Optimizing Reaction and Processing Times in Automotive Industry's Quality Management

A Data Mining Approach

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Abstract. Manufacturing industry has come to recognize the potential of the data it generates as an information source for quality management departments to detect potential problems in the production as early and as accurately as possible. This is essential for reducing warranty costs and ensuring customer satisfaction. One of the greatest challenges in quality management is that the amount of data produced during the development and manufacturing process and in the after sales market grows rapidly. Thus, the need for automated detection of meaningful information arises. This work focuses on enhancing quality management by applying data mining approaches and introduces: (i) a meta model for data integration; (ii) a novel company internal analysis method which uses statistics and data mining to process the data in its entirety to find interesting, concealed information; and (iii) the application Q-AURA (*quality - abnormality and cause analysis*), an implementation of the concepts for an industrial partner in the automotive industry.

Keywords: Data Mining, Quality Management, Apriori Algorithm, Automotive Industry.

1 Introduction

Numerous methods and concepts exist for establishing and structuring quality management in companies (e.g., Six Sigma [10]), but typical systems are not capable of integrating and analyzing information of the entire business process. Such an integrated data set is necessary to extract new, unknown meaningful information. Specific approaches, such as data mining methods, enable analyzing of large data sets in order to identify concealed relationships.

Q-AURA[1] (*quality - abnormality and cause analysis*) is being developed in cooperation with *BMW Motoren GmbH*, located in Steyr, Austria, which is part of the *BMW Group*, a major player in the premium automotive industry. *BMW Motoren GmbH* as a component producer builds most of the benzine and diesel

[1] Qualität - Auffälligkeiten und Ursachenanalyse (German).

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engines for BMW automobiles. The competence center of the diesel engine development is also located there. In recent years, innovation cycles became shorter, resulting in reduced development and test time periods. Consequently, the number of engines manufactured within a year has increased: while 700,000 engines were built in 2009, the production volume reached 1.2 million units in 2011 [3].

With the higher manufacturing demands, also those of the quality management rise. As a result of a higher production rate, potentially more faulty engines could be produced, especially if the time between the fault causation in the engine development process and the productive correction is not decreased. The main goal of Q-AURA is to accelerate the problem solving process, which comprises diagnostics, reaction, and processing time. Q-AURA reduces both reaction and processing times by performing the following tasks: (i) detecting relevant engine faults (i.e., those that occurred more frequently in recent weeks), (ii) detailed fault analysis to find interesting attribute distributions in car and engine features, and, most importantly, (iii) identifying the critical technical engine modifications that may have caused the faults.

This paper is organized as follows: Section 2 discusses the central problem and associated challenges. Section 3 describes relevant approaches. In Section 4, an explanation of Q-AURA, its underlying concepts, and the evaluation of the quality management experts is provided. Section 5 concludes with future research directions and improvements to Q-AURA.

2 Problem Statement

This work makes three contributions, of which each addresses a particular problem. The first one is *overcoming the complex and heterogenous structure of the underlying information systems (IS)*. Many systems at different process steps store important data. Each individual (database) system has a different scope, which results in individual independent data models that, in turn, hinder a global (integrated) view of the entire data. Consequently, the demand for data integration is very high. For this purpose, we developed a meta model which structures the information and supports integration. We focus on an engine life cycle, which contains (i) the development phase, containing bills of materials (BOM) and technical modifications to the engine, (ii) the engine production phase followed by the car manufacturing phase, which store additional information about the engine and the car (e.g., time stamps), and (iii) the after-sales phase, which contains information about engine and car faults gathered by the dealers' workshops.

The second task is the development of a *data analysis process*. Its main purpose is to identify the technical modifications that most likely provoke a specific technical vehicle fault. Additionally, faults that progress negatively are automatically detected and analyzed in detail using statistical and data mining methods. All time-based calculations are done automatically based on the engine production time, which is also a new feature accomplished by Q-AURA. The information about the exact engine production time enables (i) to calculate relevant technical modifications that might be the cause of an analyzed fault and (ii) consequently, it enables to determine the exact engine production volume that is affected by a particular fault. The determination of technical modifications that may be relevant for a fault (based on their effective date in the assembly process) was done manually e.g., by contacting experts of the development department and using different systems for car and fault information. These manual tasks are now replaced by the proposed tool, Q-AURA, which needs a fraction of the processing time. The trends of entire faults are calculated weekly, the critical ones are automatically processed, and the results are presented to the quality management expert. Q-AURA also provides a user-driven analysis in order to start additional executions.

