Functional failure diagnosis approach based on Bayesian network for manufacturing systems

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Abstract—**The failure of traditional manufacturing systems mostly refers to the physical failure of the production equipment that constitutes the manufacturing systems. With the advancement of manufacturing technology and the improvement of the level of intelligence, the physical failure of the conventional equipment in the daily operation of the system is rare, but the quality of the work-in-progress (WIP) is unqualified frequently. Especially the hidden functional failures such as reliability degradation of the final product have become increasingly prominent. How to model and characterize the functional failure of manufacturing systems has become a bottleneck restricting the application and development of holistic PHM (Prognostic and Health Management) technology of manufacturing systems. Therefore, a novel functional failure modeling and diagnostic strategy for intelligent manufacturing systems based on RQR chain is proposed in this paper, which includes the manufacturing system reliability (R) data, manufacturing process quality (Q) data and the produced product reliability (R) data. Firstly, the definition of the functional degradation process and principle of manufacturing systems is clarified from the perspective of RQR chain. Secondly, based on the established RQR chain, the functional fault connotation of manufacturing systems is defined, and the KPCs (key product characteristics) in the Bayesian network of integrated manufacturing systems are utilized. Big data are analyzed to model and predict the functional fault state of the running manufacturing systems. Thirdly, based on the relationship of RQR chain from right to left, the holistic functional fault diagnosis strategy is given. Finally, a case study of a manufacturing system for cylinder head is presented to verify the proposed approach.**

Keywords- Manufacturing systems, Functional failure, Failure diagnosis, RQR chain, Bayesian network (BN)

I. INTRODUCTION

Highly qualified product is the output of highly reliable manufacturing systems, which is becoming increasingly the primary target of most manufacturing industries. And prognostic and health management (PHM) considering production quality has been a research hotspot in reliability and diagnosis field. Jin et al. [1] proposed a co-effect relationship between manufacturing system reliability and production quality, and established the conceptual quality – reliability (QR) chain. Based on the QR chain, Sun et al. [2] presented a reliability modeling and analysis approach that considered dimensional quality, tool degradation, and system configuration. Lin and Chang [3] proposed the limited manufacturing network model, and after mining operating failures and rework data, an analysis model of manufacturing system reliability was established. Gong et al. [4] explored an adaptive maintenance model of the process environment to diagnose the progressive faults in manufacturing systems.

In addition to the mentioned literature, a few studies have examined reliability monitoring and management in production. Xie et al. [5] proposed a control scheme based on the cumulative quantity between observations of defects to monitor the failure process of components or systems. Jin et al. [6] proposed a framework based on six sigma to deploy high product reliability commitment in distributed subcontractor manufacturing processes. He et al. [7, 8] proposed the concept of RQR chain and the product qualified probability to provide a method to model manufacturing systems dynamically, which is also introduced in this paper for its capacity of representing the correlation among components of manufacturing systems.

To meet the demand of high quality and efficiency of production, manufacturing systems are in urge need of powerful diagnosis method for detecting possible fault sources that result in unqualified products and failures in field. However, traditional manufacturing system reliability modeling tends to follow the classical reliability block diagram method, like fault tree analysis, which makes the comprehensive analysis and dynamic evaluation of manufacturing systems become complicated or inconvenient. With the ability of analyzing huge volume of data and referencing the cause-effect relationships among variables, Bayesian network appear to be suitable solution to model the multistate of the running complex manufacturing systems.

The Bayesian network (BN) is a probabilistic pattern model. It is an extension of the Bayesian method and it is one of the most effective theoretical models in the field of uncertain knowledge representation and inference. S. Dey et al. [9] developed a diagnosis approach based on BN for incorporating process metrics from sensors to identify toot cause of process variations. Anna Lokrantza et al. [10] presented a machine learning framework using Bayesian networks to backtrack the

The National Natural Science Foundation of China

root cause of failures and deviations. And Persis et al. [11] proposed an application of both Bayesian methods and fault tree analysis for risk assessment. Previous studies are inspiring in BN modeling while does not pay significant attention to the functional state diagnosis of manufacturing systems regarding the highly qualified outputting product.

