# HOW TO INTEGRATE INFORMATION ABOUT PAST ENGINEERING CHANGES IN NEW CHANGE PROCESSES?

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## Abstract

When implementing engineering changes (EC) in companies many information about ECs and associated processes is stored and forgotten. However, an extraction of information about correlations in past ECs can have advantageous. In the decision phase of ECs, it is very crucial to identify the relevant stakeholders and to know which further parts could be affected by the proposed EC in order to create a good basis for decision. Especially for ECs in complex products, which can affect the whole product lifecycle it is an important and difficult task.

This paper presents an approach of how information about past EC processes can be extracted by knowledge discovery in database (KDD) methods in order to support the EC coordinator. The EC coordinator gets recommendations based on past interrelations of EC data and for probably relevant stakeholders and affected parts. Here the data mining technique association rule is applied.

The approach was developed while using a real and large database of approximately 53,000 past ECs of a car manufacturer. A preliminary test has been conducted and the feasibility of the approach was proven as well as first positive results.

**Keywords**: Information management, engineering change process, Decision making

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# 1 SITUATION AND MOTIVATION

Today's industry faces many engineering changes (ECs), which means modification in fits, functions, materials, dimensions, etc. of a product and constituent components after the design is released (Huang and Mak, 1998). In the year 2005, Ford, GM and DaimlerChrysler counted only the number of internal ECs in their supply chain. The result was 350,000 ECs per year for the three companies together and estimated costs of $50,000 per each EC (hidden costs included) (Wasmer et al., 2011). These enormous numbers and costs of ECs highlight the importance of engineering change management (ECM). In recent decades, many companies have focused on becoming more efficient in implementing ECs. They introduced Workflow Management Systems (WfMS) in order to pass ECs more efficiently through the bureaucratic EC process. Thereby a lot of information about the process is stored (Huang and Mak, 1998). However, it has become clear that efficiency is not the only crucial success criterion and companies also have to improve their effectiveness, so that they are able to make the right changes at the right point in time in the design process (Brown and Boucher, 2007).

Nevertheless, companies have less support in their decision process and people involved in the process do these tasks primarily manual (Eigner et al., 2011). It is very difficult to find information in current systems especially when the information is stored in different databases and different programs or systems are required. Thus, a lot of time in the EC process is spent for searching for information (Riviere et al., 2003).

A very important and helpful information about past and similar ECs is the impact of the EC and involved stakeholders because the EC coordinator can then better select the persons to be involved in the EC process. Due to the increasing complexity, dependencies between subsystems and the high numbers of ECs in large and complex systems, it is even more important to understand interrelations (Siddiqi et al., 2011). Not to involve the right persons in the EC process can lead to fatal and wrong decisions.

The goal of this research is to develop a concept of how useful and appropriate information of correlations of past EC processes can be identified and provided directly in an EC process in order to support the EC coordinator. The information should be adjusted for the specific and present EC case and provided in form of recommendations. Hereby the data mining technique association rules should be applied in order to extract correlations of ECs, components, products and stakeholders in a large dataset of past ECs in form of rules. Through the specific provision of information, the effort for information retrieval is reduced and the quality of the EC process improved due the reduction of possible failures.

# 2 METHODOLOGY

Based on a literature review and discussions with EC managers in industry the initial need for an approach arose, which supports EC coordinator by using information of past EC processes, which is hidden in EC databases. The methodology within this paper is orientated on the design research methodology according to Blessing and Chakrabarti (2009). The focus within this work is on the Research Clarification (RC) and an initial Descriptive Study I (DS-I). In a first step, the aim of research within the article was clarified and defined. Therefore, we conducted a literature review, studied approaches in the scope of the research field, and formulated the research question:

How can an EC coordinator be supported by selecting the right stakeholders and identifying affected parts of a proposed EC by using data of past EC processes?

In a next step, we established an approach by using a real and large database of approximately 53,000 ECs of one company. We developed the approach according to a KDD process and based on a part of the database. The remaining EC data are used to evaluate initially the gained results.

