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DETERMINING THE DRIVERS FOR LONG LEAD TIMES OF ENGINEERING CHANGE ORDERS: A DATA MINING APPROACH

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1. Introduction

The automotive industry has reached a certain maturity state and is no longer characterized by high growth rates. The market is characterized by a fierce competition, leading to new requirements for the producers. A major trend for the industry involves increasing product diversity. For example, it is stated that the number of new vehicles launched each year by Renault quadrupled in the 20 years from 1990 to 2010 [Beaume et al. 2009], but naturally the amount of new product launches differs depending on the company. Moreover, the same development can be observed for nearly every other car producer as well. This affects product development in several ways.

First of all, the development of more product types leads to more complexity, which makes the management of the product development more difficult. In dealing with this complexity, a lot of enterprises put an emphasis on new management techniques or new development paradigms like, for example, concurrent engineering, lean development and so on.

Secondly, the innovation cycles are getting shorter. If a company brings more new products to market there is less time to develop new features. Moreover, the time to market has been decreasing rapidly in the automotive sector within the last years [Beaume et al. 2009]. Therefore, one of the imperatives for survival in the automotive industry is to constantly strive for shortening the time to market.

Time to market is influenced greatly by the engineering change process. The engineering change (EC) processes are present at the back end of almost all product development projects. EC processes usually change parts, drawings/designs, software of the product, in order to meet variations in internal and external requirements. Therefore, Engineering Change Management (ECM) is crucial for overall success of the PD project, because it is used to coordinate process activities which drive the maturity progress of the product. This is particularly true for mature industries, such as the auto and home appliances industries, which tend to invest their product development efforts mainly in incremental innovation projects. These projects consist of changing the existing products in order to improve them. In fact, these changes are the core of new product development in these industries and an efficient ECM is essential for success in their respective markets.

During the EC processes, a lot of information is generated. Greiner [Greiner et al. 2007] compared different knowledge management approaches and observed that organizations focus on the re-use of existing knowledge in times when they are mainly pursuing a strategy to improve efficiency. Therefore, whenever large amounts of data are available, the development and use of approaches such as Knowledge Discovery in Databases (KDD) is very important for improving business efficiency. However, the application of these approaches (and especially of KDD) in the domain of engineering change management is still new and largely unexplored. Starting from the question of what useful knowledge can be extracted from the analysis of a large database of engineering change orders (ECO), this research describes an application of a KDD methodology in analysing EC processes. The main motivation that drives this research is the possibility of extracting valuable knowledge about what causes lead time delays in EC processes. Hence, the aim of our research is to use KDD to identify the main drivers of long process times from historical data. More specifically we try to answer the following research questions:

1. Which theoretical drivers for long process times of ECOs can be found in literature and how can they be structured?
2. When analyzing complexity drivers for long process time, which empirical main drivers can be derived using KDD methods?

This paper is structured as follows. First our methodology is explained and the results of our conducted work is presented, including the state of current research regarding the drivers for the process time of ECOs. Afterwards, one of those drivers - the complexity, is further investigated and the data mining results are presented. Finally a short conclusion is drawn and the outlook in the last section is given.

2. Methodological approach

Although there has been some research in the engineering domain and automotive industry using data mining methods, there are surprisingly few studies or articles in the context of product development of car manufacturers, despitethe huge costs incurred by ECOs, a fact which implies a potential to significantly reduce costs. Thus, this paper tries to use data mining methods to generate new insights into the context of ECM.

In order to answer our research questions we used a database with historical ECOs and the associated ECRs of a leading European automobile manufacturer. To ensure the quality of our approach an established concept is used [Fayyad et al. 1996]. This concept allows for a systematic analysis and is widely used in research as well as in industry.

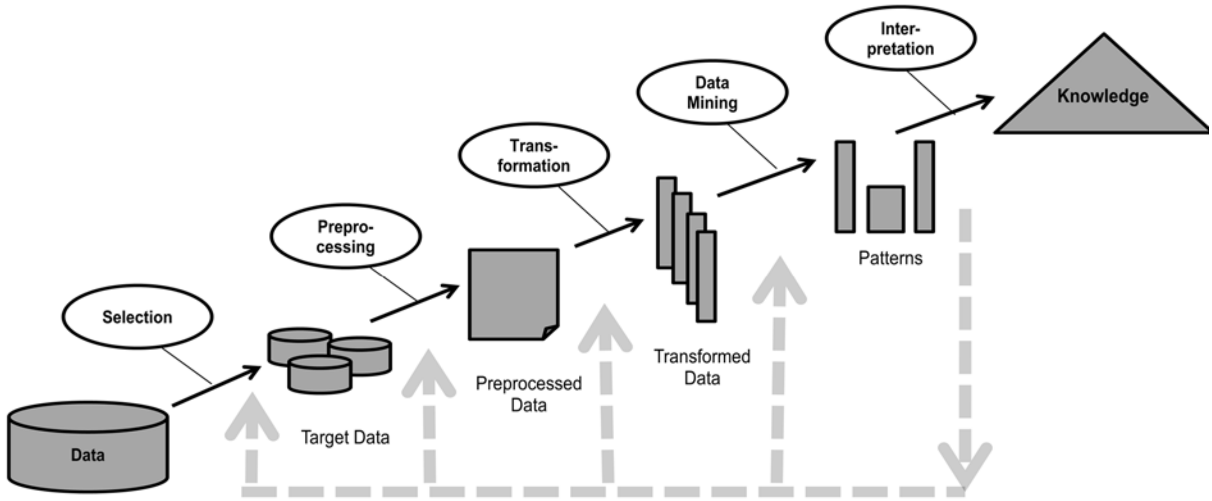

Figure 1. KDD process [Fayyad et al. 1996]