Therefore, a methodology using BN to analyze the big operational data of manufacturing systems is proposed to evaluate its functional status and diagnose potential failure sources in this paper.

II. Basics of Functional Failure for Manufacturing Systems

A. Connotation of RQR Chain

A manufacturing system is a physical and organized system built to achieve scheduled production tasks, which usually consists of a complex working environment with multiple equipment and various related factors of operation procedure. To represent the intricate interaction relationships and highlight its function of outputting qualified production, as shown in Fig. 1, a quality oriented RQR chain is presented.

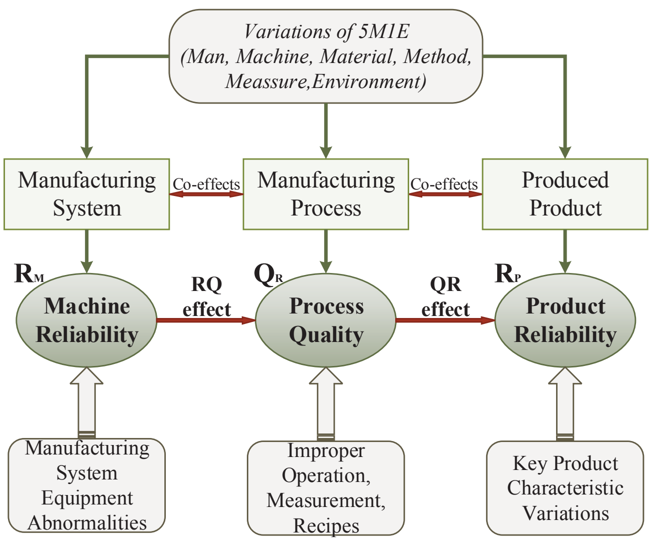

Figure 1. RQR chain model

As shown in Fig. 1, the RQR chain is to describe co-effects among reliability of manufacturing system equipment R_m, quality of production process Q_p (which is measured by criteria of process stability like operation level in this paper), and product inherent reliability R_p (which is represented by key quality characteristics of product).

Equipment is the physical carrier for executing production tasks. Reliability of machine like the automatic lathe is one of the basic effect factors influencing craft precision and other critical process parameters. Apart from affecting product quality through machining process, equipment reliability could also have a direct impact on product. For instance, the quality of work-piece surface is subject to the hardness and stableness of cutting tools to some large extent. Quality of manufacturing process Q_p, which is partly affected by machine, also has an influence on product with multilevel of operation, machining recipe, etc. Applying improper recipe in machining process may cause invisible defects in product, which possibly lead to degradation of product inherent reliability R_p.

As product pass on through process flow successively, unqualified output of former manufacturing process may propagate quality variations to next process, during which deviations accumulate to an unwanted extent. In conclusion, the reliability of final output product in manufacturing systems is determined by various interactions of different components and factors. To quantify product inherent reliability, key product characteristics (KPCs) detected after each machining process such as dimension parameters are proposed. KPCs' accordance with design parameters represents qualified degree of the output of each process, which are the symptoms of functional failures of manufacturing systems.

B. Definition of Functional Failure of Manufacturing Systems

Since small variations resulted from imperceptible abnormalities of manufacturing systems sometimes generates unqualified products, the conception of functional failure state is introduced in this paper for diagnosis modeling to help guarantee produced production quality. Functional failure refers to the failure when the equipment fails to meet the specified requirements, and cannot continue to complete its own functions, like losing its normal working ability, its working ability drops significantly, or the quality and reliability of its outputs can't reach the standard.

It can be divided into the following three categories shown in Fig. 2. Distinguished from physical fault which mainly aimed at equipment degradation, the functional fault of manufacturing systems is also assessed by unqualified workpiece and products. A low qualified rate of workpiece and products indicates an inferior state of function. In manufacturing process, deviations of KPCs in workpiece are continuously transferred and accumulated to the lower levels, which eventually leads to quality problems of the products (which are quantified by the key quality characteristics KQCs) when there is no obvious fault in the equipment. And deviations of KPCs mainly result from degradation of equipment and disqualification of processing.

