Managing change propagation in product development projects based on the similarity of propagation effects

إدارة انتشار التغيير في مشاريع تطوير المنتجات بناءً على تشابه تأثيرات الانتشار

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Résumé : Les modifications techniques dans le développement des produits est une question délicate pour répondre aux besoins des clients et à la dynamique du marché. Afin d'intégrer la propagation du changement basée sur des stratégies efficaces de re-conception des recommandations, notre article présente un processus innovant permettant de résoudre deux problèmes clés: comment établir la méthode de prévision du changement et identifier les composants intégrant des changements similaires du produit. Pour mesurer les chemins potentiels de propagation, nous avons construit un modèle structurel à l'aide d'une matrice de structure de conception de produit. Ensuite, à partir de la mesure de propagation combinée intégrant l'influence des composants intermédiaires, nous avons construit la matrice de similarité du produit. Les résultats d'une étude de cas industrielle montrent les stratégies de conception et de recommandations efficaces en se basant sur un algorithme de pas aléatoire avec redémarrage.

***Mots Clés*:** Projet de développement, Matrice de structure de conception, Méthode de prévision du changement, Algorithme de pas aléatoire, Gestion de projet.

Abstract : Engineering changes in the development of the product is a challenging issue to address the customer needs and the dynamic of markets. To incorporate the requirements-driven change propagation for efficient recommendation redesign strategies, this paper presents an innovative design process to solve two key problems: how to establish the change prediction method (CPM) and how to identify components that incorporate similar changes of the product. For measuring the component's potential propagation paths, we build a structural model to address design changes using a product design structure matrix (DSM). Then, from the combined change propagation measure that incorporates the influence of intermediate components, we build the similarity matrix of the product. Results on an industrial case study show an efficient recommendation design strategies within component's similarity by using the random walk with restart algorithm.

***Key Words*:** Product Development, Design Structure Matrix, Change Prediction Method, Random Walk Algorithm, Project Management.

JEL Classification: M11.

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Introduction :

The occurrence of engineering changes is not limited to the development phase but covers the whole product lifecycle, from concept development, over detail design, to manufacture, and service (Sosa et al., 2013). Predicting the change propagating from the initiated component changed to the affected process aimed at aiding investigation, analysis and prediction of design change process (Lawless et al., 1999; Gemser and Leenders 2001; Hamraz 2012, 2013; Hein et al., 2017). An effective redesign recommendation towards change propagation analysis still poses a challenge for industry (Zhao and Li, 2014; Goknil et al., 2014; Du et al., 2015; Fernandes et al., 2017). While many companies recognize engineering changes as being important for their businesses, very few have implemented dedicated change management tools with even fewer claiming that they can handle change issues successfully (Rahmani and Thomas, 2011). A recommendation strategies towards product's change usually relies on probability of design changes to derive component's similarity (i.e., the one that implement the engineering change), and then ranks the product's component according to their similarity (Georgiou and Tsapatsoulis 2010; Biau et al., 2013).

The Change Prediction Method (CPM) is concerned with prevention, early detection, effective selection, efficient implementation and continuous learning from changes (Rahmani and Thomas, 2011, Hamraz et al., 2013;). However, in common with most other methods that predict likelihood of propagation through dependencies, CPM has three critical limitations: 1) subjectivity of input data (Hamraz et al., 2012); 2) capability to model generic cases only (Giffin et al., 2009) ; and 3) lack of recommendation regarding the integrated likelihood (Suh et al., 2007; Hamraz et al., 2013; Koh et al., 2013).

However, the aforementioned approaches make the decisions on effective scheme of product redesign based mainly on the coupling relationships among the propagated components, without accounting for other important properties, such as the similarity of the component's change (Ioannidis 2013; Sundar et al., 2014) , and can also struggle to determine the ressource contraint by the time and the cost for implementing the changes (i.e., the development manpower) (Wang et al., 2013).

This paper has argued that these limitations could be resolved by incorporating information from interface management into change prediction by using design recommendation. We extend the previous CPM algorithm to identify three-order propagation paths in the product architecture and implement random walk with restart algorithm (Gan, 2014) to allow stable design proposition with recommendation strategy regarding different path propagation and similarity rank. In fact, the proposed method combines knowledge from the Design Structure Matrix (DSM) (Eppinger and Browning, 2014) and random walk theory.

The paper contributes a new approach that synthesizes new and existing techniques. The approach harnesses CPM method through modeling the similarity matrix and identifying the recommendation strategy related the redesign process. It builds structural models (DSM) to capture the initial and propagated change, with the component's similarity. Implementing efficient recommendation stagegies towards the product redesign suggests improved structures that will better reflect the development time and cost attributed to the redesign process in complex PD projects.

