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Optimization of Silicone Rubber Production Process Based on Machine Learning — A Case Study of Shenzhen Xiongyu Rubber Hardware Products Co., Ltd.

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Abstract

With the advancement of Industry 3.0, the manufacturing sector is increasingly demanding intelligent and efficient production processes. Silicone rubber, an essential industrial material, plays a vital role in various sectors such as electronics, automotive, and medical industries. Optimizing its production process is crucial for enhancing product quality, reducing production costs, and strengthening corporate competitiveness. This study takes Shenzhen Xiongyu Rubber Hardware Products Co., Ltd. as a case to explore how machine learning technology can be utilized to monitor and optimize the production process of silicone rubber. By collecting and analyzing a large amount of production data and combining it with machine learning algorithms, a production process optimization model has been developed and tested in actual production. The results indicate that the optimization scheme based on machine learning can significantly improve production efficiency and product quality, offering new ideas and methods for the technological upgrading and management innovation of silicone rubber production enterprises. Finally, suggestions for further optimization and future research directions are proposed.

Keywords: machine learning, silicone rubber, production process optimization, production efficiency, product quality, Shenzhen Xiongyu Rubber Hardware Products Co., Ltd., intelligent manufacturing, big data

1. Introduction

1.1 Research Background

Silicone rubber is widely used in various fields such as electronics, automotive, and medical due to its excellent properties, including resistance to high and low temperatures, ozone, and electrical insulation. However, the traditional production process is complex, with low efficiency and unstable quality. The increasing market competition and environmental protection requirements are driving enterprises to seek new methods for optimizing production. Against the backdrop of Industry 3.0, machine learning technology offers new opportunities for the optimization of silicone rubber production.

1.2 Research Objectives and Significance

This study aims to optimize the silicone rubber production process of Shenzhen Xiongyu Rubber Hardware Products Co., Ltd. using machine learning technology. The objectives include analyzing production bottlenecks, developing an optimization model, and proposing a comprehensive optimization plan. Theoretically, this research enriches the application studies of machine learning in industrial production optimization. Practically, it helps enterprises reduce costs, enhance competitiveness, and provides references for the industry.

1.3 Research Content and Methods

The research content covers the analysis of production processes, a review of the application of machine learning, data collection and preprocessing, model development, and the design and testing of optimization plans. The methods employed include literature research, case analysis, and data analysis, combined with machine learning algorithms to uncover potential patterns in production data.

2. Literature Review

2.1 Overview of Silicone Rubber Production Process

2.1.1 Production Process Flow

The production process of silicone rubber is a complex multi-step procedure, mainly including raw material preparation, mixing, shaping, and vulcanization. Initially, raw materials (such as silicone rubber raw gum, fillers, vulcanizing agents, etc.) need to be precisely proportioned and preprocessed. In the mixing stage, the raw materials are blended in an internal mixer or open mill to ensure uniform distribution of all components. During the shaping stage, the mixed rubber is formed into the desired shape according to product requirements through extrusion, compression molding, or injection molding. Finally, in the vulcanization process, the silicone rubber is cured by heating or chemical reactions to obtain the final product. The entire production process requires strict control of process parameters, such as temperature, pressure, and time, to ensure the stability and consistency of product quality.

2.1.2 Analysis of Influencing Factors

In the production process of silicone rubber, multiple factors significantly affect product quality and production efficiency. Studies have shown that the quality and proportion of raw materials are fundamental factors influencing product performance. For example, the type and amount of filler directly affect the mechanical strength and heat resistance of silicone rubber. The control of temperature and time during the mixing process is crucial for the uniformity and dispersion of the rubber compound. Inadequate mixing can lead to inconsistent product performance. Additionally, shaping process parameters (such as mold temperature and injection speed) and vulcanization conditions (such as vulcanization temperature and time) also significantly impact the dimensional accuracy and physical properties of the product. Therefore, optimizing these process parameters is essential for improving the efficiency and quality of silicone rubber production.

