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IMPACT OF ARCHITECTURE TYPES AND DEGREE OF MODULARITY ON CHANGE PROPAGATION INDICES

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Abstract

Change propagation has been investigated in many case studies; anyway, the effect of architectural choices like the degree of modularity or the presence of bus elements is still unclear. This paper evaluates the probability density functions of three change propagation indices (Incoming Change Likelihood, Incoming Change Impact and Outgoing Change Risk) in order to understand if architectural choices affect the change propagation behaviour of a technical system. The indices are obtained from 13,824 DSMs generated with Monte-Carlo methods; on each DSM, 12 feasible change behaviour samples are mapped. First, a small set of synthetic results is compared with a case study as an initial validation. Then, the three indices' overall distributions are shown. Finally, the entire indices' database is subdivided into four clusters (Integral, Modular, Star, Modular-Star) according to the architecture type of the original DSM. The comparison of the clusters shows that the presence of modules in the architecture significantly decrease the risk for change propagation, while the presence of bus components has a more limited effect.

Keywords: Product architecture, Change propagation, Design engineering

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1 CHANGES AND CHANGE PROPAGATION

The increasing complexity of technical systems (Hubka and Eder 1988; Lindemann et al. 2009), as well as the growing interplay between technical and societal aspects (de Weck et al. 2011), pose a challenge that needs to be addressed by suitable Engineering Design approaches. As the complexity of the technical systems increase (Lindemann et al. 2009), so do the uncertainty and the resources required in the development process. For this reason, many projects are based on legacy systems that are modified from one generation to another (Brcina et al. 2009; Efatmaneshnik and Nilchiani 2012) in a tension between new features and the use of proven components (Gerst et al. 2001).

The evolution of a complex system has to face a major difficulty, though: change propagation (Giffin et al. 2009). Changes are responsible for relevant costs in the product development process, as highlighted for example in (Vianello and Ahmed-Kristensen 2012; Shankar et al. 2012). Therefore, several methods and strategies have been proposed to study and control (or dampen) change propagation, in particular regarding the change management process (Jarratt et al. 2011; Hamraz et al. 2013) and product features to ensure "changeability", "flexibility" or "adaptability" (Saleh et al. 2003; Fricke and Schulz 2005; Ross et al. 2008; Lafleur and Saleh 2010). In particular, change management methods can be organized into three clusters, according to the models used to map changes: matrices, databases or "other concepts" (Helms and Behncke 2014).

This paper investigates the interplay between a system's underlying architecture and resulting patterns of change propagation. In fact, while it is acknowledged that changes propagate through interfaces (Clarkson et al. 2004), it is not clear what the effect of architectural choices on change propagation is. It is commonly hypothesized that a higher degree of modularity (Gershenson et al. 2003) and a low number of bus or hub elements dampen the extent of change propagation, but since much of the literature in the field is based on single case studies, comparisons between architectures are difficult to make. This issue (common to most of Engineering Design research) can limit the scope and validity of the research results and, ultimately, can hinder the growth of the research field as a whole (Blessing and Chackrabarti 2009).

In this work, a matrix-based method proposed in (Koh et al. 2013) will be used to compare the statistical change propagation behaviour of several canonical architectures generated synthetically through a Monte Carlo process. In this way, the authors mean to answer the following research question: how does the type of architecture and its associated degree of modularity affect the change propagation in a complex technical system? One of the fundamental underlying assumptions is that these propagation patterns are independent of the particular application domain but are driven only by the underlying system architecture.

The remainder of the paper is structured as follows: Section 2 introduces the change propagation indices selected to characterize change propagation behaviour; Section 3 explains how the system architectures and the change probabilities were generated. Section 4 provides an initial validation of the indices computed by Monte Carlo process, while Section 5 aggregates these results and quantifies how architectural features change the probability density function of the computed change propagation indices. Conclusions are summarized in Section 6.

2 INTRODUCING THE CHANGE PROPAGATION INDICES

In this section, basic terminology and the computation steps to derive a set of change propagation indicators are explained.

