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A Review of Process Monitoring Method and Rule Extraction Method for Manufacturing Process Quality Control

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ABSTRACT

Nowadays, scholars have explored many methods for manufacturing process quality control. This paper presents the current research progress in these two areas in manufacturing process quality control by exploring the two areas of process monitoring and rule extraction, and analyzes the strengths and weaknesses of the current research. In the review of process monitoring, the paper introduces a variety of research methods based on different data characteristics of the manufacturing process, which makes the differentiation of different data characteristics and the applicability of the methods more obvious. In the research review on rule extraction, this paper will introduce the characteristics of excellent rule extraction algorithms and introduce various rule extraction algorithms and their applications. Finally, this paper expects to combine the two to put forward some suggestions on future research directions.

KEYWORDS

Process Monitoring; Rule Extraction; Data Characteristics

1. INTRODUCTION

In today's competitive market environment, manufacturing companies are faced with increasing quality requirements and customer expectations, so quality control of the manufacturing process is particularly important. Quality control not only ensures that products meet the required standards, but also improves production efficiency, reduces production costs, enhances the competitiveness of enterprises and establishes a good brand image. Therefore, manufacturing process quality control has become an important and indispensable part of manufacturing enterprises.

The diversity of manufacturing process quality control methods is an important guarantee of product quality. Traditional quality control methods include Statistical Process Control (SPC), Six Sigma, Quality Function Deployment (QFD), etc. These methods are able to improve product quality to a certain extent, but face the challenges of large data volume and high complexity. With the development of information technology, quality control methods have been greatly enriched and expanded, among which data-driven quality monitoring model and rule extraction algorithms that can explore the intrinsic connection of things have received wide attention.

Data-driven quality monitoring model is one of the important means in manufacturing process quality control, which can well cope with the large amount of data generated in today's manufacturing process and monitor the product quality according to the data characteristics. Commonly used quality monitoring models include principal component analysis, artificial intelligence models, neural network models, etc. These models can monitor and analyze the key parameters in the manufacturing process in real time, detect abnormalities in a timely manner, and help enterprises quickly adjust the production process to ensure stable and reliable product quality.

Rule extraction algorithm, on the other hand, is a method based on data mining and machine learning, which is able to mine the hidden laws and patterns from the massive data to provide decision support for the quality control of the manufacturing process. Through rule extraction algorithms, potential problems and room for improvement in the manufacturing process can be found to help enterprises optimize the production process and improve product quality. Common rule extraction algorithms include GA algorithm, PSO algorithm, etc., which can effectively extract the frequently occurring rules from the data and provide valuable reference basis for quality control.

In summary, the importance of quality control of the manufacturing process is self-evident, and the quality monitoring model and rule extraction algorithms, as an important technology of the quality control method, provide manufacturing enterprises with more comprehensive and accurate quality management tools.

2. RESEARCH OBJECTIVES AND SIGNIFICANCE

The purpose of this paper is to explore the research progress of quality monitoring methods and rule extraction algorithms in manufacturing process quality control, analyze the advantages and shortcomings of both, and propose future research outlook. The specific research objectives include:

1. To systematically sort out the development history of quality monitoring methods and rule extraction algorithms, and dig deeper into their application in manufacturing process.

2. Analyze the advantages and shortcomings of quality monitoring methods and rule extraction algorithms, and explore the problems and challenges in their practical applications.

3. Propose the improvement direction and future research direction for quality monitoring methods and rule extraction.

The research of this paper has theoretical and practical significance:

Theoretical significance: by systematically summarizing and analyzing the research progress of quality monitoring methods and rule extraction algorithms, it can provide an in-depth understanding of the mechanism of the role of these methods in the quality control of the manufacturing process, and provide theoretical support for academic research in related fields.

Practical significance: quality monitoring methods and rule extraction algorithms are important tools for manufacturing enterprises to realize quality management, and the study of the advantages and shortcomings of the two will help enterprises better choose the quality control methods suitable for their own situation, and improve product quality and production efficiency.

In summary, this paper aims to study quality monitoring methods and rule extraction algorithms in depth, to explore their application and development in manufacturing process quality control, and to provide theoretical and practical support for improving product quality, reducing production costs, and enhancing enterprise competitiveness. Through this study, it will provide more effective quality management tools for manufacturing enterprises and contribute to the sustainable development of the manufacturing industry.

3. REVIEW OF PROCESS MONITORING AND RULE EXTRACTION

3.1. Process monitoring related research

In general, manufacturing process monitoring can be divided into three categories: model-based manufacturing process monitoring, knowledge-based manufacturing process monitoring and data-based manufacturing process monitoring. The model-based approach is the most traditional of these approaches and is usually used to produce accurate results by building reliable models of the system.