The rest of the paper is organized as follows. After reviewing relevant literature in Section 2, Section 3 presents a quantitative model of the change redesign paths based on product component interactions, proposes an improved combined change propagation and defines the similarity matrix to efficient product's redesign. Section 4 describes how we implement the random walk with restrat algorithm to find appropriate and efficient recommendation regarding the components network. Section 5 applies the approach to an industrial example. Section 6 concludes the paper.

1. Literature Review

Research in engineering design has investigated several models of design change propagation. Change propagation analysis presents that the design change of one component can propagate through the interdependent components until all components can work together to perform the intended function (Maier et al., 2014; Baldwin et al., 2014). Many change propagation studies use the component-based design structure matrix (DSM). For example, Cohen et al. (2002) used this matrix to represent the interdependencies between design decisions based on the key attributes of a product's design to predict change propagation when a requirement is revised. To predict the redesign effort for future changes, Martin and Ishii (2002) assessed the direct dependencies between components using a component-based DSM that captures the degrees of coupling between components. Suh et al. (2007) proposed a change propagation index (CPI), calculated as the total difference between the change received and propagated from a component. Smaling and De Weck (2007) developed a component based Change DSM to compute the number of design changes required for a new technology. These studies do not consider change propagation through indirect dependencies of components. However, the Change Prediction Method (CPM) developed by Clarkson et al. (2004) was the first to evaluate indirect change propagation through the influence paths between components. CPM also considers the likelihood and impact of change propagation from one component to another, using DSMs whose entries capture both likelihood and impact of change propagation but only consider under diagonal dependencies. Hamraz et al. (2013) applied similar algorithm to CPM including several domains for considering upper and under diagonal dependency (i.e., element's interdependencies), such as components, functions, requirements, processes and organizations. Part of the measurement effort is the development of parameters, such as Incoming Change Likelihood, Incoming Change Impact and Outgoing Change Risk (Koh et al., 2013).

Despite DSM data on component interdependencies being used to understand the change-related component's requirement, the random walk based similarity asserts recommendation strategies toward engineering changes (Stinchcombe, 2000). Before searching for redesign recommendation, the notion of components similarity needs to be understood in the context of customer requirements (McAdams and Wood, 2002). In other words, if two components share a common function, such as store energy, and this function is related to important customer needs, these two components have a design-relevent similarity. When comparing more than two components, the notion of more or less similar becomes more relevant (Agrawal, 2009). Adapting a random walk process to a design or redesign process helps the project managers to predict and recommend new interactions in the components network due to the investigation of ressource constraint and cost (Du et al., 2015). Thus, the methodology of random walk does not depend on the history of redesign compared to conventional data-driven modeling to describe the quality propagation in manufacturing projects (Mondal et al., 2013). Researchers widely used random walk theory (as describe with Markov model (Gasparini 1996)) to investigate recommendation regarding the redesign in manufacturing process; they show empirical evidence that the redesign has significant impact on the quality of the product (Wang et al., 2010; Colledani and Tolio, 2011). However, some authors investigate the change propagation for maching systems by applying information feedback of each design posiibility with customer perception (Li and Huang 2007; Du and Xu, 2012). In spite of the obove effort in the literature about the relationship between an improved redesign process related to random walk theory, the current research work assume that each stage of redesign process in manufacturing is independent, and this can only occur after the completion of the redesign process. The related literature is reviewed and new directions are provided by Inman et al. (2013).

The models presented in this paper extend the existing literature on similarity product that do not consider common functions or requirements of the components. As the similarity measure is computed in real time, including the direct and indirect design change, the only data that need to be accessed to allow for broad application of this method are customer requirements weighted design change propagation.

2. Single Likelihood of Different Change Propagation Path

2.1. Direct Change Propagation

The first stage of CPM is to allow preliminary examination of direct impact on component dependencies. The engineering change is defined as any alteration to a product sub-system's design and is originated from customer needs, reliability requirement, cost reduction and so on (referred as change requirement in this paper). In this paper, change propagation is thought as a process during which initiating change components causes subsequent changes. Within the Product DSM (i.e., *P_DSM*) the column headings show *instigating* components and the row headings the *affected* components. Let $SL^{(1)}(m,n)$ be the *single likelihood* of first-order change propagation resulting from the direct impact of design change of component *n* on component *m*. This type of network has been used to represent the relationship between components for further analysis of change propagation (Johannesson et al., 2017; Yang and Duan, 2012). Since, the *P_DSM*, per definition already includes the direct links of change between the instigating component *j* and the affected component *i*, it must equal to $SL^{(1)}(m,n)$:

$$SL^{(1)}(m,n) = DSM(m,n) \tag{1}$$

where *m* and *n* $\in \{1,2,\ldots,N_C\}$. As the diagonal elements of the *P_DSM* are zero, only change propagation between two different components will be considered.