The evaluation of change propagation has been conducted following the measures proposed by (Koh et al. 2013), where the authors proposed three indicators for each component or subsystem of the system architecture, each varying between 0 and 1:

1. Incoming Change Likelihood (ICL): the likelihood that a change somewhere else in the system leads to a change in the evaluated component or subsystem;
2. Incoming Change Impact (ICI): the extent of resources involved in changing the evaluated component or subsystem. Typical resources for this measure are time and cost for change;
3. Outgoing Change Risk (OCR): the resultant effect of a change in the evaluated component on the remainder of the system. It is the combination of the likelihood of novel propagated changes and the overall impact of these changes.

In the model proposed, self-propagation of the component changes on itself is not considered.

Changes in complex systems can be clustered in two main sets: native and propagated. Native changes are desired or undesired modifications of components in the system; propagated changes are undesired changes arising from previous changes. Native changes can be further differentiated in emergent and initiated changes (Eckert et al. 2004). Initiated changes are generated by changes outside of the system boundary usually but not always associated with a requirements change, while emergent changes derive from problems or mistakes discovered during the design activity. The changeability evaluation method takes into account these differences, as the indices are derived through numerical combination of four kinds of change propagation properties: the likelihood and impact of native changes and the likelihood and impact of propagated changes between two related components. These parameters have been collected into the Likelihood Matrix and the Impact Matrix, two modifications of the Design Structure Matrix (Eppinger and Browning 2012) that will be called Change Structure Matrices (CSM) in the rest of the paper. According to (Koh et al. 2013), the CSM must be populated from data generated by the Change Management process during design. Alternatively, the data can be elicited from previous knowledge from experts in the field. Thanks to statistical elaboration of these data, a system's change propagation behaviour can then be inferred. The mathematical details of the method can be found in (Koh et al. 2013) and (Clarkson et al. 2004). At the end of the computations, each component is characterized by its own ICL, ICI and OCR indices, which can be used to identify the most critical components in the system.

Although the proposed method provides useful information and has been validated on real case studies, it presents some weaknesses, as far as the prediction of change propagation is concerned. First, it assumes that the firm in question has a Change Management process able to collect the data during the project. Then, it is feasible only when the design of a product is architecturally similar to a previous one. Finally, it is a descriptive tool, in that it does not provide any suggestion regarding how to reduce change propagation likelihood or impact.

In order to answer the research questions mentioned in the introduction, many architectures have to be compared in order to highlight the relationships between architectural features and change propagation. The number of systems to be analysed would have been too high for a proper evaluation, even undertaking an extensive literature review. Furthermore, robust results can be achieved only observing several change propagation patterns on the same architecture. It was therefore decided to use the same indices to quantify change propagation, but to compute synthetic DSMs and CSMs instead. The following section will explain the computational method adopted.

3 GENERATING ARCHITECTURES AND CHANGES

This section will explain how the synthetic architectures (in the form of DSMs) and changes (in the form of CSMs) have been generated numerically with a Monte Carlo process.

The analysis is framed as a computer experiment, therefore a factorial design of experiments plan was devised. The factorial variables are reported in Table 1. The intervals are reasonable values derived from the nine examples of product architecture DSMs presented in (Eppinger and Browning 2012).

Table 1. Design of experiments plan

Features in the system	Parameters in the DSM	Values
Number of components	Size of DSM	40 - 60
Density of interfaces	Average density of DSM	1/7 – 1/5
Number of modules	Number of clusters	2 – 6
Number of components in modules	Fraction of components in clusters	6/10 – 9/10
	Size and proportions of clusters	9 feasible combinations
Number of bus elements	Number of highly connected components	0-2
Number of components in busses	Fraction of interfaces for bus	0.5 - 1

The dimension of the system and the density of interfaces are taken as measures of the complexity of the technical system; the number of clusters, their dimensions and their heterogeneity represent the degree of modularity; finally, a certain number of bus elements were introduced, representing elements with high connectivity. These six aspects of the system architectures are varied in a two-point interval, as described in Table 1. As it will be illustrated, this choice allowed a 2^k full-factorial design of experiments.

