17TH INTERNATIONAL DEPENDENCY AND STRUCTURE MODELING CONFERENCE, DSM 2015
FORT WORTH, TEXAS, USA, NOVEMBER 04 – 06, 2015

How to build up an Engineering Change dependency model based on past change data?

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Abstract: Coping with engineering changes (EC) is a challenge in engineering design of complex products, since changes prone to propagate and produce further changes on components and processes. This is due to the high connectivity of components in complex systems. There has been a lot of research regarding methods based on product structure models (e.g. in form of DSMs) to predict and assess the propagation of engineering changes. These models are normally generated in interviews with experts, which estimate the propagation of ECs on component-level. Thus, the procedure is very time-consuming and methods are often not profitable applicable. This paper aims to present an approach of how an EC dependency model can be generated with less effort by applying the MDM methodology combined with data mining techniques by using commonly available EC data in industry. Data mining techniques enable the extraction and quantification of the dependencies in the model.

Keywords: engineering change propagation, engineering change data

1 Introduction

Engineering changes (EC) have always been a necessary part of engineering design. They are used to improve and adapt products or to reach a defined status of the product that has not been met (Eckert et al., 2004). ECs are modifications in fits, functions, materials, dimensions of a product and its components after the design release (Huang et al., 2003). However, it is a challenge to cope with ECs to complex products due to the high connectivity of components between each other. Changes on one part can lead to changes on other parts of the product. To support the assessment of those EC effects, several methods are available, which are based on product structure models like the design structure matrix (DSM). In general, a lot of effort is necessary to build up the models during expert interviews. For example, Clarkson et al. (2004) constructed a product model of a helicopter comprising 19 components, which required more than 20 hours of interviewing. Hence, the number of components considered for the model and the subsequent effort to build it up has to be balanced carefully.

In contrast, a large amount of data of past EC processes is stored in companies (Giffin et al., 2009; Sharafi et al., 2010), for example due to the use of workflow-management systems and legal requirements regarding the documentation of ECs. In addition, data mining techniques already provide appropriate algorithms to analyze large datasets to e.g. extract patterns of ECs. Nevertheless, the established methods concerning change propagation consider neither this data nor available data mining techniques to generate an EC dependency model. Hence, the aim of this research is to build up a model for the prediction of EC effects based on historical EC data by using Multiple-Domain Matrix methodology (MDM) combined with data mining techniques.

2 Methodology

The paper provides first the background on matrix-based models for change prediction, EC data and relevant data mining techniques, which are the fundamentals of the EC dependency model. We use then the procedure of structural complexity management from Lindemann et al. (2008) for modelling complex systems that consist of multiple domains connected by various relationship types. The methodology consist of five steps: system definition, information acquisition, deduction of indirect dependencies, structure analysis and product design application. While the focus lies on the first two steps, i.e. system definition and data acquisition.

3 Background

3.1 Models to predict Change Propagation

In recent decades, a lot of research has focused on predicting change propagation. A review published in 2013 identified 54 change management support approaches in literature (Hamraz et al., 2013). Most research is based on product structure models (networks, graphs, matrices), which describe the dependency of components to each other, for example based on physical relations. Further approaches use product attributes or design parameter (Cohen et al., 2000; Ollinger and Stahovich, 2004) to build up the relations between components or enhance the model by adding different levels of granularity (Ariyo Owolabi et al., 2007). Koh et al., (2009) include additional domains in the product model (attributes, features and components) to enable a domain-spanning analysis of change propagation.

Newer approaches consider additional dependencies in the design process in order to identify change propagation not only for products but also within the design process (Ouertani, 2008; Chua and Hossain, 2012; Ahmad et al., 2013; Wynn et al., 2014).

The change prediction method (CPM) proposed by Clarkson et al. (2004) is still the basis model for many further models, has been applied in different case studies (e.g. Eckert et al., 2004) and is the most cited method for change propagation (see figure 1).