Before starting with the KDD process, one has to develop an understanding of the domain and more importantly, of the critical questions and issues that the KDD process is supposed to address. This initial stage is known as “business understanding”. After that, the relevant data has to be selected from the database. Unfortunately, data is usually not stored in a directly accessible and reusable way. Often there are missing values or values are stored incorrectly. Thus, the selected data has to be cleaned and preprocessed. In order to apply data mining methods on the preprocessed data some additional work has to be done. Projection and data reduction is necessary to reduce the amount of data. This is achieved by reducing attributes to their most prominent features or even deletion in case of irrelevance. The next step is the application of data mining algorithms to the data. These algorithms or

methods can by divided into four fundamental categories: Clustering, classification, regression and association rules [Fayyad et al. 1996]. While clustering aims to divide the data set into different clusters without pre-defining one attribute for division, classification tries to split the data in such a way that different examples with one common attribute value belong to the same class. Plenty of methods have been developed for this task such as decision trees, neural networks, Bayesian networks and many others. Association rules are used to detect dependencies between examples and regression enables the numerical prediction of attributes. Many of these methods are explained in detail by [Fayyad et al. 1996] or [Witten and Frank 2005]. Finally, the results have to be validated and interpreted. This is done by checking the significance of the applied model or by comparing the results of a training data set and a test data set. In this context interpretation means the transformation of the results into knowledge by describing the results or with the help of visualizations.
New results can change ones perception of a topic and due to new knowledge the original hypotheses might change. Additionally, unexpected obstacles may arise, requiring new solutions or the input of new data. This is why the data mining process is often described as explorative and iterative and why most of these steps are executed several times within a project, every time with small adjustments.

3. Findings

3.1 Framework of drivers for long process times

Different researchers regard different influence factors to be responsible for delaying ECOs. While some are convinced that batching is the main driver, others do not agree and propose that congestion is responsible or even a mixture of different factors like scarce capacity or complex approval processes [Loch and Terwiesch 1999]. [Hedge et al. 1992] claim that "Despite the theoretical research indicating ECOs cause severe problems and need to be managed effectively, very little empirical evidence exists that quantifies the negative impact […]". Since then, insufficient work has been conducted to accomplish this goal and little has been achieved in terms of reaching a consensus or coming up with strong empirical evidence [Loch and Terwiesch 1999]. Consequently, there is a lack of research comprehending the drivers and empirically determining their influence.
For this reason, we compared several studies and papers and structured them in a framework, which provides an overview of different drivers. Please note, that in order to perform this task we consulted a vast amount of literature which we did not reference in this paper. The reason for this is the limited number of references set by the conference organisers. For the full list of references, please refer to the authors of this paper. In order to be as authentic as possible not every possible influence factor is included, instead we focused on work which has been conducted in the field of the process time of ECOs and when possible, on studies conducted mainly in the automotive industry. There is no framework of process time drivers for this field available yet, rather each study focuses on a single selection of factors givren priority by the particular researchers. Hence, we analyzed several studies and came up with a framework that describes the impact of different factors on the process time of ECOs in the automotive industry (see Figure 2).
This framework is based on the work of different researchers who had already tried to determine the drivers for long process times.
[Clark and Fujimoto 1989] came up with a rough schema, which divides the influence factors for lead times in two categories: Workload and Capacity. The basic idea is that the time for solving problems solely depends on the workload of the problems and the capacity to solve them. This fundamental principle is still valid, but the work of others suggests, that in such a complex environment, one can further distinguish the drivers and that also additional influence factors exist, which cannot be assigned to one of these two categories. Therefore, we retained these categories, but extended the concept and developed a broader framework to structure the different drivers.