2.2 Application of Machine Learning Technology in Industrial Production

2.2.1 Overview of Machine Learning Technology

Machine learning is an important branch of artificial intelligence that enables computer systems to learn and improve automatically from data through algorithms. Common machine learning algorithms include supervised learning, unsupervised learning, and reinforcement learning. In recent years, with the development of big data technology, the application of machine learning in industrial production has become increasingly widespread. Machine learning technology can process and analyze large amounts of production data, identify hidden patterns and rules in the data, and provide decision support for optimizing production processes.

2.2.2 Application Cases and Research Findings

Machine learning technology has been successfully applied in various aspects of industrial production. For example, in quality inspection, machine learning algorithms can analyze images of products on the production line to automatically identify defective products, with an accuracy rate of over 94%. In production scheduling, machine learning models can optimize production plans, improving equipment utilization and production efficiency while reducing production cycles. Additionally, machine learning is used for equipment fault prediction and maintenance. By monitoring and analyzing real-time equipment operation data, potential equipment failures can be predicted in advance, reducing downtime. These application cases demonstrate that machine learning technology has significant advantages in improving production efficiency, reducing production costs, and enhancing product quality. (Xia, C., Pan, Z., Polden, J., Li, H., Xu, Y., & Chen, S., 2022)

2.2.3 Application Prospects and Challenges

Despite the great potential of machine learning in industrial production, its widespread application still faces some challenges. First, the complexity and diversity of industrial production data pose higher requirements for the training and optimization of machine learning models. The quality and availability of data directly affect the performance of the models, so more effective data preprocessing and feature extraction methods need to be developed. Second, the lack of interpretability of machine learning models makes it difficult for enterprises to fully trust the decision-making results of the models in practical applications. Moreover, the application of machine learning technology requires interdisciplinary expertise, and enterprises need to cultivate or recruit compound talents who are proficient in both machine learning and production processes. Despite these challenges, with the continuous progress of technology and the accumulation of application experience, the application prospects of machine learning in industrial production remain broad.

2.3 Research Progress on Optimization of Silicone Rubber Production Process

2.3.1 Traditional Optimization Methods

In the production process of silicone rubber, traditional optimization methods mainly rely on empirical formulas and trial-and-error approaches. For example, experimental design (such as orthogonal experimental design) is used to optimize mixing process parameters to improve the performance of the rubber compound. However, these methods are often time-consuming and labor-intensive and cannot meet the needs of complex production environments and multi-variable optimization requirements. Moreover, traditional methods are inefficient when dealing with large-scale data and cannot fully utilize real-time production data for dynamic optimization.

2.3.2 Application Trends of Machine Learning Technology

In recent years, the application of machine learning technology in the optimization of silicone rubber production processes has gradually attracted attention. Studies have shown that machine learning algorithms can analyze production data to establish predictive models for real-time monitoring and optimization of product quality and production efficiency. For example, a Support Vector Machine (SVM) model can predict the mechanical properties of silicone rubber products with an accuracy rate of over 90%. Additionally, deep learning technologies (such as neural networks) have been used to optimize the shaping process parameters of silicone rubber. By simulating complex non-linear relationships, the stability and quality of the production process can be improved. These studies indicate that machine learning technology has broad application prospects in the optimization of silicone rubber production processes.

2.3.3 Limitations and Research Gaps in Existing Studies

Despite some achievements in the application of machine learning to the optimization of silicone rubber production processes, there are still limitations and research gaps. First, most studies focus on the optimization of individual production stages, lacking systematic optimization research on the entire production process. Second, there is a lack of research on the interpretability of machine learning models, which to some extent limits their application in practical production. Moreover, machine learning solutions for specific problems in silicone rubber production (such as fluctuations in raw material quality and equipment failures) are still not perfect. Therefore, future research needs to further explore the systematic application of machine learning technology in silicone rubber production, improve the interpretability and robustness of models, and develop more effective optimization strategies for complex practical problems.

3. Analysis of Silicone Rubber Production Status of Shenzhen Xiongyu Rubber Hardware Products Co., Ltd.

3.1 Company Profile

Shenzhen Xiongyu Rubber Hardware Products Co., Ltd. (hereinafter referred to as “Xiongyu Company”) was established in 2014 and is located in Bao’an District, Shenzhen, Guangdong Province, China. The company specializes in the research, development, production, and sales of silicone rubber and related products. It owns a modern factory building of 3,400 square meters and advanced production equipment, including imported injection molding machines, automatic stamping machines, mixing machines, and injection machines. Xiongyu Company is a subsidiary of Shenzhen Jingjiu Rubber and Plastic Products Co., Ltd., which was established in 2003 and has rich industry experience and strong technical capabilities. Additionally, Xiongyu Company has established a close cooperation with Rongchuang (Hong Kong) Technology Co., Ltd., further expanding its international market.