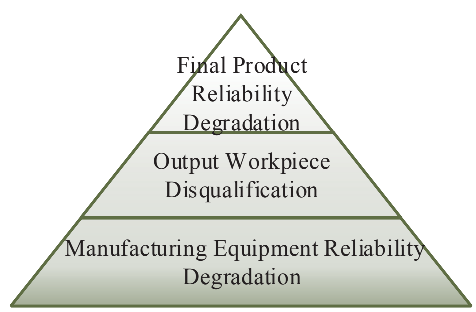

Figure 2. Classification of functional failures

By obtaining a series of KPCs through inspection in process and KQCs through final product quality test, the functional state of manufacturing systems can be quantified by evaluation approach proposed in this paper. And diagnosis strategy based on system functional failure is also developed for fault location.

With such methodology, accumulation of quality deviations in machining process may be detected and avoided, and preventive maintenance for certain process can be carried out purposively.

III. Functional Failure State Evaluation Based on BN for Manufacturing Systems

A. Basis of Bayesian Network

Bayesian network (BN) is widely used in probabilities inferencing with the ability to evaluate uncertainty and represent causal relationships in graphical structure. By taking advantage of it, evaluation and diagnosis model can be built with data and expert knowledge. The mathematics of BN is based on Bayes' theorem. Given a hypothesis θ, which is represented in the form of prior probability $p(\theta)$, observed data $D=\{d_1,\ldots,d_N\}$, and background knowledge δ, the probability distribution for θ given D and δ using Bayes' theorem may be stated as follows:

$$p(\theta|\, D,\delta)=\frac{p(\theta|\,\delta)\;p(D|\theta,\delta)}{p(D|\delta)} \tag{1}$$

For a Bayesian network of variables $X=\{x_1,x_2,\ldots,x_k\}$ with pa_i to denote the parent nodes of x_i, the joint probability distribution for variables X of number k is represented as:

$$p(x)=\prod_{i=1}^{k}p(x_i|pa_i) \tag{2}$$

By incorporating previous knowledge of process as well as present observed evidence, Bayesian network is able to evaluate how the process is behaving possibly.

B. Probabilistic Graphical Structure of BN Based on Process Flow

Taking into consideration that relationships between product failures and their causes in a manufacturing system are complex and indirect, a graphical structure needs to be identified to characterize quality variations in product flow. Structure learning is utilized to learn the links between nodes of Bayesian network from the relationships of data, while aided by prior knowledge.

Since product quality variations usually accumulate along the manufacturing process and operation procedure, prior knowledge of product process and expert experience is added to form basic structure of network. In this BN model, each manufacturing process is identified as a basic unit to propagate quality variations which finally lead to product defects or key quality characteristics (KQCs) deviations (as shown in Fig. 3), and each unit can be divided into several nodes of machine reliability, process stability and key product characteristics (KPCs) in production procedure.

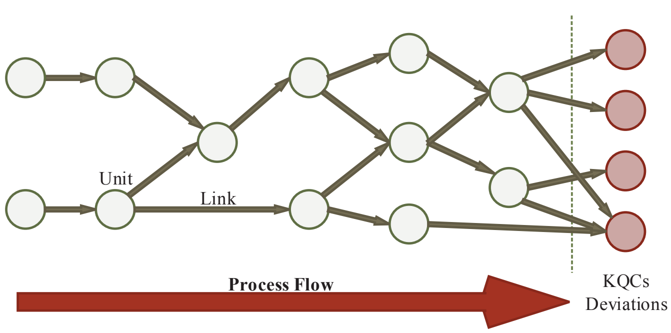

Figure 3. Example of probability graph based on process flow

The relationships among components of manufacturing systems are recognized on the basic of RQ effect and QR effect from RQR chain shown in Fig. 1. And the graph representing their correlation under framework of BN is given below as Fig. 4.

