A Real-Time Quality Control System Based on Manufacturing Process Data

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ABSTRACT Quality prediction is one of the key links of quality control. Benefitting from the development of digital manufacturing, manufacturing process data have grown rapidly, which allows product quality predictions to be made based on a real-time manufacturing process. A real-time quality control system (RTQCS) based on manufacturing process data is presented in this paper. In this study, the relationship between the product real-time quality status and processing task process was established by analyzing the relationship between the product manufacturing resources and the quality status. The key quality characteristics of the product were identified by analyzing the similarity of the product quality characteristic variations in the manufacturing process based on the big data technology, and a quality-resource matrix was constructed. Based on the quality-resource matrix, the RTQCS was established by introducing an association-rule incremental-update algorithm. Finally, the RTQCS was applied in actual production, and the performance of RTQCS was verified by experiments. The experiments showed that the RTQCS can effectively guarantee the quality of product manufacturing and improve the manufacturing efficiency during production.

INDEX TERMS Quality management, production control, prediction methods.

I. INTRODUCTION
In recent years, the manufacturing industry has become more and more personalized and automated [1], [2], which has created opportunities for the use of quality control measures for manufacturing processes. To realize intelligent manufacturing, the application of artificial intelligence and Internet of Things (IoT) technology in the monitoring and diagnosis of production processes has been studied widely [3]–[6]. The historical data generated in product manufacturing processes have been used to build models of the relationship between manufacturing process data and the product quality. The advantages of product quality diagnosis and prediction models have been demonstrated for the applications of various industrial processes [7]–[9], such as design [10], logistics [11], and fault detection [12]. The decision-making basis has changed from relying on experts to data-driven processes in many fields of manufacturing by introducing artificial intelligence technology. However, with the progress of the product manufacturing process, the operating status has changed over time. Consequently, quality diagnosis and prediction models based on historical data have difficulty adapting to the requirements of current production. The updating mechanism of prediction model was studied by some articles [13], [14]. However, due to the complexity of manufacturing system, the combination of historical data information and measured data flow information in practical application needs to be further studied. For this problem, the real-time quality control system (RTQCS) was established. In the RTQCS, the quality prediction model is updated dynamically as the manufacturing process progresses by combining historical data information with measured data flow information.

The quality is affected by the entire product manufacturing process. In this process, the formation of the product quality characteristics is impacted by quality resources, including man, machine, materials, method, measurement, and environment [15], [16], which are associated with the quality characteristics in multiple dimensions. This leads to difficulties collecting and expressing quality data.

In recent years, the use of the IoT has become more and more mature [17]–[22]. Complex multi-dimensional data...
using IoT technology have been collected in many fields of manufacturing, such as material distribution [17], production monitoring [18], [19], fault prediction [20], and quality prediction [23], [24]. Product quality data can be collected and stored comprehensively using the IoT technology [21], which establishes a database for a real-time quality control model.

By combining an IoT environment with big data analytics algorithms, product quality in some specific scenarios in manufacturing have been simulated and predicted [2], [25], [26]. At present, the prediction of quality is mainly based on the Statistical Process Control (SPC) [23], [27], [28] or artificial intelligence algorithms [29]–[31]. In the context of the rapid development of machine learning, the use of learning algorithms to predict quality has produced many research results [24], [32], [33]. Some studies [34] have proposed that the real-time data of current production time will be further converted into historical data with the production. Quality process control knowledge would be obtained from massive historical data through big data mining analysis. Limited by the effectiveness of the algorithms, manufacturing process quality control research has focused on prediction, prevention, or after-the-fact compensation. In this study, real-time online manufacturing quality control was studied based on real-time manufacturing process data acquisition. The relationship between the quality characteristics and quality resources and that between the quality characteristics in the process of product formation were analyzed, and a quality control model was constructed. A theoretical basis for the establishment of a real-time quality control system was subsequently provided.

In this study, a real-time quality control system (RTQCS) was established in an IoT environment. By analyzing the influence of manufacturing resources on the quality characteristic variations based on the theory of quality variations, correlations between manufacturing resources and quality characteristics were constructed. The quality-resource matrix was then constructed. Based on the quality-resource matrix, the real-time quality predictions of products in the manufacturing process were realized.

For the development of the RTQCS, this paper provides an in-depth analysis of the process of the formation of quality characteristics and the mapping relationship between the quality characteristics and manufacturing resources. Based on this mapping relationship, the relationship between the product quality status and product manufacturing process was expressed mathematically. Furthermore, the product quality prediction model based on the quality resource data in the product manufacturing process was established. Finally, the application framework for the prediction model was built.

