# A Data Services-Based Quality Analysis System for the Life Cycle of Tire Production

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**Abstract.** In the background of actual production demands, we develop data services to solve the problem of "information isolated island" in the tire production for achieving the unified management for data from diverse production systems. Based on the data services, the management system for tire production is designed. The system uses the decision tree algorithm with data fitting and data screening technologies to analyze the data from the whole production process and realize the forecast of product quality and defects analysis. The system has been applied to the production by Shandong Linglong Tire Co., Ltd. The practice has proved that our data services and system not only improve the tire pass rate and production efficiency, but also help enterprises to achieve the efficient management of production. In addition, we apply the service to the actual manufacturing industry, which plays a positive role in the promotion and improvement of service application.

**Keywords:** Data services · Data extraction · Quality analysis · Big data · Tire

## 1 Introduction

With the rapid development of society and the continuous innovation of information technology, the concepts of automated production and management have been well applied to the modern tire manufacturing enterprises. The automation not only means mechanization of production, but also means a programmable logic control system which seamlessly connects data generated from different stages of the production to realize the automated management of the whole process of production [1]. In the tire manufacturing industry, the tire production process includes many stages such as *rubber compound mixing*, *woven/steel cord preparation*, *building/curing* and *quality inspection* [2]. For some of tire manufacturing companies, although they have achieved the automated production of tires, the production workshops in different stages have separate management systems and data stores. Therefore, they can't achieve the efficient management of the whole tire production process. Figure 1 shows the four major stages of the tire production process, including *rubber mixing, semi-components, building/curing* and *external inspection*. Each stage has an independent management system. There are logic associations between those systems, but the data have different structures and storage modes, which leads to the information isolation and brings a lot of inconveniences to


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the production of tires and quality inspection. The data generated in the tire manufacturing process are not uniformly collected, processed, analyzed and fully utilized, which causes the tire enterprises not to make accurate defects analysis and prediction of the product, and restricts the improvement of the production efficiency and the quality of the tire.