The final task is *implementation and verification of the invented analysis concept* to demonstrate the improvement in the quality management process(es). Q-AURA was implemented for, and is now successfully used by, the BMW quality management.

3 Related Work

Statistics and data mining techniques are a field of competence, which has been gaining more popularity in recent years. Work related to the subject of this paper can be considered under two headings: (i) state-of-the-art data mining concepts that are applied in the proposed approach (Q-AURA) and (ii) approaches that have a similar objective or apply data mining concepts similar to those in the proposed approach.

3.1 State-of-the-Art Data Mining Algorithms

Data mining applications are divided into four classes according to the type of learning: *classification*, *clustering*, *association rule mining*, and *numeric prediction* [11]. Q-AURA uses methods from the association rule mining and numeric prediction.

The purpose of *association rule mining* is to find relevant associations between features. A typical application area is market basket analysis: the goal is to find rules between sets of attributes with some defined minimum confidence, for example, that 90 % of the people who purchase bread and butter also buy diet coke. In this case bread and butter are called the *antecedent* and diet coke is the *consequent*. The relative amount is the *confidence factor*. An association rule is in accordance with well-known IF-THEN rules and should be as specific as possible while satisfying the specified minimum support [1]. Q-AURA uses the association rule mining algorithm *Apriori* [2] which is a fast discovery approach with the special characteristic that the possible item sets (set of attributes) are determined in a one-step way to improve the performance [1] [2].

Numeric prediction is used when the predicted outcome is not a discrete class but a numeric quantity. Consider, for example, two sets of values of which each value corresponds to a value in the other set. In a diagram, each pair of values is represented by a point. Depending on the application it may be attested that these points are not randomly distributed, but range more or less around a smoothed curve called *curve of regression*. If the graph resembles a straight line, the term *line of regression* is used [12]. Q-AURA uses linear regression, a numeric prediction concept, for identifying fault trends.

3.2 Related Approaches

Buddhakulsomsiri et al. [4] introduced an approach whose objective is similar to that of Q-AURA. They used association rules on warranty data in the automotive industry with the goal to identify significant relationships between attribute values and specific problem-related *labor codes*. They use various attributes of automobiles and warranty costs. The algorithm yields rules that have a variable set of attributes in the IF clause and a specific *labor code* in the THEN clause.

The difference between the Q-AURA approach and the method introduced by Buddhakulsomsiri et al. is that the main goal of Q-AURA is to find relevant technical modifications, which increases the task's complexity because of the lower ratio between attributes and fault code instances; identification of attribute characteristics that describe a specific fault is an additional benefit. Warranty cost information is ignored in the Q-AURA analysis since it does not help with finding the fault's cause.

There are several approaches that address the manufacturing industry in general, among them Harding et. al. [6], which categorized the projects by application area. To the best knowledge of the authors, there exists no approach that focuses on product improvement by analyzing faults of cars in the after sales market and finding potential faulty modifications. Q-AURA addresses this problem by using data mining concepts as described in the following section.

4 Supporting Quality Management with Data Mining Methods

This chapter describes the extent to which data mining methods can be applied to enhance quality management. Q-AURA is a system that monitors faults gathered from warranty information systems, calculates relevant attribute distributions, and identifies technical modifications that may be responsible for increasing fault rates in a specific time period. The process addressed by Q-AURA encompasses phases from early development of an engine to the after sales market. During the development phase, information about technical modifications and their position in different BOMs is documented. Data Sources of the engine production phase are queried to identify produced engines (engine serial numbers), their production time stamps, and the manufacturing BOM, which establishes the connection between an engine and its technical modifications. The following phase is the automobile production, where the connection between the engine and the car as well as attributes of the car itself (e.g., vehicle order country, vehicle type) are retrieved. The after sales information comprises warranty claims, fault codes, and other attributes that describe a particular fault. For Q-AURA, we developed a meta model to structure and harmonize this distributed and heterogeneous information.