The DSMs were populated thanks to random generation of interfaces, constrained by the control variables and ensuring a fully connected system. To this end, some meta-DSMs were first generated, from which the DSM samples were then derived. Meta-DSMs are matrices that do not show interfaces between components, but the probability of having an interface between components; their use allowed to enforce a constrain on the average density while assigning interfaces randomly. Each non-diagonal value of the DSM was assigned a probability of having an interface; modules and busses were modelled in the meta-DSM as elements whose average density of interfaces is higher than the outside average density. Every DSM was generated as a sample from the probability field described by the meta-DSM.

Each DSM sample then generates the two CSMs required by the indices evaluation method. As mentioned in the previous section, changes in complex systems can be subdivided into native and propagated changes. Due to this diversity, the CSMs are composed of two different sets of indices. On the diagonal, the likelihood or the impact of native changes from within each component are presented; the off-diagonal terms represent the likelihood and impact of propagated changes going from a column element to a row element. All the values in the two matrices were generated randomly from a uniform distribution. From this point onwards, the process follows the same methodology presented in the previous section. It is important to note that the alpha parameter, which models the decreasing probability of having multiple cascading change propagation events, was set to a value of 0.4, as suggested by (Koh et al. 2013). In other words, the maximum allowed number of generations of propagated changes is four. After a preliminary sensitivity analysis, it was chosen to generate 12 samples of CSMs from each DSM.

The numerical experiments generated a total number of 13,824 architectures and 165,888 CSMs. The architectures were subdivided into four groups. If more than 50% of the components were part of modules, the architecture was called “Modular”. If there was at least one bus element, the architecture was named “Star”. “Modular-star” architectures were the ones with more than 50% of their components in modules and at least one bus element. All the remaining architectures were considered as “Integral”. Since the Integral architectures were randomly generated, it is possible that some of them are implicitly Modular or Integral due to accidental creation of groups of clustered components. Anyway, the randomness of the generation process should have assured that the properties of integral architectures are overall different from the modular and integral ones.

The presented approach has some limitations. While the prediction accuracy and the usefulness of the changeability indices has already been demonstrated in previous work, the statistical analysis of the changeability issues is based on assumptions that need to be validated. In particular, it is not clear if a random assignment of change likelihood and impact can generate meaningful change propagation patterns. For this reason, before detailing the full-scale analysis of all the indices, the next section will provide a comparison of the numerical results with a real case study.

4 A PARTIAL VALIDATION OF THE NUMERICAL RESULTS

The set-up described in the previous two sections has been applied to a real case study, based on a previous complex technical system’s development project (Giffin et al. 2009). The project involved the design of a large-scale sensor system and took about eight years to complete. The entire change database contained more than 41500 change records in various subsystems, including hardware, software and documentation. Due to the heterogeneity of the subsystems, we will use the word “area” instead of “component” to designate an element in the system at the current level of hierarchical decomposition. The software was the area where most of the changes occurred, since the hardware was mostly re-used from a prior design. For every change, data about the type of change (native or propagated), parent-child relation, area affected and magnitude of change were recorded.

In order to reduce the scope and simplify the exposition of the results, out of the 41,500 changes a small subset of 87 changes was considered. They belong to a critical and well-studied group of changes that occurred during the integration and verification phase and affected 12 areas out of 46 (26% of the entire system). The small subset of the architecture consists of highly coupled areas (the average density of interfaces is 0.22) with one bus element connected to nine other areas.