In this paper, changes propagate between the network of dependent components (initiating change components causes a series of subsequent changes). We define $SL^{(2)}(m,n)$ as the *single likelihood* of second-order change propagation paths resulted from the indirect impact of design change of component *n* on component *m* through an intermediate component *p*. Only three different components are taken into account for $SL^{(2)}(m,n)$ as presented in Fig. 1(a). The likelihood of second-order (indirect) change propagation path from *n* to *m* through component *k* (i.e., $C_n \to C_p \to C_m$) is:

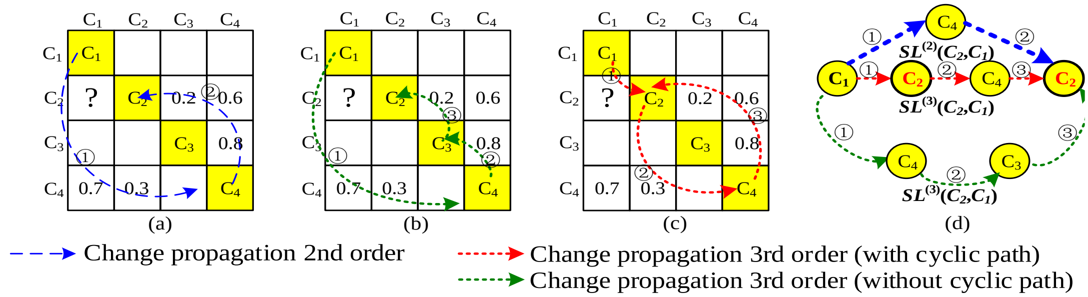
$$SL_p^{(2)}(m,n) = DSM(p,n) \times DSM(m,p) \qquad (2)$$

where $p \in \{1, 2, ..., N_C\}$, $m \neq n$, $n \neq p$, $m \neq p$. For example, in Fig.1(a), C_4 is the intermediate activity of second-order change propagation paths from C_1 to C_2, so $SL^{(2)}(2,1)$=DSM(4,1)×DSM(2,4)=0.7×0.6.

Further, the single likelihood of all second-order change propagation paths from *n* to*m* through all possible intermediate components can be calculated as follows:

$$SL^{(2)}(m,n) = \sum_{p=1}^{N_C} SL_p^{(2)}(m,n) = \sum_{p=1}^{N_C} DSM(p,n) \times DSM(m,p) \qquad (3)$$

Fig. 1 : « An example of the first, second and third order change propagation »



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The calculation of second change paths extend the work of Hamraz et al. (2013) by applying this order of change in independent view from previous changes (i.e., direct and indirect) for a given process DSM including a change cyclic change. In pratical cases, the cycle is considered as the repetition of change design due to the different parameters affecting the components, which is a feature of change design processes that lends itself to modeling (Tang et al., 2016). The cyclic path propagation is a propagation loop that ends with the initiated change (i.e., the starting activity affected and initiated by the project manager and engineers), which may exist as a form of iteration. Avoiding the iterative problem required by cyclic path propagation is likely to involve higher coordination costs between redesign teams (Sosa et al., 2013).

Moreover, $SL^{(3)}(m,n)$ represents the single likelihood of third-order change propagation paths resulted from the indirect impact of design change of activity *n* on *m* through two intermediate components. Fig.1(b) and Fig.1(c) describe two situations for third-order change propagation paths, which are change propagation with cyclic path and without cyclic path respectively.

For the situation of the change propagation without cyclic path (see Fig.1(b)), the third-order (indirect) change propagation path for $C_n \rightarrow C_p \rightarrow C_q \rightarrow C_m$ through two intermediate components *p* and *q* can be calculated:

$$SL_{p,q}^{(3)}(m,n) = DSM(p,n) \times DSM(q,p) \times DSM(m,q) \qquad (4)$$

where $q \in \{1,2,...,N_C\}$ .For example in Fig.1 (b), $SL_{(4,3)}^{(3)}(2,1)$=DSM(4,1)×DSM(3,4)×DSM (2,3)=0.7×0.8×0.2 along path (C_1, C_4, C_3, C_2).

