

Defining system boundaries in change propagation analysis: A diesel engine case study

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Abstract: This paper explores how change propagation analysis can be affected by the way system boundaries are defined. This is an important issue as engineering change can in reality propagate out of the system modelled and back through components that were not considered. The work builds on a diesel engine case study to examine the difference in analysis results generated based on a full system model (i.e. entire engine) and those generated based on a set of partial system models (e.g. sub-assemblies). It was found that partial system models with boundaries defined by physical sub-assemblies can produce analysis results that are highly correlated with the one produced using a full system model. It was also revealed that modelling more components (i.e. a more complete system model) does not necessarily increase the level of correlation. The findings can be used to support system boundary decisions in change propagation analysis.

Keywords: Change propagation, Changeability, System boundaries

1 Introduction

It is widely accepted that complex engineering systems are often designed through modifications of existing ones (Giffin et al., 2009; Shankar et al., 2012; Fernandes et al., 2015). Such an approach can facilitate the reuse of components and knowledge from previous designs. However, it is documented that changes initially perceived as simple can sometimes propagate undesirably, resulting in costly delays (Eckert et al., 2004; Duran-Novoa et al., 2018). Hence, modelling approaches have been developed to support the management of engineering change propagation in design projects (Siddiqi et al., 2011; Koh et al., 2012; Maier et al., 2014; Lee and Hong, 2017; Ma et al., 2017) and across life cycle of products and systems (Vianello and Ahmed-Kristensen, 2012; Hu and Cardin, 2015; Luo, 2015).

While efforts have been made to discuss how change analysis results can be affected by model granularity (Maier et al., 2017) and the types of change data used (Koh, 2017), few studies discuss how change analysis results can be affected by the way system boundaries are defined. System boundary decisions are especially important in change propagation analysis as engineering change can in reality propagate out of the system modelled and back through components that were not considered (See Figure 1). Yet, the issue of system boundaries in change propagation analysis is often overlooked as the components to be modelled are usually pre-defined based on the needs and constraints of the analysis. For example, engineering change analysis may be conducted on an engine short block, an entire engine, or an entire truck, depending on whether the analysis is for a supplier of engine parts, a producer of engines, or a truck manufacturer. In addition, information on

components designed by other stakeholders (e.g. suppliers, collaborators) may be unavailable for modelling. Even if all system components are designed within the same organisation, the resources required to model the full system can be a challenge as well. Therefore, it is not uncommon to see change propagation analysis conducted based on partial system models rather than full system models (e.g. analysing an engine instead of a full truck). This raises several questions: Can partial system models produce valid change propagation analysis results? Will the validity of change propagation analysis improve when more system components are modelled? How might the validity of change propagation analysis be affected if the boundaries for the partial system to be modelled were arbitrarily determined due to a lack of information? To address these questions, this paper presents an exploratory study that discusses how change propagation analysis results can be affected by the way system boundaries are defined.

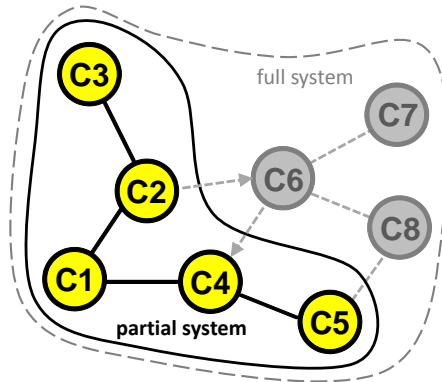


Figure 1: An example of a partial system model missing a change propagation path (C2 to C6 to C4) during analysis

2 Research Approach

To ensure that realistic change analysis results can be generated and analysed, the modelling data used to create system models in this work were extracted from the industry case study published in (Koh et al., 2013). For consistency, the change analysis method used to analyse the data is also adapted from (Koh et al., 2013). The goal is to examine whether change analysis carried out using partial system models can produce results that are as valid as the one produced using a full system model. In this paper, results produced by partial system models are considered to be as valid as the one produced using the full system model if they are found to be correlated, resulting in similar design decisions. The following sections provide details on the modelling data used (Section 2.1), the change analysis made (Section 2.2), and the correlation study carried out in this work (Section 2.3).