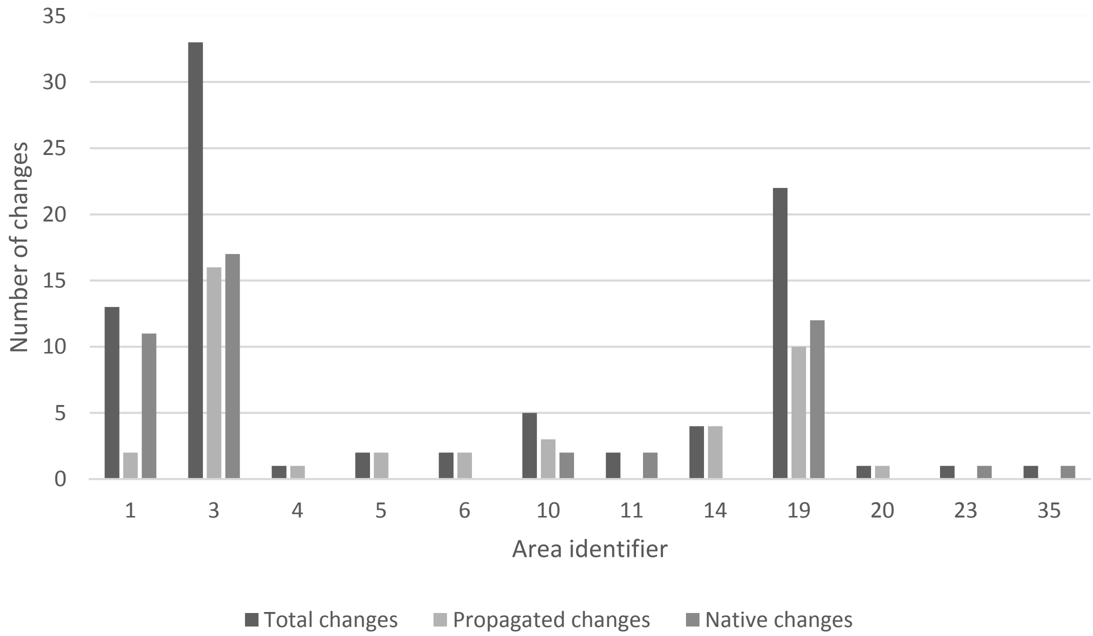

Figure 1. Number changes in the dataset by area

Figure 1 shows the 87 changes, organized by affected area. Most of the changes occurred in areas 1, 3 and 19, where also the major part of the native changes arose. Some areas, namely 11, 23 and 35, did not experience propagated changes, while others were subject only to propagated changes. In this particular example, the algorithm developed for this work did not generate a random DSM from similar architectural features, but it randomly created 300 CPMs based on the given architecture. Furthermore, the native changes likelihood and impact vector were generated based on the distribution of the real native changes. The resulting OCR, ICL and ICI indices were than compared to aggregated measures in the dataset, as reported in table 2.

Table 2. Correlation analysis between numerical data and case study statistics

Change indices (numerically derived)	**Statistics from case study**	**Pearson Correlation**	**P-value for null correlation test**
ICL	Average number of change	0.80	0.002
ICI	Average impact of changes	0.73	0.008
OCR	CPI	0.52	0.081

The comparison was carried out by means of Pearson correlation index; furthermore, the no-correlation hypothesis was tested. Three change measures from the real data were compared to the change propagation indices obtained numerically. Change likelihood is the number of changes in the area divided by the total number of changes; change impact is the sum of the change magnitudes in the area divided by the sum of the magnitudes in all the areas. Finally, the Change Propagation Index (CPI) is computed as the difference between changes from a given area to other areas and the changes from other areas to a given areas (Giffin et al. 2009). The more negative the CPI is, the more inbound changes are not propagated further into other areas (absorber-type behavior); in the opposite case of ("multiplier" behavior), a change in the area gives rise on average to several changes in other areas.
Table 2 shows a strong correlation between the ICL and ICI on one side and change likelihood and change impact on the other, as also confirmed by the small p-values. On the other hand, a correlation index of 0.52 and a p-value of 0.08 display a weaker correlation between OCR and CPI.
While the proposed correlation cannot be considered an exhaustive validation of the results from the numerical algorithm, the presence of significant correlation between the computed indices and the

change indicators from the dataset is considered sufficient as an initial verification. Deeper analyses and characterizations will take place in future work.