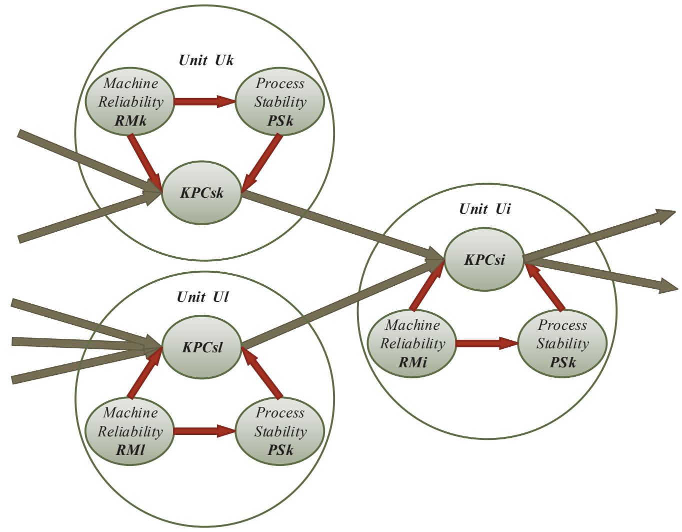

Figure 4. Nodes of variations sources in each process unit

The influence of 5M1E (Man, Machine, Material, Method, Measure and Environment) in manufacturing systems is represented by co-effects of the RQR chain. Accordingly, nodes of machine reliability, process stability and KPCs are proposed to demonstrate those factors. As QR effect described, product quality quantified by KPCs are influenced by quality variations from former process (propagated by semi-finished products) and present process stability. As RQ effect indicated, manufacturing system abnormality may have an impact on process stability as well as product characteristics represented by KPCs. Consequently, based on the product quality variation sources introduced before, the variations in the operating part come from:

- **Machine Reliability:** The precision, performance, efficiency and maintenance status of manufacturing equipment has direct effects on product quality during operation procedure, which can be represented by machine reliability (*RM*).
- **Process Stability:** Concept of process stability contains condition of method, operation, measurement and so on, which get influenced by the status of machining equipment. And unqualified manufacturing process usually leads to quality deviation of product.
- **Product Quality:** Potential failures in product can be propagated to the next manufacturing process through process flow. Hence, product's quality quantified by KPCs can regarded as one of the variations' sources.

C. Learning Parameters from Prior Information

Apart from structure definition and identification steps proposed above, prior and conditional probabilities of each node also need to be learned from given database to use BN model for system analyzing. As shown in Fig. 5, the state of each node is identified by different indexes proposed in last subsection: machine reliability is evaluated by reliability model with its possible value of fault probability distribution, based on the presence of direct sensor monitoring data or prior knowledge/ experience; process stability is graded by method of Process Failure Modes and Effects Analysis (PFMEA); products quality is under real-time monitoring by detection of KPCs in each machining process and by final QA(Quality assurance) test.

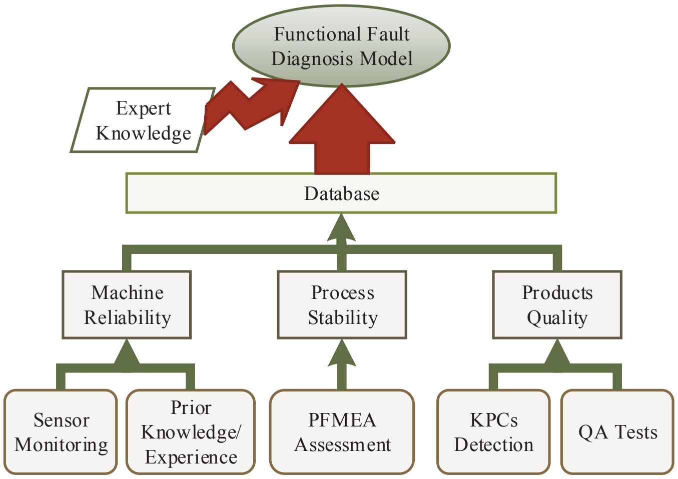

Figure 5. The data basis of BN model

Application of BN learning includes using database of training examples to update prior belief on the parameters using Bayes' theorem. As production tasks continuously go on over time, variations like machine degradation or raw material change may occur, hence the BN model also needs to be updated along with database. And by associating the status of parent nodes and conditional probabilities, possibility of one certain status of the child node can be computed.