It has been used for troubleshooting in many fields such as aerospace, power systems, etc. However, with the development of modern industry and the increasing complexity of many industrial processes, the complexity of the model-based approach has increased, as has the cost and, in some cases, the difficulty of building a model. Knowledge-based approaches rely more on the past experience of experts and rely heavily on a mature industrial system to support their conclusions. Data-based approaches to manufacturing process monitoring do not require complex modelling and do not rely on expert knowledge. With the development of modern technology, the feasibility of data-based approaches to manufacturing process monitoring is increasing as the mass recording and collection of data from industrial processes becomes a reality. In addition, breakthroughs in machine learning methods, data mining and other fields have provided many new feasible techniques for data-based manufacturing process monitoring, which have attracted more attention from scholars and have been more widely applied in reality [1].

Statistical Process Control (SPC) is a traditional production process quality control method, which can scientifically distinguish random fluctuations and abnormal fluctuations, and provide feedback on abnormal changes in the product process, so as to help managers take measures to restore the production process to normal and achieve the purpose of improving product quality. However, traditional SPC is a type of univariate quality control that does not take into account the correlation between variables, making it easy to produce omissions and difficult to implement when there are more system variables. Multivariate Statistical Process Control (MSPC) is a typical data-based quality control method for manufacturing processes, which considers the statistical process control analysis of multiple variables based on SPC. Compared with SPC, it has unique advantages in dealing with high-dimensional and highly coupled data, so more and more scientists are willing to conduct research based on MSPC. Principal component analysis (PCA) and partial least squares regression (PLS) were the main statistical methods used in the early days of MSPC. Venkatasubramanian [2] reviewed many statistical process control methods based on PCA and PLS and summarised their applications in various fields such as smelting, electrical engineering and aerospace. However, the use of traditional PCA and PLS methods is based on the assumption that the manufacturing process follows a Gaussian distribution, and scientists Negiza and Cinara [3] found that these PCA and PLS methods fail when the manufacturing process data are not Gaussian distributed. However, in reality, a large number of manufacturing process data does not obey the Gaussian distribution, and at the same time, these data often have non-linear correlation, manufacturing process data dynamics and other characteristics, which in all aspects makes the performance of PCA and other statistical process methods in many cases impaired or even not applicable. Scholars have done a lot of research to improve the old methods and introduce new methods to solve the manufacturing process quality control problems, in order to cope with a variety of data characteristics. In this paper, the current status of manufacturing process quality control research in various countries is described in detail on the basis of various data characteristics.

3.1.1. Non-Gaussian manufacturing process quality control

Independent component analysis (ICA) is a widely used method for quality control of non-Gaussian manufacturing processes. PCA can only impose the independence of second-order statistical information, but ICA is able to look for components that are statistically independent and non-Gaussian distributions, which involves higher-order statistics of the data. Therefore ICA tends to reveal more meaningful information in non-Gaussian manufacturing process quality control. Li and Yan [4] found in their study that the method of using a fast ICA algorithm to extract the independent components of the manufacturing process and optimising the monitoring results of the underlying model with the NSGA-II algorithm with the integration of the learning technique, Bayesian method fusion, can be well applied to the complex and variable real industrial process The manufacturing process information generated and a case study of a wastewater treatment plant and TE benchmarking process demonstrate that this research significantly improves the performance and generalisation of the whole process quality control.

In addition to ICA there are many other methods that have been used for non-Gaussian manufacturing process quality control. For example, scholars Chang et al. [5] argued that ICA drops some smaller independent components when selecting independent components, which inevitably leads to data loss in feature extraction and thus triggers inaccuracy in quality control. Therefore they proposed a quality monitoring method based on fourth-order matrix (FOM) and singular value decomposition (SVD) to avoid this data loss and make the quality control process more accurate. Wang and Zhao [6] expanded the method of non-Gaussian distribution analysis by improving the phase anisotropy analysis (DISSIM), which was originally only applicable to Gaussian manufacturing processes, to the GDISSIM method that can monitor both Gaussian and non-Gaussian information. Scholar Wang et al. [7] proposed a multi-block NMF model that can be used for quality control of non-Gaussian manufacturing processes based on non-negative matrix factorisation (APNMF) and Bayesian inference. Scholar Zhang et al. [8] took the manufacturing process quality control in semiconductor companies as the research object, and combined domain-preserving embedding (NPE) with Gaussian mixture model (GMM) to achieve the reduction of the computational complexity of GMM while maintaining more local information of the current window dataset. Scholars Li et al. [9] combined GMM with fuzzy c-mean clustering algorithm (FCM) to avoid the problem of dimensionality catastrophe caused by anomaly detection while improving the accuracy of classification of sensitive feature sets.

