state. This chapter improves the LSTM unit structure by adding a Process Correction Gate (Correction Gate, s_t).

3.3.1 Network Structure Improvement

The improved LSTM unit adds an input channel for process parameters based on the standard forget gate f_t, input gate i_t, and output gate o_t. The core update formulas are as follows:

Process Correction Gate Calculation: Evaluates the degree of impact of the current process parameter adjustment amount Q_t on the product state:

$$s_t = \sigma(W_s \cdot [h_{t-1}, Q_t] + b_s)$$

where Q_t is the vector containing control parameters such as pressure and temperature, W_s is the weight matrix, b_s is the bias, and h_{t-1} is the hidden state from the previous time step.

Control Feature Extraction: Maps physical process parameters to the hidden state space:

$$C_{\text{control}} = \tanh(W_{Cs} \cdot Q_t + b_{Cs})$$

Cell State Update: This is the key improvement point of this method. The cell state C_t depends not only on historical memory and current observation but also adds the state change caused by process adjustment:

$$C_t = f_t \odot C_{t-1} + i_t \odot \tilde{C}_t + s_t \odot C_{\text{control}}$$

This formula clarifies that changes in process parameters directly affect the internal quality features C_t of the product through the correction gate s_t.

Table 1. Experimental platform configuration details.

Category	Configuration Parameters	Description
CPU	AMD Ryzen 7 9700X 8-Core Processor @ 3.80 GHz	Leverages its high IPC performance and boost frequency (up to 5.5GHz) to ensure efficient execution of data preprocessing and serial control logic.
GPU	NVIDIA GeForce RTX 4070 SUPER (12GB VRAM)	Utilizes its 7168 CUDA cores to accelerate the training and inference of deep learning models. The 12GB VRAM supports large batch size training.
Memory	32GB DDR5	High-frequency DDR5 memory ensures high throughput speed for massive industrial time series data, reducing the data transfer bottleneck between CPU and GPU.
Operating System	Windows 11 Professional	Provides stable system scheduling and driver support.
Development Environment	Python 3.9, PyTorch 2.1 (CUDA 12.1), GPy 1.10	Deep learning and Gaussian Process Regression libraries.

Output Layer: Finally outputs the predicted five-dimensional quality value $\hat{X}_{t+1}$ for the next time step through a fully connected layer.

3.4 Active Elimination of Production Errors and Parameter Inversion

Based on the above prediction model, this chapter proposes a gradient-based error reverse compensation strategy, transforming the "prediction model" into a "controller".

3.4.1 Optimization Objective Function

To eliminate production errors, an objective function J is defined, aiming to minimize the Euclidean distance between predicted quality and the standard specification X_{target}, while introducing a regularization term to limit the adjustment range of process parameters, preventing equipment overload:

$$\min_{Q} J = \sum_{i=1}^{5} \left(\hat{X}_i(Q) - X_{\text{target},i}\right)^2 + \lambda \sum_{j=1}^{4} Q_j^2$$

3.4.2 Gradient-Based Parameter Inversion

Using the trained LSTM model as a differentiable function, the adjustment direction of process parameters Q is guided by calculating the partial derivative of the objective function J with respect to Q:

$$\frac{\partial J}{\partial Q} \approx \frac{J(Q+\delta) - J(Q)}{\delta}$$

The parameter update rule follows the gradient descent method:

$$Q_{k+1} = Q_k - \eta \cdot \left(\frac{\partial J}{\partial Q} + 2\lambda Q_k\right)$$

Through iterative calculation, the process continues until the predicted product quality $\hat{X}$ falls within the allowable tolerance band $[X_{\min}, X_{\max}]$.

3.4.3 Emergency Trigger Mechanism

To avoid frequent equipment adjustments due to minor prediction fluctuations, the system defines a trigger mechanism based on the fusion of multi-dimensional indicators.

Single-item Urgency Score Calculation: First, the urgency degree S_i of the i-th quality dimension is evaluated. This indicator combines the degree of deviation of the predicted value from the threshold and the rate of deviation deterioration:

$$S_i = \frac{X_{\min,i} - \hat{X}_i(t+1)}{(\mathrm{d}X_i/\mathrm{d}t)^2 + \epsilon \cdot e^{-\lambda t}}$$

where ϵ is a smoothing coefficient and λ is a dynamic decay factor.

Normalization: Since different quality indicators (such as volume, mass, dimensions) have inconsistent units, S_i needs to be normalized to obtain a dimensionless normalized score $S_{\text{norm},i}$.