II. RELATED THEORIES

The RTQCS is a system that enables the real-time prediction of product manufacturing process quality by establishing a mapping between the manufacturing resources and the product quality characteristics. As the manufacturing process progresses, changes in the product quality characteristic measurements are called variations, and the quality problems are essentially interpreted as a suprathreshold for the characteristic variations. Variations in product-specific process quality characteristics are derived from two parts:

1. Variations in the error formation in the processing of product quality characteristics themselves.
2. Variations formed by associated quality characteristics.

In a specific machining process, there are usually six sources of variations: man, machine, material, method, measurement, and environment, which are collectively abbreviated as 5M1E. The complex correlation between the quality characteristics leads to difficulties and challenges for establishing the impact mechanism of manufacturing resources on product quality in the process of product processing. As the basis of the real-time prediction of product processing quality, the correlation between the product quality status and product processing was established based on the correlation of the product quality characteristics. The relationship between the quality characteristics and manufacturing resources are analyzed in this section based on the formation of the quality characteristics during product processing.

A. FORMATION OF MANUFACTURING RESOURCES AND QUALITY STATUS

In this paper, each change in the quality of the product is referred to as a manufacturing activity. Because of the correlation and transmission of quality characteristics, the result for each manufacturing activity is based on the last manufacturing activity during the manufacturing process. The mathematical symbols used in the analysis are summarized in Table 1.

| Quality status defined | Mathematical expression |
|-----------------------|-------------------------|
| Quality status         | $x$                     |
| Manufacturing activities| $k$                     |
| Quality characteristic | $x(k)$                  |
| Values of manufacturing|                         |
| activity $k$           |                         |
| Quality status of     | $X(k) = \{x(i) | i = 1, 2, 3, ..., n\}$ |
| manufacturing activity $k$ |                        |

In the process of machining complex parts, the quality status at each moment corresponds to multiple quality characteristics. The machining process may not process every quality characteristic. Therefore, the state of characteristic $x_i$ of process $K$ may be affected by the value of the characteristic $x_j$ of process $K - M$ ($M > 1$). The $x_j$ characteristic is not processed from the $(k - m)$th to $(k - 1)$th manufacturing activity and is only affected by part processing deformation and other random errors. To build a unified description model, the $x_j$ characteristics of the $(k - m)$th ($m > 1$) operations are still passed to the $(k - 1)$th manufacturing activity for such problems, i.e.,

$$x_j(k - m) = x_j(k - m + 1) = x_j(k - m + 2) = \ldots = x_j(k - 1)$$
In summary, the process of the product formation can be described as a quality characteristic delivery network, as shown in Figure 1.

During the production process, the quality status $X(k)$ for each manufacturing activity is a mapping of an $n$-dimensional vector composed of the quality characteristics. The overall manufacturing activity flow can be regarded as a process of the quality status $X(k)$ approaching the $n$-dimensional vector of the quality characteristics step by step. If the number of manufacturing activities is $m$, then $X(m) = a$. Figure 2 shows the change of the quality status.

$X(k)$ is the product state after the manufacturing activity unit is executed, $\delta_i$ is a function of the manufacturing activity unit, i.e., the method of converting the input to the output, $I_i$ is the input of the manufacturing activity unit, and $O_i$ is the output of the manufacturing activity unit, which is the result of the manufacturing activity that directly or indirectly affects the product status. The product development system is a complete system, and the various components are interrelated and mutually constrained, each with its own constraint set, feature set, and operating domain, forming the product state.

From the perspective of task execution, the execution function is the core element of manufacturing activities. In an IoT environment, it is assumed in this paper that the 5M1E resources needed in the manufacturing process are all active and inevitable. The 5M1E specifically participates in all aspects of the manufacturing process and serves as the input of the manufacturing activities. From the perspective of quality data, the manufacturing activity is a process of transforming an input into an output through a processing mechanism under certain constraints and following certain principles. If the input and output of manufacturing activities are regarded as data, manufacturing activities are essentially a process of data collection, transmission, and use and results processing. The product is the final physical expression of the data, and product status data is the data expression of the physical products. The manufacturing activity is abstracted as a data processing unit. In the physical space, $X_i$ is processed by the 5M1E of the current process and the result of processing $X(k-1)$. $X(k)$ is the result of processing the parameters after the virtual active unit terminates the incoming parameters based on the product status $X(k-1)$ of the previous process for process $i$. $X(k)$ is strongly related to 5M1E and $X(k-1)$ in the $k$th manufacturing process. We can express this relationship with a function as follows:

$$X(k) = X(k-1) + f(5M1E_k).$$

By representing 5M1E separately, the upper formula can be changed to the following:

$$X(k) = X(k-1) + f_k(M_1^i, M_2^i, M_3^i, M_4^i, M_5^i, E_k),$$

where $X(k)$ represents the status of the product after process $i$ in the manufacturing process, and the product status consists of a series of product quality characteristics; $f_k$ represents the process of mapping the input parameters of the active unit by process $i$ in the virtual space; $M_1^i$ denotes “man” (one of the six elements that causes quality variations), which refers
to factors such as the operator’s knowledge of the quality, technical proficiency, and physical condition; $M^2$ denotes “machine,” which refers to the accuracy and maintenance status of the equipment, tools, and fixtures; $M^3$ denotes “material,” which refers to the composition, physical properties, and chemical properties of the material; $M^4$ denotes “method,” which includes the processing technology, tooling selection, and operating procedures; $M^5$ denotes “measurement,” which refers to whether the method adopted during the measurement is standard and correct; E denotes “environment,” which refers to the temperature, humidity, lighting, and cleaning conditions of the workplace.

The measured values of quality characteristics were continuous in manufacturing. State of the product was changed based on its current measurement. Based on this view, some studies used stream of variation to predict the quality status of products in the manufacturing. However, due to the uncertainty of measurement error and error source, the prediction of complex product in manufacturing was not acceptable.

### B. ANALYSIS OF QUALITY CHARACTERISTIC CORRELATION

Product quality is a set of requirements of the inherent characteristics of the product. To facilitate the measurement of the product quality, it is necessary to convert this set of characteristics into measurable, valuable characteristics and quality characteristics. Quality characteristics can be divided into three categories depending on the object space [35]:

1. The product quantity characteristic (PQC) focuses on the description of the product’s nature.
2. The realization quantity characteristic (RQC) focuses on 5M1E in the implementation of various manufacturing processes, such as product manufacturing and assembly, and the description of such processes.
3. The organization quantity characteristic focuses on the description of organizational management and work quality characteristics in the product development process.

The PQC is the most basic and original feature and the foundation for the study of the quality features in other dimensions. As an external measure of the product quality, the PQC gradually evolves from the user requirements during product development. If the product consists of N quality characteristics, then we can use an N-dimensional vector $a = (PQC_1, PQC_2, \ldots, PQC_N)$ to define the PQC of the product. The product development process is a process of gradually filling the parameters in the N-dimensional vector $a$, as shown in Figure 5.

The RQC is represents the characteristics of the product from the initial state to the application requirements step by step. The manufacturing process is a realization process of the PQC using the RQC. As the product manufacturing process continues, the quality characteristics are constantly enriched, and the parameters in the N-dimensional vector $a$ are gradually obtained. In the formation process of a part, the quality characteristics are related and influence each other. In the production process, quality characteristics are transferable. In the process of gradually obtaining the parameters in the N-dimensional vector $a$, the quality characteristic parameters that are implemented first will have a decisive influence on the quality characteristic parameters associated with them that are implemented later. Considering PQC1 and PQC2 as examples, PQC1 is determined by PQC2 and PQC3, and PQC2 is determined by PQC4, PQC5, and PQC6, as shown in Figure 6.

### C. ANALYSIS OF RELEVANCE OF PRODUCT QUALITY STATUS AND TASK PROCESS

Taking into account the continuity of the quality status, the raw material status of the product is recorded as operation 0, and the input parameters of the virtual activity unit
of the product in the raw material state are $M_{10}, M_{20}, M_{30}, M_{40}, M_{50}, E_0$. In this study, the relationship between the product quality status and the task process is expressed as follows:

$$X(k) = \sum_{i=0}^{k} f_i(M^1_i, M^2_i, M^3_i, M^4_i, M^5_i, E_i)$$

We can determine that the product state in the manufacturing activity $K$ is determined by all the manufacturing resources of the product manufacturing process. In this paper, the manufacturing resources involved in the process of product manufacturing are written in the form of a matrix, which is called the resource-state matrix under the manufacturing activity $K$. The matrix has a mapping relationship with the product quality status $X(k)$:

$$X(k) \sim \begin{bmatrix} M^1_0 & M^2_0 & M^3_0 & M^4_0 & M^5_0 & E_0 \\ M^1_1 & M^2_1 & M^3_1 & M^4_1 & M^5_1 & E_1 \\ M^1_2 & M^2_2 & M^3_2 & M^4_2 & M^5_2 & E_2 \\ \vdots \\ M^1_k & M^2_k & M^3_k & M^4_k & M^5_k & E_k \end{bmatrix}$$