5 THE STATISTICAL ANALYSIS OF CHANGE INDICES

In Section 2, we explained how the architectures and the change propagation indices were derived. Section 3 provided an initial validation of the numerical results, which were confronted with real change data. In this section, the analysis of the indices distribution and the influence that the control variables have on such distributions is given. This is the rationale: if there are significant differences between the distributions of change indices, it is possible to show that architectural decisions have an impact on change propagation. To this end, 13,824 synthetic architectures were generated based on the design of experiments in Table 1. For each architecture, 12 change propagation statistics were derived in the form of CSMs, leading to a total number of 165,888 samples. All the figures in this section display the histograms of the indices normalized to represent probability density functions. To simplify the notation, the terms "probability density function" and "(probability) distribution" will be used interchangeably.
Figure 2 shows the probability density function of the total population of ICL, ICI and OCR indices in all the 165,888 cases.

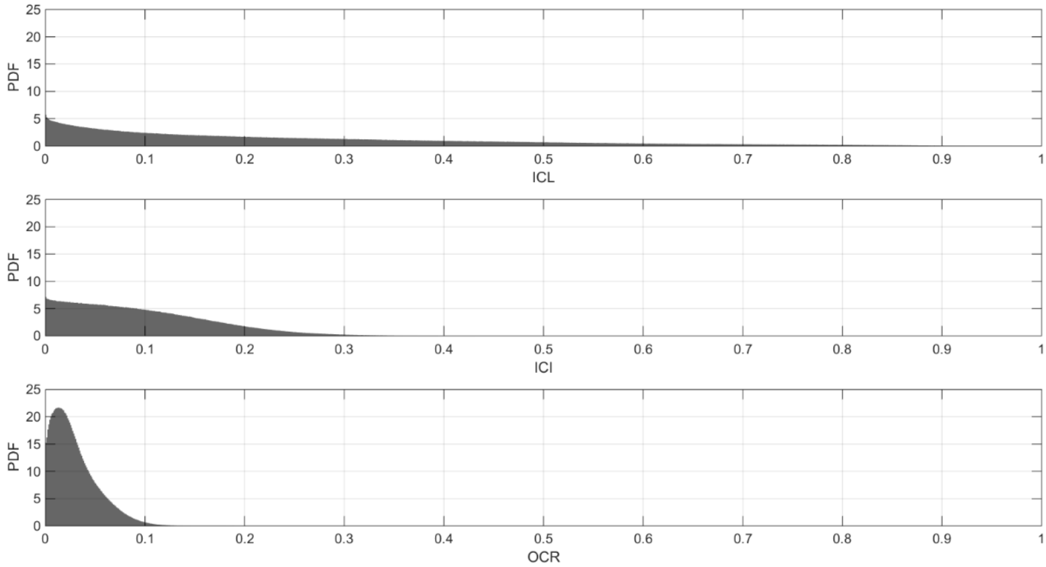

Figure 2. Probability density functions for three change propagation indices ICL, ICI and OCR

All indices have asymmetrical distributions, with a highly positive skewness and a long right tail, even though the CPMs contained only parameters coming from uniform symmetric distributions. Long-tail and fat-tail risk distributions have already been observed not only in change propagation data (Siddiqi et al. 2011), but also in other fields, like for example in financial transactions (Farmer and Geanakoplos 2008). There are profound differences between the indices, as well. ICL is the most dispersed distribution, with values ranging from 0 to 1, and a near linear decrease of the initial value of probability. The ICI index has an almost flat distribution until the value of 0.1, then it falls off quickly, even though some components still present high values. Interestingly, the ICL and ICI distributions show almost the same likelihood of having a component with index close to zero. The OCR distribution is much more condensed, with a high peak and a rapid decay.
Some observations can be made regarding the prediction of change propagation as predicted by the model. These distributions imply that the number of changes in a technical system can vary considerably, probably depending on the topological characteristics of the architecture. On the contrary, costs and time required for change are mainly condensed in a small subset of components that dominate the entire system.

In order to test if different architecture types have an effect on the probability density functions of the indices a set of parametric and non-parametric numerical tests were carried out. Analysis of Variance (ANOVA) would have been the most intuitive tool to this end. Unfortunately, all the resulting distributions are right-skewed, so the results of ANOVA could be biased. As a box-cox transformation on samples did not provide normal distribution in the results, the Kruskall-Wallis non-parametric test was chosen and carried out. For each of the indices, the samples from different architecture types were compared pairwise. The result was very conclusive. According to the test, for all indices and all architecture types, the samples do not come from the same population, as their p-values are well below the standard threshold of 0.05 and actually close to the minimum value computable by the statistical software used. Therefore, it can be said conclusively that the presence of modules or bus elements (hubs) does affect the statistical behavior of change propagation. The remainder of the section will show graphically how the samples differ by architecture type.
Figure 3 shows the samples of ICL divided according to the type of architecture they come from.