3.1.1 Workload

The workload is mainly defined by the complexity of the affected product. It is not surprising that it requires more work to change parts of a military helicopter than of a bicycle, because "Complex

products can display chaotic behaviour, in that a very small change can have a significant effect on the entire product." [Eckert et al. 2006].
Due to the mechanism that small changes lead to more changes, because of dependencies between several components, this effect is sometimes also called "snowball effect" [Terwiesch and Loch 1999]. Most often such dependencies or couplings exist between several components of a subsystem like the push tube and its screws, where the replacement of the one part might also require the replacement of the other. But there can also be dependencies between the product and the process itself, where they equally increase complexity [Terwiesch and Loch 1999]. An engineering department should ideally always be aware of such dependencies in order to reduce as far as possible changes on parts with high dependencies. Therefore, a lot of research covers this topic, but it is still very difficult to track and even more difficult to predict dependencies. We are going to tackle this problem with the help of data mining methods in the next chapter. Also other parameters influence the complexity like the number of parts a product is built of or the material it consists of [Hedge et al. 1992].
Not only complexity has an impact on the workload, also deviations in the emerging of ECOs can cause problems and time delays. This deviation can be expressed as variance and its influence is as follows: a rising variance is directly leading to increasing waiting times. This might be surprising, but is based on a trivial fact: With an increasing variance the capacity utilization of the resources (like engineering time) decreases as the resources are sometimes not used at all, and sometimes there are simply too many requests to deal with, which leads to congestion.

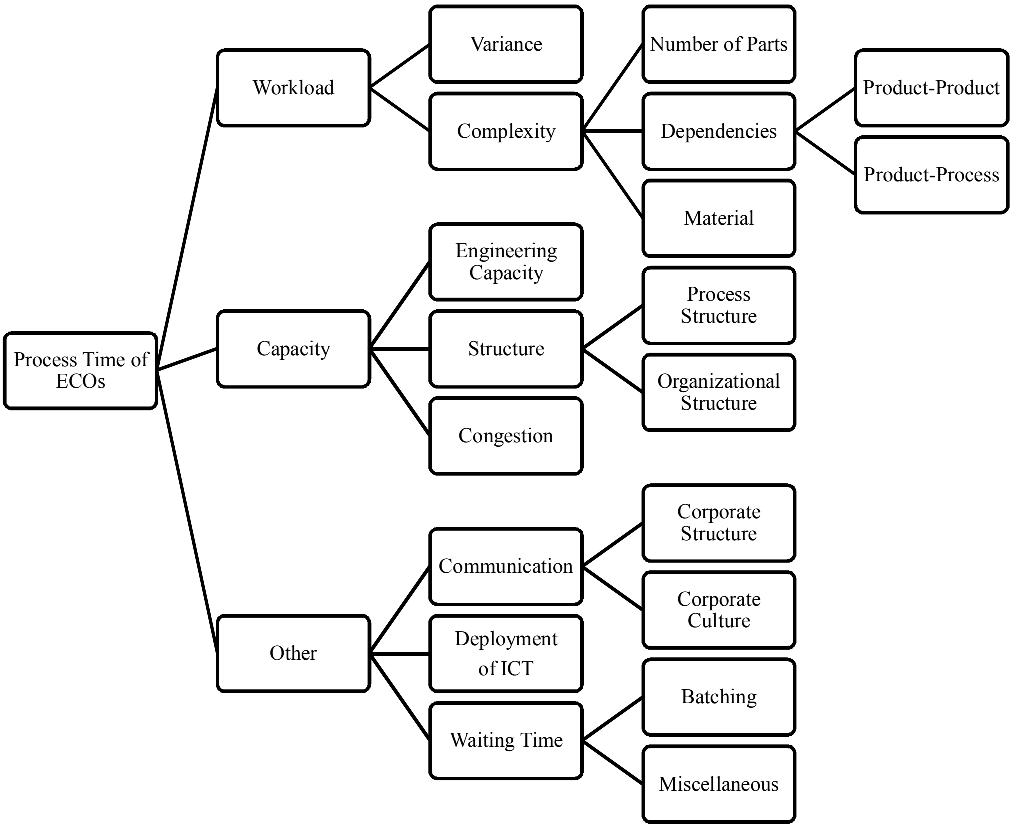

Figure 2. Drivers influencing the process time, derived from literature

3.1.2 Capacity

The time which is needed to solve problems is not only determined by the workload of the problems, but also the capacity to deal with them. In a broader context, capacity means any kind of resource which is necessary to perform a task, while in the specific context of the PDP we usually refer to the engineering capacity. Typically, this capacity is determined by the individual engineer who is responsible for a task and his or her weekly hours of work [Terwiesch and Loch 1999].

If the workload exceeds the capacity some of the ECOs have to wait to be processed. In a well managed process, those with least priority should be made to wait. This particular problem is inevitable, if an enterprise does not want to build up overcapacities and consequently, one might argue that the negative impact on the total process time of capacity is only natural and inevitable. On the one hand, that is a valid argument, but it is also important to understand that the negative impact often results from bottlenecks and therefore, can be minimized. A bottleneck takes place, if in a sequential process chain most resources have a low degree of utilization while one of them is used to full capacity, limiting the other resources and constraining the total capacity. Consequently, [Terwiesch and Loch 1999] recommend paying close attention to them. Simulations indicate that bottlenecks might be one of the most important drivers for long waiting times in many environments [Hedge et al. 1992].

Another limiting factor for the capacity lies in the nature of the process itself. The PDP is typically iterative which means that an ECO does not pass through the process in a strict sequential way, rather it has to undergo some stages again, for example, due to delayed error detection. If at that point in time a lot of iterations occur exactly at the bottleneck they intensify the negative impact. Combined with a bottleneck this can function as a multiplier effect and worsen the problem.