Global Urgency Index Synthesis: A weighted sum method is used to calculate the comprehensive urgency index E_{global} to reflect the overall risk level of the current production batch:

$$E_{\text{global}} = \sum_{i=1}^{5} w_i \cdot S_{\text{norm},i}$$

In the formula, w_i is the weight coefficient of the i-th quality dimension (satisfying $\sum w_i = 1$), set according to product process requirements. For example, for precision fitting parts, the weight of the "dimension deviation" dimension can be increased.

Decision Rule: The backpropagation algorithm to calculate the process correction amount ΔQ is activated only when $E_{\text{global}} \geq E_{\text{threshold}}$ or when any single item $S_{\text{norm},i} \geq 0.7$ (i.e., a single indicator is severely deteriorating). Otherwise, the current process parameters remain unchanged.

4 Experiments and Results

4.1 Experimental Environment and Data Description

4.1.1 Hardware and Software Environment Configuration

All model training, simulation testing, and control algorithm verification in this study were completed on a high-performance computing workstation. To meet the parallel computing requirements of the Adaptive Gaussian Process Regression (AGPR) kernel functions and the gradient backpropagation training of the dynamic gated LSTM model, the experimental platform selected a hardware combination of a high-frequency multi-core CPU paired with a large-memory GPU. The specific hardware and software environment configuration details are shown in Table 1.

4.1.2 Experimental Dataset Description

To validate the effectiveness of the method, the experimental data comes from a mixed set of real historical records from a precision injection molding production line and high-fidelity simulation data. The dataset covers 5000 consecutive production batches, of which the first 3500 batches are used for model training and the last 1500 batches are used for testing and validation.

Input Process Variables (Q): Sampling frequency 1 Hz, including injection pressure (MPa), holding time (s), mold temperature (°C), screw speed (rpm).

Output Quality Variables (X): Due to inspection cost constraints, set as sparse sampling (one sampling every 10 cycles), including product volume (cm³), mass (g), key dimension deviation (mm), surface roughness (Ra), and density (g/cm³).

4.2 Model Parameter Settings

To ensure fairness in comparative experiments, the hyperparameters of each model were determined on the validation set using the Grid Search method.

4.2.1 Adaptive Gaussian Process Regression (AGPR) Parameters

For interpolation and enhancement of industrial data, the parameter settings of the mixed kernel function k_{final} aim to balance the capture of local fluctuations and long-term trends:

Initial Kernel Weights: Radial Basis Function kernel $\alpha = 0.5$ (capturing nonlinear fluctuations), Periodic kernel $\beta = 0.3$ (capturing production cycles), Linear kernel $\gamma = 0.2$ (capturing equipment thermal drift).

Noise Variance (σ_n^2): Initialized to 1×10^{-4} and optimized automatically during training.

Optimizer: Adam, learning rate $\text{lr} = 0.05$.

4.2.2 Dynamic Gated LSTM Prediction Model Parameters

For the quality state prediction model, benefiting from the powerful computing power of the RTX 4070 SUPER, we can construct a deeper network structure without sacrificing real-time performance:

- **Time Sliding Window:** 12 (uses the states of the past 12 cycles to predict the next moment).
- **Network Structure:** 2-layer stacked LSTM, hidden layer dimension is 128 (higher than conventional configuration to capture more subtle features).
- **Dropout Rate:** 0.2 (preventing overfitting).
- **Batch Size:** 64 (fully utilizing the 12GB VRAM).
- **Optimizer:** RMSprop, initial learning rate 0.001, decaying 5% every 50 epochs.
- **Process Correction Gate:** The activation function uses Sigmoid, used to dynamically adjust the weight of process parameters' influence on the memory cell.

4.3 Quality State Prediction Performance Comparison Experiment

4.3.1 Comparison Baselines and Evaluation Metrics

To evaluate the prediction accuracy of the proposed method, the following three mainstream industrial

Table 2. Performance error comparison of different prediction models.