D. Evaluation of Manufacturing Functional Failure State

With observed nodes and learned structure and parameters in BN model, final deviations of key product quality as well as their possibilities can be assessed. Accordingly, state of manufacturing system functional failure is evaluated by considering deviations' impact on product quality $\Psi=\{\psi_1,\psi_2,\ldots,\psi_n\}$, deviations' degree $D=\{d_1,d_2,\ldots,d_n\}$ and their probabilities of emergency $P=\{p_1,p_2,\ldots,p_n\}$. The functional state is defined as follows (D, P, Ψ are vector variables consisting of distinct variables):

$$F_M=f(\Psi,D,P) \tag{3}$$

Steps to evaluate manufacturing functional state are proposed in Fig. 6.

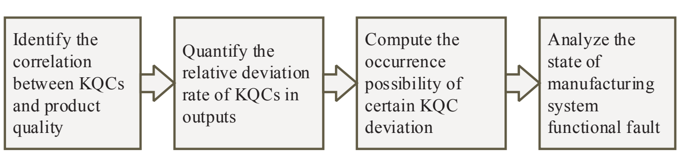

Figure 6. Evaluation approach for manufacturing systems

Details of the proposed approach are given as follows:

a) Identify the degree of correlation between key quality characteristics and product quality from the aspect of customer needs and required function. The stronger the correlation is, the worse impact key quality characteristic deviation has on final product quality. With aid of expert knowledge, values of $\{\psi_1,\psi_2,\ldots,\psi_n\}$ are obtained after complete analysis.

b) Quantify a series of relative deviation rate of product key quality characteristics, which are represented by $\{d_1,d_2,\ldots,d_n\}$. Characteristic with greater relative deviation rate tend to result in more evident defect in product.

c) Obtain the possibility of certain deviation state occurrence $\{p_1,p_2,\ldots,p_n\}$ by applying BN model. With machine state, process stability and KPCs being monitored, the final outputs' level of quality and their probability can be acquired before the production tasks are achieved.

Therefore, the functional failure state of manufacturing systems is evaluated by carrying out the above procedures iteratively.

IV. Functional Failure Oriented Diagnosis Strategy

When a functional fault of unqualified key product characteristics is detected, root cause identification will be executed by using this BN model. By observed nodes and parameters of conditional probabilities, fault probabilities of parent could be computed. Based on the BN structure built by experts and information obtained by compute, the most possible fault propagation path is identified with the maximization expectation. When root cause units of functional fault are discovered, deeper reasons of variations from equipment or process could be analyzed with RQR chain co-effects and expert knowledge. Furthermore, method of maintenance on certain equipment could be taken purposively to improve the performance of manufacturing systems.

Under the situation that the BN model fails to diagnose the root cause of product quality deviation, updating of Bayesian belief should be conducted as Fig. 7 illustrates.