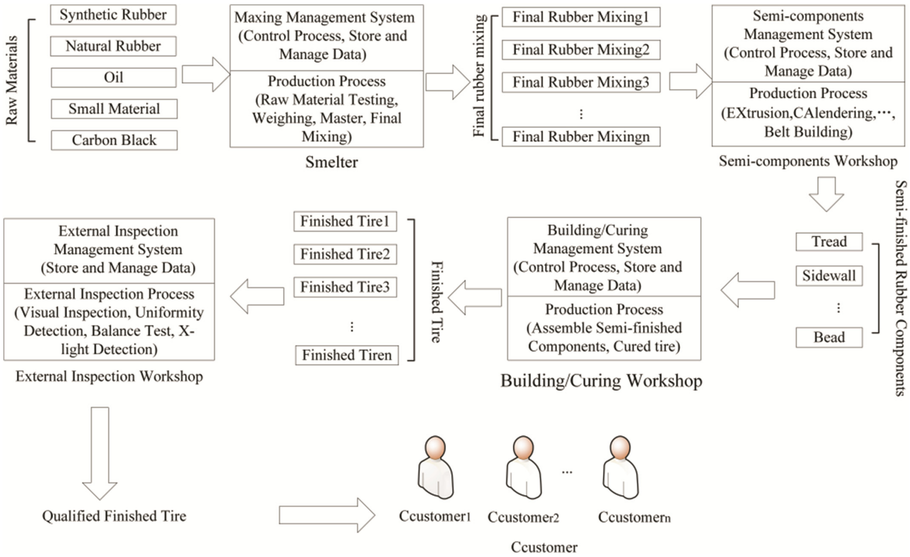


**Fig. 1.** Tire production process

In order to solve the above problems, Ruan et al. [3] designed a tire production process monitoring system realizing the data acquisition, processing, query and real-time monitoring. However, this system only monitors the tire production process and does not support the quality defects analysis of product. Abou-Ali et al. [4] proposed a comprehensive tire defects diagnosis expert system. By using an integrated diagnostic program, the system can diagnose the possible reasons of tire defects and realize the tire quality defects diagnosis. But it does not support the quality prediction. As the development of science and technology and social progress, service computing has been promoted and popularized in many fields of industrial production. Combining enterprise architecture with cloud computing services, Zimmermann et al. [5] proposed the service-oriented enterprise architecture. For the openness, dynamics and uncertainty of service oriented large-scale distributed computing environment, Li et al. [6] designed a reliable service computing platform for cross organizational workflow application. The platform has a significant impact on the integration of the modern enterprise management tactic, inter-organizational workflow services and heterogeneous systems. The risk assessment model of service oriented cloud computing system is established [7]. The model can realize the identification, prediction and evaluation of the security risk of cloud computing. Taking dynamic services into account, based on the event driven mechanism, Lv et al. [8] proposed a composite service adaptation method which can handle a variety of different types of dynamic services in real time, automatically check and update the composite services. Di Cosmo et al. [9] proposed a distributed software system based on complex services for automatic deployment and configuration of services. The software system not only meets the user requirements and related software dependencies, but also has the minimum the number of virtual machines. Ichikawa et al. [10] developed a data mining platform regarded as a service to open to the users. The platform can provide a variety of data mining algorithms for the users to deal with data in low-cost and simple way. Based on service agents, an approach to managing of autonomous and context aware resources is presented for cloud services [11]. Besides, a cloud service oriented management framework is proposed for service aggregation and service provision. Meanwhile, two kinds of support algorithms are designed to realize the service self-organization process. Service computing can not only solve the problem of technical platform and architecture, but also integrate and manage the business itself. In recent years, with the increasing maturity of service computing technology, it has become an indispensable technology in modern manufacturing enterprises.

In summary, a lot of methods of the management of tire production are mentioned above, but they can't completely solve the problems in Shandong Linglong Tire Co., Ltd. Services computing is a web oriented new paradigm. It uses a standardized, loosely coupled and transparent application integration approach to improve the interactive and agile ability of enterprise internal system, and to achieve fast, seamless integration and cooperation between application systems. Combining the advantages of service computing and the actual needs of the enterprises, we develop data services and design quality analysis system for tire production. This paper makes the following contributions: we develop data services to realize the unified management of data from different databases with multiple storage modes. The data services provide complete and standard data for other application systems through interfaces, which is convenient for design of the product management systems. Based on the data services, we realize the data correlation analysis of the whole production process to predict the product quality and track the reasons of the product defects. We apply services to industrial production, improving the quality of products and production efficiency, promoting the promotion and use of services.