For the situation of the change propagation with cyclic path (see Fig. 1(c)), the third-order change propagation path would also allow the propagation path $C_n \rightarrow C_m \rightarrow C_p \rightarrow C_m$, which includes a loop for the second component C_m. It can be calculated as follows:

$$SL_p^{(3)}(m,n) = DSM(m,n) \times DSM(p,m) \times DSM(m,p) \qquad (5)$$

For example, Fig.1(c) shows along cyclic path (C_1,C_2,C_4,C_2) a loop in component C_2. So, $SL_4^{(3)}(2,1)$=DSM(2,1)×DSM(4,2)×DSM(2,4) =0.8×0.3×0.6.

Further, the single likelihood of all third-order change propagation paths from *n* to*m* through all possible intermediate components can be calculated as follows:

$$SL^{(3)}(m,n) = \sum_{p=1}^{N_C}\sum_{q=1}^{N_C} SL_{p,k}^{(3)}(m,n) + \sum_{p=1}^{N_C} SL_p^{(3)}(m,n) \qquad (6)$$

The third order change is the prior DSM including cycle paths, which is a necessary condition of iterative process. Furthermore, the proposed CPM is performed assuming that changes would not propagate appreciably beyond three steps, which is a reasonable assumption based on previous CPM research where they found that combined change does not vary if the propagation is calculated on the basis of at least three steps (as presented in Fig. 1(d)) (Cohen et al., 2000; Clarkson et al., 2004; Giffin et al., 2009; Pascal and De Weck 2011).

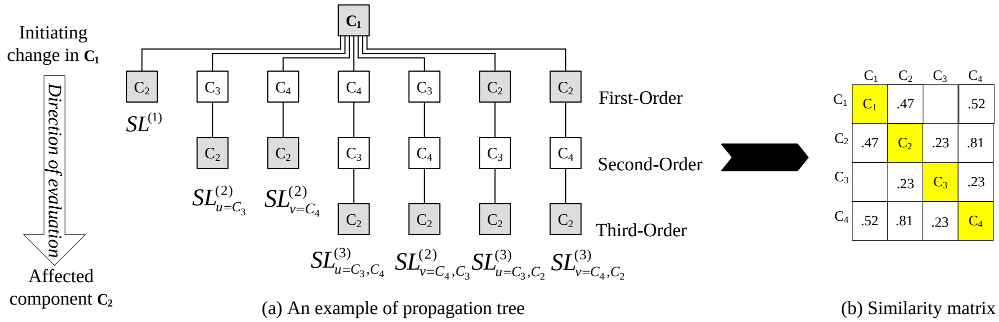
2.2. Construction of Indirect Change Propagation with similarity network

The purpose of constructing a product similarity network instead of using all calculated similarities is to remove negative influences of some dependencies and reveal dominant one. In the network construction process, we first calculate similarities between components via Jaccard similarity index modified by Suer et al. (2010). By treating each component as a set that containing components affected by a change; the set corresponding to the m-th component is xm={k:xkm=1, 1≤ k ≤0} (see Fig. 2(a)) and the set corresponding to the n-th component is xn={l:xln=1, 1≤ l ≤0}. These two sets can be derived from the three change propagation paths. The proposed method calculates the similarity between two components as the ratio of the affected common change proportional to their total affected change, as:

$$S(m,n) = \frac{|x_m \cap x_n|}{|x_m \cup x_n|} \qquad (7)$$

The sets of xm and xn are defined as the change probability of components m and n expressed in term of their integrated combined likelihood (i.e., the common affected components) across their possible change propagation paths (i.e., all the components affected by the change of m and n simultaneously) (see Fig. 2(b)):

Fig. 2 « An example of deriving similarity related the redesign process »



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2.3. Combined Change Likelihood

The combined change likelihood between two components is defined as the integrated probability of all possible change propagation paths across their intermediate interface (see Figure 1 (a)).We use the propagation paths shown in Figure1 (b), (c) and (d) to reflect the combined likelihood from C1 to C2 through change path 1, 2 and 3 (i.e., the amount of intermediate components are 0, 1 and 2 respectively). Through analyzing the intermediate components, probabilities of change from C1 to C2 can be calculated as follows (Clarkson et al., 2004):

$$SL_u^{(3)}(C_2,C_1) \cup SL_v^{(3)}(C_2,C_1) = 1 - \begin{pmatrix} \left(1 - SL_{u=C_3,C_4}^{(3)}(C_2,C_1)\right) \\ \times\left(1 - SL_{v=C_4,C_3}^{(2)}(C_2,C_1)\right) \\ \times\left(1 - SL_{u=C_3,C_2}^{(3)}(C_2,C_1)\right) \\ \times\left(1 - SL_{v=C_4,C_2}^{(3)}(C_2,C_1)\right) \end{pmatrix}$$