Consequently, the structure of the process is of great significance for the waiting time. Especially the approval process is often very complex and seems to take an inappropriate high amount of time [Terwiesch and Loch 1999]. Changes of a complex product like a car consume a lot of resources and therefore, a good handling of them can be critical for the success of an enterprise. The aim to save money by avoiding unnecessary changes often leads to complex approval processes with the disadvantage of high time consumption. It is obvious that these rivaling aims have to be kept in balance, but it seems that complex approval processes are often historically grown and can no longer satisfy the need for short development cycles.

In a broader context also the structure of an organization has an impact on the process and therefore, could be regarded as a driver as well. [Menon et al. 2002] point out that bureaucracy most certainly has a negative influence, slowing down decisions. Therefore, lean organizations have an advantage in terms of EC processing speed. In the automotive industry in general there seems to be a "[…] dominating culture of cost management and, at the same time, relatively little emphasis on time management." [Terwiesch and Loch 1999]. This is expressed in the implemented incentive mechanisms which are often designed in such a way so that they strictly penalize budget exceeding while little is done to overt time delays.

3.1.3 Other drivers

Apart from factors influencing workload and capacity, several other drivers have been found in literature, which have an indirect influence on the process. Basically, those belong to the following three categories: Communication, deployment of ICT and waiting time.

During the PDP it is often required to solve problems simultaneously and due to outsourcing and offshoring initiatives, the engineers who have to solve those problems are often globaly distributed making a well managed communication crucial for fast and efficient solutions. The patterns of communication itself are influenced by various drivers like corporate culture, environment or corporate structure.

The corporate structure influences the communication mainly by its degree of centralization and the geographical distribution. While some authors points out that the influence of corporate culture is widely overestimated due to its fuzzy nature and that, in fact, other factors are responsible for the relations between various performance indicators and corporate culture. Some other authors are convinced that especially the engineering domain is not paying enough attention to corporate culture.

The second driver is labeled as deployment of ICT which expresses the fact that especially computer tools and other emerging technologies, which heavily influence the way of communication, have an impact. [Huang et al. 2001] claim that the throughput time of ECs can be drastically reduced by a web-managed ECM and other computer tools like computer aided design have been facilitating the process for many years up to present day.

The last factor which should be taken into account is waiting time. A lot of different people, ranging from engineers to managers, who are responsible for the budget, are involved with an EC during its lifetime. This automatically leads to waiting times, because the requests literally lie on someone's desk waiting to be processed. This effect cannot be completely eliminated, but taking these days time pressure into account, it is surprising how long the waiting time sometimes is compared to the problem-solving time. Case studies indicate that in the automotive industry the lead time often exceeds the value adding time by a factor of 10, and consequently, it is estimated, that non-value adding time accounts for about 70%-90% of total process time [Loch and Terwiesch 1999]. Keeping that in mind, it is not surprising that many experts see a huge improvement potential in this area.

3.2 Business understanding

The empirical results were achieved with the help of the KDD process of [Fayyad et al, 1996] which starts with the concept of business understanding. A statistical analysis is not explicitly mentioned in the process model, but nevertheless, it had often been carried out and was indeed very helpful in terms of understanding the data and gaining hints for further investigations. Consequently, this stage is included here to give an overview of the data and share initial insights.
The focus of this paper is on the process time of ECOs, hence the following figure shows its distribution.