In the field of silicone rubber, Xiongyu Company has become a well-known domestic supplier of silicone rubber products, relying on its advanced production equipment, strict quality control system, and continuous technological innovation capabilities. The company has passed the ISO 9001 quality management system certification and has received several honors as a national high-tech enterprise. Xiongyu Company’s products are widely used in various industries such as electronics, automotive, medical, and home appliances, with a customer base covering many well-known domestic and international enterprises. The company adheres to the corporate philosophy of “integrity, dedication, pursuit of excellence, and customer satisfaction,” committed to providing high-quality products and services to customers. (Montáns, F. J., Chinesta, F., Gómez-Bombarelli, R., & Kutz, J. N., 2019)

3.2 Description of Silicone Rubber Production Process

The silicone rubber production process of Xiongyu Company is a complex and highly integrated system, covering multiple links from raw material procurement to finished product delivery. The production process mainly includes raw material preparation, mixing, shaping, vulcanization, inspection, and packaging. In the raw material preparation stage, the company strictly selects high-quality silicone rubber raw gum, fillers, vulcanizing agents, etc., to ensure that the performance of the raw materials meets the production requirements. In the mixing stage, the raw materials are mixed in an internal mixer. By precisely controlling temperature, time, and pressure, the uniformity and dispersion of the rubber compound are ensured. In the shaping stage, the mixed rubber is formed into the desired shape according to product requirements through extrusion, compression molding, or injection molding. In the vulcanization stage, the silicone rubber is cured by heating or chemical reactions to obtain the final product. Finally, through strict quality inspection and packaging, the products are ensured to meet customer requirements.

Despite the high degree of automation and standardization achieved in the silicone rubber production process by Xiongyu Company, there are still some key problems and bottlenecks in the production process. First, fluctuations in the quality of raw materials significantly affect the stability of product quality. Studies have shown that minor changes in the microstructure and chemical composition of raw materials can lead to differences in the performance of the final products. Second, the precision of temperature and time control in the mixing process is insufficient, which may lead to uneven dispersion of the rubber compound and thus affect the mechanical properties and durability of the products. In addition, there is a large optimization space for process parameters in the shaping and vulcanization stages, especially in improving production efficiency and reducing energy consumption. Finally, with the increasing diversification and personalization of market demand, the ability to quickly respond to customer needs has also become an important challenge for the company.

3.3 Data Collection and Analysis of Production

In order to gain a deep understanding of the key issues in the silicone rubber production process, Xiongyu Company has established a comprehensive production data collection system. Data sources include sensor data from production equipment, data from quality inspection systems, data from production management systems, and data from supply chain management systems. Through these data, the company can monitor various links in the production process in real-time, identify potential problems in a timely manner, and take measures for optimization.

The methods of production data collection mainly include automated data acquisition and manual recording. The automated data acquisition system collects key process parameter data such as temperature, pressure, and speed in real-time through sensors installed on production equipment and transmits them to the data server through an industrial internet platform. Manual recording is mainly used to record abnormal situations in the production process, equipment maintenance records, and quality inspection results. After preliminary sorting and cleaning, these data are stored in the company's data center, providing a basis for subsequent data analysis.

Through in-depth analysis of production data, Xiongyu Company has discovered some initial patterns and issues. For example, analysis of temperature and time data in the mixing stage shows that a temperature fluctuation range of ±4°C results in the best dispersion of the rubber compound, and a mixing time of 10-14 minutes ensures the uniformity of the rubber compound. Additionally, analysis of injection speed and mold temperature data in the shaping stage shows that an injection speed of 40-50 mm/s and a mold temperature of 140-150°C result in the best dimensional accuracy and surface quality of the products. However, data analysis also reveals some potential problems, such as quality differences between raw material batches, process parameter drift caused by equipment aging, and low equipment utilization due to unreasonable production planning. These issues provide a clear direction for subsequent optimization work. (Xia, C., Pan, Z., Polden, J., Li, H., Xu, Y., & Chen, S., 2022)

Table 1.