# 3 RELATED WORK

## 3.1 Analysis of historical EC data

In the research field of ECM a lot of literature is available. Hamraz et al. (2013) proposed a framework for the categorization of ECM literature oriented on the EC process and categorized 427 publications. Especially in the prechange stage, a lot of literature is existing concerning concepts to prevent or to ease the implementation of ECs before they occur. In contrast, the postchange stage involves less

publication and deals with the ex post facto exploration of effects of implemented ECs. This stage refers mainly to the strategy "learning". The analysis of EC data belongs to the latter stage and there are only few approaches existing based on the analysis of past EC data in large and complex technical systems. Table 1 presents a brief overview of available approaches and highlights the differences referring the applied type of analysis, the analyzed attributes or dimensions of ECs, the time and aim of the analysis. Then a more detailed description follows in the remainder of this section.

*Table 1. Overview of different approaches concerning analysis of past EC data*

|  | Type of analysis | Analyzed attributes / dimensions of ECs | Time of the analysis | Aim of the analysis |
|---|---|---|---|---|
| Siddiqi et al., 2011 | Statistical analysis (frequencies) | Time, space (change location) and cost | posteriori | Multidimensional understanding of change activity in large systems to identify better design and management strategies |
| Sharafi, 2013 | Knowledge discovery in databases (KDD) | All available (in an industry database) | posteriori | Identification of patterns in large datasets to gain insights to improve ECM and product development |
| Giffin et al., 2009 | Statistical Analysis | Change networks, patterns and propagation over time (based on change magnitude and status) | posteriori | Understand the nature of change and change propagation for future development programs |
| Kocar, 2006 | Sequential pattern mining algorithms | Components, changed attributes and status of the EC over time | real-time (in the EC process) | Prediction of EC effects and prioritization of ECs |
| Mehta, 2010 | Statistical analysis (Bayes's rule) | Attributes defined in the STEP data model | real-time (in the EC process) | Identification of similar ECs and prediction of EC effects |

Within the work of Siddiqi et al. (2011), EC data from a large and longstanding development project is analyzed posteriori, this means after completion of the project. The aim of the statistical analysis is to gain useful insights regarding the developed system. These insights are used then to improve next designs and design strategies in similar systems or projects. Focus of the analysis is on the EC attributes time, space (change location or initiating subsystem) and cost. Other attributes of changes, such as change cause, people involved in the EC, are explicitly excluded. The attributes time, space and cost were investigated because, according to the authors, these are the most important existing attributes, they are recorded and stored by most of the companies. Out of a combination of the three attributes, arise six different ways for analyzing EC data: time only, location only, cost only, time-location, location-cost and time-cost.

Sharafi (2013) applies Knowledge Discovery in Database (KDD) methods to analyze historical EC data in order to gain insights in form of patterns within the database. The intention is to use the resulting insights to improve ECM and product development. Compared to data mining KDD is the overall process to extract useful knowledge from volumes of data - herein data mining is a particular step. Besides data mining there are several steps necessary to extract useful knowledge from the data: data preparation, data selection, data cleansing, incorporation of appropriate prior knowledge and proper interpretation of the results of the mining (Fayyad et al., 1996b). Sharafi (2013) analyzed a large real data set of past ECs (approximately 53.000) of an automotive manufacturer in order to assess the application of KDD in the context of ECM. The dataset includes all ECs requested within a period of five years, from all projects and products of the company. Hereby all available and through the WfMS documented attributes of ECs were analyzed.

In particular, the data mining methods clustering, classification, association analysis and text mining are applied. The approach is very general and lacks a concrete application of the gained insights and a concrete user in order to display the usefulness.

