Research on Intelligent Decision System of Fireworks Production Line

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Abstract

With the country's demand for intelligent manufacturing, this paper proposes a smart transformation and design of a traditional fireworks production line located in the central and western regions of China, and finally can realize a complete set of control system solutions, while improving the safety of the production line and improving the product. Quality, using a combination of several machine learning algorithms, can be applied to the application model through sample training, and can be deployed on the production line system. This intelligent fireworks generation line system is mainly divided into PLC control part, information communication part and machine learning algorithm part. The PLC control part and the communication part are mainly used for feedback control of the model output result, and data acquisition and preprocessing are performed by using various sensors on the production line. The remote monitoring is realized by GPRS mobile communication between them, and the machine learning algorithm mainly utilizes neural network ,SVMAnd the random forest algorithm, through experiments found that the security level of the judgment object, the latter model performance is better, its robustness is stronger, thus effectively improving product quality and personnel safety.

Keywords

Intelligent manufacturing, Safety control, Fireworks production.

1. Introduction

In the traditional way of working with fireworks, it has always been based on hand-made. Historically, it has also experienced the scale of production from the small workshops with low annual output value to the current industrial production of millions or even billions of output. The production equipment for fireworks production is still relatively simple, and the degree of automation is at a low level. In some high-risk steps, manual operations are still performed, workers' operational errors, lack of safety awareness, and safety accidents often occur. In recent years, national intelligent manufacturing is being carried out effectively, high-tech production is also constantly replacing high-risk, the distribution of fireworks production will be more concentrated, and large companies will continue to merge with small and medium-sized enterprises, thus providing a certain economic force to transform fireworks. Production, making intelligent transformation of fireworks production, to low-cost, safer, more efficient, more diversified production development, and ultimately to vigorously improve the market competitiveness of enterprises[1,2].

Under this background, this paper proposes to use the networked production management mode to build an intelligent hardware cloud platform and discuss the intelligent production with the main goal of security and rapid data fusion. Each collection point collects information on the devices at all levels on the production line, and transmits the collected information to the platform in the form of big data through the network to train and process the analysis, and then feeds the results back to the supervisor's control. At the end, remind the supervisors of the possible bad behavior of the equipment. If the information received by the platform is always in a non-standard state, an alarm will be triggered. This intelligent feedback control will improve the most important characteristics of the fireworks production. The level has a great effect on the safety of fireworks production[3].

2. Fireworks production process analysis and algorithm basis

2.1 Fireworks production safety process

The working process of the production module of the system is that the transport tray group provides the tray, and the transporter 1 transports the pallet to the quantitative feeder, and the quantitative feeder uniformly distributes the original medicine according to the specific formula, and evenly distributes it into the tray, and the distribution is completed. Thereafter, the tray is conveyed to the automatic granulator by the conveyor 2, and after the granulation is completed, the automatic screening machine is transported by the conveyor 3, and after the screening is completed, it is sent to the palletizer through the conveyor 4, and palletizing is performed in the area. At the same time, the shelf group transports the shelf to the palletizing machine via the conveyor 5, and after the palletizing is completed, the product is transported to the drying device through the conveyor 6, and after the process is completed, the finished product is conveyed to the unloading machine through the conveyor 7 to complete the manufacture of the product. , production process flow chart (see Fig. 1).

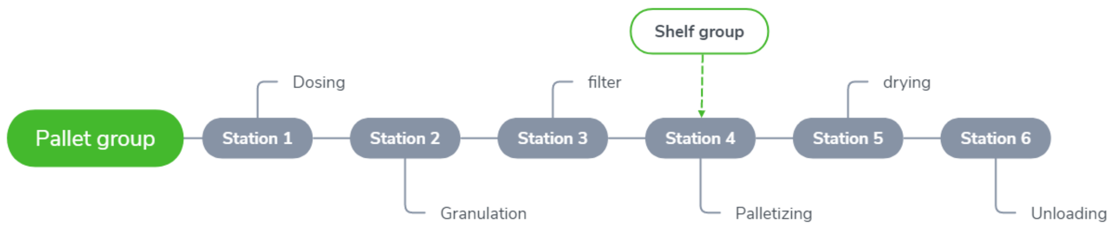

Fig. 1 Overall system architecture

The probability of an accident at the drying station is much greater than that of other stations. In the actual production, since the raw materials are all flammable and explosive, they are often affected by the temperature in the production. If the temperature is too high, the product may be explosive, and if the temperature is too low, the quality of the product will be unqualified. The drying part is mainly an automatic dryer, and the temperature inside the equipment is the highest[4,5]. Once the equipment is abnormal, the temperature will be unqualified. If the temperature is too high, it will easily lead to a safety accident, resulting in loss of personnel equipment, so the system is drying the station. Temperature alarms are extremely necessary and meaningful.