The rest of the paper is organized as follows. Section 2 introduces data and fault management in SOC. Section 3 gives the design and implementation of data services. Section 4 describes the framework of the system and the model of quality and analysis. Section 5 presents the feasibility and usefulness of data services and the system. Section 6 ends the paper with the conclusions and for future work.

## 2 Data and Fault Management in SOC

Data quality is very important in SOC, and it not only affects the calculation results, but also relates to the calculation speed. How to effectively manage the data to ensure the authenticity of the data, integrity, correctness and unity, is one of the urgent problems we need to solve. At present, many methods have been put forward to manage and improve data. In order to solve the problems of multi data sources, Yu [12] built a service components pipeline model that is open with multi-source data extraction, service data packet mode and transparent access. Meanwhile, in order to avoid potential bottlenecks and conflicts (structural conflicts and data collision) in various service components of workflow, the model can adjust pipelining segment system from a single-stage workflow continuously and dynamically. Tao et al. [13] proposed an on-line point cloud data extraction algorithm for spatial scanning measurement of irregular surface in copying manufacture. Based on the algorithm, they presented a data extraction framework that can handle data points set of arbitrary size, density and shape. In addition, the framework can reduce the amount of the dense cloud data to ensure the accuracy of the data. Data standardization makes the value of data attributes drop in a certain range. Support vector machine is widely used in the kernel to transfer the data from the feature space in the input space to another feature space. On this basis, a linear algorithm is used to solve the classification problem. The standardization of the data will change the value of the data in the feature space [14]. Chatterjee et al. [15] introduced a standard data acquisition and analysis model. This model provides a method for checking the quality of standard data for achieving data extraction and standardization for multi-platform and multi-system, but it is not perfect for the big data with high requirements. Analyzing the time series, using exponential smoothing model and grey prediction model, Ma et al. [16] studied the quality of the gearbox shell in manufacturing process and forecasted the trend of the product quality. Zhao et al. [17] established a regression system based on phase. The system can make a quantitative evaluation for the online prediction results, which is helpful to improve the quality of the product. Using Apriori algorithm, the association prediction model of product quality forecasting data is constructed [18]. In addition, it uses k- means algorithm to achieve the link between the patterns. In order to meet the needs of quality analysis and processing quality problems, a causal relation analysis method is proposed in [19]. The model explores how to identify the causal relationship between production process variables and product quality variables. According to the causal relationship between process variables and product quality variables, a scheme to improve the quality of product is presented. A new intelligent product quality analysis and improvement system is proposed in [20]. It analyzes the problem to find out the cause of the problem by using decision tree and neural network and gives the method to improve the quality of the product. These methods of product quality analysis and prediction can predict the product with simple process. However, for tire production, its' process is more complex. For example, many parameters are used to evaluate the quality of the product. Therefore, these methods are not suitable for the analysis and prediction of the tire quality defects.