4.1 Q-AURA Approach

The Q-AURA process is divided into six steps, illustrated in Figure 1. The first step reduces reaction time, while steps 2 to 6 reduce processing time. The most recent six weeks of warranty claims (for cars that were produced in the past three years) are used to detect current problems, which are classified by engine type, fuel type, and car brand (cf. Figure 1-1). *Regression Analysis* [12] is used to calculate the characteristics of the six-week fault pattern. We tested three different approaches to regression analysis: first, we used various convex functions to generate regression curves. Then we tested a three-point smoothing function. However, this method eliminates the first and the last value in the dataset, which are both important in Q-AURA because a sufficiently large and recent time slot must be considered to derive reliable conclusions about the trend of the fault patterns. Finally, we tested regression analysis using straight lines, which achieved the best outcome (Equation (1)):

$$y = k * x + d, \tag{1}$$

where y and x are the coordinates of a data point on the regression line, and k is the gradient. d is equal to the value of y at the point $x = 0$. We calculated the *gradient* k, the *mean value* $\bar{y}$ and the *coefficient of determination* R^2 and use these for evaluation. The gradient indicates how much the number of faults increases from one week to the next. The mean value shows the average number of faults per week, and the coefficient of determination describes the steadiness of the curve. Equation (1) shows that the regression line depends on only one variable. For this special case the coefficient of determination is equal to the square of *Pearson's Correlation Coefficient* r_{xy}^2 (Equation (2)) [8]:

$$R^2 = r_{xy}^2 = \frac{s_{xy}^2}{s_x^2 s_y^2}. \tag{2}$$

Thresholds for measures are individually defined, evaluated, and adjusted in cooperation with the quality management experts according to their domain knowledge. A fault is considered significant and analyzed further if all of these thresholds are exceeded (in this case: $k \geq 1.8$, $\bar{y} \geq 10$, $R^2 \geq 0.2$). In the second step (cf. Figure 1-2) the production week histogram of the engines with a particular fault is generated. It plots the two-year failure characteristics of up to three-year-old cars and is normalized by the total number of produced engines belonging to the same class (vehicles with the same car brand, fuel type, and engine type). Finally, the result is smoothed by a 5-point smoothing function to eliminate the outliers. Significant increases must be identified to determine the starting point of periods in which more than the average number of faulty engines were produced. In the next step (cf. Figure 1-3) significant decreases are determined, resulting in a set of time periods that are bounded by a significant increase and the subsequent decrease. Each period is analyzed in detail by initially generating a BOM distribution and normalizing it in order to identify the critical BOMs (cf. Figure 1-4). Then, the technical modifications are retrieved from the BOMs and limited by those that were set operational in a time period before and after the corresponding significant increase (cf. Figure 1-5). Finally, the subset of modifications that most likely caused the fault is computed. Two methods were implemented for determining candidate technical modifications: the first determines technical modifications which are included in most of the critical BOMs, and the second uses the *Apriori* [2] algorithm for the same task.

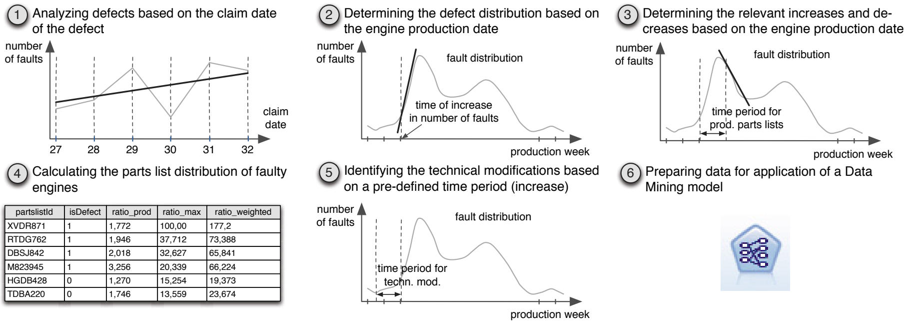

Fig. 1. Q-AURA process in detail

A more detailed description of the input and output is given in Figure 2. The first column in the input table identifies an engine (engine serial number). The next column *isDefect* determines whether the record is a faulty one or not followed by the relevant technical modifications (mod) of the corresponding BOMs. The dataset is processed by the Apriori algorithm and results in an output table, which consists of different rules that satisfy a given threshold for the calculated quality metrics *support* and *confidence*. A rule consists of at least one technical modification (mod). The modifications of a particular rule are aggregated by a conjunction operator and are those which take the Boolean value *true*. The conclusion (right-hand side of rule; currently analyzed fault code) gets true, if and only if, the premise (left-hand side of rule; technical modifications) is also true.

