Automation and Machine Learning (2023)
Clausius Scientific Press, Canada

DOI: 10.23977/autml.2023.040311
ISSN 2516-5003 Vol. 4 Num. 3

Research on advanced manufacturing process monitoring and fault prediction method based on machine learning

Xinrui Wang, Hang Shang*, Ning Li

College of Arts & Information Engineering, Dalian Polytechnic University, Dalian, Liaoning, 116400, China
**Corresponding author*

Keywords: Machine learning; fault prediction; monitoring; advanced manufacturing

Abstract: With the rapid development of advanced manufacturing technology, efficient monitoring and fault prediction of manufacturing process has become an important link to realize intelligent manufacturing. The purpose of this study is to explore the advanced manufacturing process monitoring and fault prediction method based on machine learning, so as to improve the stability and reliability of the production process. In the aspect of monitoring, by effectively integrating multi-source data and adopting advanced data preprocessing methods, the real-time monitoring of manufacturing process state can be realized, which provides strong support for finding anomalies in time. Aiming at fault prediction, this study discusses the performance of support vector machine (SVM) in different manufacturing environments, and proposes a fault prediction method based on improved SVM to improve the prediction accuracy and generalization ability. Through empirical research, the proposed method is verified. The training result diagram clearly shows the relationship among support vector, training error pipeline and regression approximation results, while the prediction result diagram shows the excellent performance of the model on test data. These research results have important theoretical and practical value for promoting the development of intelligent manufacturing and improving the intelligent level of production process.

1. Introduction

In today's increasingly competitive manufacturing environment, achieving high efficiency, reliability and maintainability of the production process is one of the key elements for enterprises to succeed. In order to meet this demand, manufacturing industry is actively turning to advanced manufacturing process monitoring and fault prediction methods [1]. With the rapid development of machine learning technology, especially the rise of deep learning, it provides unprecedented opportunities for the manufacturing industry to monitor the production process and predict potential failures more accurately and in real time.

The purpose of this study is to explore the method of advanced manufacturing process monitoring and fault prediction based on machine learning, so as to improve the efficiency and production quality of manufacturing industry. The introduction of machine learning technology has brought unique advantages to manufacturing industry. By studying and analyzing a large number of production data, the system can continuously optimize its performance and make real-time decisions in real-time environment. Compared with the traditional rule-based monitoring method, this method is more adaptive and intelligent.

Manufacturing process monitoring is one of the key steps to ensure the stable operation of the production process. By collecting sensor data and applying machine learning algorithm, we can realize real-time monitoring of production parameters, equipment status and product quality. This real-time monitoring not only helps to prevent potential problems, but also can adjust production parameters in time to optimize the whole production process [2-3]. On the other hand, fault prediction goes further, aiming at identifying and predicting the factors that may lead to equipment failure or production interruption. By analyzing the historical fault data and operating conditions, the machine learning model can identify potential fault modes and issue warnings in advance so as to take appropriate maintenance measures. This predictive maintenance method not only helps to reduce production downtime, but also reduces maintenance costs and improves equipment utilization.

2. Manufacturing process monitoring

In today's competitive manufacturing environment, it is very important for the success of enterprises to realize efficient, reliable and excellent quality production process. To meet this challenge, advanced manufacturing process monitoring has become one of the key strategies to improve production efficiency, reduce costs and ensure product consistency [4]. With the rapid development of science and technology, especially the rise of machine learning, Internet of Things and big data analysis, the manufacturing industry has ushered in a new wave of opportunities for change, providing a more intelligent and comprehensive solution for manufacturing process monitoring.

The core of advanced manufacturing process monitoring is real-time data acquisition and analysis. By deploying various sensors on production equipment, data about production parameters, equipment status and product quality can be captured in real time. As the input of the monitoring system, these data are analyzed in real time by machine learning algorithm, so that the production manager can know the state of the production process at any time. This real-time performance not only helps to find potential problems in time, but also can realize accurate control of the production process and maximize production efficiency [5-6]. The architecture design of manufacturing process monitoring system is shown in Figure 1.