The above studies introduce some methods for data extraction, data standardization, product quality analysis and prediction. However, in the actual environment of tire production, these methods are not applicable. Therefore, considering the actual needs of the tire business and researching the existing technology, the paper designs a quality analysis system for the full life cycle of tire production based on data services.

# 3 Data Services

This section will introduce the design (Sect. 3.1) and implementation (Sect. 3.2) of data services.

## 3.1 Services Design

The data of tire production are stored in different databases. In order to keep the performance of original system when extracting data, we designed data services considering multiple storage sources and the dependence relationship for the data, as shown in Fig. 2. Data services contain six components that are extraction engine, data standardization, data cleaning, exception handling, automatic job scheduler and resource monitor-predictor.

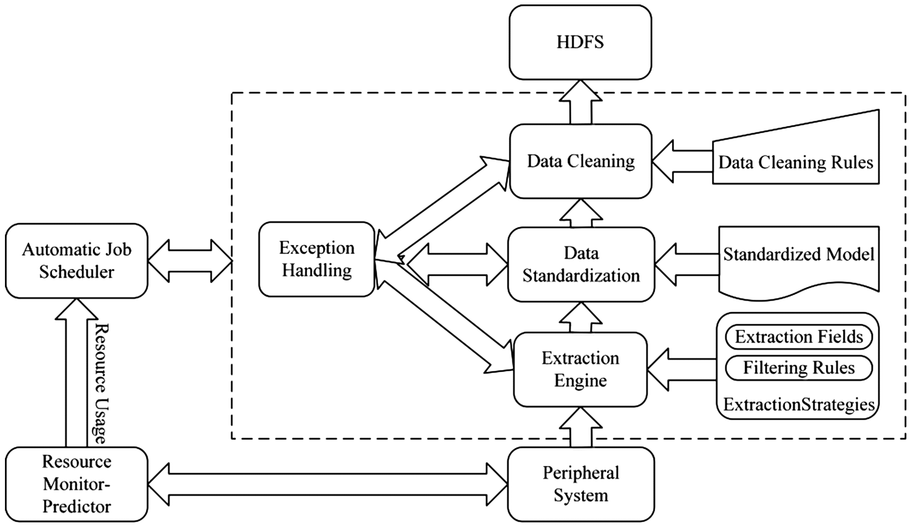


**Fig. 2.** A schematic diagram of data services architecture

According to the extraction strategies, the extraction engine extracts the data from the peripheral system. The extraction strategies contain the customizable extraction fields and the filtering rules. The customizable extraction fields allow the user to define the fields of the extraction so that the engine can only extract the useful data fields instead of the entire data records, which reduces the quantity of data transmission. Data in multiple systems are generated in order and they can be joined by “bar code”. Therefore, according to existing standardized data sets and the filtering rules, the engine removes partly unrelated or dirty data to reduce the amount of data and the impact on the original system as much as possible. Due to the original data format is diverse and not uniform, the data can't be used directly. According to the standardized data model, based on Hadoop technology, standardized module uses multiple tasks in parallel to process the original data and achieve rapid data standardization. There may be dirty or incomplete data in the standardized data. Therefore, according to the rules of data cleaning, we clean the data. In order to quickly complete the cleaning work, we run the data cleaning tasks in parallel. Next, the data are classified into multiple data domains (e.g., sales data, production data, analysis data, environmental parameter, material information, etc.). Finally, these data are stored in a distributed file system (HDFS) to facilitate the application of the upper layer. When the extraction job, standardization job and cleaning job run, there may be errors caused by network, operating systems, procedures, or data resulting in the abnormal termination. Exception handling module captures the exception errors, which is convenient for users to view and process the errors. Resource monitor-predictor is responsible for monitoring all kinds of resources of peripheral system (IO, memory, CPU) to get the load capacity of database servers. It also informs the job scheduler of the servers' load capacity. The job scheduler will reasonably execute jobs according to the load capacity. When the database servers load seriously, job scheduler will delay the extraction jobs or divide them into a number of small extraction jobs to minimize the effects on the performance of original applications. When extraction job is finished, the job scheduler will automatically execute standardization and data cleaning job.