The product’s status is determined by the manufacturing activities it has successively experienced during the manufacturing process. For a product with a quality problem, the problem must have been caused by one or more combinations of the manufacturing resources involved in its production. With the progress of the manufacturing process, many quality problems and manufacturing resource correspondence data are accumulated by the RTQCS based on the mapping relationship between the quality problems and manufacturing resources. Using big data analysis tools, the factors that cause quality problems can be accurately identified at the manufacturing resource level by excavating the relationship between the quality problems and the manufacturing resources. Similar quality problems will be avoided by intelligent production systems in future production. The quality control efficiency will be improved effectively, the cost of quality control will be reduced, and the production process quality control will be changed to pre-production control.

### III. REAL-TIME QUALITY CONTROL SYSTEM FRAMEWORK FOR DATA-DRIVEN MANUFACTURING PROCESSES

The RTQCS is a decision-making system that collects and analyzes production data in real-time in a manufacturing process by relying on the IoT system in the manufacturing environment. As shown in figure 6, the manufacturing resources and product quality status for product manufacturing activities are obtained immediately during product processing. Based on the collected data, the quality-resource matrix was combined. Then, the matrix was processed and analyzed by the RTQCS. The results of the analysis are applied for quality prediction, quality traceability, or production research allocation based on different scenarios.

The decisions of the RTQCS depend on the processing of the data. Based on large amounts of empirical data, decision-making functions are developed. To enable quick-decision functions and improve the decision accuracy of the RTQCS, a dynamic evolution mechanism for the prediction algorithms was constructed based on empirical data. The dynamic evolution is shown in Figure 8.

The manufacturing activity that the product is currently involved with is called the current manufacturing activity,
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FIGURE 7. Dynamic evolution mechanism for the prediction algorithm.

FIGURE 8. Classification of product quality characteristics.

and the manufacturing activities that the product have previously experienced are called historical manufacturing activities. The intelligent decision algorithm predicts the product quality based on the product quality status and historical manufacturing activities. At the end of the current manufacturing activity, the RTQCS updates the intelligent decision algorithm with the data collected from the current manufacturing activities (manufacturing resources and quality status) as the result parameters and collects the real-time data as historical data. The quality of the manufacturing activities of the products continues to be predicted by the updated intelligent decision algorithm.

The real-time quality control system makes recommendations and evaluations for the allocation of production resources during production activities. In the production process, the current quality status of the product and the experienced manufacturing resources are collected through the IoT in the enterprise. With the quality characteristics of the product, the resource-state matrix corresponding to the current quality status of the product is built. Based on the analysis of the resource-state matrix, the real-time feedback suggestions for the allocation of production resources are given by the RTQCS.

A. ESTABLISHMENT OF KEY QUALITY CHARACTERISTIC VECTORS

The quality control and quality prediction of complex products have been studied extensively. However, complex products have complex structures and parts, and many quality characteristics are involved in their processing and manufacturing. Identifying key quality characteristics is an important part of quality control and quality prediction [32], [33], [36], [37].

The main purpose of product design is to provide product functions to meet user demands. The purpose of quality features is to ensure the realization of product functions. Based on the role of the quality features in the product manufacturing process, they can be divided into functional quality features, direct quality features, and indirect quality features:

1. The functional quality characteristic refers to a product function that ensures the user’s needs are met, such as the rotatability of a propeller of a helicopter.

2. The direct quality characteristic meets the requirements of the functional quality characteristic, such as providing the rotation force to ensure the propeller is rotatable.

3. The indirect quality characteristics are the quality characteristics derived during the design process to ensure direct quality characteristics, which are usually directly related to the product structure.

The classifications of product quality characteristics are shown in Figure 9.