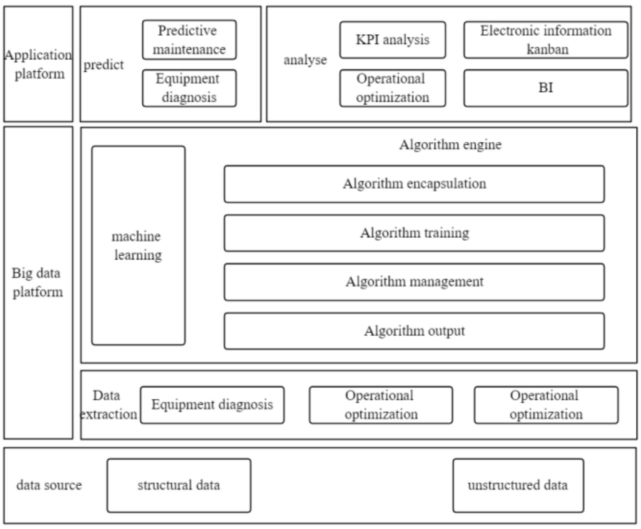

Figure 1: Architecture of manufacturing process monitoring system

Compared with the traditional rule-based monitoring system, the advanced monitoring system based on machine learning is more adaptive. By constantly learning and adjusting the model, the system can adapt to different production environments and changes, thus better adapting to the complex and changeable manufacturing process. This adaptability enables the monitoring system to maintain efficient performance in the face of new production scenarios or changing market demand.

The introduction of machine learning technology provides opportunities for continuous improvement of manufacturing process monitoring. By collecting a large number of historical data, the monitoring system can continuously optimize its own performance. This iterative optimization process enables the monitoring system to adapt to the changing market demand and production environment, and provides enterprises with more flexible and efficient manufacturing solutions [7-8].

3. Fault prediction method

3.1. Fault prediction in modern manufacturing industry

In modern manufacturing industry, fault prediction is very important to ensure the stable operation of production system, reduce downtime and improve equipment utilization. Advanced manufacturing process fault prediction provides a more intelligent and predictive method for enterprises to manage equipment faults by combining advanced data acquisition technology and machine learning algorithm, thus achieving higher production reliability and efficiency.

The core of fault prediction in advanced manufacturing process is data-driven predictive analysis. By deploying sensors on production equipment and collecting a large amount of operation data, the system can identify potential failure modes by using machine learning algorithms. This data-driven method allows the system to learn the normal and abnormal modes of equipment operation from historical data and provide early warning for possible faults in the future. The fault prediction of advanced manufacturing process not only pays attention to the analysis of historical data, but also emphasizes real-time monitoring. By continuously monitoring the running state of the equipment and comparing it with the predetermined normal state, the system can detect potential problems in real time [9]. Once the system detects an abnormality, it can give a timely alarm, so that the maintenance team can take measures quickly to prevent the fault from developing further.

By implementing advanced manufacturing process fault prediction, enterprises can effectively extend the life of production equipment. By finding and solving potential problems in time, the wear and damage of equipment can be reduced and the reliability of equipment can be improved. This not only saves the cost of replacing equipment for enterprises, but also ensures the continuity and stability of the production process. The traditional maintenance mode is often to maintain the equipment after it breaks down, while the failure prediction model can take preventive maintenance measures before the failure occurs, thus avoiding the emergency maintenance. This not only reduces the maintenance cost, but also improves the availability of the equipment.

With the continuous progress of artificial intelligence and machine learning technology, the fault prediction of advanced manufacturing process will be more accurate and intelligent. Integrating more data sources, adopting deep learning technology and combining with the Internet of Things will make the fault prediction system more comprehensive and reliable, and provide a higher level of production management and maintenance efficiency for the manufacturing industry. Through continuous investment and research, the fault prediction of advanced manufacturing process will become the key factor to promote the development of manufacturing industry in an intelligent and sustainable direction.

3.2. Fault prediction method using SVM machine learning method

Support Vector Machine (SVM) is a supervised learning algorithm, and its main goal is to find a hyperplane that can effectively separate different data points. In fault prediction, SVM establishes a decision boundary that can divide two kinds of data by learning the relationship between normal and abnormal states in historical data sets. This enables the system to judge whether the new data points tend to be normal or abnormal when they appear, so as to take necessary maintenance measures in advance. SVM has good generalization ability and strong classification ability for new and unknown data points. This enables it to maintain high performance in dealing with changing manufacturing environments [10]. This paper puts forward a method of fault prediction using SVM machine learning method.

The improved SVM is the optimization and improvement of the traditional SVM, and its principle is based on finding an optimal decision boundary to separate the data points in normal state and fault state more accurately. Compared with the traditional SVM, the improved SVM has some improvements in dealing with complex data structures, improving classification accuracy and generalization ability.