Thus, the combined change likelihood (CL) between components m and n refers to the integrated change probability in the design of component n leading to a design change in component m through all potential change propagation path z. It can be calculated as follows:

$$\begin{aligned} CL(m,n) &= SL^{(1)}(m,n) \cup SL^{(2)}(m,n) \cup SL^{(3)}(m,n) \\ &= 1 - \prod_{z=1}^{3}\left(1 - SL^{(z)}(m,n)\right) \end{aligned} \quad (8)$$

We deduce that:

$$S\left(m,n\right)=\frac{\sum\limits_{l\in x_m \cap x_n} CL(l,m)+CL(n,l)}{\sum\limits_{l\in x_m \cup x_n - x_m \cap x_n} CL(l,m)+CL(n,l)} \tag{9}$$

Because, the value of total combined change between two components is always bigger or equal to the value of common combined change so, the intensity of similarity and the number of affected components need to be considered for an efficient recommendation.

3. Redesign Recommendation Based Random Walk Algorithm With Restart

The random walk with restart process usually facilitate the recommendation of candidate objects (i.e., components) (Gan, 2014). The basic idea of our method is to simulate the process that a random walker wanders in the component similarity network. The walker starts the journey at random from one of the components that have selected the query component (i.e., the one affected by a change). Then, in each step, the walker may either move at random to a neighboring component or start on a new journey with a certain probability. Finally, the probability that the walker stays at the query component is used as the score that reflects the preference of the query component to anther query component.

First, we calculate the transition matrix T(m,n) by performing a column-wise normalization of similarity matrix. T(m,n) reflects the degree of the initiating change similarity on component n that might influence changes over component m compared to all affected changes occured (i.e., adjusted component's similarity related all potential similarities of change):

$$T(m,n)=\frac{S\left(m,n\right)}{\sum\limits_{m=1}^{q} S\left(m,n\right)} \tag{10}$$

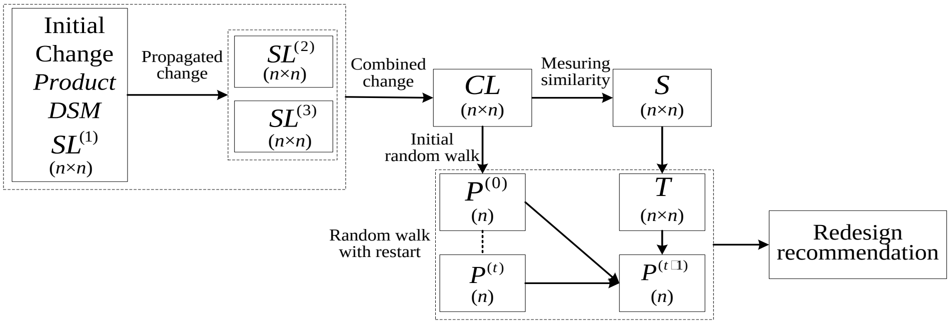
where *q* is the intermediate component of path propagation *z*. The *m*-th column in matrix T represents the probabilities that the random walker moves from the *m*-th component to other components. When starting a new journey, the random walker starts at random from one of the components affected by the change. We represent the initial configuration using a vector $p^{(0)}$, as: $p_n^{(0)}=\frac{CL(m,n)}{\sum_{m=1}^{0} CL(m,n)}$. Then, let $p^{(t)}$ be the vector composed of probabilities that the random walker stays in all components at step *t*, the iteration formula can be expressed as follows:

$$p^{(t+1)}=(1-\gamma)\cdot T(m,n)\times p^{(t)}+\gamma\cdot p^{(0)} \tag{11}$$

where γ is the restart probability.

After a number of steps, the probabilities will converge to the steady state, which aims to enable the design to evolve a new stable statut of the design. This is obtained by performing the iteration until the difference between $p^{(t)}$ and $p^{(t+1)}$ is sufficiently small. Finally, by repeating this random walk procedure for each component, we are able to rank the components according to their engineering change. It has been shown that such a random walk model is not sensitive to parameters involved, though a relative larger restart probability benefits the performance (Medo, 2013). Hence, we select default parameters as γ=0.9. The similarity is a necessary condition to understand the state of the design and the connectivity between the product's feature. The main steps of the proposed approch could be summarized as following (Fig. 3):

Fig. 3 « Overview of redesign change propagation, similarity measuring and random walk procedures »



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Step 1: Select from the initial change Product DSM the propagated changes for each change propagation path;
Step 2: Implement iteration process to determine the combined change propagation (combined likelihood);
Step 3: Measure the component's similarity, which is the input of tha random walk algorithm and determine the initial random walk probability based on CL and the transition matrix T as an initial state of product's change;
Step 4: Implement a randam walk with restart probability for design stability;
Step 5: Derive redesign recommendation towards similarity rank.