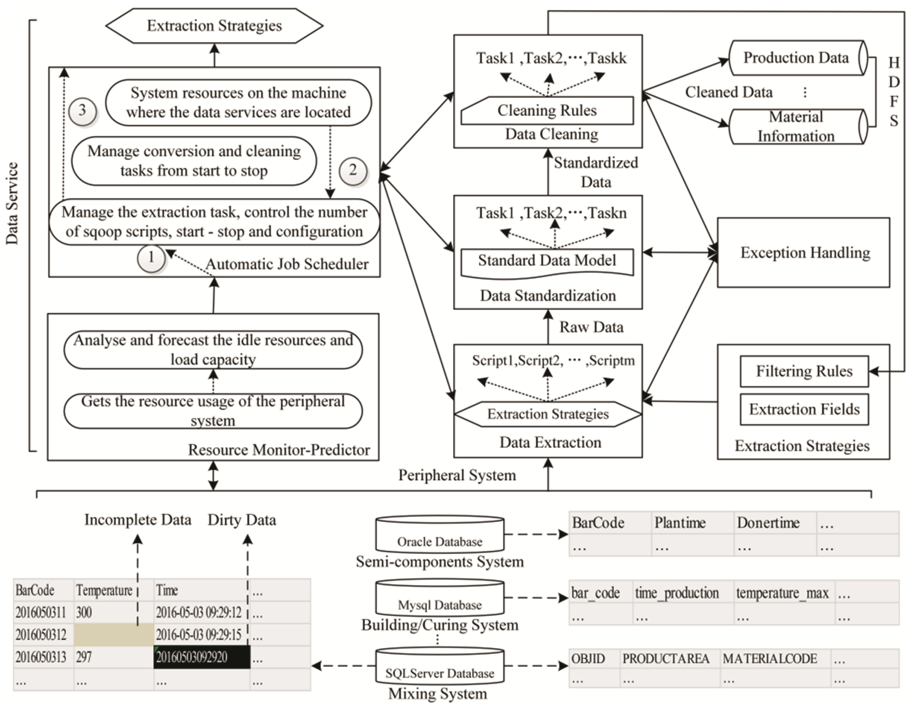


**Fig. 3.** Description of data services

### 3.2 Implementation Details

Data services realize four functions: data extraction, data standardization, data cleaning and job scheduling, as shown in Fig. 3.

In the peripheral system, diverse systems use different databases with different data storage formats. The *mixing* system uses the SQL Server database, the *semi-components* system uses the Oracle database, and the *building/curing* system uses the MySQL database. These databases have their own storage structures and naming rules. Meanwhile, for different workshop management systems, software designers are not necessary the same. Therefore, the attribute naming rules in database tables are diverse. As shown in Fig. 3, the SQL Server database uses the lower case letters and underline to name attributes, Oracle uses the first capital letters to name the attributes, and the MySQL database uses the full capitalization method to name attributes. The variety of attribute naming methods brings many difficulties to data processing. In each sub management system, there may be some useless data. For example, in the SQL Server database, the value of "time" in the third line is not standard. This kind of data calls dirty data. The "Temperature" value in the second line is empty. This kind of data is incomplete data. Through the intermediate database, the paper realizes the unity of the data formats and data structures. Meanwhile, the filtering rules help achieve the data cleaning and provide cleaned data for the upper applications.

```
                 Job scheduling algorithm
GenerateExtractJob:
     Get the database connection to extract;
     Get the extract fields;
     Get the filtering rules;
     Generate extract script;
     Generate the database connection for next extract;
JobScheduler:
     Obtain the load of the system by monitor;
     If system is idle
          Execute extraction job;
     Else
          Wait();
    If   system is not idle
       If extraction job is emergency;
         Split extraction job into k small jobs j1,j2…jk;
         Execute extraction job j1,j2..jk;
       End if
    Else
       Execute extraction job;
    End if
    Execute data conversion job;
    Execute data cleaning job;
    Generate filtering rules;
    Generate next extraction job;
```

The data services mainly include two stages: the extraction job and the job scheduling, as indicated below. First, the extraction engine uses *GenerateExtractJob* to read the extraction fields and the filter rules and generate extraction scripts. Then the extraction job is submitted to *JobScheduler*. *JobScheduler* analyzes the load of database servers. If the server is idle, the extraction job is performed. If the current system is busy and the job is urgent, the extraction job is divided into a number of small extraction jobs to decline the impact on the original system. If the job is not urgent, it is delayed until the system has enough resources. After extraction job, job scheduler calls data standardization and data cleaning job to achieve the unification of data formats and clean-up. Next, the data are stored in HDFS and the bar codes of the extracted data are stored in the filtering rules. Finally, *GenerateExtractJob* is called to produce the corresponding data extraction job of the next system.