Giffin et al. (2009) analyzed 41,500 ECs requested during the design phase of a complex product within a period of 8 years. The aim of the analysis was to understand the propagation of ECs during engineering design. Therefor EC networks are decomposed into one-, two-, and three-node motifs as the basis elements of change activity. Then a statistical analysis disclosed that some motifs occur much more frequently than others. Additionally a set of indices is proposed in order to classify areas of the systems as acceptors or reflectors of ECs and a normalized change propagation index. The EC attributes applied within the statistical analysis are the components, their occurrence in EC requests and point in time of the occurrence.

Mehta (2010) developed a method to determine the impact of proposed ECs by using information of past ECs. A detailed evaluation of each proposed EC is time-consuming and inefficient. Therefore, the aim of this method is to identify ECs that might have a significant impact and evaluate only those ECs in detail. The method utilize the STandard for the Exchange of Product model data (STEP). The important elements of a STEP data model are the entities, relations and attributes. Entities are for example parts or shapes, the attributes define the entities, and the relations define the relations between the entities.

The prediction of EC impacts based on ECs history is among others an aim of the Virtual Collaborative Design Environments (ADVICE) (Kocar, 2006). Within the approach, data mining techniques are applied in order to provide users support for the prioritization of changes and prediction of change propagation. For the prioritization, historical data is used to extract sequential patterns that occur frequent among company's products range. Input for the data mining method with the APRIORIALL Algorithm is the data about product model, component and changed attributes. For the prediction of change propagation, a data mining technique with the MINEPI Algorithm is utilized in order to investigate pattern within the same model.

In summary, while five approaches analyzed statistically historical EC data only two of them applied data mining techniques thereby. The aims of the approaches also differed and can be divided into two sections: gaining a deeper understanding of ECs in product development or predicting characteristics of ECs based on past EC processes. With exception of Sharafi (2013) all approaches employed only attributes concerning the scope of the EC in contrast to attributes about the EC process such as persons involved in the EC process.

## 3.2 Knowledge Discovery in Database

Nowadays companies collect and store an enormous amount of data generated in different areas of the company. Such as in ECM through the increasing IT support and introduction of quality management systems (cf. ISO 9001). However, the growing volume of data exceed the human analysis and visualization capability and therefore new generations of methods arise like data mining (Fayyad and Stolorz, 1997). With data mining techniques specific patterns and structures can be detected in huge data sets. Most data mining methods are based on proven techniques from machine learning, pattern recognition, and statistics such as classification, clustering, regression, and so on (Han et al., 2007).

### 3.2.1 Association rules

Within the present approach, the data mining technique association rules is proposed. The classic example for this data mining technique is the market basket analysis. Herein dependencies between purchased products are analyzed. Assuming records of each customer transaction at a large bookstore are available; with an association analysis, it is possible to determine for a particular book, which other book purchases occurred. With this information, it is possible to recommend other books to the customer, which may be interesting for him. This application of an association analysis is a recommender engine (Nisbet et al., 2009).

Agrawal $et\ al.$ (1993) established a formal model for the association analysis. Simplified the model includes $I = \{\ i_1,\ i_2,\ ...,\ i_n\ \}$ a set of binary items and $D = \{\ t_1,\ t_2,\ ...,\ t_m\ \}$ a set of $m$ transactions (a database). Each transaction has a unique ID and represents a subset of items in $I$. In Table 2 an example of a supermarket is presented with the items $I = \{$milk, bread, butter, wine$\}$ and the transaction database $D$ and the description of the measures and sets is given.

*Table 2. Example of a transaction database D*

| ID | milk | bread | butter | wine |
|----|------|-------|--------|------|
| 1 | 1 | 1 | 0 | 0 |
| 2 | 0 | 1 | 1 | 0 |
| 3 | 0 | 0 | 0 | 1 |
| 4 | 1 | 1 | 1 | 0 |
| 5 | 0 | 1 | 1 | 0 |

The association rule is defined as an implication

$$X \Rightarrow Y \text{ with } X, Y \subseteq I \text{ and } X \cap Y = \emptyset \tag{1}$$

X and Y are sets of items, so called item sets. For the example a possible rule is {milk, bread} ⇒ {butter}.