4. An Illustrative Example

The proposed model is applied to a wrapping machine for cereal bars from the Italian Cavana Group. The customer's requirement is to grant a performance of his line by a higher speed flowpack. Cavana's challenge is to supply a packaging line featuring a row pieces multiplier in order to reduce a number of incoming rows by increasing the number of pieces per row. We interviewed 10 engineers from the design technical departments and raised the following questions: 1) How much does the redesign of one component influence other components? 2) How to evaluate the similarity between components with different change propagation pattern? 3) How to elaborate design recommendation strategies toward potential change propagation?

4.1. Modeling process

The product is simplified and the main modules integrating specified components are constructed to demonstrate the initial evaluation of the method (Fig. 4(a)). First, the wrapping machine is decomposed into five modules (A, B, C, D and E in the Fig. 4(b)) with six possible change requirements using conventional technique (Eppinger and Browning, 2012). We asked about four types of interfaces between components: physical connections, influenced functions, energy consumed and related information flow. We elicited change routes and probabilities between directly connected components via experience-based estimations by the project manager and designers. Then, the dependency between a couple of components are acquired through analyzing the parameters of every two components. Finally, based on the number of requirement change between two components to the total number of requirement change, the first change propagation path is determined.

Fig. 4 « Design change requirements of the wrapping machine »

ID	Module's Name	Their Components	Design Change
A	Row Pieces Multiplier	Sealing Wheel; Dwell Gear Box; Stream in Feed; Stucking Device	High Flow Rate; Low Energy Usage; Low Cost
B	Row Distributing System	Differential Box; Row Preparation; SBF Loader; Pull Nose System	High Flow Rate; Rapid Cooling
C	Horizental Buffer	Lane Reducer; Screen HMI; Buffer Fifo; Transfert Unit	Low Vibration; Low Cost
D	Loading System	Conveyor; Electrical Panel; Crimper Jaws; Loading System	Low Cost; Rapid Cooling
E	Zero5 Wrapper	Zero5 wrapper; Servo Motor;	Rapid Cooling; Low vibration

(a) Modules of the wrapping machine (b) Change's requirement by component's modules

Source: illustrated by the authors

To derive the original likelihood DSM and improve its modeling efficiency, the requirement-component relationship is elicited from the chief designers, sales managers and project managers. These steps are also used in the literature (Tang et al., 2016). based on the equations (1)-(3), $SL^{(1)}(m,n)$ and $CL(m,n)$ are show in Fig. 5 (a) and (b) respectively.

Fig. 5 « Change Likelihood DSM »

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
Sealing Wheel	1	1	.3		.6											.4			
Zero5 Wrapper	2	.5	2									.7	.7			.3			
Differential Box	3		.8	3			.8	.5									.5		
Servo Motor	4	.5	.8		4					.8									
Dwell Gear Box	5			.8		5												.5	.3
Conveyor	6			.3			6												
Lane Reducer	7		.8	.1				7		.5								.9	
Electrical Panel	8								8										
Screen HMI	9	.4		.3	.1					9									
Row Preparation	10							.6			10			.6					
Buffer Fifo	11	.1										11							
Stream In Feed	12												12						
SBF Loader	13								.8					13					
Crimper Jaws	14			.5						.4			.2		14	.3			.6
Loading System	15	.7														15			
Stacking Device	16			.8								.1					16		
Pull-Nose Device	17					.7												17	
Transfert Unit	18										.4								18

(a)

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1	1	.55		.63					.48		.55	.07			.93			
2	.63	2		.72					.69		.48	.60			.98			
3			3															
4	.76	.98		4					.87		.78	.85			.85			
5					5													
6	.62	.46		.54		6					.93	.26			.45			
7	.25	.32		.29			7		.65						.87			
8								8										
9	.85	.83		.91					9		.93	.89			.88			
10	.76			.91			.65	.93	.80	10			.76					
11	.62	.46		.15							11	.69			.25			
12	.42	.93		.31							.39	12			.49			
13								.33					13					
14	.76	.89	.93	.77			.74	.88	.78	.89			.86	14	.87			.84
15	.93	.49		.39					.93		.39	.37			15			
16	.31	.31	.56								.93	.62				16		
17					.83												17	
18							.43	.43	.02	.93			.21					18