# 4 Quality Analysis Management System

In the above, we have introduced the design and implementation of data services. This section will show the frame design of the system (Sect. 4.1) and quality analysis process (Sect. 4.2).

## 4.1 Framework of the System

The full life cycle quality analysis system of tire production mainly consists of five parts. From bottom to top, they are peripheral systems, data services, distributed storage platform, big data computing platform and graphical display, the framework of the system is shown as in Fig. 4.

The peripheral system is a general designation for all the sub management system of the tire production, such as MES-Manufacturing Execution System (*mixing*, *semi-components*, *building/curing*), PDM-Product Data Management system, ERP-Enterprise Resource Planning system and Sale system. It stores all the original ecological data generated from the production to the sales, which provides data support for the system designed by this paper. Data services are responsible for obtaining data from a number of peripheral systems. Meanwhile, they standardize and clean the data in order to provide complete and effective data for system. The distributed storage platform is mainly used to store the basic data that are transferred from the data services and the result data generated by the upper applications. The storage system, which can provide high storage performance for mass data, is constructed based on Hadoop, Hive and Spark. The big data computing platform mainly makes the quality analysis calculation. The quality analysis calculation is used to predict the quality of tire and analyze the reasons of tire's quality defects. Graphical interface uses diverse and graphical visual interface display technology (e.g., echart, amchart, etc.) to more vividly and clearly show the results. Graphical display contains the functions that are the analysis of quality defects and unqualified reason analysis.

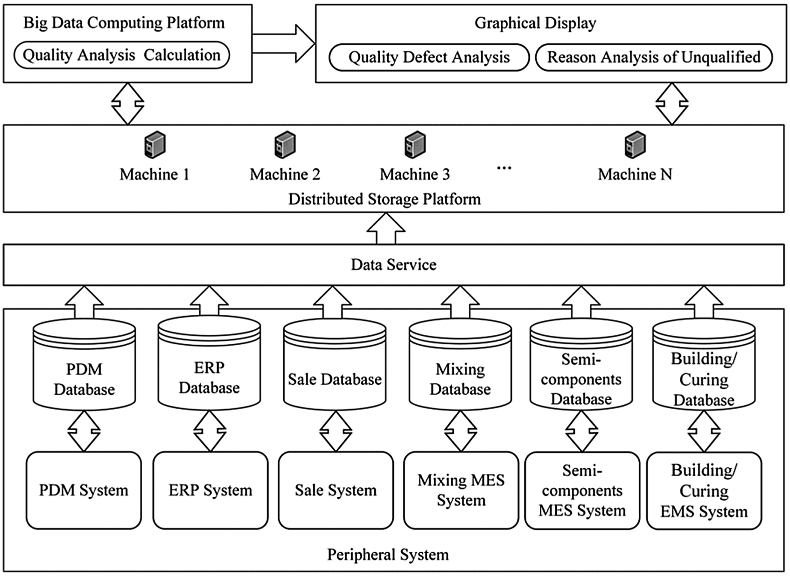


**Fig. 4.** A framework of the management system for the full life cycle of tire production

## 4.2 Quality Analysis Model

The process of tire quality analysis is shown in Fig. 5.

First, all the existing tire production data are regarded as a sample to train a decision tree. The paths of the decision tree are the rules of the qualified/unqualified product. Then the tire production data are matched with the path of the tree to judge whether the tire is qualified or not. If it is unqualified, the unqualified reasons can be found on the branches of the tree. The key steps in the tire quality analysis are the generation of rules and the analysis of data match. The following will introduce these two steps. In this paper, the decision tree algorithm is used to generate a variety of rules. First, the characteristics of the product are extracted as training sets from six aspects: man, machine, material, method, measure and environment. The characteristics contain operator, machine, material coding, steamer, temperature, pressures, formulation process, inspectors, inspection standards, and inspection machine. Then the decision tree is generated by ID3 algorithm, as shown in Fig. 6. Nodes' selection is an important step in the process of decision tree generation. First, an attribute is selected. According to this attribute, the training sets are divided into several sub sets. Next, the entropy of each subset is calculated. Based on entropy, the information gain is calculated. The information gains of other attributes are calculated in the same way. The attributes with the maximum information gain will be the root node of the decision tree. The other nodes are gotten in the same way. When the current attribute sets has only one attribute, the attribute is the leaf node. The tree may be too lush, which is not conducive to be understood or used. Therefore, the paper uses the post-pruning method to cut off the branches with small weight, which makes the tree more intuitive and easier to be used. The final decision tree is shown in Fig. 6.