That means, when a customer purchases milk and bread then he probably buys butter too.

Rules have two important measure: support and confidence. The support of an item set $X$, supp $(X)$, is defined as the portion of transactions in the database, with $X$ including. The support of a rule

$$\text{supp}(X \Rightarrow Y) \text{ is supp}(X \cup Y) \tag{2}$$

is defined as the support of the combined item sets $X$ and $Y$. The support is interpretable as statistical significance. In the example the item set {milk, bread} occurs in 2 out of 5 transactions (see Table 2), so supp({milk, bread})= 2/5=0,4. That means within 40 % of the transactions milk and bread occur together. The confidence of a rule is defined as

$$\text{conf}(X \Rightarrow Y) = \text{supp}(X \cup Y)/\text{supp}(X) \tag{3}$$

and measures the strength of a rule. For the example rule {milk, bread} ⇒ {butter} the confidence is supp({milk, bread, butter})/ supp({milk, bread}) =0,2/0,4 = 0,5. That means for 50 % of the transactions, which include milk and bread, the rule is correct. Association rules have to reach a user-defined minimal support s and minimal confidence c. A rule is defined as strong when both threshold value are satisfied. The method of association rules is a search for strong rules in two-steps (Agrawal et al., 1993):

1. Search all frequent item sets in the database (= all item sets with minimal support)
2. Form strong rules with the most frequent item sets and the minimal confidence c

There are different algorithms for the association rule analysis available. The Apriori algorithm was developed first by Agrawal et al. (1993) and a relative new algorithm is FP-growth (Han et al., 2007).

### 3.2.2 Process model for KDD

The identification and extraction of unknown, non-trivial and important information from large data sets is a challenging task, which is only successful with a systematic approach. So different process models are developed to facilitate people working with data mining. The most important process models are the KDD process according to Fayyad et al. (1996) and the Cross Industry Standard Process for Data Mining (CRISP-DM) (Chapman et al., 2013). In the following, the description is limited to the CRISP-DM process because this process is based on the original process of Fayyad but is more detailed in order to meet industry needs. The sequence of phases in CRISP-DM is not fix; there can be many iterations, depending on the quality of the results gained in the process. CRISP-DM describes the six phases as follows (Chapman et al., 2013):

**Business Understanding:** aim of this phase is to gain an understanding about the objectives and requirements of the company and to define the problem to be solved by the data mining project

**Data Understanding:** collecting data, working with them to gain insights about the data and data quality, and formulating hypothesis about potentially hidden information

**Data Preparation:** selection of relevant attributes, transformation and cleansing of the data and assembling for the analysis

**Modeling:** selection of the right data mining algorithms depending on the problem. Often there are different techniques for similar problems possible. The result is the model for the analysis

**Evaluation:** before applying the model, the quality of the model is evaluated in relation to the problem and the economic boundary conditions.

**Deployment:** after applying the data mining model, the organization or stakeholder get the results in a useable representation

# 4 AN APPROACH TO INTEGRATE PROCESS INFORMATION IN EC PROCESSES

The aim of the developed approach is to support EC coordinators by providing specific and useful information and knowledge about past EC processes. The information provided is in form of correlations of past EC processes, for example correlations between stakeholders, components, products and further EC attributes of changes. In this work, we focus on the decision phase of ECs and provide recommendations for the EC coordinator, while

- Selecting stakeholder to be informed, asked for statements or EC approval
- Identifying affected components or products by the EC.