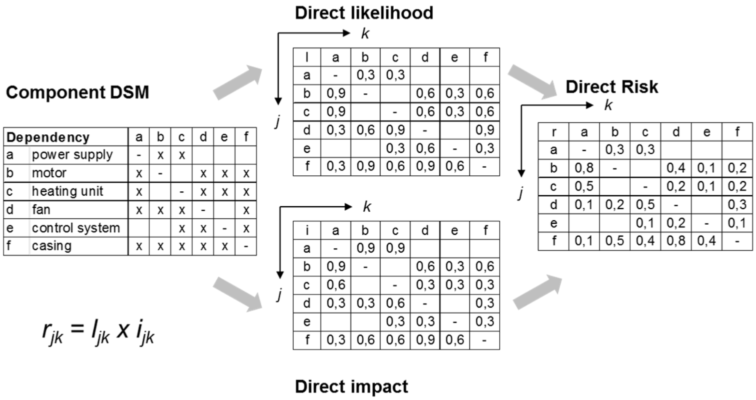

Figure 1. Likelihood, impact and risk DSMs (Clarkson et al., 2004)

The CPM uses a product structure model based on DSMs, which is build up by interviews. Herein the experts estimate change propagation between sub-systems and assesse pairwise the likelihood and impact. The likelihood is defined as the average probability that an EC on one component will lead to an EC on another. The impact is the average proportion of the design work that has to be redone in case of change propagation (Clarkson et al., 2004). The result is a component-, a likelihood- and direct impact-DSM, which are used to create the direct risk DSM.

Although the CPM has been greatly advanced in the last decade, there is still a lot of effort needed to build up the models by expert interviews. This leads to the compromise between the number of components, which determine the level of detail, and the subsequent cost of modeling. Although Clarkson et al. (2004) mention the possibility of using past ECs, up to date a systematic approach of how to integrate data of past ECs is still missing. Such an approach would significantly decrease the effort required to build up the DSMs – which would enable to consider more components, to reach a more detailed product model and to promote the application in industry.

3.2 EC data and related data in PDM systems

ECs generate an increasing number of data associated with the product (Peng and Trappey, 1998). One reason for this is the legal significance of EC processes for example regarding product liability. Therefor companies have to carefully document ECs in order to be able to trace ECs regarding their causes and persons directly involved (Eigner, 2014).

Usually, EC data comprise a unique identification number (EC number) and refer always to the objects to be changed (parts, drawings or software of a product). Lindemann and Reichwald (1998) include further data about the trigger, cause, effect as well as status and stage of the EC. Beyond that, data about the EC process is normally stored, for example the persons involved in the process plus their role (e.g EC coordinator or decider) and activities with timestamps (Wickel and Lindemann, 2014). Also, some empirical studies confirm the availability of well-structured EC process data in companies (Giffin et al., 2009; Pasqual and de Weck, 2012) in form of relational databases (Sharafi, 2013) as depicted in figure 2.

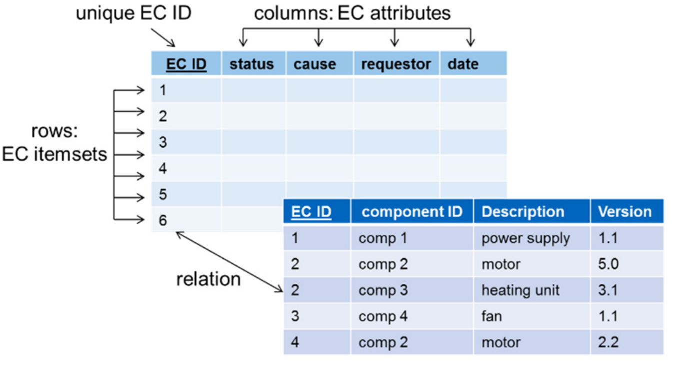

Figure 2. Relational database of EC data

General information about products or parts are stored in companies' PDM or PLM systems. Within these systems, there are two types of data: master data, which are independent and without relation to other data meaningful and structure data, which describe relationships between characteristics of master data. Latter are, for example, product structure data like the bill of material (BOM) or functional structure data. The numbering system of parts or products often represents also the product structure (Eigner, 2014).