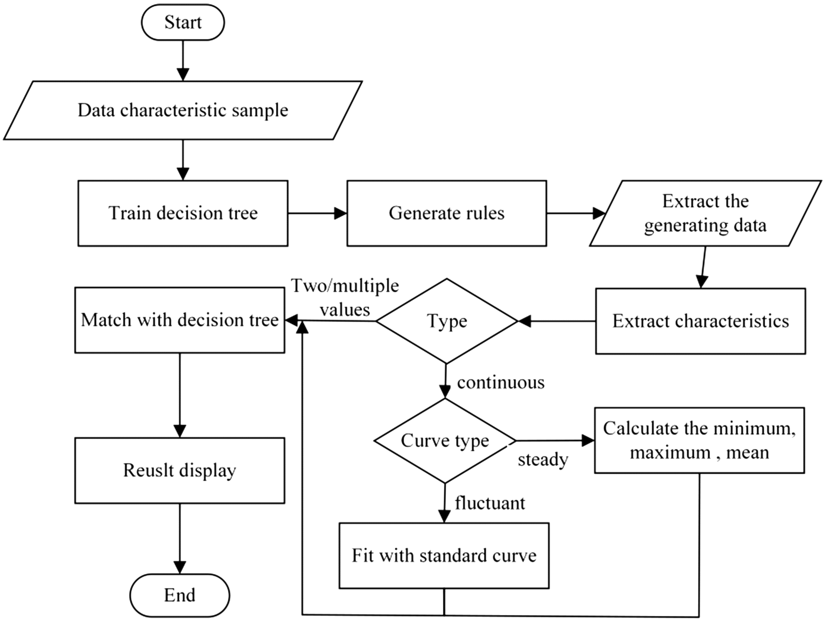


**Fig. 5.** Process of product quality analysis

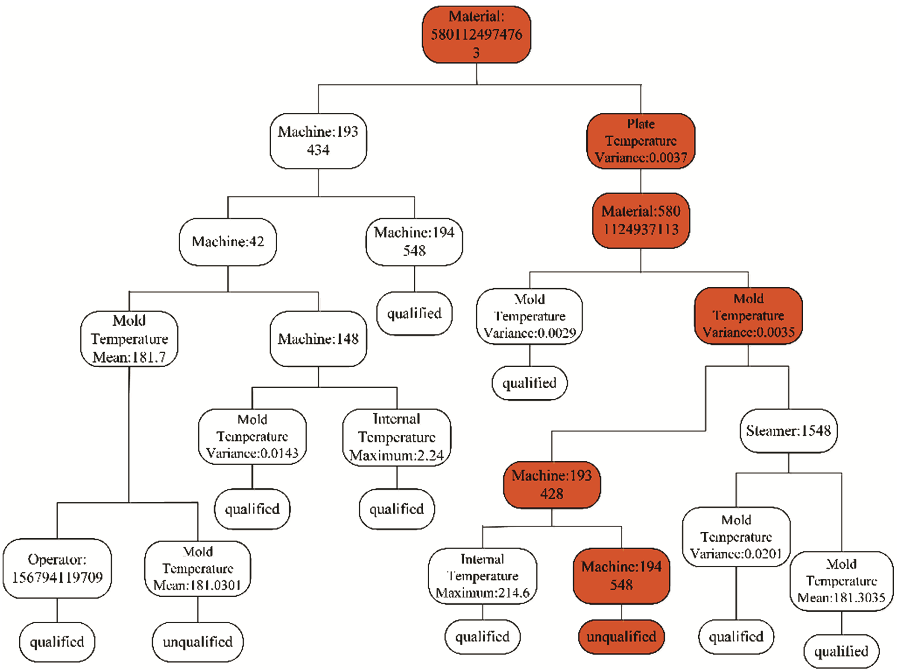


**Fig. 6.** Decision tree of product quality analysis (Color figure online)

Data matching analysis matches the characteristics information of product with the decision tree rules to decide whether the product is qualified or not. The characteristics information of the tire can be classified two categories: curve type and two or multiple value. For the characteristics information with two or multiple value, we can directly match them with the rules. The curve type information can be classified two categories: stable curve (e.g., mold temperature in vulcanization stage), and fluctuant curve (e.g., top bolt pressure in the mixing stage). For the stable curve, it needs to calculate the maximum, minimum and mean that are regarded as the judgment conditions in the decision tree. For the fluctuant curve, we firstly calculate a standard curve. The standard curve can be generated by the existing qualified product sample. The fluctuant curve is fitted with standard curve. The difference square sum (Q), regression error (S) and curve correlation ratio (R) are used to match the rules. Finally, we can know whether the product is qualified or not. For example, there is a product characteristic information (Material: 5801124983756, Plate Temperature Variance: 0.0038, Material: 5801124948215, Mold Temperature Variance: 0.0036, Machine: 196124). It matches the path with brown color in the decision tree shown in Fig. 6. From Fig. 6, we know that this product is not qualified and the path indicates the reason for the failure. Through practical applications, the accuracy rate of the decision tree model proposed in this paper is up to 90 %.

# 5 Feasibility and Usefulness

This section describes the feasibility of data services and system (Sect. 5.1), and discusses the application value in industry (Sect. 5.2).

## 5.1 Feasibility

As described above, the system proposed in this paper can analyze and display the reasons of the quality problems in each production stage of tire. These reasons can be used as the reference by skilled technicians. As shown in Fig. 7.

It shows the process of tire quality defects analysis in practical applications. The analysis results show the reasons for all kinds of unqualified product in the form of a tree. In the picture, the orange path indicates the reasons for unqualified. By fitting these rules, we can find the nonconforming product. In the bottom of Fig. 7, the list shows the process of product quality analysis. Figure 8 shows the analysis process of reasons for leading to off-specification product. The graphic display of the stage includes three parts: material properties, causality diagram and sample information. In the material properties section, the user can enter the material information to view. From the man, machine, material and other aspects, the causality diagram shows the cause of the failure of the product in the form of figures and tables. The sample information shows the information of substandard product in detail. The system can clearly show the process and results of the tire quality analysis, and it is feasible for the analysis and prediction of the tire quality defects.