(b)

Source: illustrated by the authors

4.2. Change propagation process

According to the results in Fig. 5 (b), a total of 60 new dependency of change appears between the affected components while applying the CPM procedure in the Matlab® 15 software. The total CL of an affected component is calculated as the avearge of the sum of its initiating components of change (which corresponds to the sum of the row of the affected component) to the number of product's component (Koh et al., 2013). The *CL* of the Crimper Jaws (14) is the highest to meet change requirements being not suitable for standardization. In contrast, the Pull-Nose Device (17) has relatively lower *CL* than most of the other components. This suggests that the Pull-Nose Device is less likely to change and hence is a good component for standardization. System components, such as the Differential Box (3), the Dwell Gear Box (5) and the Electrical Panel (8) are the best components for standardization (CL=0). However, based on these incoming change characteristics, it is unclear wether the component is affected by multiple components or just heavily afected by one or two components. Therefore, further analysis is required for these system components. This is carried out by examining the similarity between components to assess their influence.

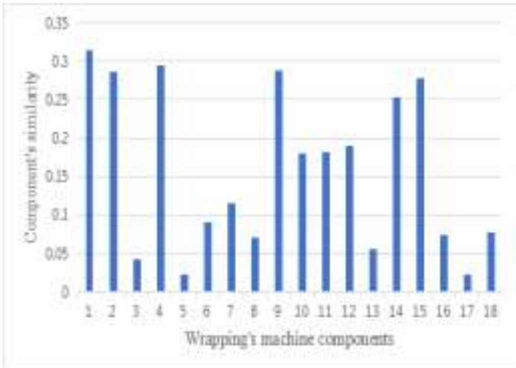
From the similarity perspective between two interdependent components, more they are affected by common components, more they are similar. For example, from the SL matrix (Fig. 5 (a)), we observe that the initiating change from the Loading System (15) to the Sealing Wheal (1) would be affected by their common intermediate components Zero5 Wrapping (2) and Crimper Jaws (14) with three cycle propagation paths, which also represent the highest combined likelihood in CL matrix (Fig. 5 (b)). In fact, the similarity between the Loading System (15) and the Sealing Wheal (1) is the highest (Fig. 6(a)).

By ranking the components based similarity, the project manager might identify the suitable system components for improvment. System components with high similarity have a strong influence on other system components and thus should be made less likely to avoid further propagating changes to others. Conversely, system components with low rank (or similarity), do not affect other system components as much and hence should be made easier to change to absord futur changes. The similarity of each component is calculated as the sum of its affected change (summing the column of the initiating change from the similarity matrix). Following the Fig. 6(b), we observe that the Sealing Wheel (1), the Servo Motor (4), the Screen HMI (9), the Zero5 Wrapping (2), the Loading System (15) and the Crimper Jaws (14) have stong similarity and higher rank, respectively, compared to the other components of the wrapping machine. So, they are more sensitive for the implemented changes. Besides, the Pull-Nose Device (17), the Dwell Gear Box (5) and the Differential Box (3) are not sensitive for the change (lowest rank related to their similarity).

Fig. 6 « Analyis of the similarity in the machine's components »

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1	1	.59		.69		.31	.12		.66	.38	.58	.24		.38	.93	.15		
2	.59	2		.85		.23	.18		.76		.47	.76		.44	.73	.15		
3			3											.48		.28		
4	.69	.85		4		.27	.14		.89	.44	.46	.58		.36	.62			
5					5												.41	
6	.31	.23		.27		6					.46	.13			.22			
7	.12	.18		.14			7		.31	.33				.37	.43			.21
8								8		.46			.16	.44				.21
9	.66	.76		.89			.31		9	.40	.46	.44		.36	.90			
10	.38			.44			.33	.46	.40	10			.33	.44				.46
11	.58	.47		.46		.46			.46		11	.54			.32	.46		
12	.24	.76		.58		.13			.44		.54	12			.43	.31		
13								.16		.33			13	.43				.10
14	.38	.44	.48	.36			.37	.44	.36	.44			.43	14	.43			.42
15	.93	.73		.62		.22	.43		.90		.32	.43		.43	15			
16	.15	.15	.28								.46	.31				16		
17					.41												17	
18							.21	.21		.46			.10	.42				18