3.1.2. Dynamic manufacturing process quality control

Due to certain random noise and process disturbances that may be present in the manufacturing process, the input and output variables of the manufacturing process sometimes have dynamic data. If these dynamic data are not included in the control model, then a misleading result may be obtained in the end. Therefore, there are also many scholars who have carried out research on the dynamic characteristics of data in the manufacturing process, and the main methods used are dynamic MSPC, time series analysis, and so on. Scholars Xiao et al. [10] used decentralised dynamic PCA for correlation and redundant variable selection and applied it to large-scale dynamic process quality control. Scholars Chen et al. [11] proposed an autoregressive extreme learning machine (ARELM) applied to nonlinear dynamic process quality monitoring, while Wan et al. [12] proposed a temporal sequential multiblock (TSMBM) modelling approach to solve the same kind of problems, both of which achieved promising results.

3.1.3. Non-linear manufacturing process quality control

In traditional manufacturing process quality control it is usually assumed that different process variables are linearly related to each other, but with the rapid development of the modern process industry, many processes may be operated under different conditions, and the relationship between various process variables tends to be complex, in which case the use of the traditional linear approach may not give good results. The kernel method is an approach that has been applied by a number of scholars in nonlinear manufacturing processes; Cui et al. [13] and Deng et al. [14] used an improved method based on kernel principal component analysis (KPCA) to solve the quality control problem of nonlinear manufacturing processes; and Si et al. [15] used an improved method of kernel partial least squares (KPLS). However, Chen et al. [16] argued that choosing the appropriate parameters in the kernel method is extremely difficult, and therefore most and learning methods are each unsatisfactory. Artificial Neural Networks (ANNs) can extract the required components from nonlinear data very well and make up for the shortcomings of classical Canonical Correlation Analysis (CCA) in this respect, so they combined the principles of the two and proposed a novel method, namely Artificial Neural Correlation Analysis (ANCA), for the quality control of manufacturing processes. Due to the excellent learning ability of neural networks and their ability to cope with nonlinear data, many other neural network methods have been applied to nonlinear manufacturing process quality control. Chen et al. [17] introduced a variety of deep neural networks (DNNs) combined with CCA. Scholars Jiang and Yan [18] experimentally analysed DNN-CCA in numerical analysis with the Tennessee dataset for its use in regularised deep correlation representation in nonlinear process quality control. Wang et al. [19] developed a probabilistic generative deep learning model based on the variational autoencoder (VAE), which includes both supervised and semi-supervised learning versions, and the process does not require the introduction of any hyper-parameters, which is more conducive to solving the manufacturing process quality control problem under the situation of insufficient targets in the training data. Zhang et al. [20] also used VAE to solve the nonlinear manufacturing process quality control problem, and they improved VAE into a method that can cope with both Gaussian and non-Gaussian distributions, resulting in enhanced generalisation performance.

3.1.4. Application of manufacturing process quality monitoring in aviation logistics equipment manufacturing

These process monitoring methods have also been applied by a number of scholars to the monitoring and optimisation of the manufacturing process of aviation logistics equipment.Imran et al. [21], Tyystjärvi et al. [22] have all used deep neural network methods, respectively, from the real-time quality defects detection of aircraft, the automated defects detection in the digital radiographs of the welds, and the assembly process of aircraft from the of intelligent fault diagnosis technology from three perspectives, contributing to various aspects such as safety, reliability, and productivity improvement of aviation logistics equipment.

3.2. Research on Rule Extraction

Rule extraction is an important method that helps neural networks understand how to solve problems. The performance of a rule extraction algorithm can usually be judged in five ways:

(1) Intelligibility, which lies in the extent to which people can understand the extracted rules;

(2) Fidelity, which refers to the proportion of extracted rules that agree with the classifier in terms of class labels;

(3) Accuracy, which is the performance of classifying accurately despite inputting data that has not previously existed;

(4) Scalability, i.e., the ability of the model to handle large data sets and large input spaces;

(5) Generality, i.e., the generalisation performance of such rule extraction algorithms for various application scenarios.