4.2 Application Scenarios

Q-AURA can be applied in two scenarios, which determine, on the one hand, how the user interacts with the application and, on the other, the complexity of the provided Q-AURA functionalities. The first one periodically calculates new results and the second one is a user-driven approach.

Periodical analysis is executed weekly, and therefore user interaction is not necessary. The process steps are analogous to those depicted in Figure 1, but

Input

engineNr	isDefect	GHST321	DKSCT65	AKSDT23	Z2374A0	...
73829418	1	x	x			...
10294832	0			x	x	...
23402103	1		x		x	...
30493829	1	x	x		x	...
17549219	0	x		x		...
29384753	0		x		x	...
...	...	...	...	...	...	...

Rules

$rule_1$: $mod_2(DKSCT65) \cap mod_1(GHST321) \Rightarrow FaultCode_1$
$rule_2$: $mod_2(DKSCT65) \Rightarrow FaultCode_1$
$rule_3$: $mod_4(Z2374A0) \Rightarrow FaultCode_1$
$rule_4$: $mod_2(DKSCT65) \cap mod_4(Z2374A0) \Rightarrow FaultCode_1$
...

$mod = \{mod_1 \dots mod_n\}$

Output

rules	support	confidence	description	...
$rule_1$	65,8	45,23	test1	...
$rule_2$	94,3	67,23	test2	...
$rule_3$	23,42	54,23	test3	...
$rule_4$	10,32	23,12	test4	...
$rule_5$	8,32	12,32	test5	...
$rule_6$	27,23	34,21	test6	...
...	...	...	...	...

Fig. 2. Input table and output table of the Apriori approach

additionally different attribute distributions are calculated to derive which cars are mainly affected by the fault (e.g., vehicle order country). For users who have some prior knowledge what the corresponding problem could be – before the system identifies them as critical – Q-AURA provides a user-parameterized analysis. We distinguish between two types of analysis: the first relies (like the periodical analysis) on fault codes, and the second requires a set of engine serial numbers or a set of vehicle identifiers. The latter one is advantageous when richer contextual information is available since it takes time until a significant number of customers observe a particular problem. Therefore, a distribution of fault codes is calculated to get deeper insights into the problem history.

Q-AURA has been evaluated, since the application is used by BMW quality management experts every day. Due to the success beside Steyr the application is deployed at the Munich and Hams Hall plants. The problem solving time was recorded before Q-AURA was applied by the quality management experts in Steyr. After Q-AURA has been used for one year it was measured again. The result was that the problem solving time concerning engines which were produced in Steyr has been reduced approximately by 2%.

5 Future Research Directions

Validation of the context matching of technical modifications with those of analyzed faults is completely subject to user interpretation. We have thus started to implement two improvements to Q-AURA. The first aims for earlier fault detection and will therefore reduce reaction time, while the second improves the accuracy of the analysis and will reduce processing time.

The first approach uses warranty and fault information available in different databases and at different stages of approval. Combining fault trends at various stages will increase the accuracy compared to using only one source, but the data must be evaluated/qualified using different data quality metrics [7]. Failure curves of the data sets are calculated and future values are predicted, which are weighted by the data quality of the corresponding data source. Significant faults are calculated by combining the predictions. Afterwards, the predictions are compared with new values of the following production week and weightings are adjusted.

The current approach identifies relevant technical modifications by means of statistics and heuristics. The second optimization incorporates also context information to improve accuracy. First, relevant data sources with additional information about technical modifications are identified and quality metrics are calculated. Afterwards, technical modifications are classified on the basis of their meaning. We propose two different models: (i) a *knowledge-based model*, based on string matching [5] and a semantic network, and (ii) a *data mining model* enriched with technical modification attributes based on classification [9]. Afterwards the *assignment* between faults and modification categories is performed. Two different approaches are proposed: (i) a *supervised* machine learning approach integrating user feedback, and (ii) an *unsupervised* machine learning approach, using string comparisons [5] and a semantic network. In the final step, the Q-AURA result tables with the modifications are filtered by context.

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