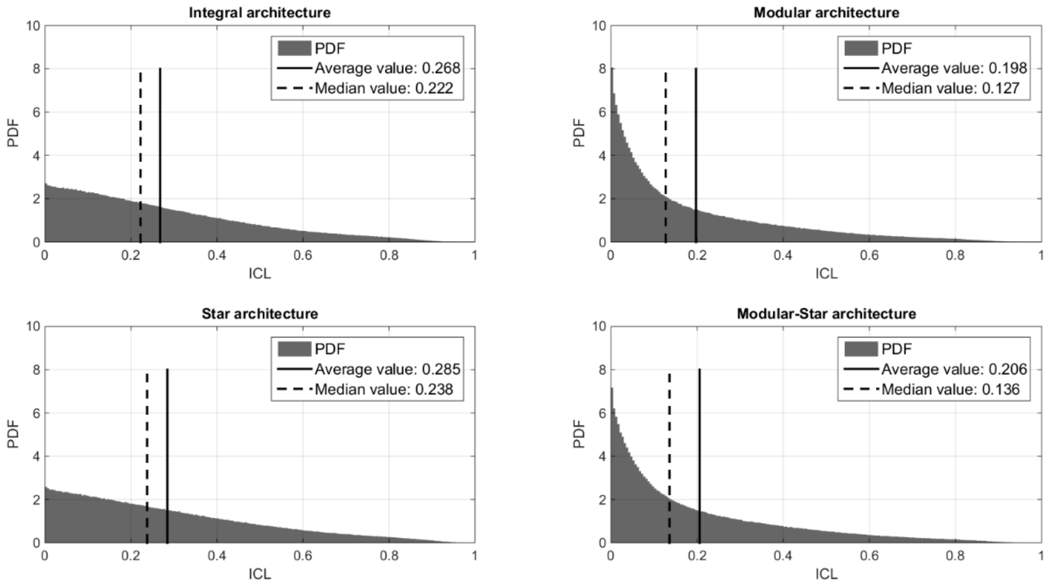

Figure 3. Probability density functions for ICL clustered by origin architecture type

Two main different distribution shapes can be noted. Integral and Star architectures have a probability decreasing linearly with the ICL score, while Modular and Modular-Star architectures have a hyperbolic distribution shape, with an higher number of components in the left part of the diagram.
Furthermore, the average and median values decrease significantly in the presence of modules.