In summary, companies have databases with data of past ECs, which include inter alia an EC number and affected parts or products. With PDM systems, additional information about the parts or components and their integration in the overall product can be derived. This data is relevant to build up the Engineering Change Dependency Model (ECDM).

3.3 Data Mining technique: association rules analysis

Due to the growing volume of data exceeding the human analysis and visualization capability, new methods like data mining arise to face these challenges (Fayyad and Stolorz, 1997). In this paper, we apply one data mining technique - the association rules analysis - for discovering frequently co-occurring items. An example for this data mining technique is the market basket analysis. Herein, dependencies between purchased products are analyzed. There are different algorithms available for the association analysis, for example the Apriori Algorithm and the relative new algorithm FP-growth (Han et al., 2007). The association rules describe dependency between items (A and B) statistically by the following measures:

- **Support**: the relative frequency of a itemset (for example item A) in a database
- **Confidence**: the proportion of itemsets that contain for example item B when also item A is included

- **Lift**: the importance of a dependency of items by indicating how much the confidence exceeds the expected confidence

4 Building an Engineering Change Dependency Model based on historical EC data

4.1 System definition

Within this paper, the ECDM is build up by data of past ECs, for example EC data of a terminated development project. Hence, we define a system by the domains ECs and affected components, because components are involved and documented in the ECs. Furthermore, we introduce the domain "design groups", similar to sub-systems of previous methods (cf. Clarkson et al., 2004), to generate a more general model and to determine the level of detail for the resulting ECDM. The basic idea is that development projects on similar products with a similar process will produce a similar behavior regarding the EC propagation. To be able to compare and transfer the patterns of different development projects they have to be on the common denominator - the design groups.

Figure 3 depicts the meta-model of the Multiple-Domain Matrix (MDM), with the three domains and their interrelations. Sub-matrices containing one domains are Design Structure Matrices (DSM), when they contain different domains they are called Domain Mapping Matrices (DMM) (Lindemann et al., 2008).

	Engineering Changes	Components	Design groups
Engineering Changes		"comprise" (1)	"affects" (3)
Components			"belong to" (2)
Design groups			"changed with" (4)

(1) and (2): from the EC database and PDM system
(3) and (4): calculated from (1) and (2)

Figure 3. Meta-model of the system (read from row to column)

The MDM contains four kinds of relations:

- (1) Engineering Change comprise components: ECs are modifications to technical products, which concern different components of a product.
- (2) Components belong to design groups: Components are related to generic design groups.
- (3) Engineering Changes comprise design groups: ECs comprise design groups indirectly by comprising their components, which belong to design groups.

- (4) Design groups are modified together: The relations are derived from (1) & (2) and represent relations between design groups by being affected by same change.

4.2 Information acquisition

This section describes the information acquisition of the dependencies of the MDM (Figure 3). The EC-component DMM (1) is derived from an existing EC database containing past ECs. The component-design group DMM (2) is build up by using product structure data from PDM system. The DMM (3) and DSM (4) is calculated by using the native DMM (1) and DMM (2).

The remainder of this section describes the procedure of data acquisition for the four matrices based on an example:

(1) EC-component DMM

The EC database, containing information about past EC processes, is transformed into an EC-component DMM (see figure 4). Hereby all ECs with their unique ID are entered into the rows of the matrix, all affected components are described in the columns of the matrix by stating their unique identification number. It is important to ensure that there are no duplicates of changes and components in rows respectively columns of the matrix. Afterwards the matrix is filled by setting "1" into the matrix according to the EC databases, that means when a specific EC comprises a component.