## 4.1 Overview

Figure 1 shows the three essential parts of the whole approach. The backbone represents the EC process, in which many different roles or actors are involved and work temporarily together depending on the particular EC. Focus of the approach is on the highlighted process phase "specification of and decision for change". The second essential part is the company's database, which contains data of past ECs as well as related information of the products for example bill of materials or data in PDM or ERP systems. The KDD process is the bridge between EC process and database. Herein the aim is to generate the recommendations with the data mining technique association rules according to the proposed EC case in the EC process and based on the available database.
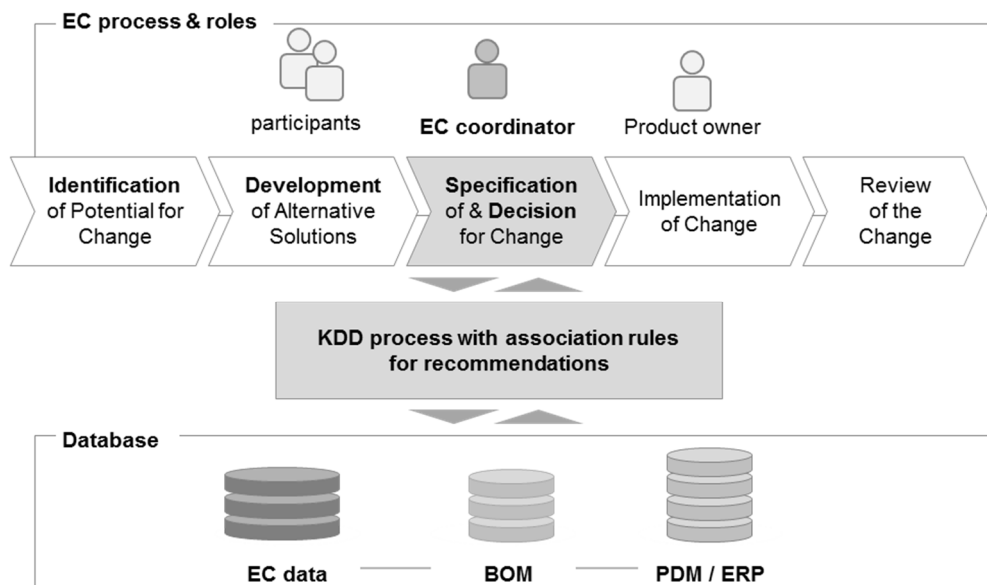


*Figure 1. Overview of main parts of the approach*

## 4.2 Engineering Change Process

According to Kocar (2006) the EC process is one of the most complicated and problematic processes in an organization because of the high number of ECs, involving a large number of components in complex products, which again involve many components or parts and which belong to different product families. A challenge is handling the interactions of components with each other, with the manufacturing, tools and processes in the organization. Thereby many different actors or roles are involved and have to be coordinated. In general, there are four important roles in EC processes: imitator, coordinator, members of an EC board and stakeholder from different departments (Kocar, 2006).

EC processes differ from each other, depending on the company, change situation and change type. However, there is a consensus on some general phases of ECM processes in industry and literature as

depicted in figure 2 (Jarratt et al., 2011; Hamraz et al., 2013; Wickel et al., 2014; Wasmer et al., 2011; VDA 4965 - Part 1, 2010).
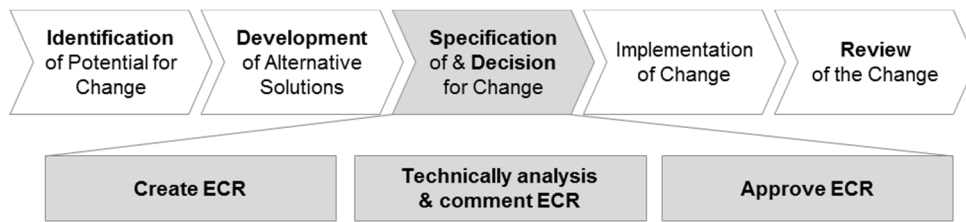


*Figure 2. Engineering Change Process*

The phase "Specification of & decision for Change" is the first formal phase in which the official engineering change request (ECR) is recorded and a lot of communication and coordination is required. The phase consist of the sub phases: create ECR, technically analysis and comment on the ECR as well as approval of the ECR (VDA 4965, 2010; VDA 4965 - Part 1, 2010). In decision processes in general, information is collected that is necessary to prepare a decision and to provide a decision foundation. In EC processes, the decision is about the implementation of a developed solution. The decision is always a branching point and the quality of the decision depends strongly on available information about the situation (Eigner et al., 2011).