2.1 Modelling data

The full data set used in this work describes a heavy-duty diesel engine comprising of 32 components. Figure 2 shows an excerpt of the modelling data presented in the form of

Design Structure Matrices (DSMs). Each row and column heading represents a particular component. For example, ‘CB’ refers to the ‘Cylinder Block’ and ‘P’ refers to the ‘Piston’ (not all component names are disclosed for confidentiality reasons). The DSM on the left of Figure 2 describes the change likelihood of each component. For instance, the diagonal cells in the DSM describe the likelihood of changing a given component due to exogenous factors, such as a change in design requirements. The off-diagonal cells describe the likelihood of changing a given component (indicated by the row heading) due to changes in another component (indicated by the column heading). Note that the entries were based on a quantitative {0; 0.25; 0.5; 0.75} scale that represents ‘Nil’, ‘Low’, ‘Medium’, and ‘High’ strength levels, respectively. For example, the likelihood of changing the Cylinder Block (CB) due to exogenous factors is ‘Medium’ (i.e. Entry for Column 2 and Row 2 is ‘0.5’), and the likelihood of changing the Cylinder Block (CB) due to changes in the Piston (P) is also ‘Medium’ (i.e. Entry for Column 3 and Row 2 is ‘0.5’).

Change Likelihood		Initiating					
		CH	CB	P	CS	EA	...
Affected	CH	0.25	0.50	0.50	0.00	0.50	...
	CB	0.75	0.50	0.50	0.50	0.50	...
	P	0.25	0.25	0.25	0.00	0.00	...
	CS	0.00	0.50	0.50	0.25	0.00	...
	EA	0.75	0.50	0.00	0.00	0.25	...

Change Impact		Initiating					
		CH	CB	P	CS	EA	...
Affected	CH	0.75	0.75	0.50	0.00	0.50	...
	CB	0.75	0.75	0.75	0.50	0.50	...
	P	0.25	0.50	0.75	0.00	0.00	...
	CS	0.00	0.75	0.25	0.75	0.00	...
	EA	0.25	0.25	0.00	0.00	0.25	...

Figure 2: An excerpt of the modelling data used (adapted: Koh et al., 2013)

The DSM on the right of Figure 2 describes the change impact of each component. The diagonal cells describe the average change impact (based on redesign cost) of changing a given component while the off-diagonal cells describe the average proportion of redesign work required if changes propagate from a given component (indicated by the column heading) to another component (indicated by the row heading). For example, the impact of changing the Cylinder Block (CB) in terms of redesign cost is ‘High’ (i.e. Entry for Column 2 and Row 2 is ‘0.75’). The impact of changing the Cylinder Block (CB) due to changes in the Piston (P) is also ‘High’ in terms of the average proportion of redesign work required (i.e. Entry for Column 3 and Row 2 is ‘0.75’).

Based on the full data set of the entire diesel engine, the 32 engine components were later sorted based on how the diesel engine was divided into sub-assemblies. For example, each engine component has a unique four-digit serial number with the first two digits indicating the sub-assembly that it belongs to. By sorting all the serial numbers, it was found that the engine consists of six sub-assemblies with distinct components in each sub-assembly (see Table 1). Sub-assembly A has 18 components. It is the main sub-assembly and forms the ‘Long Block’ of the engine. Sub-assembly B has 6 components. Sub-assembly C and D have 3 components each. Sub-assembly E and F have 1

component each. Subsequently, by organising the sub-assemblies into groups, 6 sets of system model were created as shown in Table 2 (see SM1 to SM6). SM1 is the full system model of the diesel engine and comprises all the sub-assemblies. It was created as the reference model to be compared with. SM2 to SM6 were created based on boundaries defined by the sub-assemblies and represent scenarios where only parts of a full system are modelled. For instance, SM2 is a partial system model of the diesel engine consisting of just the main sub-assembly (i.e. Sub-assembly A, the ‘Long Block’). SM3, SM4, and SM5 are partial system models created by adding more sub-assemblies to SM2, with the purpose of exploring the effect of modelling more components (i.e. towards a more complete system model compared to SM2). SM6 is a partial system model that excludes only the main sub-assembly (i.e. Sub-assembly A) and was created to better understand the influence of the main sub-assembly in this work.

Table 1. A breakdown of diesel engine sub-assemblies

Sub-assembly reference	Number of components
A	18
B	6
C	3
D	3
E	1
F	1
Full system	32

Table 2. A breakdown of system models to be tested

System model reference	Description
SM1	Full System
SM2	A
SM3	A + B
SM4	A + C
SM5	A + D + E + F
SM6	B + C + D + E + F
SM7	Random 1
SM8	Random 2
SM9	Random 3

As mentioned, SM2 to SM6 were created based on boundaries defined by physical sub-assemblies and identified through serial numbers. However, in practice, there might be cases where it may not be easy to identify the boundaries for the partial system to be modelled. A hypothetical example is when a junior engineer tries to analyse the ‘Long Block’ of the engine, but does not know what components to include in the model. Hence, in an attempt to explore the scenario where the boundaries for the partial system to be modelled were arbitrarily determined, 3 further sets of partial system model were created by randomly removing 50% of the engine components from the full system model (see SM7 to SM9 in Table 2). The removed components were identified by using Microsoft Excel to generate a random decimal number next to each component and subsequently ranking the components based on the random decimal numbers generated.