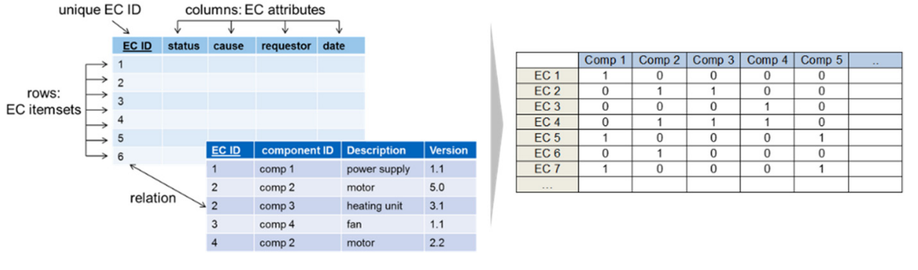

Figure 4. Creation of the EC-component DMM based on EC data

(2) component-design group DMM

PDM systems of companies contain further information about components affected by ECs. Herein information about generic part categories are available which are necessary to derive more generalized relations of ECs and which are independent of the specific component. Often companies have a sophisticated numbering system of their components, which contain information about the classification and the relation to a design group (Eigner, 2014). It is also possible that the relation of components to design groups is stored as an attribute of the component in the PDM system. With both kind of information a component-design group DMM can be build up (see figure 5). Herein the components from matrix (1) are described in rows, the design groups are stated in the columns and the "1" depict the relation between component and design group: "component belongs to design-group".

	DG 1	DG 2	DG 3	DG 4	...
Comp 1	1	0	0	0	
Comp 2	0	1	0	0	
Comp 3	0	0	1	0	
Comp 4	0	0	0	1	
Comp 5	0	0	0	0	
Comp 6	0	0	0	0	
Comp 7	0	0	0	0	
...					

Figure 5. Creation of the component-design group DMM with data from the PDM system

The resulting DMM is a matrix to transform the EC-component DMM, which is very specific for the development project, into a more general EC-design group DMM, consisting of general design groups.

(3) EC-design group DMM

By using the MDM methodology, it is not necessary to fill all relevant submatrices (DSMs, DMMs) with present and native data. It is possible to calculate certain matrices by indirect dependencies. The EC-Design group DMM is calculated by matrix-multiplication of DMM (1) and DMM (2) and represents the dependency “EC affects design group”.

	DG 1	DG 2	DG 3	DG 4	...
EC 1	1	0	0	0	
EC 2	0	1	1	0	
EC 3	0	0	0	1	
EC 4	0	1	1	1	
EC 5	1	0	0	0	
EC 6	0	1	0	0	
EC 7	1	0	0	0	
...					

Figure 6. Calculation of the EC-design group DMM

(4) Design group DSM

The design group DSM describes which design groups occur together in past ECs of the database and represents the ECDM. The DSM is derived indirectly from the EC-design group DMM by matrix-multiplication of the transposed EC-design group DMM with the EC-design group DMM. The diagonal of the resultant matrix lists the total number of ECs of the particular design groups while the remaining fields of the matrix contain the number of ECs which affect two design groups.

	DG 1	DG 2	DG 3	DG 4	...
DG 1	3	0	0	0	
DG 2	0	3	2	1	
DG 3	0	2	2	1	
DG 4	0	1	1	2	
...					

Figure 7. Calculation of the ECDM (design group DSM)

5 Simulation Model

For analyzing and predicting change propagation, the resultant design-group DSM (cf. figure 7) requires additional data: the likelihood of change propagation. Commonly engineers and managers estimate this data in interviews (see e.g. Koh et al., 2009). Within this approach, the likelihood of change propagation is derived by using association rules analysis. The likelihood defined by Clarkson et al. (2004) (cf. section 3.1) correspond to the measure confidence of the association rule analysis. The confidence represents the relative frequency of changes in which for example design group 2 is changed together with design group 3. The calculation bases on the ECDM (design group DSM) which contains relevant values of ECs for the association rules (cf. figure 8).

The *confidence* is calculated by the number of ECs, which affect design group 2 and 3, divided by the number of EC on design group 2. In the example in figure 8, the confidence means that in 67 % of ECs on design group 2, also design group 3 is affected. Conversely, when design group 3 is affected then in 100 %, also design group 2 is changed.