The knowledge, which is necessary for a decision in the EC process, is distributed in the whole company and thus several stakeholders have to provide their knowledge for the decision. This is due to complex products, wide-ranging impacts and the division of labor. The change coordinator has the task to identify relevant stakeholders and request an analysis and assessment of the proposed EC. This allows stakeholder to add further relevant information such as affected components, documents and figures, and statement about implications (Wasmer et al., 2011). In view of knowledge management, EC processes are complex and knowledge intensive, since the results depend strongly on the knowledge of participating actors, which usually require a long time to gain that knowledge and additionally many contingencies and uncertainties are involved in the process. The former is especially true for the decisions makers (for example EC board members) and EC coordinators. The complexity arises from the number of involved participants and required process steps, large dependencies between them and dynamics in the process (Eppler et al., 2008). Within the approach, the EC coordinator will get recommendations based on past and similar EC processes of whom to involve and ask for assessment of the EC impact and which parts or components may be affected.

## 4.3 Engineering Change Data and related Databases

Within EC processes, many data is generated and stored thereunder data about the EC itself such as the reason for EC, involved parts, assemblies, modules or documents. But also data about the process such as who was involved in which activity or how long was the duration of the task. Figure 3 shows a categorization of this data in relation to the sub phases of the decision phase.



*Figure 3. Data within EC processes according to Wickel and Lindemann (2014)*

Additionally there are related data and information for the part to be changed available in companies. For example the bill of material (BOM) contains the following information of a part: next higher

assembly, concerning product model/assembly, part number, description of the part, BOM hierarchy (Level of BOM), quantity per assembly, unit, revision, cost (for home parts) or price (for purchased parts). This data are in Product Data Management (PDM) systems, which belong again to PLM solutions. PLM solutions manage product related information through the product lifecycle (Eigner et al., 2011). The related data are used additionally in this approach in order to gain more information.

## 4.4 Knowledge Discovery in Engineering Change Processes

The KDD process is the bridge between the introduced EC process and the database. With the KDD process the relevant knowledge is extracted. According to the steps of CRISP-DM the objective of the application of KDD in EC processes is clarified firstly. The aim is to create rules for

- who should be involved in the EC process as a stakeholder
- which parts may be affected by the EC

based on past EC data and the specific EC case. The hypothesis is that there is hidden knowledge about interrelations of past EC processes in the data, which can support the identification of the right stakeholders and affected parts in the second sub phase of the "specification of and decision for change" phase. Therefor data and attributes, which are available at that time, can be utilized for the "if" part (the premise of the rule), that means the data from the first sub phase "create ECR" (see figure 3, left column). In the data mining process a database is generated which contains all necessary data in a processible form.