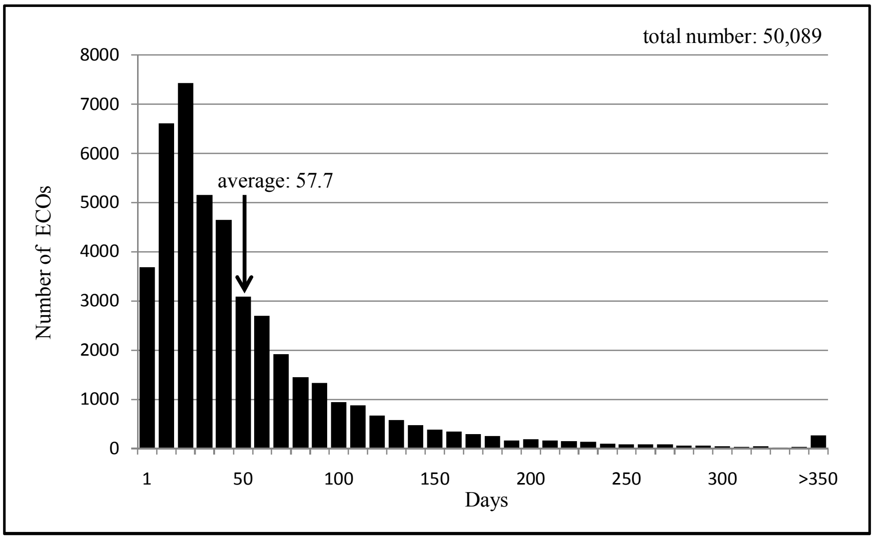

Figure 3. Distribution of total process time

There is a significant number of ECOs which is processed within one day or less (~7.2%), but most belong to the class ranging from 21 to 30 days. The median is at precisely 39 days and the average time at 57.7 days, leading to a distribution with a strong positive skew. This distribution corresponds with the findings of others, who presented similar distributions in their empirical studies [Loch and Terwiesch 1999]. However, there is a striking difference to former studies: The process time is characterized by a emphasized long-tail distribution. A possible explanation for this difference is that other studies we know of did not have such a huge data set spanning over five years and therefore, underestimated how many ECOs need require even 200 days or more. This result cannot be explained with outliers as still a significant number of ECOs features show a long process time.
The time distribution of the ECOs results, among others, from a complex approval process which is often regarded to be a significant driver for lead times [Terwiesch and Loch 1999]. In our specific case the total time was calculated by summing up the time which was needed for three process stages: creation, conception and acceptance test. We do not discuss the details of the approval process here as it is unique in every company and not the focus of our work. An exemplary process can be seen at [Terwiesch and Loch 1999]. Nevertheless, the distribution of the process time and its reasons are of high importance, therefore, Table 1 shows more details of the distribution.

Table 1. Process time in days

	1. Quartil	Median	3. Quartil	Modus	Min	Max	Average	STD
Stage I	9	18	33	14	<1	666	27.2	32.5
Stage II	1	5	13	<1	<1	647	14.4	30.6
Stage III	2	7	16	<1	<1	1,101	16.1	33.1
Overall	21	39	71	21	<1	1,227	57.7	61.2

The overall process time is separated for the three stages: creation, conception and acceptance test, whereby the first stage contributes the most time, while nearly the same amount of time is needed for stages two and three.

3.3 Data collection and preprocessing

To answer our second research question we analyzed a data base of a European car manufacturer. The data consists of over 50,000 historical ECOs which emerged in the years from 2005 to 2010. To our knowledge the data set is the largest which has been scientifically explored in this domain so far. The process model of [Fayyad et al. 1996] is not designed for multi-relational data mining, so firstly the relevant data was selected and then transformed, preprocessed and combined.

To perform these tasks the open-source data mining tool RapidMiner® was used, which provides a graphical user interface and includes a lot of methods covering nearly all steps from data loading and reprocessing to visualization.

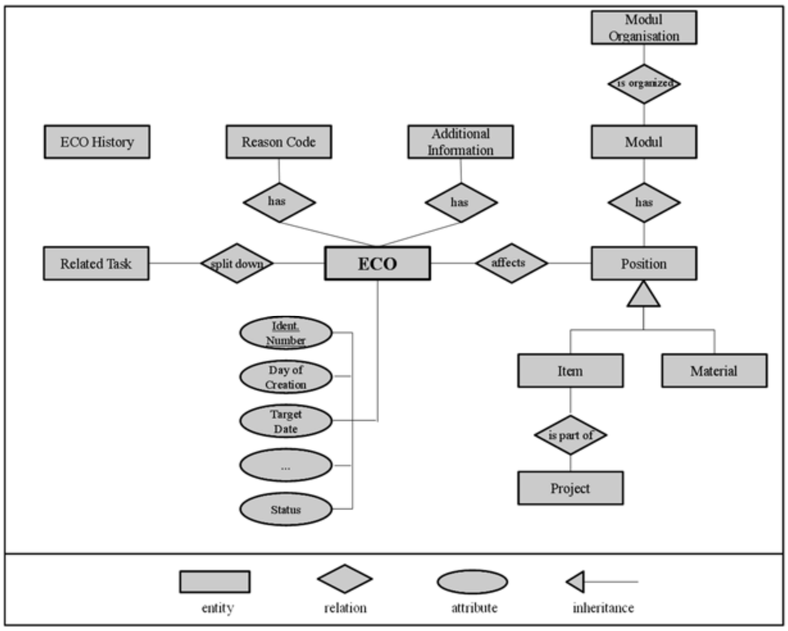

Figure 4. Entity-relationship-model of top level data view

The outcome of the preprocessing consists of two relevant tables: one table is used for statistical analyses which are presented in the chapter business understanding, and the other serves as a basis for data mining. This table was achieved by combining several relations and the data mining results which could be obtained with it are presented in the following section.

3.4 Data mining - association rules

Our framework of process time drivers provides an overview of a variety of different factors. Instead of analyzing each of them we focused on one area: the complexity and more specifically, the