Components that were ranked in the top 50% were removed while those in the bottom 50% were selected to form a partial system model. The process was repeated 3 times to create the 3 randomly generated models – SM7, SM8, and SM9. A breakdown of the number of sub-assembly components in these randomly generated models is presented in Table 3.

Table 3. A breakdown of the randomly generated models

Sub-assembly reference	Number of sub-assembly components in model		
	SM7	SM8	SM9
A	8	10	9
B	3	3	3
C	3	2	0
D	1	1	3
E	0	0	0
F	1	0	1

2.2 Change analysis

The change analysis method documented in (Koh et al., 2013) is adapted in this study to process the system models described in Section 2.1. The method is a matrix-based technique that systematically examines the changeability of system components by considering exogenous changes (e.g. new customer requirements) and endogenous changes (e.g. change propagation between components). It extends the conventional Change Prediction Method introduced by (Clarkson et al., 2004) by considering the reachability of change propagation in its algorithms, which effectively limits the maximum length of change propagation paths to be examined by taking into account resource constraints for changes to propagate further. The analysis results derived from the method can be used to rank system components in terms of change risk and support design decisions, such as the planning of modularisation efforts based on the rankings produced (Koh et al., 2015).

Figure 3 shows how the data presented in Figure 2 were processed. The first step was to revise the change propagation likelihood between components using Equation 1 to 4 expressed as follows:

$$L_{k,j}^* = L_j \times L_{k,j} \quad (1)$$

$$L_{k,j} = 1 - \prod_{z \in Z} [1 - (l_z \times \alpha_z)] \quad (2)$$

$$l_z = (l_{k,k-1} \times l_{k-1,k-2} \times \dots \times l_{j+1,j}) \quad (3)$$

$$\alpha_z = (\alpha_{k,k-1} \times \alpha_{k-1,k-2} \times \dots \times \alpha_{j+1,j}) \quad (4)$$

$L_{k,j}^*$ represents the revised change propagation likelihood from component ‘j’ to ‘k’ where L_j represents the likelihood of changing component ‘j’ due to exogenous factors and $L_{k,j}$ represents the combined (direct and indirect) change propagation likelihood from component ‘j’ to ‘k’, with ‘j’ representing the change initiating component and ‘k’ representing the last component in change propagation path ‘z’ and ‘Z’ representing the entire set of change propagation paths from component ‘j’ to ‘k’. l_z represents the change

propagation likelihood for a particular path ‘z’ where the individual $l_{k,k-1}$ represents the direct change propagation likelihood between successive components along path ‘z’. α_z represents the change propagation reachability for a particular path ‘z’ where the individual $\alpha_{k,k-1}$ represents the change propagation reachability between successive components along path ‘z’.