In figure 4 an example shows how rules are derived for identifying the right stakeholders for a change on "part 1" by using the database and the attributes: "current phase in the product life cycle" (of the part) and "department of the requestor" of the EC.
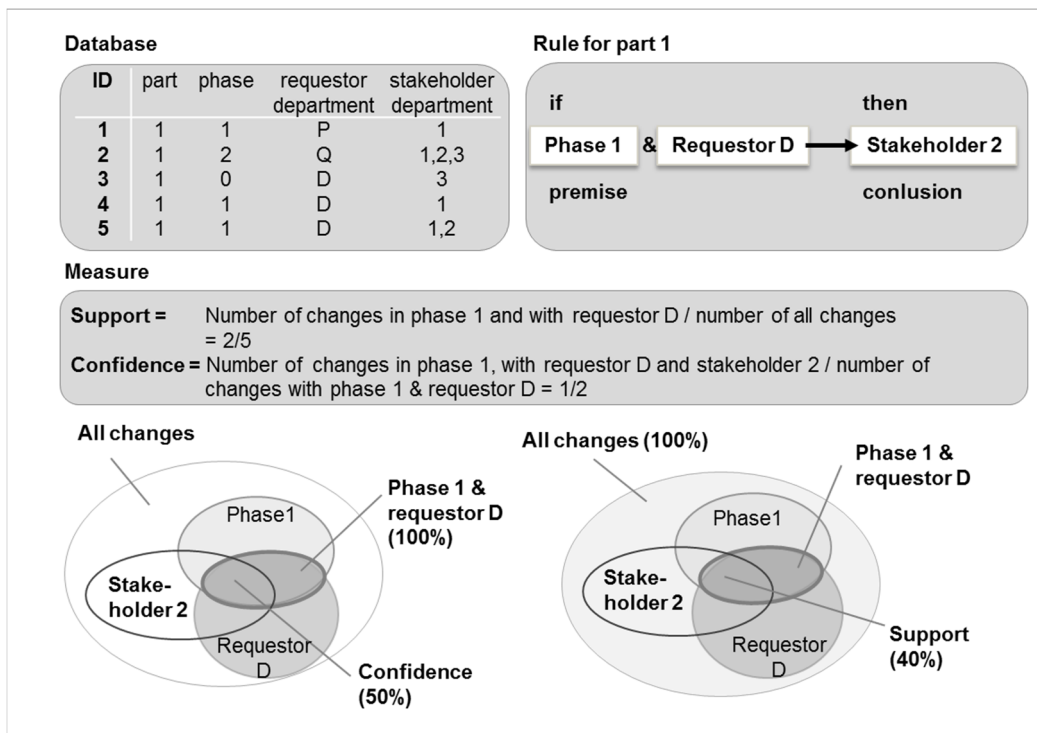


*Figure 4. An example of how to create association rules based on selected EC attributes*

The support with 40 % represents the number of times a rule occurs in the database. However, the confidence reflects the strength of the relationship by the number of transactions that support this rule in relation to the total number of transactions that satisfy the premise. Rules with a comparatively low support are also often interesting, especially since strong rules often represent known and obvious relationships with high support. A high confidence value indicates a strong dependence between the observed items.

For developing this approach, we applied an EC database of a car manufacturer with 53,000 ECs. At first the attributes were determined, which are available at that point in time in the EC process such as requestor of the EC, reason for change, current phase in product lifecycle and scope of the EC, that

means involved parts, products or modules. Then rules were derived for a proportion of the database in order to be able to use the remaining part for an evaluation of the developed rules. The first results were positive because we identified rules with high support and confidence.

It is intended to provide the established rules directly in the EC process for example integrated in the WfMS, based on the beforehand made input data. Figure 5 depicts a possible user interface with on the left side the description of the EC and typical entries for WfMS for creating ECR and on the right side, the recommendations based on the past EC data. The EC coordinator thereby has the possibility to get support if desired.



*Figure 5. left side available data from previous phases; right side information support provided by an analysis of past ECs*

The recommendations are in the form: "In similar EC cases the service department was asked for a statement" and the change coordinator decides to accept or not accept the recommendation.

## 5   CONCLUSION AND OUTLOOK

An approach of how a company can improve their decisions in EC processes by using information of past ECs has been described. The knowledge is generated during a KDD process in particular the CRISP-DM process, with the data mining technique association rules. The approach applies commonly available EC data of past ECs and related data in PLM systems, so that there is no additional effort for data acquisition necessary - only data cleaning and preparation steps. The association rule consists of premise and conclusion. In present approach, the premise consists of a combination of available attributes of the ECR and the conclusion is the desired output such as affected parts by the EC. First results seem to be positive, because rules with high support and confidence were derived.

Nevertheless, the approach is at the beginning and the time necessary for computing is high because of the number of used attributes. In further work, we will optimize the approach and reduce this number by experiments with the database. Furthermore, the approach will be evaluated in detailed, discussed with experts and applied in further companies.

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