dependencies between several products considered to be one of the most important drivers. But how can one make such fuzzy terms like complexity or the dependencies between products feasible?
Usually an ECR or an ECO do not solely affect one product or type of automobile, but several. If there is a change request affecting product A and B at the same time, those two products have to have some part in common, like having the same exhaust system and consequently, we consider them to be related. The use of common parts (Commonality) is currently a trendy method to decrease the number of different parts and thereby reduces development costs and saves resources [Kim and Chhajed 2000]. Unfortunately, the over 50,000 ECOs affected about 200 different products or product types resulting in a table with about 10e7 entries, each stating whether a product was affected by a change or not, making it difficult to gain any relevant information directly. In order to deal with this huge amount of data the concepts of association rules and frequent item sets were applied. These are often used in the context of market basket analysis to asses the behavior of the customers, but are useful for any context with large data sets. Frequent item sets are a combination of items which occur regularly in a data set. A short example illustrates that if 90% of all ECOs affected product A and product B and 10% affected product C (A,B) would be a frequent item set. Additionally, those item sets can be used to derive association rules. For our example an obvious association rule would be (A→B), which means that if A occurs it is likely that B occurs as well. Of course, that does not say anything about a direction so the vice versa rule (B→A) would be valid as well.
Applied to the data set 116 frequent item sets and for a confidence of 0.7 or higher (which is a statistical measurement for the reliability) 419 association rules, showing the inter product dependencies, were derived with the frequent pattern growth algorithm (also called FP-growth).

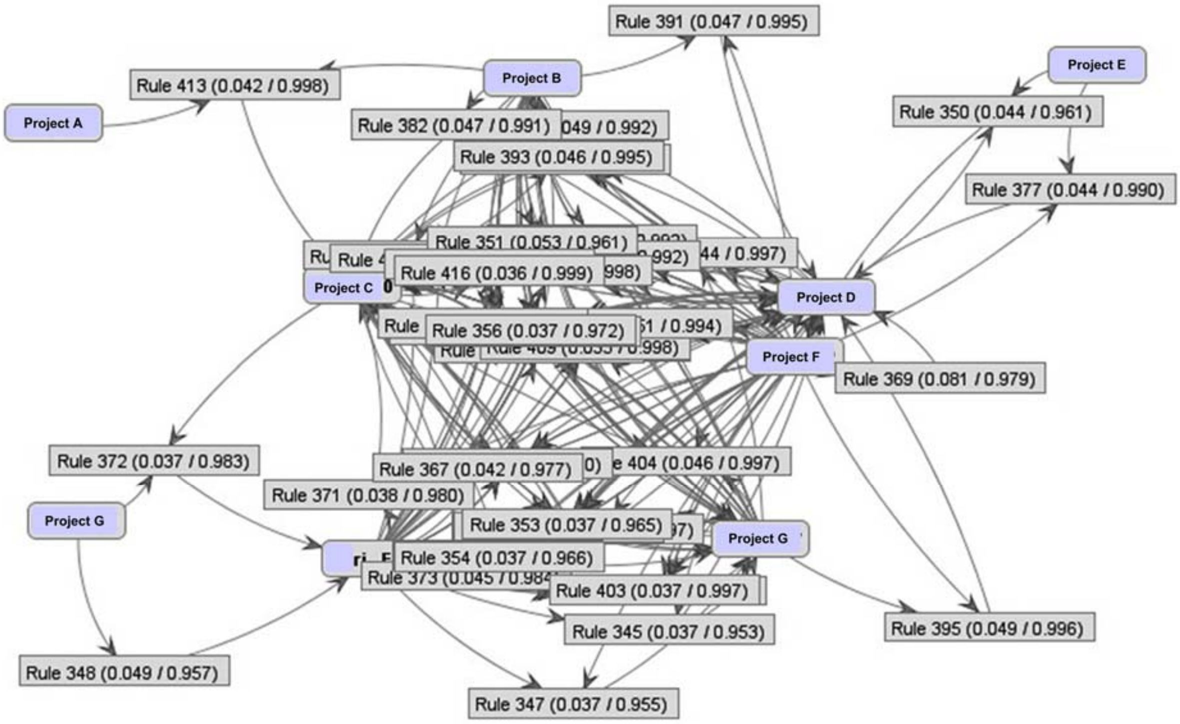

Figure 5. Map of association rules (reduced to those with confidence > 0.9)

Association rules are usually stored in a table, each entry representing a rule like (A,B→C). For a better overview Figure 6 illustrates 177 of these rules (with the highest level of confidence). This map illustrates the dependencies and it attracts ones attention to the fact that these are unevenly distributed among the different products. Consequently, such a map can be used while evaluating if there should be a change to a specific product, likewise to estimate automatically which other products might be affected and therewith determine if the change is worth implementing. Furthermore, such a map can help to figure out which are the central products. These are products which have a lot of connections and therefore, are high risk candidates to propagate any changes. Being aware of such products could motivate the engineers to keep closer track of them and by reducing to the minimum the amount of ECs.

3.5 Data mining - classification

It is important not only to determine the dependencies, but also to find out whether they influence the process time or not and if it is possible to use them to predict the process times. Therefore, each of the ECOs was labeled with the information if it needed more than the average time or not. Afterward, classification algorithms were applied to predict if an ECO needs more than the average time or not. The algorithm was based only on the data set which contained the information on which products are affected by an ECO. The basic idea behind this approach is that if we are able to make a good prediction only based on the information of affected products, this would prove that the dependencies influence the process time. Additionally, the strength of the impact is also demonstrated as better results indicate a stronger impact.

To achieve significant results ten different models have been built and applied to the data. In order to avoid over-fitting, which means that the results are only valid on a specific data set and cannot be used for other applications, 10-fold cross-validations have been used.