(a) Similarity Matrix



(b) Component's similarity in the wrapping machine

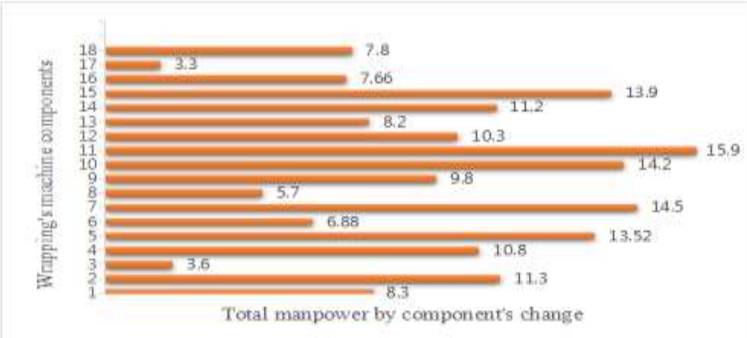
Source: illustrated by the authors

4.3. Recommendation process

An effective recommendation process should rank the components additionnaly based on the consumption of ressources, the development time and cost of each component's change (Fergusson et al., 2013; Levandowski et al., 2015; Tang et al., 2016; Johannesson et al., 2017). We describe the manpower as the product of the workload and the development cost; the workload is expressed as the product of the number of developped designers and the development time. The manpower was also used in other researchers to assess product's modularity (Tripathy and Eppinger, 2013). For example, if a design change is performed by two designers within 5h with 10 dollars per hour, the workload is 10 (5x2=10) and the manpower is 100 (10x10). The manpower of each change component, and then the total manpower of each change propagation path is obtained. Based on the analysis results, the project manager select and implement the scheme of design change with the least workload and the highest similarity rank.

We interviewed 10 more engineers across different department of planning group and technical designers. Each of them had the experience with the wrapping machine project and had been involved in manpower planning and allocation. We asked them to identify the deliverables of their respective tasks of each performed components. They were also asked to assign, for each task related redesign, the manpower time allocation and the cost per hour consumed. The split of task time related redesign of each component and the allocated cost are developped regarding each change propagation path. The total manpower regarding the change process, as shown in Fig. 7, is plotted as a column graph, which determines that the Differential Box (3) is the least and the Buffer Fifo (11) is the most. Thus, this solution of design change should be avoided as far as possible due to its high rank similarity (i.e., intensity of change of the intermediate affected components in the process).

Fig.7 « Total manpower by component's change in wrapping machine»



Source: illustrated by the authors

Based on the above, recommendation is that the change propagation of the least manpower and least similarity should be given priority and efforts of implementing changes. Hence, it is found that the manpower of the standard component for change, i.e. the Pull-Nose Device (17), is identified as the optimal originating change component. While comparing results of the similarity rank and the manpower, the result maches suggesting that the best components for change are the components 3, 16, 18, 8. This process could be implemented continuousely until the optimal scheme is found, which will improve the product comprtition in the market.

Conclusion :

A proposed approach for measuring design change with random walk based similarity is developed to evaluate design change recommendations. This paper propose an improved CPM method by integrating three path's level to measure the combined likelihood of change in the development design across intermediate components. To propose an efficient design change recommendation, this paper presents the similarity matrix between components integrating the combined change. According to both similarity rank and the manpower of change (i.e., consumption of ressource and cost) may lead to the optimal recommendation strategy towards the implemented change. A random walk with restart model establishes an efficient product development strategy regarding multiple engineering changes to select and implement efficiently the optimal scheme of design change. An example is illustrated to verify the effectiveness of our proposed models.

In practice, the project manager can utilize our models to: (i) predict the potential change affected by the initiating components and customer requirements, (ii) determine similar components affecting less or more the product's design, and (iii) select effective implemented change regarding to the manpower consumed.

Several aspects of the model presented in this paper merit further examination. First, this paper's model about combined change likelihood related to component interfaces for a single product does not explore how component changes over time. Quantitative approaches that can capture component change likelihood over time will be useful to track these measures across several product generations. Doing so can improve our understanding of how product's change affect the network properties of each component. Second, the workload determined as time and cost consumed to implement component's change is based on expert's opinion (i.e., estimation given by designers working on similar engineering systems). Although this methodology captures implicit knowledge from the designers and the project manager, the data could be subjective and the elicitation process could be time consuming when the product has more components. Thus, more efforts are still required to improve the elicitation of change data efficiently. Finally, the random walk with restart model could bring more integrated framework while the number of parameter, complexity of component's dependency increase to bring new research opportunities and more tests against change process.

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