The quality problem can be regarded as a lack of design functions, which is often caused by the deviation of the measured value of the direct quality characteristic from the design value. The manufacturing process achieves direct quality characteristics by ensuring indirect quality characteristics. From the perspective of product manufacturing, the key quality characteristics can be considered to be the combination of direct and indirect quality characteristics that are highly correlated with the direct quality characteristics. In this study, the direct quality characteristics are represented by the vector DQC, the key indirect quality characteristics are represented by the vector IDQC, and the key quality characteristics are represented by the vector KQC. Thus,

\[ KQC = (DQC, IDQC). \]

The theory of quality characteristic variation propagation is introduced to identify key quality characteristics. In the process of actual product development, due to the disturbances of various interference factors, there is always a difference between the actual values of the quality characteristics and the target values, which are referred to in this study as the variation of the quality characteristics. Under the same
production conditions, the difference in the quality characteristics between different products is called the quality characteristic variation. In the product manufacturing process, the quality characteristics of different products are correlated, i.e., variations of the quality characteristics of one product will affect the quality characteristics of the other products. The process of identifying key indirect quality characteristics can be transformed into the identification of the correlation between the individual indirect and direct quality characteristics.

The quality characteristics of each product are collected at the end of manufacturing activities by the RTQCS. The collected quality characteristics are concatenated to form a high-dimensional vector. The quality characteristic data contains M + 1 samples, and each sample has n quality characteristics, which determines that the data set D consists of m + 1 N-dimensional vectors. The quality characteristic measurement value of product I (i = 1, 2, . . . , m) is expressed as an n-dimensional vector Di = di1, di2, . . . , dim, where dij represents the measurement value of the quality characteristic PQCj (j = 1, 2, . . . , n):

\[
D = \begin{pmatrix}
    d_{11} & d_{12} & \cdots & d_{1,n-1} & d_{1,n} \\
    d_{21} & d_{22} & \cdots & d_{2,n-1} & d_{2,n} \\
    \vdots & \vdots & \ddots & \vdots & \vdots \\
    d_{m-1,1} & d_{m-1,2} & \cdots & d_{m-1,n-1} & d_{m-1,n} \\
    d_{m,1} & d_{m,2} & \cdots & d_{m,n-1} & d_{m,n} \\
    d_{m+1,1} & d_{m+1,2} & \cdots & d_{m+1,n-1} & d_{m+1,n}
\end{pmatrix}
\]

The difference in the measurements between the product i and the same quality characteristic of the product i + 1 is treated as a single variation. The matrix of the quality characteristic data set V is obtained using the quality attribute data set D, Vj = Di+1 − Di. In dataset V, each row represents the variations in the overall quality status of the product, which is recorded as vij (i = 1, 2, . . . , n). The measurements of the same quality characteristics in different products are recorded as vij (i = 1, 2, . . . , n). As the manufacturing progresses, the matrix of quality variation is obtained:

\[
V = \begin{pmatrix}
v_{11} & v_{12} & \cdots & v_{1,n-1} & v_{1,n} \\
v_{21} & v_{22} & \cdots & v_{2,n-1} & v_{2,n} \\
\vdots & \vdots & \ddots & \vdots & \vdots \\
v_{i1} & v_{i2} & \cdots & v_{i,n-1} & v_{i,n} \\
\vdots & \vdots & \ddots & \vdots & \vdots \\
v_{m-1,1} & v_{m-1,2} & \cdots & v_{m-1,n-1} & v_{m-1,n} \\
v_{m,1} & v_{m,2} & \cdots & v_{m,n-1} & v_{m,n}
\end{pmatrix}
\]

Assuming that the product quality characteristic PQCk is a direct quality characteristic, the direct quality characteristic variation series in the product manufacturing process can be expressed as vik (i = 1, 2, . . . , m). The quality characteristics corresponding to the columns in the matrix V, whose variation trends are similar to vik (i = 1, 2, . . . , m), are the key quality characteristics. The product has multiple direct quality characteristics, and the quality characteristics that are strongly correlated with any direct quality characteristic variations are regarded as key quality characteristics. Before the correlation calculation, each value in the matrix V is a dimensionless value. In the following analysis, the parameters in the matrix V are regarded as non-dimensionalized values. The judgment process of key quality characteristics are explained by taking the correlation process of vij (i = 1, 2, . . . , m) and vik (i = 1, 2, . . . , m) as an example.