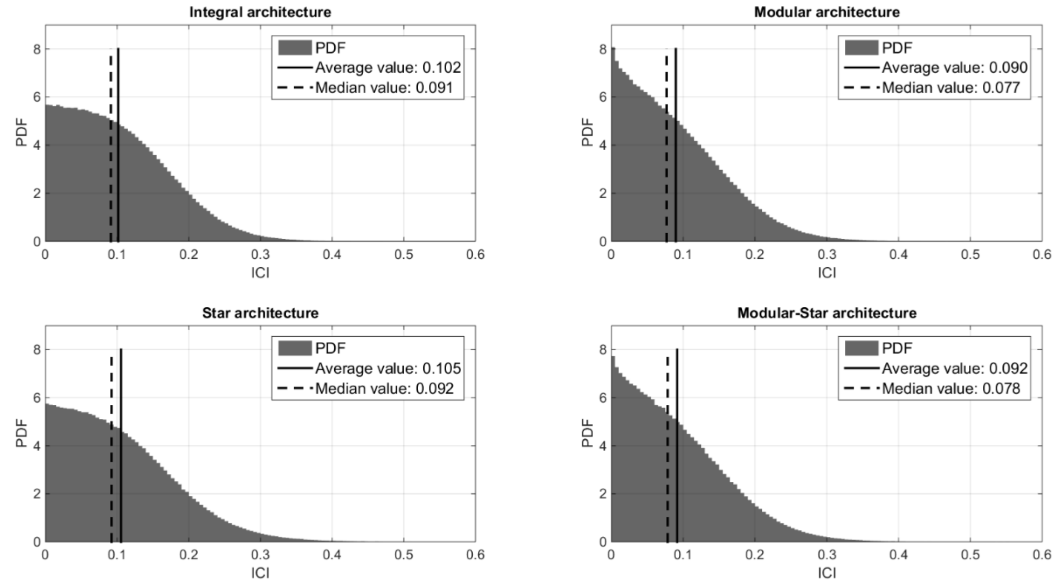

Figure 4. Probability density functions for ICI clustered by origin architecture type

ICI distributions are represented in Figure 4. As in the previous figure, there is a clear difference between Integral- and Star-based ICI and the other ICI. Compared to ICL, though, the dissimilarity is less striking. Modular and Modular-Star architectures are characterized by a higher peak in the low values and a steeper decrease of components with bigger ICI values. Integral and Star architectures have similar averages and medians, like Modular and Modular-Star architectures.

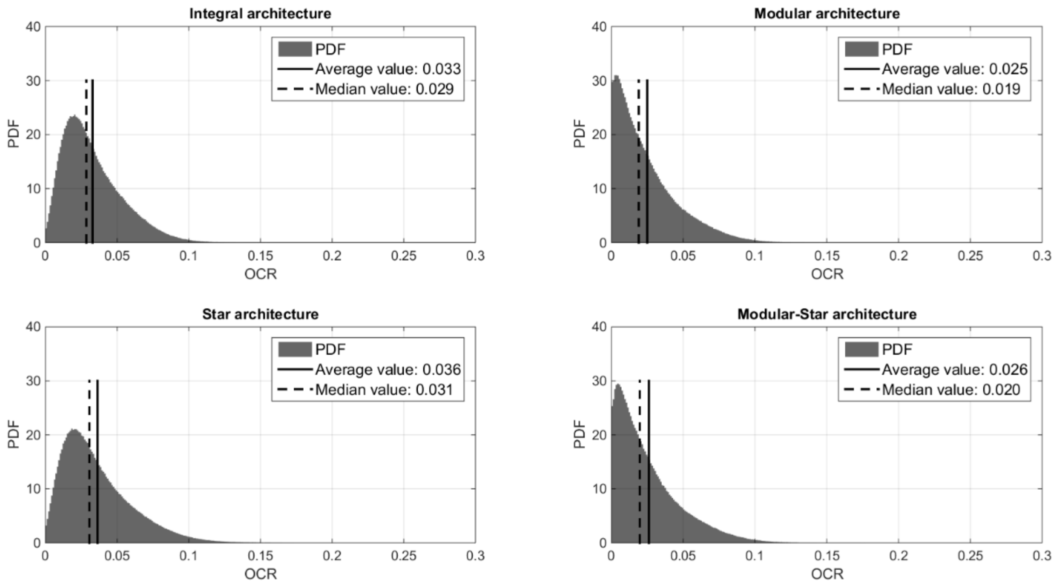

Figure 5. Probability density functions for OCR clustered by origin architecture type

Finally, OCR probability density functions are presented (Figure 5). As happened for the previous indices, also in Figure 5 the presence of modules in the architecture substantially changes the shape of the distribution. In this case, Modular and Modular-Star samples have a lower mean value and are more positively skewed. Furthermore, among those samples there are more components with values close to zero. The presence of modules decreases the average and median values by almost 30%.