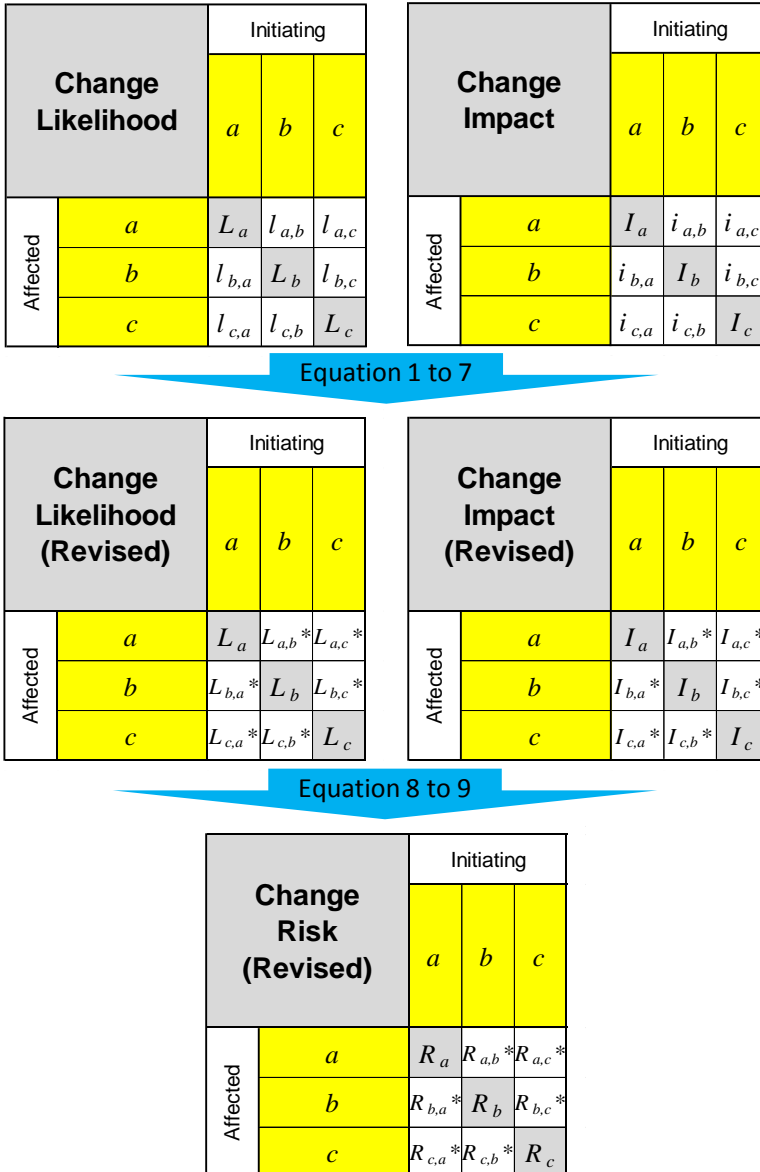


Figure 3: Using change likelihood and impact to compute change risk

Subsequently, the change propagation impact between components were revised using Equation 5 to 7. The equations are expressed as follows:

$$I_{k,j}^* = I_{k,j} \times I_k \tag{5}$$

$$I_{k,j} = \frac{1 - \prod_{z \in Z} [1 - (i_z \times \alpha_z)]}{L_{k,j}} \tag{6}$$

$$i_z = (i_{k,k-1} \times I_z) \tag{7}$$

$I_{k,j}^*$ represents the revised change propagation impact from component ‘j’ to ‘k’ where I_k represents the impact of changing component ‘k’ in terms of the average cost of redesigning component ‘k’ and $I_{k,j}$ represents the combined change propagation impact in terms of the proportion of redesign work through the change propagation paths. i_z represents the change propagation impact for a particular path ‘z’ where $i_{k,k-1}$ represents the direct change propagation impact on the last component caused by the penultimate component in path ‘z’.

After the revised change propagation likelihood and impact were computed, the revised change propagation risk between components (endogenous change risk), the change risk of each component due to exogenous factors (exogenous change risk), and the overall change risk of each component (endogenous and exogenous change risk) were calculated using Equation 8, 9, and 10, respectively. The equations are expressed as follows:

$$R_{k,j}^* = L_{k,j}^* \times I_{k,j}^* \tag{8}$$

$$R_k = L_k \times I_k \tag{9}$$

$$CR_k = \frac{R_k + \sum R_{k,j}^*}{n} \tag{10}$$

$R_{k,j}^*$ represents the revised change propagation risk from component ‘j’ to ‘k’. R_k represents the change risk of component ‘k’ due to exogenous factors. CR_k represents the overall change risk of component ‘k’ due to exogenous factors and change propagation from all other components in the system (see Figure 4). n is the number of components in the system. The above process was repeated for all the system models shown in Table 2.

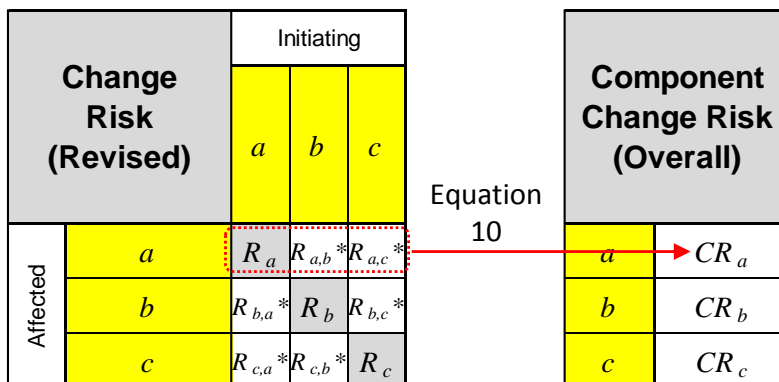


Figure 4: Computing overall component change risk

2.3 Correlation study

Table 4 shows the ranking of components according to their overall change risk based on the change analysis carried out using the full system model (SM1). The table reveals that the Cylinder Block (CB) was ranked 1st as it has the highest overall change risk with a normalised *CR* value of ‘1.00’. The Piston (P) has a normalised *CR* value of ‘0.34’ and is ranked 12th. As discussed previously, the ranking can be used to support design decisions such as the planning of modularisation efforts. For instance, components with higher ranking have greater change risk and should be assigned a higher priority to be made more modular (Koh et al., 2015). Therefore, with reference to Table 4, the Cylinder Block (CB) should be considered for modularisation ahead of the Piston (P).