1) CALCULATION OF GRAY CORRELATION COEFFICIENT OF REFERENCE AND COMPARISON SERIES

The degree of correlation is essentially the degree of geometric difference between the curves. Therefore, the differences between the curves can be used as a measure of the degree of association. The correlation coefficient ξj(t) of vij (i = 1, 2, . . . , m) and vik (i = 1, 2, . . . , m) in column t is calculated by the following formula:

\[
\xi_j(t) = \frac{\min \min |v_{ij}(t) - v_{ij}(t)| + \min |v_{ik}(t) - v_{ij}(t)|}{\max |v_{ik}(t) - v_{ij}(t)| + 0.5 \cdot |v_{ik}(t) - v_{ij}(t)|}.
\]

2) CALCULATION OF RELEVANCE

The correlation coefficient is the correlation degree of each measurement value in vij (i = 1, 2, . . . , m) and vik (i = 1, 2, . . . , m). If the values are greater than one, the information is too scattered to facilitate the overall comparison. Therefore, it is necessary to collect the correlation coefficients of each measured value into a single value. In this study, the average value is treated as the value of the degree of correlation between vij (i = 1, 2, . . . , m) and vik (i = 1, 2, . . . , m). It is expressed as rj, which is calculated as follows:

\[
r_j = \frac{1}{m} \sum_{t=1}^{m} \xi_j(t).
\]

The quality characteristics whose correlation degree between the variations of the indirect and direct quality characteristics was greater than 0.7 were regarded as key quality characteristics. If the number of key quality characteristics is l, the vector of the product key quality characteristics can be expressed as follows:

\[
KQC = (kqc_1, kqc_2, \ldots, kqc_l).
\]

B. ESTABLISHMENT OF RESOURCE-STATE MATRIX

Along with the gradual growth process of products from intangible to tangible, from fuzzy to clear, and qualitative to quantitative, a large amount of product quality data is measured, collected, stored, and integrated into the RTQCS. The data collected in each manufacturing activity are classified into two categories: product quality status data and manufacturing resource data. Product quality status data are a data set formed by the measurements of each key quality characteristic of the product after a manufacturing activity.
which is represented by vector \( X(K) = (x_1, x_2, \ldots, x_K) \). The manufacturing resource data are formed by the data of the manufacturing resources involved in the manufacturing process of the product.

During the product manufacturing process, the product and product resource data are collected after every manufacturing activity. They are processed, analyzed immediately, and stored, and the relationship between them is established.

The manufacturing process of a product is the activity of the time sequence. In the manufacturing process, product quality characteristics are enriched over time. As the manufacturing process progresses, there is continuity between the various quality status of the product. The product quality status is affected by all the manufacturing activities involved. The product quality status is impacted by all manufacturing resources involved in the manufacturing activities.

The RTQCS combines the manufacturing resource data collected in each row into a six-dimensional vector \( r = (m_1, m_2, m_3, m_4, m_5, e) \). When manufacturing activity \( i \) is completed, the vector group \( r(k)|k = 1, 2, \ldots, i \) is formed and combined with the key quality characteristic vector to form the resource state matrix of the product in manufacturing activity \( i \).

\[
X(i) \sim \{r(k)|k = 1, 2, \ldots, i\}.
\]

C. ESTABLISHMENT AND APPLICATION OF PRODUCT QUALITY PREDICTION MODEL

Most of the manufacturing resource data collected and stored by the RTQCS in product production is a label of a certain manufacturing resource, which has no specific meaning and cannot be described using specific numerical values. The R-SLI algorithm [38] is used to build a product quality prediction model.

Based on the relationship with the matrix-based SLIG algorithm, the R-SLI algorithm is constructed by adding a tree structure. The intrinsic relationship between the association rules is represented through a custom frequency set tree. The dynamic update algorithm is introduced for subsequent transaction database updates and minimum support parameter changes. The quality status of the product is strongly correlated with experienced manufacturing resources. At the end of the manufacturing activity, the collected data are processed as a matrix corresponding to the current manufacturing activity. The matrix is processed as follows:

1. The parameters in the vector \( X(i) \) are converted to the form of "Quality Characteristic Name + Status Quantity" according to the requirements of manufacturing activity, with the status quantity recorded as 1 when the quality is acceptable, and the status recorded as -1 when the quality is not acceptable. The key quality characteristic parameters that have not yet been processed are removed.

2. The parameters in the resource matrix are combined into a single vector based on the processing sequence in the form of \( (r(1), r(2), \ldots) \), called the manufacturing resource vector.

3. The vector \( X(i) \) is combined with the manufacturing resource vector in the form of \( (r(1), r(2), \ldots, X(i)) \), e.g., (Jack, L-002, C-002, Tom, B-006,67, A-axis 1, B-side -1).

At the end of the manufacturing activity, the processed vector can be used as a collection in the R-SLI. As the manufacturing activities progress and collections grow, the R-SLI algorithm is used to determine the correlation between the product quality status and manufacturing resources.