The measure *support* describes the relative frequency of changes on a design group within the complete database. We calculate the support for a design group (or set of design groups) by the number of ECs on that design group (or set of design groups), divided by the total number of ECs in the database.

The *lift* represents the importance of the dependency between design groups by indicating how much the confidence exceeds the expected confidence. In the example in figure 8 the lift is 2.38, which means, that design group 3 is 2.38 times more often affected, when there is a change on design group 2 than other design groups.

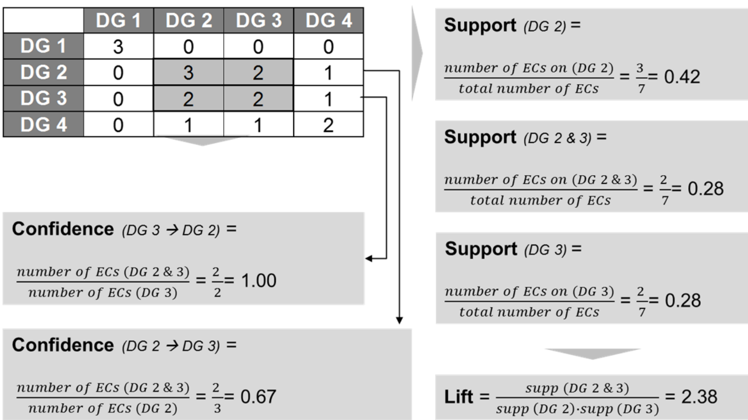

Figure 8. Exemplary measures derived from the EC-design group DMM for the dependency of design group 1 and 3

The likelihood DSM includes for each dependency the confidence, which represents the probability that design groups are changed together, and as additional information the lift of the dependency (the importance). For the continuous example of this paper, figure 9 depicts on the left side the two resultant DSMs (for confidence and lift) and on the right side a combined view.

Confidence DSM

	DG 1	DG 2	DG 3	DG 4	...
DG 1		0	0	0	
DG 2	0		0,67	0,33	
DG 3	0	1		0,5	
DG 4	0	0,5	0,5		
...					

Lift DSM

	DG 1	DG 2	DG 3	DG 4	...
DG 1		0	0	0	
DG 2	0		2,33	1,17	
DG 3	0	2,33		1,75	
DG 4	0	1,17	1,75		
...					

Combined: Conf. & Lift DSM

	DG 1	DG 2	DG 3	DG 4	...
DG 1		0	0	0	
DG 2	0		**0,67** (2,33)	**0,33** (1,17)	
DG 3	0	**1** (2,33)		**0,5** (1,75)	
DG 4	0	**0,5** (1,17)	**0,5** (1,75)		
...					

Figure 9. ECDM comprising the measures confidence and lift

The derived ECDM includes the likelihood for change propagation between different design groups based on past EC cases. This matrix is used for further analyses regarding change propagation for example the critical path of changes.

6 Conclusion and outlook

This paper provides an approach of how EC databases of companies can be utilized in order to derive general engineering change dependencies between components, which can then be used to predict change propagation. Usually these dependencies are inquired within interviews with experts, what is rather time-consuming causing high effort.

By using data mining techniques and the MDM methodology, we defined the dependencies based on available past EC data. Finally, three measures from association rules analysis describe the dependencies between couples of components statistically.

Thus, there is less effort needed to build up the model and less subjectivity involved. In addition, there are no constraints regarding the number of components. However, there are some underlying assumptions: (1) different ECs were documented separately (no bundling of ECs); (2) the behavior regarding ECs is similar for similar products (for example for products, which are part of the same product line); (3) the EC data have a sufficient quality.

We applied the presented methodology in a case study using EC data of one development project of a car manufacturer. Thereby we could show the applicability and the realization of dependencies with strong measures. Next steps comprise the application of the methodology in further development projects and a comparison of the results.

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Acknowledgments

We thank the German Research Foundation (Deutsche Forschungsgemeinschaft – DFG) for funding this project as part of the collaborative research centre “Sonderforschungsbereich 768 – Managing cycles in innovation processes – Integrated development of product-service-systems based on technical products”.

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