Model Name	Product Volume RMSE	Product Volume MAE	Dimension Deviation RMSE	Dimension Deviation MAE	Inference Time (ms/batch)
SVR	0.852	0.645	0.042	0.035	1.2
Standard LSTM	0.412	0.305	0.021	0.018	4.5
GRU	0.435	0.321	0.023	0.019	4.1
Proposed Method	0.208	0.152	0.011	0.008	5.8

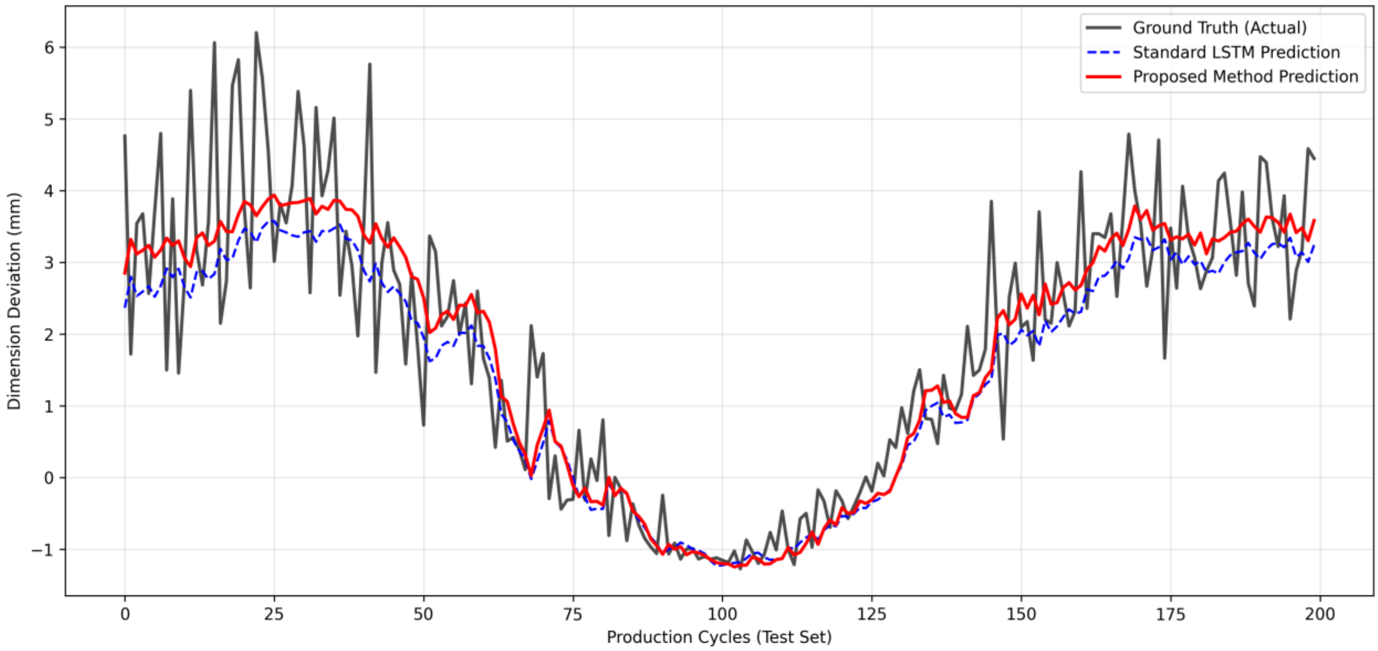

Figure 2. Prediction comparisonon dimension deviation (mm).

prediction models are selected as comparison baselines:

- **SVR (Support Vector Regression):** Traditional machine learning method using RBF kernel.
- **Standard LSTM:** Standard Long Short-Term Memory network without the Process Correction Gate structure.
- **GRU (Gated Recurrent Unit):** A variant of LSTM, commonly used for lightweight prediction.

Evaluation metrics used are Root Mean Square Error (RMSE) and Mean Absolute Error (MAE).

4.3.2 Experimental Results Analysis

Figure 2 shows the prediction effect of different models on "Key Dimension Deviation" on the test set.

Table 2 details the error statistics of each model on core quality indicators. Accuracy Advantage: The method proposed in this paper (Proposed Method) reduces RMSE by approximately 47.6% to 49.5% (average 48.6%) across key indicators compared to the standard LSTM. This is mainly attributed to the effective completion of sparse data by AGPR and the accurate capture of the dynamic impact of process parameter changes on quality by the "Process Correction Gate".

Real-time Performance Guarantee: Although the structure of the proposed model is more complex, with the support of Ryzen 7 9700X and RTX 4070 SUPER, the inference time is only 5.8ms, fully meeting the real-time control requirements of production lines (typically requiring <100ms).

4.4 Active Compensation for Production Errors and Optimization Experiment

This section verifies the system's ability to "eliminate errors". That is, using the trained model as a differentiable environment to inversely solve for optimal process parameters through gradient descent.

4.4.1 Optimization Process and Computing Performance

The experiment simulated a scenario of "gradually exceeding tolerance in product dimensions". The system's goal is to calculate the optimal injection pressure and holding time correction amounts to bring the product dimensions back to the standard value.