The three change propagation indices provide a very interesting insight. It is clear that the presence of modules in the architecture has a net effect on all the indices probability density functions. In particular, not only do modules decrease the average value of the indices (thus reducing likelihood and impact of change propagation), but they also increase the number of components with index equal to zero. For example, the number of OCR smaller than 0.0001 goes from 530 in the Integral architectures sample to 8046 in the Modular architectures sample. Modularity had already been qualitatively associated with relative ease of change in the engineering design literature, without measuring its impact on change propagation quantitatively. For example, (Fricke and Schulz 2005) consider modularity and encapsulation adoption as a basic principle for changeability implementation. In (Saleh et al. 2009), the authors state that modularity and platform design are relevant fields for the study of flexibility in product design, while (Holtta-Otto and de Weck 2007; Gu et al. 2009) takes modularity into consideration in the development of a design method for adaptability. Finally, (Engel and Reich 2012) propose the use of modules as building blocks to evaluate real options at the architecture level. At the same time, while modularity reduces the average and median values of all the change indices distributions, the degree of the reduction depends on the indices itself. In fact, ICL and OCR are more influenced by the presence of modules than ICI. Modularity tends to reduce the change probability and the effects arising when a component is changed, but has little effect on the overall resources required to carry out the changes themselves.

Another interesting aspect is the low impact of bus components. Since changes are assumed to propagate through interfaces, having a highly centralized architecture was expected to lead to an increase in propagation risk. On the other hand, even though the Kruskall-Wallis test proved that the presence or absence of a bus does matter, the distributions of integral and star architectures (the center of the star being the bus) are very similar for all the three indices.

As far as prescriptive recommendations are concerned, two suggestions can be inferred. First, it is important to evaluate the need for changeability before the system architecting phase, because systems' structure does affect the likelihood, impact and risk of change propagation. Second, in case of projects with high likelihood of native changes, the results seem to recommend modular architectures over integral ones. At the same time, the presence of bus elements seems to have a weak influence over the change indices, especially in combination with high modularity.

6 CONCLUSIONS AND RESEARCH DIRECTIONS

This paper shows how architectural elements like modules and busses can affect change propagation in complex technical systems. In order to achieve statistically robust results, a method for the stochastic generation of architectures and change probabilities was generated; and the numerical results were partially validated on data from a case study. After generating a wide number of architectures, each element was rated according to a changeability measure from the literature, and the probability density functions of these measures were analysed.

The validation of the results showed a good correlation between the numerical indices and the data from the case study, which included 87 propagated changes. In particular, the indices' prediction accuracy showed to be sensitive to the initial distribution of native changes. In predicting the future changes, it is therefore important to quantify the uncertainty surrounding the systems, converting as many "unknown unknows" as possible to "known unknowns" (McManus and Hastings 2006).

As far as the main research question is concerned, the results of the Kruskall-Wallis test clearly indicate that module and bus elements play an impactful role on change propagation behaviour. In general, the indices' probability density functions have a positive skewness and present a long tail, as predicted by previous literature. In particular, the presence of modular elements has a profound impact on the indices distributions, since it reduces the average and increase the asymmetry. Modules decrease the average Incoming Change Likelihood by 26%, the Incoming Change Impact by almost 12% and the Outgoing Change Propagation index by the 30% circa. The bus elements' presence, even though relevant, has smaller effects than modules' presence.

These results confirm the beneficial role of modules for changeability, as reported in previous literature, but also characterize more precisely how architectural choices affect change propagation. In this sense, it would be interesting to compare how the decrement in change propagation due to modularity is balanced by a decrease in other system's performance or an increase in costs (Holtta-Otto and de Weck 2007; Efatmaneshnik and Nilchiani 2012; Ripperda and Krause 2014). Furthermore, the mathematical tool developed could be adopted to rank several architectures based on their changeability distributions, so that a tradespace analysis can be carried out.

Future research directions include a broader and more precise validation and an extended sensitivity analysis, e.g. with a larger set of 41,500 changes (Giffin et al. 2009). A complete validation of the Monte Carlo process can be carried out comparing the entire dataset from the case study in Section 4 with the complete numerical results. The sensitivity analysis needs to evaluate not only high-level architectural features like the presence of modules and busses, but also general and local topological features, like the architecture clustering coefficient and the components' betweenness. Furthermore, there seems to be a relevant similarity between the change propagation indices and the DSM singular values shown in (Holtta-Otto and de Weck 2007). An underlying principle could be discovered with in-depth comparison of the indices. All these directions are currently being developed by the authors.

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