Table 4. Ranking of component overall change risk based on the full system model (SM1)

Component	Normalised CR	Ranking
CB	1.00	1
CH	0.77	2
...
P	0.34	12
...
EA	0.02	31
GR	0.00	32

Given that the ranking of components may vary if the change analysis was conducted using a different system model, a Spearman’s rank correlation study was carried out to examine whether the rankings produced by the partial system models (i.e. SM2 to SM9) are correlated with the one produced using the full system model (i.e. SM1, reference model). As partial system models have fewer components compared to the full system model, components that do not appear on both sets of ranking during correlation study were removed to create ranking sets with the same number of components. For example, in the correlation study between SM1 and SM2, components that are not in Sub-assembly A were removed from the full system ranking to create two sets of ranking with exactly 18 components, ranking from 1st to 18th (see Table 5). A given partial system model is considered to have produced change analysis results as valid as the one produced using the full system model if the component rankings were found to be correlated (i.e. both models produced rankings that will lead to similar design decisions). Results of the correlation study is presented in Section 3.

Table 5. Ranking of Sub-assembly A components based on SM1 and SM2

Sub-assembly A Components	SM1		SM2	
	Normalised CR	Ranking*	Normalised CR	Ranking
CB	1.00	1	1.00	1
CH	0.77	2	0.66	2
...
P	0.34	7	0.35	7
...
EA	0.02	17	0.00	18

*Only components from Sub-assembly A are included

3 Results

Table 6 shows the results of the Spearman's rank correlation analysis carried out in this work. It can be seen that the Spearman's coefficients range from '0.94' to '0.98' with partial system models that were defined based on physical sub-assemblies (i.e. SM2 to SM6, see Table 2). However, the Spearman's coefficients for randomly generated system models (i.e. SM7 to SM9, see Table 2) are lower and range from '0.65' to '0.81'.

Table 6. Spearman's rank correlation coefficient for SM2 to SM9

	SM2	SM3	SM4	SM5	SM6	SM7	SM8	SM9
Spearman's coefficient* (rank correlation with SM1)	0.96	0.94	0.96	0.98	0.97	0.81	0.78	0.65
Components modelled (out of 32 in SM1)	18	24	21	23	14	16	16	16
Components modelled (out of 100% in SM1)	56%	75%	66%	72%	44%	50%	50%	50%

*P-value less than 0.01

The results shown in Table 6 reveal that partial system models with system boundaries defined based on physical sub-assemblies (SM2 to SM6) can produce change analysis results that are highly correlated with the one produced using the full system model (SM1). However, the validity of change analysis carried out using randomly generated partial system models (SM7 to SM9) is questionable as the correlation can go as low as '0.65' (see SM9 in Table 6). Although it is unlikely that one would knowingly carry out change analysis on randomly generated partial systems, the result suggests that partial system models with poorly defined system boundaries can affect the validity of change analysis.

The results also show that the level of correlation is insensitive to the number of components modelled in the full system. For example, SM3 has 24 components (75% of the full system) and is the largest partial system model. However, the Spearman's coefficient for SM3 is lower than the other partial system models that were not randomly generated (i.e. SM2, SM4 to SM6). In fact, even though SM6 is the smallest with 14 components (44% of the full system), it produced a Spearman's coefficient that is greater than SM2, SM3, and SM4. This suggests that modelling more components (i.e. a more complete system) does not necessarily result in higher validity.

4 Conclusions

The propagation of engineering change is a recognised phenomenon in design. A common challenge in engineering change propagation analysis is to define the system boundaries to be examined. Based on the analyses conducted in this work, it was revealed that partial system models with system boundaries defined based on physical sub-

assemblies can produce change analysis results that are highly correlated with the one produced using a full system model. It was also found that modelling more components (i.e. a more complete system) does not necessarily increase the level of correlation. Future work will examine a wider range of engineering systems with different change analysis methods.

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