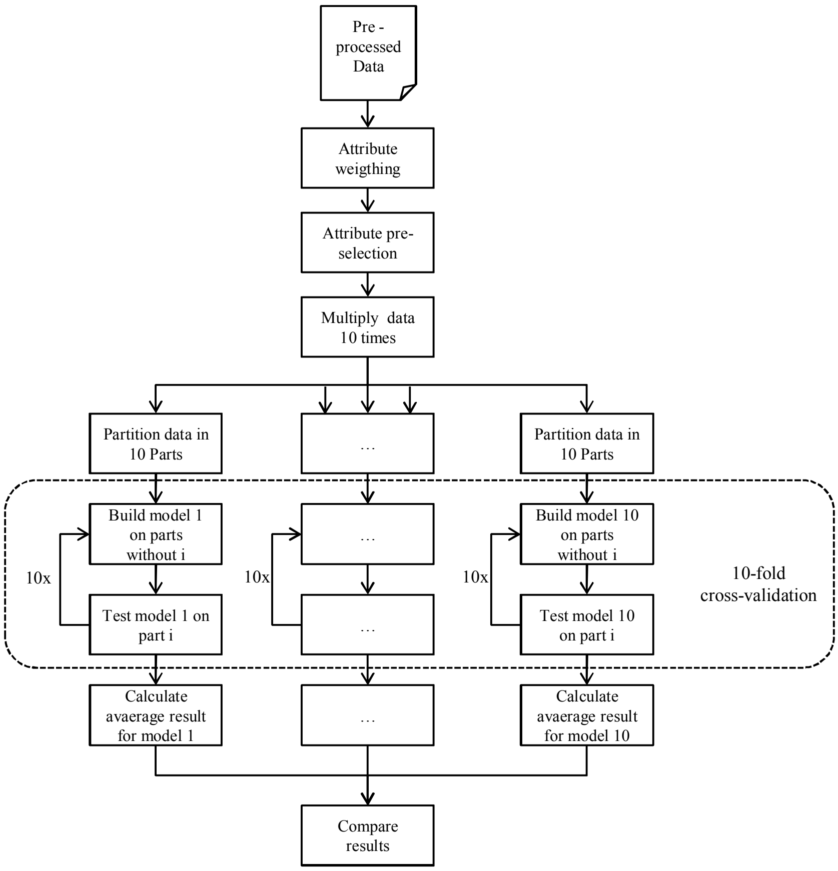

Figure 6. The course of action within the data mining process stage

Figure 6 illustrates the approach beginning with an attribute pre-selection as the original data set with all attributes has shown to be not computable. After this last preprocessing step, ten different models were created and applied to the data via a 10-fold cross-validation. Thereby, a critical question usually is which algorithms should be chosen from the hundreds available? . [Wu et al. 2008] presented a research paper with the ten most beneficial and widely accepted data mining methods. From there we picked (for our context) the most suitable ones, and tested them with different parameters. Additionally, some other algorithms (models 8-10) have been used to balance the approach and to test if they perform differently. Table 2 gives an overview of the results obtained.

Accuracy is a measure for the proportion of correctly classified instances and therefore, was selected to rank the different models. It is noteworthy that the resulting accuracy is uncommonly similar (except Naïve Bayes) which we trace back to the fact that such a huge data set has been analyzed evening out random effects. Additionally, the data had been transformed to only one data type making differences in terms of handling different attributes less important.
Naïve Bayes usually achieves good results in the case of stochastically independent variables. This is obviously not the case here. That can be seen as another evidence of the previous result and the hypothesis that dependencies between various products have an influence on the process time of ECOs.

Table 2. Comparison of different models classifying ECOs

Model	Type	Accuracy	+-	Pruning	Rank
1	ID3	68,3%	7,1%	yes	4
2	ID3	68,1%	7,2%	no	6
3	C4.5	68,8%	6,2%	yes	1
4	C4.5	68,5%	7,4%	yes	3
5	C4.5	68,2%	7,1%	no	5
6	Naïve Bayes	51,7%	18,9%	-	10
7	Linear Regression	64,7%	4,8%	-	9
8	SVM	68,6%	5,6%	-	2
9	Logistic Regression	68,0%	7,5%	-	7
10	Linear Discriminant Analysis	67,6%	7,9%	-	8

The first five models are decision trees and one of them, C4.5 with pruning (shown below), proved to be the best one. Pruning means the reduction of a decision tree to its most prominent features after it has been built. This is done by erasing the least important leafs.