In fault prediction, the goal of the improved SVM is to find a hyperplane that can distinguish between normal and abnormal states, so that when new data points appear, the system can accurately judge their categories, thus realizing early fault prediction.

The optimization goal of the improved SVM is to minimize the loss function and maximize the margin. Common loss functions include Hinge Loss and regularization term. The expression of the optimization objective function is as follows:

$$\min_{w,b,\xi} \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n}\xi_i \tag{1}$$

Here, w is the weight vector, b is the bias term, ξ_i is the relaxation variable, C is the regularization parameter, and n is the number of samples.

The decision function is used to judge whether the new data points belong to normal or abnormal categories. For the input data x, the decision function is calculated as follows:

$$f(x) = sign\left(\sum_{i=1}^{n}(\alpha_i - \alpha_i^*)K(x_i - x) + b\right) \tag{2}$$

Where α_i, α_i^* is the Lagrange multiplier and $K(x_i - x)$ is the kernel function.

The selection of kernel function is very important for the performance of SVM. In the improved SVM, different kernel functions, such as linear kernel, polynomial kernel or Gaussian kernel, can be selected to adapt to different types of data structures. This paper uses polynomial kernel function.

Parameter tuning is a key step to improve the performance of SVM. Through cross-validation and other methods, regularization parameters and kernel function parameters can be adjusted to obtain the best fault prediction performance. The improved SVM can adapt to the complex data situation in advanced manufacturing process more flexibly, and improve the accuracy and generalization ability of fault prediction. The advantages of this method are that it can handle high-dimensional data, adapt to different kernel functions and flexibly adjust parameters.

4. Simulation study

Taking the measured data of the internationally common process simulation object "Tennessee Eastman" as an example, using the above steps, the simulation research of fault prediction with time as the independent variable is carried out. The chemical process of "Tennessee Eastman" factory involves 41 measured variables and 12 operational variables. By setting the input of 12 operating variables, the reactor mainly controls the indexes (liquid level, pressure and temperature). If no measures are taken at this time, the liquid level will go beyond the warning range after slow oscillation, which will lead to serious reactor overpressure fault.

Here, the reactor liquid level with strong randomness of signal fluctuation is selected as the characteristic variable of fault monitoring, in order to test the robustness of trend prediction by SVM method. The sampling period of the original measurement data is 5.4 seconds. In order to verify the sparsity of the solution based on SVM regression under insensitive loss function, 50 groups of sparse data are obtained by taking observation data with 40 times sampling period. Fig. 2 shows a graphical representation of the prediction results.