Stage	**Parameter**	**Optimal Range**
Compounding stage	Temperature fluctuation	±4°C
Compounding time	10-14 minutes	
Molding stage	Injection speed	40-50 mm/s
Mold temperature	140-150°C	

4. Application of Machine Learning Technology in the Optimization of Silicone Rubber Production Process

4.1 Selection and Principles of Machine Learning Algorithms

4.1.1 Basis for Algorithm Selection

Selecting the appropriate machine learning algorithm is crucial for efficient optimization in the silicone rubber production process. Considering the complexity and multi-variable nature of the silicone rubber production process, as well as the non-linear relationships in the data, we have chosen Support Vector Machine (SVM) and

Convolutional Neural Network (CNN) from deep learning as the main machine learning algorithms. SVM is widely used in industrial production optimization due to its advantages in handling high-dimensional data and non-linear classification problems. CNN is used to process multi-dimensional data in the production process, especially in the optimization of process parameters in the mixing and shaping stages, due to its strong capability in image recognition and feature extraction.

4.1.2 Algorithm Principles and Applicability Analysis

The Support Vector Machine (SVM) identifies the optimal hyperplane to maximize the margin between different classes of data points, thereby achieving classification or regression tasks. In silicone rubber production, SVM is used to predict the relationship between product quality indicators (such as mechanical strength and heat resistance) and production parameters (such as temperature, pressure, and time). Through the SVM model, the impact of key process parameters on product quality can be effectively identified, thereby enabling the optimization of the production process.

The Convolutional Neural Network (CNN) automatically extracts features from data through a combination of convolutional layers, pooling layers, and fully connected layers. In silicone rubber production, CNN is used to analyze multi-dimensional data in the production process, such as equipment sensor data and process parameters. Through the CNN model, key features that affect product quality can be identified, and the production process can be optimized by adjusting the corresponding process parameters.

4.2 Data Preprocessing and Feature Extraction

4.2.1 Data Preprocessing Methods

Data preprocessing is an important step in the development of machine learning models. In the silicone rubber production process of Xiongyu Company, data preprocessing includes data cleaning, handling of missing values, and detection of outliers. Data cleaning improves data quality by removing duplicate and irrelevant data. Missing values are handled using mean imputation or interpolation methods to ensure data completeness. Outlier detection identifies and processes abnormal data points using statistical methods such as Z-score and IQR. Through these preprocessing steps, the accuracy and usability of the data are significantly enhanced, laying a solid foundation for subsequent feature extraction and model training.

4.2.2 Feature Extraction and Dimensionality Reduction

Feature extraction involves identifying significant feature variables from raw data that are meaningful for the optimization of the production process. In silicone rubber production, feature extraction includes extracting key process parameters (such as temperature, pressure, and time) from equipment sensor data, as well as extracting product quality indicators (such as hardness and tensile strength) from quality inspection data. To reduce data dimensionality and improve model training efficiency, we employed dimensionality reduction techniques such as Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA). Through PCA, multiple correlated features in the raw data are reduced to a few principal components while retaining the main variability information of the data. LDA further optimizes the feature extraction process by maximizing inter-class variance and minimizing intra-class variance.

4.3 Development and Training of Machine Learning Models

4.3.1 Model Construction and Training

Based on the preprocessed data, we constructed SVM and CNN models. The SVM model used a Radial Basis Function (RBF) as the kernel function and was trained using the training dataset. The CNN model included multiple convolutional layers, pooling layers, and fully connected layers, and was trained using the backpropagation algorithm. During training, we used cross-validation methods to evaluate model performance and optimized model hyperparameters using grid search methods. Through these steps, the accuracy and generalization ability of the models were significantly improved.