In the process of product manufacturing, the quality status is predicted at the beginning of each manufacturing activity based on the association rules between the product quality status and the manufacturing resources. First, itemset1 is formed from the historical manufacturing activities and the current activity. The quality characteristic of the product being processed is then combined with its quality status, which is combined with the qualified state as itemset2 and with the unqualified state as itemset3. Finally, the support of itemset1 and its sub-items, itemset2 and itemset3, are calculated. If the support of itemset1 and its sub-items itemset3 is greater than that of itemset2, it is regarded as a process that will cause quality problems and a warning will be given. The product quality prediction process is shown in Figure 10.

![FIGURE 10. Product manufacturing modes based on the RTQCS.](image-url)
TABLE 2. Collected data.

| Time       | Sequence number | Name  | Quality status | Man  | Machine | Material | Method | Environment | Measure- ment |
|------------|----------------|-------|----------------|------|---------|----------|--------|-------------|---------------|
| 2020.2.21.22.08.21 | 1              | Wing  | X(1)           | Tom | B-005   | L-002    | F-009  | 63          | C-002         |
| 2020.2.21.22.08.22 | 2              | Wing  | X(2)           | Leon | B-012   | L-003    | F-010  | 64          | C-003         |
| 2020.2.21.22.08.23 | 3              | Wing  | X(3)           | Jerry | B-009   | L-004    | F-011  | 65          | C-004         |
| 2020.2.21.22.08.24 | 4              | Wing  | X(4)           | Leon | B-067   | L-005    | F-012  | 66          | C-005         |
| 2020.2.21.22.08.25 | 5              | Wing  | X(5)           | Jack | B-009   | L-006    | F-013  | 67          | C-006         |
| 2020.2.21.22.08.26 | 6              | Wing  | X(6)           | Leon | B-118   | L-007    | F-014  | 68          | C-007         |

three functions described above. To ensure product manufacturing quality and improve product manufacturing efficiency, a product manufacturing model is built based on the RTQCS. In a production process, RFID, sensors, bar code labels, or other information technology is used to identify the processed products and obtain the real-time quality status of the product. The information on the product history and current activities that is combined into the product resources-status matrix is extracted. Based on the resources-status matrix, the quality status of the product processing is predicted. If the forecast results are acceptable, the product quality status will be collected at the end of the manufacturing activity for the prediction model feedback. If the forecast results are unacceptable, the allocation of product manufacturing resources is optimized, and the new production task allocation program proposals are output. Staff members reallocate manufacturing tasks based on the recommendations. The product manufacturing modes based on the RTQCS are shown in Figure 11.

IV. CASE STUDY

In the product manufacturing modes based on the RTQCS, part A was selected in a manufacturing enterprise for quality control experiments. This part has 20 product quality characteristics, and the manufacturing process requires 43 activities.

Before the quality control experiments, the key quality characteristic vector KQC must be established. To identify the key quality characteristics of part A, measurements of the product quality characteristics in the processing of 5,000 experimental parts were collected, and the variations in the quality characteristics as the manufacturing process progressed were analyzed. The 20 quality characteristics of the experimental part were denoted as QC1...QC20, where QC1, QC2, and QC3 were direct quality characteristics, and the rest were indirect quality characteristics. The process of obtain variation of QCs was shown as Figure 12.

By analyzing the similarity of each indirect and direct quality characteristic curve (QC1, QC2, and QC3), the result of the association analysis between the quality characteristics could be obtained, as shown in Table 3.

As shown in Table 3, eight indirect quality features were critical: QC4, QC8, QC9, QC14, QC16, QC17, QC8, and QC9. Together with the direct quality characteristics, the critical quality characteristic vector KQC was formed, i.e.,

\[
KQC = (QC1, QC2, QC3, QC4, QC8, QC9, QC14, QC16, QC17, QC8, QC9).
\]
After the identification of the key quality characteristics, 10,000 product quality characteristic data points were collected during production to test the performance of the RTQCS. Of these, the 5,000 parts under the control of the RTQCS were called the experimental group, and the 5,000 parts that were not produced under the control of the RTQCS were called the control group. The production of the experimental group was carried out at the same time as the production of the control group. Statistical analyses were performed for each of the 500 parts produced. The yield of good products and the single decision-making time were compared, and the number of manual interventions in the experimental group was recorded, as shown in Figure 12.