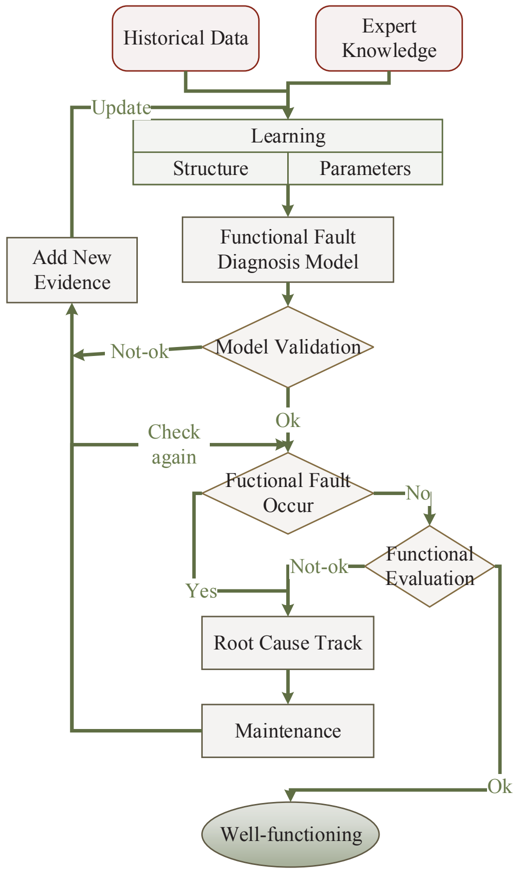

Figure 7. Modeling approach of functional fault diagnosis

As shown in Fig. 7, new evidences of nodes are added for retraining, which may lead to slight change of graphical structure and parameters, and the renewed model's validity will be checked again. Only if the model is eligible for practical diagnosis, will the updating process be stopped. Finally, the functional failure status of manufacturing systems is evaluated by steps proposed above to guide preventive maintenance. Therefore, manufacturing systems' function of producing qualified products is ensured before any visible equipment abnormalities occurs, and production and maintenance costs are deduced with less equipment downtime.

V. CASE STUDY

A. Backgrounds

The cylinder head is one of the critical components of modern automobile engine, which ensures the function of engine and other systems by coordination with fuel injectors, intake and exhaust values, and pneumatic values to control combustion of air and fuel inside the cylinder. With its significance and complex function, the cylinder head retains intricate manufacturing process and elaborate key quality characteristics of product like geometrical shape or position accuracy. While during manufacturing, quality variations may propagate along the process flow, which eventually result in declining specifications of the cylinder head when there is no obvious physical fault on equipment. Deviations of products mainly result from degradation of equipment and disqualification of processing. For this case, the key product characteristics of cylinder head is associated with surfaces and holes. And for illustration, the machining process is simplified as procedure of three steps includes milling and drilling, which is listed in Table I. The path of quality variation and relationships between final quality characteristics of output and its related machining units are represented in Fig. 8.

TABLE I. MACHINING PROCESS FLOW

Unit	Machine	Process	KPCs	Specifications
1	M1	P1: Finish milling face	K1	Surface roughness $R_a = 3.2\mu m$ *Diameter* $\emptyset_A = 12.2^{+0.025}_{-0.05}mm$
2	M2	P2: Drill hole A	K2	Diameter $\emptyset_B = 26.2^{+0.20}_{-0.08}mm$
3	M3	P3: Drill hole B	K3	Alignment $\emptyset_{AB} = 0.06mm$

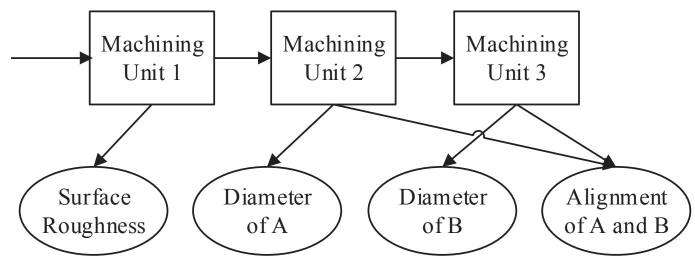

Figure 8. Machining process flow

B. Numerical Example

In addition to specifying the graph structure, the size and type of each node must be specified. To simplify the problem, all nodes are assumed to be discrete and binary. When a fault of improper alignment is detected, irrelevant links and nodes are removed before building BN diagnosis model, and final structure is built based on process flow path as well as correlation among machine reliability (R_i), process stability (Q_i), products quality (K_i) of $unit_i$ (seen in Fig. 9).