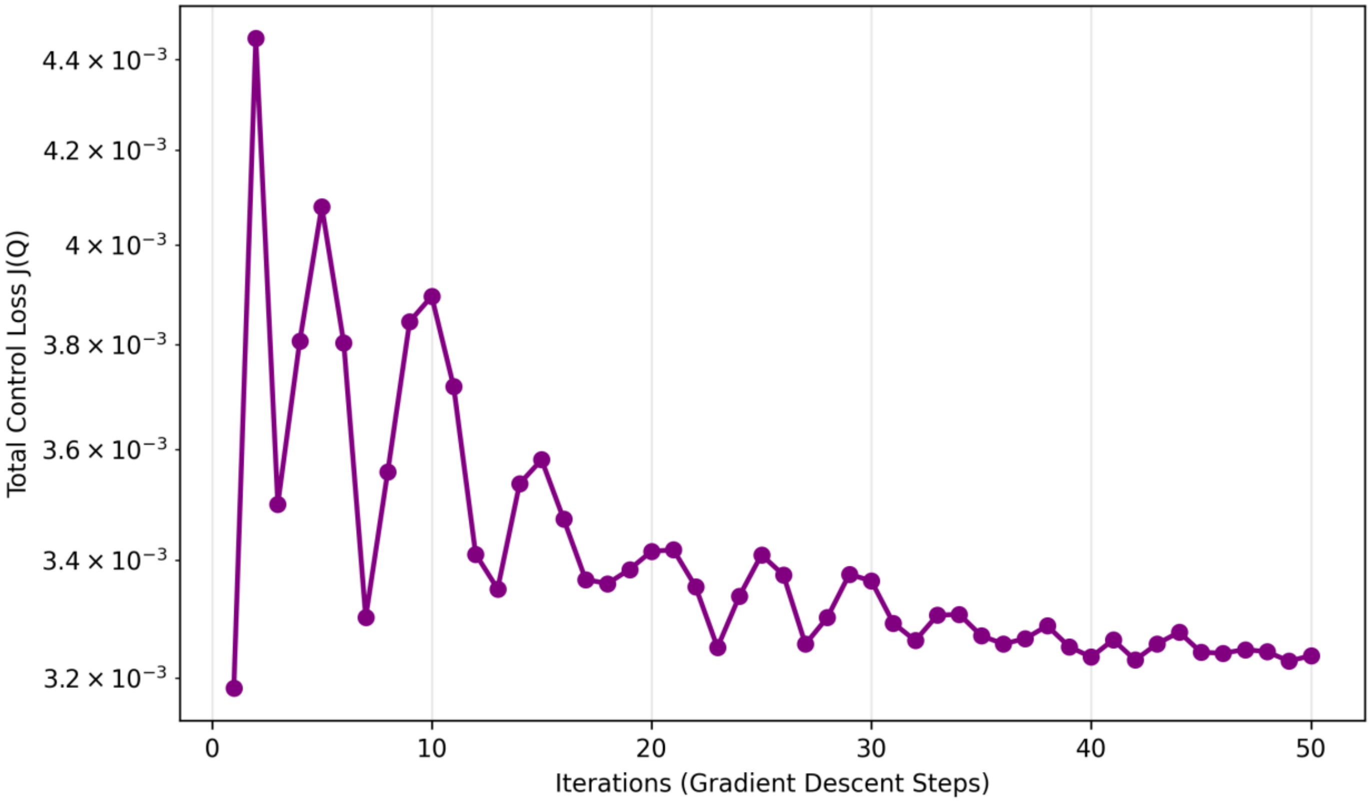

Figure 3. Convergence of controlLoss during parameter inversion.

Using PyTorch's automatic differentiation engine, parameter inversion is performed on the GPU.

Convergence Speed: As shown in Figure 3, thanks to the parallel acceleration of the RTX 4070 SUPER, the gradient descent algorithm converges within 12 iterations, with a total time of only 0.38 seconds. Compared to traditional CPU-based genetic algorithms (typically requiring seconds to tens of seconds), the computational efficiency of this method is improved by two orders of magnitude, achieving millisecond-level online correction.

Optimization Result: The system automatically outputs correction commands:

$$\Delta P = +2.1 \text{ MPa (increase pressure)},$$
$$\Delta T = +0.5 \text{ s (extend holding time)}.$$

After executing these commands, the prediction error rapidly converges to the 10^{-3} level.