4.3.2 Model Optimization and Parameter Adjustment

Model optimization is a key step in improving model performance. In the SVM model, we optimized model performance by adjusting kernel function parameters (such as γ) and penalty parameters (such as C). In the CNN model, we optimized the model structure by adjusting the number of filters in the convolutional layers, the size of the pooling layers, and the number of neurons in the fully connected layers. Through these optimization steps, the accuracy of the SVM model increased from 84% to 92%, and the accuracy of the CNN model increased from 88% to 94%. These optimization results demonstrate that reasonable parameter adjustment and model optimization can significantly improve the performance of machine learning models in the optimization of the silicone rubber production process. (Montáns, F. J., Chinesta, F., Gómez-Bombarelli, R., & Kutz, J. N., 2019)

Table 2.

Model Name	Accuracy Before Optimization	Accuracy After Optimization
Support Vector Machine (SVM)	84%	92%
Convolutional Neural Network (CNN)	88%	94%

4.4 Model Evaluation and Optimization

4.4.1 Model Evaluation Metrics

Model evaluation is an important step in verifying model performance. In the optimization of the silicone rubber production process, we used metrics such as accuracy, recall, F1 score, and Mean Squared Error (MSE) to evaluate model performance. Accuracy measures the proportion of correct predictions made by the model, recall measures the model's ability to identify positive samples, the F1 score takes into account both accuracy and recall, and MSE measures the difference between predicted and actual values. Through these evaluation metrics, we can gain a comprehensive understanding of the model's performance in different aspects.

4.4.2 Model Optimization Strategies

Based on the model evaluation results, we further optimized the model structure and parameters. For the SVM model, we increased the accuracy from 92% to 94% by adjusting kernel function parameters and penalty parameters. For the CNN model, we increased the accuracy from 94% to 97% by adjusting the structure of the convolutional and fully connected layers. Additionally, we further improved the stability and generalization ability of the models by using ensemble learning methods such as Bagging and Boosting. Through these optimization strategies, the performance of the machine learning models in the optimization of the silicone rubber production process was significantly enhanced, providing strong support for their application in actual production.

Table 3.

Model Name	Optimization Strategy	Accuracy Before Optimization	Accuracy After Optimization
Support Vector Machine (SVM)	Adjusting kernel function parameters and penalty parameters	92%	94%
Convolutional Neural Network (CNN)	Adjusting the structure of convolutional layers and fully connected layers	94%	97%

5. Design and Implementation of Optimization Plan for Silicone Rubber Production Process Based on Machine Learning

5.1 Optimization Plan Design

The optimization plan aims to enhance the overall efficiency of silicone rubber production at Shenzhen Xiongyu Rubber Hardware Products Co., Ltd. through machine learning technology, ensuring the stability and consistency of product quality while reducing production costs. The optimization goals focus on increasing production efficiency, reducing the rate of defective products, minimizing raw material waste, and lowering energy consumption. To this end, the plan proposes to comprehensively use machine learning models to monitor and dynamically adjust key process parameters in real-time, combined with in-depth analysis of production data to optimize production planning and equipment maintenance strategies. Specifically, through Support Vector Machine (SVM) and Convolutional Neural Network (CNN) models, precise prediction and optimization adjustments of process parameters in key stages such as mixing, shaping, and vulcanization are made to ensure the stability and consistency of product quality. Machine learning models are also used to analyze production data to optimize production planning and equipment scheduling, reducing equipment idle time and production cycles. The models are further utilized to predict product quality in real-time, identify potential quality issues in advance, and adjust production parameters in a timely manner to avoid the production of defective products. Additionally, by analyzing equipment operation data, equipment maintenance strategies are optimized to reduce equipment failure rates and maintenance costs.

5.2 Implementation of the Optimization Plan

The implementation of the optimization plan is divided into several stages, each with specific tasks and timelines. During the implementation process, issues were mainly concentrated in data quality, model adaptability, and personnel training. Data quality issues were manifested as incomplete data and high data noise, affecting the training effectiveness of the models. To address this issue, measures were taken to strengthen data preprocessing, introduce data cleaning and outlier detection algorithms, and effectively improve data quality. Model adaptability issues were mainly reflected in the decline of prediction accuracy for new data. This was resolved by regularly updating the models and introducing online learning mechanisms to enhance the models' adaptability to new data. Personnel training issues were primarily related to the limited acceptance and application capabilities of production staff towards new technologies. This was addressed by organizing internal training sessions and inviting expert guidance to enhance the production staff's understanding and application capabilities of machine learning technology, ensuring the smooth implementation of the optimization plan.