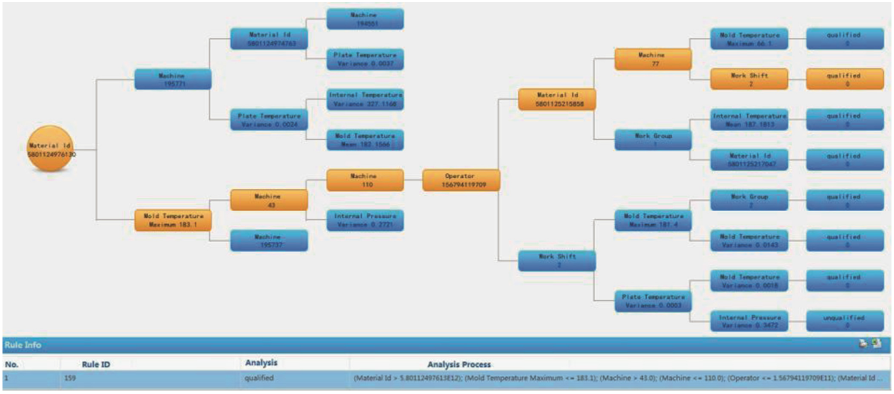


**Fig. 7.** Results of product analyzing quality defects

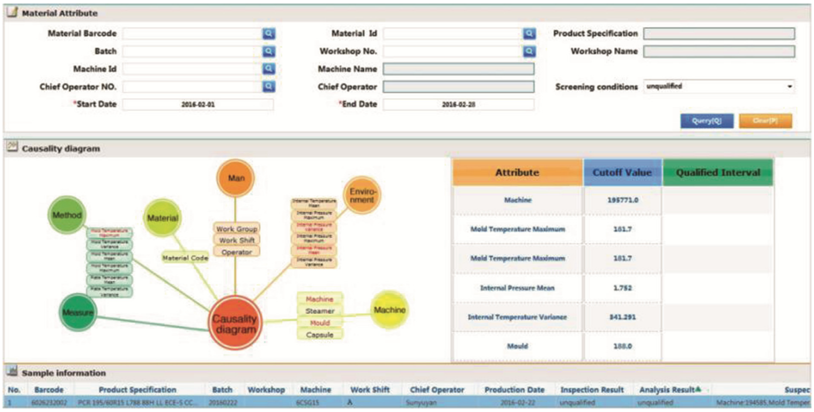


**Fig. 8.** Reasons for the failure of product

In the paper, the decision tree algorithm is used for the analysis of tire quality. Therefore, we give the performance evaluation for it, shown in Fig. 9. The horizontal axis is the training ratio. The training ratio is the ratio of the amount of the test data and the amount of the sample data for training decision tree. The vertical axis is the accuracy. The accuracy is the ratio of the number of records that the analysis results are consistent with the actual results and the total number of records. According to the definition of accuracy, we can measure the accuracy of the decision tree used to analyze whether the tire is standard or not. First, we choose a certain number of qualified/unqualified tires. The production data of those tires are used as the training sets to train our decision tree. Then we choose a certain number of tire production data measured, and with the help of the decision tree, we can know whether these tires are qualified or not. By comparing the results of the analysis with the results come from the tire quality inspection process, the accuracy of the decision tree can be got. From the Fig. 9, we can know that with the increase of training ratio, the accuracy of the decision tree algorithm increases first and then decreases. The ascending speed is relatively fast while the declining speed is relatively slow. We can also find that when the training ratio is 1.20, the accuracy of the decision tree reaches the maximum value. In the production, there are 200000 tires about millions data for each day. Therefore, there is enough sample data to train the decision tree to improve the accuracy of the decision tree.

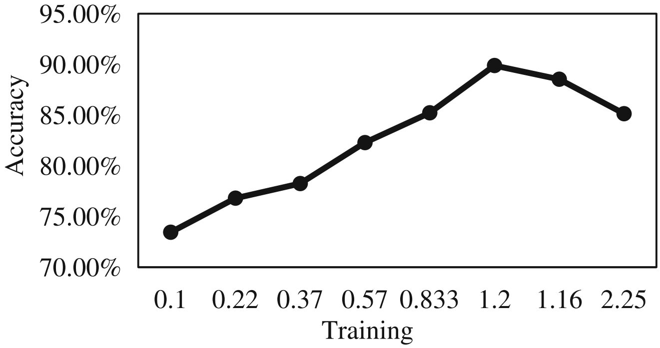


**Fig. 9.** Performance of decision tree for tire quality analysis

### 5.2 Usefulness

The data services and quality analysis system have been applied to Shandong Linglong Tire Co., Ltd. In actual production, we set every 10 min to start data services for extracting data. In 10 min, there are 10 thousand to 15 thousand records will be produced. According to the actual test, we know that the average time for the system to extract and process these data is 1.25 s. These are signs that data services can rapidly integrate the data from PDM, ERP and other systems without affecting the original application in these systems. They have a higher the efficiency and better in real time to provide a good data support for the real-time quality analysis and prediction of the tire. The process of tire production is complex and each process uses different materials. Therefore, there are a great number of factors leading to produce substandard products. It might be feasible for a small company to rely solely on manpower to analyze the reasons for each unqualified tire. However, Shandong Linglong Tire Co., Ltd. daily produces millions of tires. If for each unqualified tire, we analyze all the factors in each process, it will waste too much time. Hence, we extract the tire characteristic data to construct the decision tree and analyze the reason of the unqualified tires. In the practical application, the quality analysis can rapidly find the cause of the unqualified tire with high accuracy. Therefore, the staff can timely find wrong links and take remedial measures or recycle products that may not be qualified, which can improve the qualified rate of the tire and the credibility of enterprises. In practical applications, the accuracy of decision tree algorithm is about 90 %. The accuracy is related to the size of the training set and the extracted data characteristics. The data service and the system designed in this paper can not only solve the problems in the production of tire and help enterprises improve product quality, but also upgrade customers' satisfaction, enhance competitiveness and increase revenue. Moreover, they are not only applicable to tire industry, but also easily extended to other production areas and increase the reusability of IT assets. In this paper, the service computing is applied to the actual manufacturing industry, which plays a positive role in the promotion and improvement of service application.

## 6 Conclusion and Future Work

In order to solve the problem of information isolation among multiple heterogeneous systems in tire production, we develop data services. Based on the data services in conjunction with the big data analysis technology, the management system for tire production life cycle is designed. The paper introduces how to solve the problems of data scattered, non-uniform data format and tire quality defects existing in Shandong Linglong Tire Co., Ltd. From the aspects that are the data services implementation principle, quality analysis and forecast, this paper mines and analyzes the value of data using data service as the core. This paper also introduces the function design of the data services, and then describes the function design of the system based on the data services. At last, we give the implement processes of the data services, quality analysis and quality forecast. Practical results have proved that the data services and system developed in this paper is able to regulate the production process and improve production efficiency and product quality. In the future, we will develop monitoring services about the using of tire to help tire companies to produce tires that are suitable for a variety of geographical environments.

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