2.2 Intelligent system control

In the operation process of the production line, the system manages monitoring and control, human-computer interaction, alarm, and information communication functions. Through the analysis of the process flow of the bright bead production line, it is decided to adopt the design based on genetic BP neural network algorithm. The system adopts SIMATIC S7-300 PLC, the combination of sensors, transmitters and actuators to realize production monitoring control. Scheme (see Fig. 2).

Fig. 2 Indoor intelligent lighting control system

2.3 Algorithm basis

Random forest is an algorithm that integrates multiple trees through the idea of integrated learning. Its basic unit is the decision tree, and its essence belongs to the Ensemble Learning method, a branch of machine learning. There are two keywords in the name of the random forest, one is “random” and the other is “forest”. "Forest" We understand very well that a tree is called a tree, so hundreds of thousands of trees can be called forests. This kind of metaphor is very appropriate. In fact, this is also the main idea of random forests - the embodiment of integrated thinking. The meaning of "random" will be covered in the next section[6].

In fact, from an intuitive point of view, each decision tree is a classifier (assuming that it is now a classification problem), then for an input sample, N trees will have N classification results. The random forest integrates all the classification voting results, and specifies the category with the most votes as the final output. This is the simplest Bagging idea.

The input sample set is D={(x, y1), (x2, y2), ... (xm, ym)}, and the weak classifier iteration number T is output as the final strong classifier f(x). t=1, 2..., T:

a. The t-th random sampling of the training set, a total of m times, to obtain a sampling set Dt containing m samples.

b. Train the t-th decision tree model Gt(x) with the sample set Dt. When training the nodes of the decision tree model, select some sample features among all the sample features on the node, among these randomly selected partial sample features. Select an optimal feature to make the left and right subtree partitions of the decision tree.

If it is a classification algorithm prediction, one of the categories or categories in which the T weak learners cast the most votes is the final category. If it is a regression algorithm, the regression results obtained by the T weak learners are arithmetically averaged to obtain the final model output.

3. Conclusion

The main cause of the safety accident in the fireworks production line system is the influence of the temperature of the drying box. Therefore, the experimental control uses this factor as the main sample, and combines the samples of several other working points to form a data set with the output as the safety level. Finally, the experimental scheme considers the random forest method for training and testing, and considers the algorithm combining neural network and SVM for baseline analysis.

3.1 Sample preparation

Generally speaking, the quantity and quality of the sample determine the accuracy of the algorithm. The increase of the training sample is beneficial to improve the recognition and precision of the system. However, the environment of the fireworks production is complicated, the data collection is not easy, and excessive sampling will also have a negative impact. Excessive samples will lead to increased network training time and system performance.

(1) Determine the input variable

Selection of input quantity: Collect and summarize the temperature and time data of the drying part of the production line, and the data fluctuation of temperature and time during normal production. Collecting the temperature in the drying equipment and the drying time, including: the drying time required for the temperature fluctuation in normal time; the drying time consumed by the temperature fluctuation in the abnormal state; the temperature fluctuation when the quality is optimal The required drying time, etc. Using these data as input variables of the system network, through the analysis of the system, it is hoped that the optimal control obtained by the system can ensure safety and ensure the quality of production.

(2) Determine the output variable

Selection of output variables: For the safety accidents and product quality problems on the production line, it can truly map the safety and quality of the equipment, and can adjust the alarm according to the abnormal information.

3.2 Experimental data analysis(see Table1)

Table 1 Performance comparison of three algorithms

Method	MSE	RMSE	MAE	R2
SVM	411.666	20.356	15.586	0.632
Random Forest	23.553	4.956	2.902	0.856
Neural Network	33.284	5.689	3.712	0.785

3.3 Experimental results

From the above experimental data, we can see that the performance of random forests is significantly stronger than the other two algorithms, which again proves that integrated learning has certain advantages in the processing of structured data.

Finally, the firecracker generation line system designed according to the RF algorithm can meet the basic requirements of normal operation, but it does not realize complete intelligence. There is a certain error with the actual monitoring and adjustment, and the relationship between the parameters of the control system of the fireworks production line is lacking. Research. The control of temperature and flow in the production line is a very complicated process, and there is no strict theoretical basis for the production of bright beads. The production of bright beads is a high-risk industry, the fault tolerance rate is extremely low, and the system algorithm is accurate. The rate does not meet the expectations, and the reliability and stability of the new algorithm require further research. The theory must be combined with practice to be transformed into productivity, and it is constantly discovered and improved in production.

Acknowledgements

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