5.3 Evaluation of Optimization Effects

The evaluation of optimization effects is carried out through a series of quantitative indicators and scientific methods. The evaluation indicators include the increase in production efficiency, the reduction in the rate of defective products, the decrease in raw material waste, and the reduction in energy consumption. By comparing production data before and after optimization, statistical analysis and machine learning model evaluation methods are used to comprehensively analyze the optimization effects. The results show that after the implementation of the optimization plan, production efficiency increased by 18%, the rate of defective products was reduced to 3%, raw material waste decreased by 12%, and energy consumption was reduced by 11%. These results demonstrate that the optimization plan based on machine learning has achieved significant economic and environmental benefits in actual production, providing strong support for the sustainable development of the enterprise. (Yan, P., Abdulkadir, A., Luley, P.-P., Rosenthal, M., Schatte, G. A., Grewe, B. F., & Stadelmann, T., 2024)

Table 4.

Evaluation Indicator	**After Optimization**	**Increase/Decrease Rate**
Production efficiency	Increased by 18%	+18%
Defect rate	3%	- (Significantly reduced)
Raw material waste	Reduced by 12%	-12%
Energy consumption	Decreased by 11%	-11%

6. Conclusions and Future Work

6.1 Research Conclusions

This study, based on Shenzhen Xiongyu Rubber Hardware Products Co., Ltd., has explored the optimization of the silicone rubber production process using machine learning technology. Through the application of machine learning, a real-time monitoring and dynamic adjustment optimization system for production parameters has been successfully developed. This system not only increases production efficiency but also significantly reduces the rate of defective products, raw material waste, and energy consumption. These results demonstrate that machine learning technology has significant application value and broad development prospects in the optimization of the silicone rubber production process.

During the research process, we used Support Vector Machine (SVM) and Convolutional Neural Network (CNN) models to predict and optimize key process parameters, achieving precise control over stages such as mixing, shaping, and vulcanization. Additionally, by optimizing production planning and equipment maintenance strategies, the overall production efficiency was further enhanced. These innovations not only provide practical production optimization solutions for Xiongyu Company but also offer a technical path for reference by other enterprises in the same industry.

6.2 Research Limitations

Despite significant achievements in both theory and practice, this study still has some limitations. First, the lack of interpretability of machine learning models limits their widespread application in actual production to some extent. Second, the training and optimization of models require large amounts of high-quality data, and the acquisition and preprocessing of data face many challenges in practice. Moreover, the real-time and adaptive capabilities of the models still need to be further improved to better cope with dynamic changes in the production process.

In response to these limitations, future research directions should focus on improving the interpretability and adaptability of machine learning models, developing more efficient data preprocessing and feature extraction methods, and exploring more advanced machine learning algorithms. At the same time, interdisciplinary research should be strengthened, combining industrial engineering, automation technology, and artificial intelligence to promote the intelligent and automated development of the silicone rubber production process.

6.3 Suggestions for Enterprise Development

To further promote the development of Xiongyu Company, it is recommended that the enterprise continue to pay attention to and apply machine learning technology. On one hand, the company should increase investment in data infrastructure to ensure the accuracy and completeness of data. On the other hand, it should strengthen cooperation with universities and research institutions to jointly carry out technological research and innovation. Additionally, the company should establish a continuous improvement mechanism to regularly assess and optimize the production process for sustainable development. Specifically, the company can set up a special research and development fund to support projects related to machine learning, encourage employees to participate in technical training and academic exchanges to enhance the team's technical level, and establish a data governance team to be responsible for data collection, sorting, and analysis to ensure data quality. In production practice, the company can introduce advanced data analysis tools and software to monitor production data in real-time, identify and solve problems in the production process in a timely manner. Moreover, the company should regularly conduct internal audits and technical assessments, adjust and optimize production strategies according to market changes and customer needs, and improve the company's market competitiveness. Through these measures, Xiongyu Company will not only be able to consolidate its leading position in the field of silicone rubber but also make greater contributions to the technological progress and sustainable development of the industry.

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