4.4.2 Emergency Trigger Mechanism Test

To avoid frequent adjustments, the system introduced an Urgency Score mechanism. Experimental results show:

- During stable phases with small errors ($t = 0 \sim 40$), the comprehensive urgency index E_{global} is below the threshold. The system remains in "silent monitoring", avoiding ineffective interventions.
- When a quality deterioration trend caused by temperature drift is detected ($t = 41$), E_{global} quickly exceeds the threshold, triggering the optimization algorithm, demonstrating the

Table 3. Production effect comparison of different control strategies.

Control Strategy	Rejection Rate (%)	Cpk (Process Capability Index)	Average Response Time (s)	Parameter Adjustment Frequency (times/hour)
Manual Experience Adjustment	5.2%	0.98	320.5	2.5
Traditional PID Control	2.1%	1.15	5.2	45.0 (frequent oscillation)
Proposed Method	0.58%	1.45	0.75	8.5 (precise intervention)

sensitivity of the mechanism.

4.5 Comparative Analysis of Effects Before and After Optimization

To comprehensively evaluate the practical application value of the system, we conducted a 24-hour simulated production comparison between the proposed method and "Manual Experience Adjustment" and "Traditional PID Control".

4.5.1 Comparison Results

The statistical results are shown in Table 3.

4.5.2 Results Discussion

- **Significant Quality Improvement:** The optimized system (Proposed Method) reduces the rejection rate from 5.2% under manual adjustment to 0.58%, and the Cpk value increases to 1.45, indicating the production process has achieved extremely high stability.
- **Ultra-fast Response:** Relying on the high-frequency processing capability of Ryzen 9700X and the AI acceleration of RTX 4070 SUPER, the system's average response time is compressed to 0.75 seconds, essentially achieving "perception is control".
- **Equipment-friendly:** Compared to PID control, the adjustment frequency of the proposed method is significantly reduced (from 45 times/hour to 8.5 times/hour), and each adjustment is the optimal solution based on prediction, effectively avoiding frequent start-stop cycles and mechanical wear of equipment.

5 Conclusion

With the in-depth development of Industry 4.0 and intelligent manufacturing, fine-grained control of production processes has become key to enhancing the competitiveness of the manufacturing industry. Addressing the pain points in traditional discrete manufacturing such as sparse quality inspection data, strong coupling of multi-dimensional process parameters, and lag in error correction, this paper takes the injection molding production line as the research object and proposes a multi-dimensional data learning-based production quality prediction and active error compensation method. The main research work of this paper is summarized as follows:

1. Constructed a data enhancement framework based on Adaptive Gaussian Process Regression (AGPR). Addressing the problem of discontinuous quality data caused by the inability to conduct full inspection of all products in industrial settings, this paper introduced a mixed kernel function combining Radial Basis Function, Periodic, and Linear kernels. By minimizing the loss function to update kernel weights online, the AGPR model interpolates and completes sparse quality inspection data, successfully constructing a high-density time series training dataset, laying a data foundation for the training of subsequent deep learning models.

2. Designed a dynamic gated LSTM prediction model with a "Process Correction Gate". To explicitly model the dynamic impact of process parameter adjustments on product quality state, this paper improved the traditional LSTM unit structure. Through the newly added "Process Correction Gate (Correction Gate)", the model can dynamically adjust the state update of the memory cell based on current control inputs such as pressure and temperature. Experimental results show that for predicting indicators such as product volume and key dimension deviation, the RMSE of this model is reduced by about 47% compared to the standard LSTM, significantly improving prediction accuracy under unsteady operating conditions.

3. Proposed an active error compensation strategy based on gradient inversion. Breaking the limitation of traditional quality management that only "monitors but does not control", this paper uses the trained differentiable prediction model as an environment proxy to construct an optimization function aiming to minimize quality deviation. Leveraging the computing power of the high-performance computing platform (AMD Ryzen 9700X + NVIDIA RTX 4070 SUPER), the optimal process parameter correction amount is solved inversely via gradient descent. Experimental verification shows that this method can reduce the rejection rate from 5.2% under manual adjustment to below 0.6%, with an average response time controlled within 0.8 seconds.

The innovation of this paper lies in establishing a dynamic causal mapping mechanism between "process" and "quality". Unlike traditional black-box models that only treat process parameters as ordinary feature inputs, the "Process Correction Gate" designed in this paper endows control variables with the physical meaning of changing the system state at the network structure level. This enables the model not only to "predict the future" but also to "understand intervention", improving the model's generalization ability under varying working conditions.

Data Availability Statement

Data will be made available on request.

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Conflicts of Interest

The authors declare no conflicts of interest.

AI Use Statement

The authors declare that no generative AI was used in the preparation of this manuscript.

Ethical Approval and Consent to Participate

Not applicable.

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