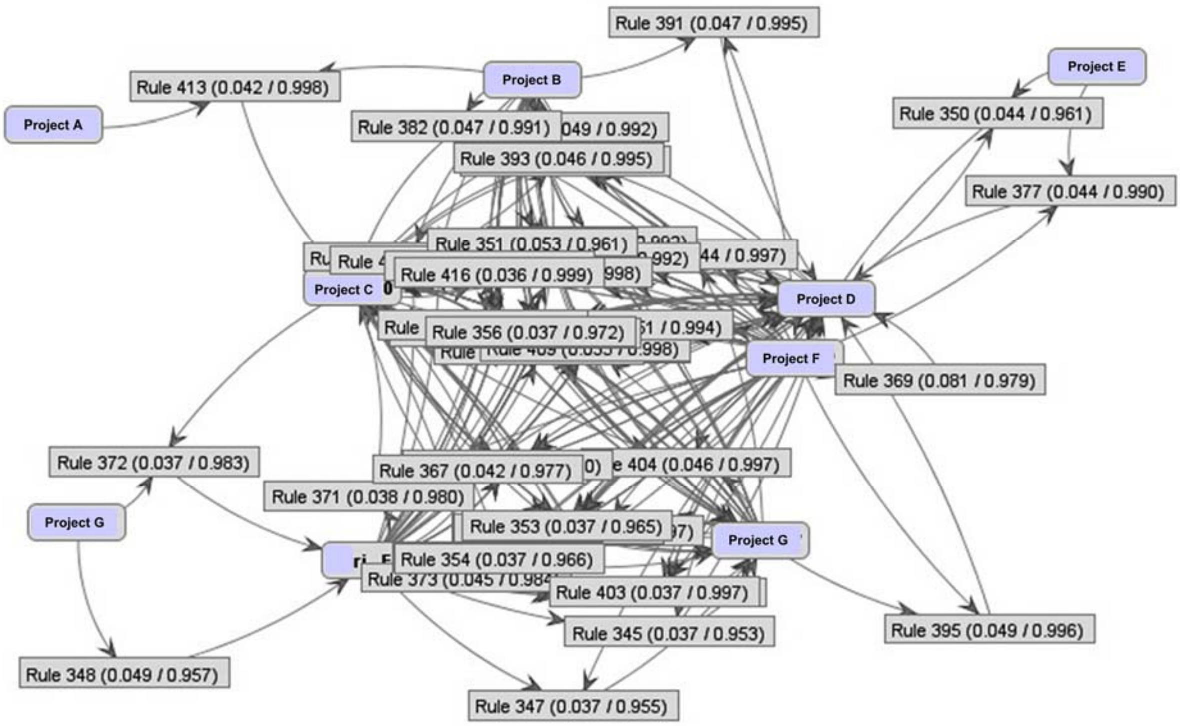

Figure 7. Best performing classifier: decision tree C4.5 with pruning

As mentioned the results do not differ much and therefore, most of the models can be selected for further practical purposes or analyses. We regard the obtained C4.5 tree to be most helpful because of another advantage of decision trees: They are easier to interpret than the results of other methods and therefore, they can be used to derive more insights or be applied in a business environment without data mining specialists.

On the one hand, a correct classification of 68.8% is quite satisfactory and demonstrates the impact of inter-product dependencies. On the other hand, the impact should not be overestimated as the average and not the median has been chosen to divide the ECOs and consequently, the data is not split up into two equal parts.

If the product complexity did not have an impact on development time, no reasonable model could be obtained. This means that the statistical significance of the models is also an indicator for the significance of product complexity. Additionally, the results might prove to be helpful for practical purposes as one can reason which of the products is causing disproportionately high process times with the simple rule that within a decision tree the attribute influence is higher the closer to the root an attribute appears. Hence, applied in practice such models, can with further improvement, serve as a basis to forecast the influences and the estimated development time of any EC.

4. Conclusion and outlook

In this paper we have shown several fundamental drivers influencing the process time of ECOs. These factors have been structured in a comprehensive framework and the way in which they influence the process time has been briefly explained for each driver. In principle, the time is determined by the workload of the problems and the capacity to deal with them. Nevertheless, other drivers which are not as easy to quantify like the corporate culture are considered to have an impact as well. Different researchers regard different drivers to be the most important ones and most likely no consensus can be reached as such a ranking depends on the specific industry branch, the specific enterprise and even how the product development process is structured.

Thus, we concentrated our empirical research on one of the drivers, the complexity and more specifically the dependencies between various products. In order to identify inherent associations the frequent pattern growth algorithm was used, indicating the existence of many relations whereby the degree of dependency differed a lot/greatly between different products. Based on the frequent item sets acquired association rules could be derived. A map depicting those association rules has proven to be an easy understandable way to present the outcome. Dealing with different classification methods, decisions trees have certain advantages in terms of interpretation and most often lead to sufficient results as in our case. They make the influence of product complexity feasible and can help to guide engineers in their decisions.

Probably an even greater accuracy of the models could be achieved by using meta-classifiers. Those rely on several fundamental data mining methods and unify their results to a single one. Such meta-classifier have the advantage of even better results, but at the cost of a more difficult and ambiguous interpretation. However, this could be a field for further research, as there is a trend of intensified use of information systems and thus, more and more data is generated increasing the need for knowledge discovery methods. Also the trend to shorter innovation cycles requires further optimizations for the product development process despite its already mature state. Consequently, further study is needed especially to grasp the impact of fuzzy drivers like corporate culture in detail, finally leading to a better understanding of the product development process in order to enable further enhancements.

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