As shown in Figure 12, at the beginning of the experiment, due to the lack of empirical data, the RTQCS did not facilitate the processing and required more manual intervention. More error suggestions were provided, and decision time during the task assignments increased. As the manufacturing process progressed and the empirical data accumulated gradually, the number of manual interventions in the processing gradually decreased, the conformity rate in the experimental group gradually increased, and the single decision-making time gradually decreased. In the third set of 500 parts produced, the experimental group’s good product rate and single decision-making time performance began to outperform the control group and stabilized at the seventh count. The number of manual interventions in the experimental group decreased gradually and then stabilized at the third count. The number of manual interventions for each part manufacturing process remained between 10 and 15. The experimental results showed that the RTQCS could effectively guarantee the quality of the product manufacturing and improve the efficiency of the product manufacturing during the production process.

V. CONCLUSION

In this paper, the development of the RTQCS and a quality control system designed to provide real-time suggestions or post-assessment feedback in the manufacturing process, e.g., to forecast the quality status before the start of the next manufacturing activity, were discussed. With the progress of the product manufacturing process, the operating status has changed over time. Consequently, quality diagnosis and prediction models based on historical data have difficulty adapting to the requirements of current production. In RTQCS, the quality prediction model is updated dynamically as the manufacturing process progresses by combining historical data information with measured data flow information. The contributions of this study were as follows.

First, based on the process of the product quality characteristic formation, the relevance of the quality characteristics and the continuity of the quality in the manufacturing process were examined. The mapping relationship between quality characteristics and manufacturing resources was established. This laid a theoretical foundation for quality predictions based on the manufacturing process data.

Second, based on the theory of product quality characteristic variations, the quality characteristic variation values of products during the manufacturing process were collected. The key quality characteristics of the products were identified using the similarity analysis method. This provided a research idea for production process control based on the product quality.

Third, the mapping between the real-time quality status of the product and the manufacturing process for the product manufacturing process was built. The dynamic prediction of the product quality status was realized. It provided a solution for the automatic and dynamic distribution of production tasks in the production of unmanned chemical plants.

Based on practical considerations, some issues are worthy of further discussion. For example, the established RTQCS quality prediction model did not account for changes in the quality status of the quality resources of the product manufacturing process, which means that the RTQCS required higher quality of manufacturing resources. This will place a heavy burden on the maintenance of product manufacturing resources. In the future, the time associated with product manufacturing resources can be considered to be a parameter to participate in the training of the quality prediction model of the product manufacturing process. This will allow the study of the relationship between different state manufacturing resources and the product quality to reduce the maintenance costs of manufacturing resources. Furthermore, in the product manufacturing process, the manufacturing resources of the same type were not distinguished, and their unique identifiers were collected through the IoT system. There has not been an in-depth study of the inherent differences in the product quality resource data. To study this, a theoretical basis for the interchangeability or mutual exclusion of manufacturing resource allocation can be provided by analyzing the

| Symbol | Correlation coefficient with QC1 | Correlation coefficient with QC1 | Correlation coefficient with QC1 |
|--------|----------------------------------|----------------------------------|----------------------------------|
| QC4    | 0.75                             | /                               | /                               |
| QC5    | 0.55                             | /                               | /                               |
| QC6    | /                                | 0.6                             | /                               |
| QC7    | /                                | /                               | 0.59                            |
| QC8    | /                                | /                               | 0.77                            |
| QC9    | /                                | /                               | 0.82                            |
| QC10   | 0.45                             | /                               | 0.11                            |
| QC11   | 0.48                             | /                               | /                               |
| QC12   | /                                | /                               | 0.44                            |
| QC13   | -0.3                             | /                               | 0.58                            |
| QC14   | /                                | /                               | 0.77                            |
| QC15   | /                                | /                               | 0.53                            |
| QC16   | 0.8                              | /                               | /                               |
| QC17   | 0.89                             | /                               | /                               |
| QC18   | /                                | /                               | 0.73                            |
| QC19   | /                                | /                               | 0.77                            |
| QC20   | 0.48                             | /                               | 0.2                             |
correlation between the inherent attributes of the product quality resources and the state of the product quality. Moreover, in the establishment of the key quality characteristic identification algorithm, the influence of the transmission path of the quality characteristic variations on the product quality status was not considered. This led to high requirements for the computing resources in the identification of key quality characteristics of complex structure products. By introducing the theory of the product quality formation mechanism and establishing a key quality characteristic recognition algorithm, the computing resource requirements will be reduced. Finally, the RTQCS controlled the product quality status through key quality characteristics. It did not focus on the key control characteristics of the product manufacturing process. The introduction of key control features may be able to greatly increase the accuracy of the quality status prediction and prediction efficiency in the manufacturing process.

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