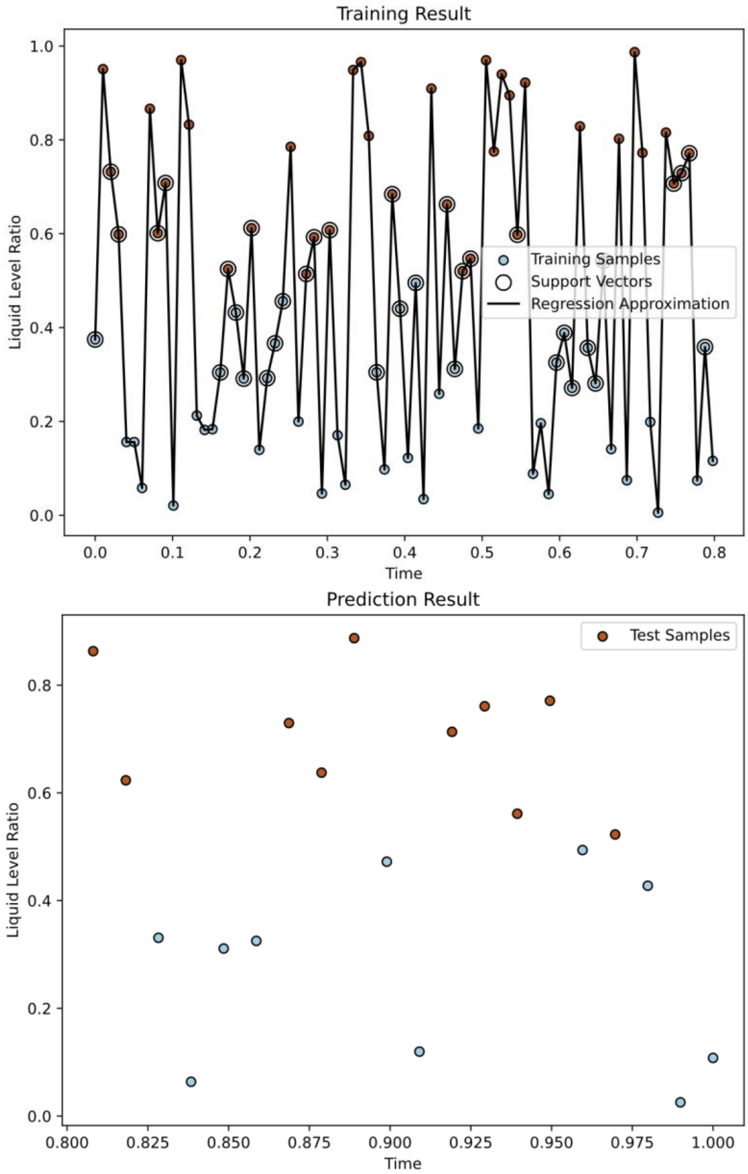

Figure 2: Training and regression results for 20 samples

It can be seen that the experimental data is more sparse. SVM method can realize fault trend prediction. At the current time t, the output after time t can be judged according to the previous n times of measurement data. If the predicted output may exceed the specified value (failure), measures can be suggested at the current time to avoid potential failure. Fault trend prediction based on SVM machine learning method is a promising method to solve small sample prediction.

5. Conclusions

With the continuous development of advanced manufacturing process, the application of machine learning technology in manufacturing industry has made remarkable progress. This study is devoted to the in-depth study of advanced manufacturing process monitoring and fault prediction methods based on machine learning. Through the discussion of related theories and methods, a series of innovative viewpoints and solutions are put forward. This study provides useful insights and methods for the research in the field of advanced manufacturing process monitoring and fault prediction. Although machine learning method has performed well in advanced manufacturing process, it still faces some challenges in practical application. For example, data quality, feature selection, model interpretation and other issues need to be further studied and solved. In addition, with the continuous development of manufacturing technology, we expect that future research will pay more attention to the integration of deep learning and traditional machine learning methods to improve the monitoring and forecasting accuracy of complex manufacturing processes.

References

[1] Bhandari, G. P., & Gupta, R. (2020). Fault prediction in soa-based systems using deep learning techniques. International Journal of Web Services Research (12), 17.

[2] Pandey, S. K., Mishra, R. B., & Tripathi, A. K. (2021). Machine learning based methods for software fault prediction: a survey. Expert Systems with Applications, 172(2), 114595.

[3] Liu, J., Ding, W., Dai, J., Wu, Z., & Yang, H. (2018). Quantitative prediction of lower order faults based on the finite element method: a case study of the m35 fault block in the western hanliu fault zone in the gaoyou sag, east china. Tectonics, 37(9-10), 3479-3499.

[4] Zhou, R., Xing, Z., Wang, H., Piao, Z., & Ma, R. (2020). Prediction of contact fatigue life of at40 ceramic coating based on neural network. Anti-Corrosion Methods and Materials, 67(1), 83-100.

[5] Xuhui, L., Yan, X. U., Jianping, Z., & Abdureyim, I. (2018). Adaptive fault tolerant fusion interpolation algorithm based on rbf network. Hanjie Xuebao/Transactions of the China Welding Institution, 39(10), 81-87.

[6] Jiang, L. (2017). Research on software fault prediction based on bp neural network. Boletin Tecnico/Technical Bulletin, 55(15), 489-494.

[7] Shatnawi, R. (2021). Software fault prediction using machine learning techniques with metric thresholds. International journal of knowledge-based and intelligent engineering systems(2), 25.

[8] Wan, L., Li, H., Chen, Y., Li, C., Energies, & Sciubba, E. (2020). Rolling bearing fault prediction method based on qpso-bp neural network and dempster–shafer evidence theory. Energies, 13(5), 1094.

[9] Grimaldi, R. B. G., Chagas, T. S. A., Montalvao, J., Brito, N. S. D., Dos Santos, W. C., & Ferreira, T. V. (2021). High impedance fault detection based on linear prediction. Electric Power Systems Research(8), 190.

[10] B. Wójcicki, & Dbrowski, R. (2018). Applying machine learning to software fault prediction. E-Informatica Software Engineering Journal, 12(1), 199-216.