In recent years, there are also a number of Chinese and foreign scholars who have made efforts to optimise these five performances of rule extraction algorithms. Odense and Garcez [24] proposed a new approach for knowledge representation based on the N-of-M rule extraction approach to make the extracted rules more intuitive and easy to understand.Ma et al. [25] proposed a two-phase hybrid ACO optimisation algorithm (TSHFS-ACO) to make the subset of rules extracted from the dataset perform better. Also, Yildirim and Alatas [26] proposed an adaptive intelligent grey wolf optimizer from an adaptive perspective, which not only can adaptively select the rule evaluation function, but also can be applied to the problem of multi-objective quantitative classification rule extraction, with better accuracy and scalability than some traditional rule extraction algorithms.

In addition to improving the performance of rule extraction, the research on rule extraction also focuses on the correlation between rule sets, i.e., association rules. Association rules consider the support and confidence between rules. Support refers to the percentage of all rules that contain both X and Y, i.e., the probability; confidence refers to the percentage of rules that contain Y under the premise that they already contain X, i.e., the conditional probability. Mining the correlation between rules, or classifying rules based on their correlation, can better discover the relationship between rules, reveal the principles behind them, and help manufacturers trace the root cause of a problem more easily. Rajab [27] proposed an association rule classification method with active pruning of the rules to avoid the training used to compute the support and confidence of other rules. data is discarded during the rule classification process, which improves rule classification accuracy and reduces rule redundancy. Hesam et al. [28] used binary harmony search to select the best subset of rules to avoid missing association rules for some important rules. Geng et al. [29] proposed a classification method based on evidence-based association rules to alleviate the overfitting of classification rules in the case of small data samples, which It improves the rule support and confidence, and also improves the classification efficiency. Mabu et al. [30] proposed a semi-supervised learning rule extraction method, which reduces the complexity of annotating rules for association rules in a fully supervised learning scenario.

Ant optimisation algorithm (ACO) is a heuristic optimisation algorithm which has a good performance in combinatorial optimisation. Rule extraction needs to consider which attributes and corresponding values to classify, and this process is consistent with the idea of combinatorial optimisation. Therefore, many scholars have used ACO algorithm for rule extraction. Zhou et al. [31] used both Genetic Network Programming (GNP) and ACO to extract time-related association rules, with good results. Ma et al. [32] used the ACO algorithm to optimise the classification of fault data and improve the accuracy of fault diagnosis. Helal and Otero [33] also improved the ACO algorithm so that it can also be applied to the data stream classification problem, i.e., the Stream Anti-Miner algorithm, which can be used to directly and effectively deal with a large amount of mixed-types of data, such as continuous and discrete data mixed. data mixing. These studies have proved that the rules extracted by ACO not only have good performance, but also have good effect on improving the support and confidence of the rules and mining association rules.

Through the above literature, we can see that scholars in the rule extraction method and its research in various fields has been relatively mature, however, the rule extraction for the quality control of the manufacturing process is still relatively simple, and few scholars will be the rule extraction method and the manufacturing process quality control of some of the excellent control methods combined. If these two methods are combined, they can better cope with the complex relationship between the input and output data of the manufacturing process, reduce the possibility of product quality anomalies, and thus avoid unnecessary time costs. At the same time, based on the expandability of most rule extraction methods, this combination can also help the manufacturing process control methods to constantly integrate new process data, making the whole quality intelligent control system more efficient, more understandable, more expandable and usable.

4. SUMMARY

It is known through the research of scholars that quality monitoring methods and rule extraction algorithms play a crucial role in manufacturing process quality management, and they have a wide range of applications, providing effective quality control means for enterprises. Scholars have proposed many improvements in this area, which continue to drive research and practice forward.

However, combined with some shortcomings of the current research, this paper suggests that these two methods can be explored in the following research directions in the future:

(1) Broadening application areas: although quality monitoring methods and rule extraction algorithms have been widely used in many fields, the methods used in some areas are still relatively limited. Future research can explore how to apply more quality monitoring methods and rule extraction algorithms to these fields to further improve the practicality and universality of the quality control of manufacturing processes in this field.

(2) Hybrid model research: attempts can be made to combine better quality monitoring models with rule extraction algorithms to construct hybrid models. Such a hybrid model may have higher accuracy and comprehensibility, and can better meet the needs of the actual production process. By integrating the advantages of different methods, a more comprehensive and effective quality management solution can be provided to enterprises.

Overall, future research should be devoted to broadening the application areas of quality monitoring methods and rule extraction algorithms, as well as exploring the creation of hybrid models to improve the efficiency and effectiveness of quality management. These efforts will help to promote the continuous improvement of quality management in the manufacturing industry and facilitate the continuous improvement and development of enterprises.

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