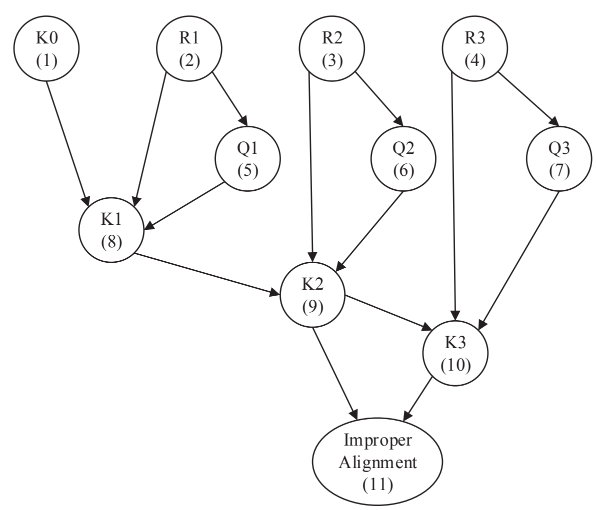

Figure 9. BN structure for variation propagation

On basic of known graphical structure, a BN model is built by Bayes Net Toolbox in MATLAB with training samples. And data used for parameter learning and result comparison are simulated from a true model whose structure and parameters are known. Fig. 10 shows the accuracy of the functional diagnosis model compared with a model disregarding RQR effects, which assumes that only the quality of inputs (K_0) and machine reliability (R_1, R_2, R_3) have a direct impact on quality of final outputs. By taking account of the interactions among manufacturing system components, model proposed in this paper has a higher accuracy at around 0.9 while the other's is about 0.65, when training data size is great than 2000.

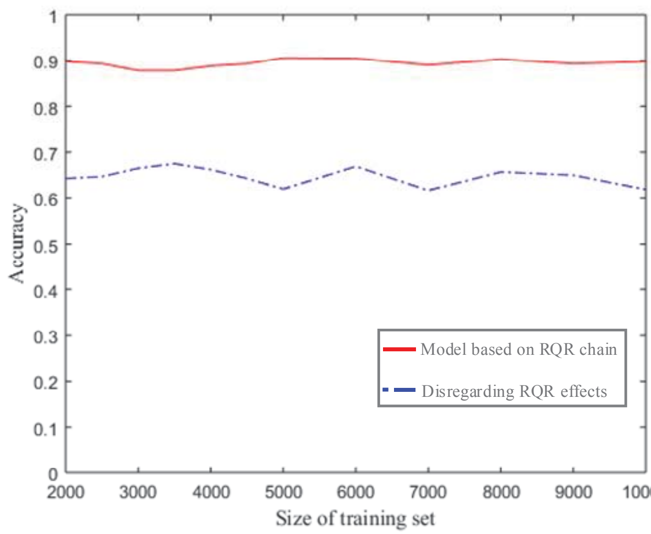

Figure 10. Comparison of diagnosis results between two models

In addition, most possibly related source could be identified with help of the proposed model when functional fault occurs. Under the situation that states of K_1, Q_1, Q_3 and alignment of A and B are identified as 'qualified, qualified, qualified, fault' (now define this event as W), marginal distributions could be obtained, which is listed in Table II('0' represents state of fault, and '1' represents state of being qualified).

TABLE II. MARGINAL DISTRIBUTIONS

Condition	Probability	Condition	Probability	Condition	Probability
P(K0=0|W)	0.0957	*P*(R1=0|W)	0.0561	*P*(Q1=0|W)	0
P(K2=0|W)	0.5743	*P*(R2=0|W)	0.2862	*P*(Q2=0|W)	0.6158
P(K3=0|W)	0.3798	*P*(R3=0|W)	0.1311	*P*(Q3=0|W)	0

It can be seen in Table II, among three suspicious machining units, output of unit 2 are in correlation the improper alignment to the most extent. And equipment 2 and process 2 are in need for inspection or maintenance.

CONCLUSIONS

In this paper, RQR chain is introduced to represent the interaction between components of the running manufacturing systems, and connotation of functional fault is clarified to break the limitations of traditional fault analysis. Thereby a strategy based on BN is proposed for evaluating manufacturing functional state. Furthermore, a functional failure diagnosis approach is put forward to guide purposively maintenance on machining equipment and improvement on process stability.

Diagnosis approach proposed in this paper can identify the most related source of functional faults when structure and parameters of BN are determined. However, it lacks the capacity for adjusting to a dynamic system on the other hand. Further research needs to be undertook to simplify the structure of BN model and to improve the efficiency of real-time diagnosis.

ACKNOWLEDGMENT

This study was supported by the National Natural Science Foundation of China (Grant No. 61473017) and the general projects (No.6140002050116HK01001 and No. JZX7Y20190242012401) funded by the National Defense Pre-Research Foundation of China.

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