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ORIGINAL ARTICLE

Design Property Network-Based Change Propagation Prediction Approach for Mechanical Product Development

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Abstract Design changes are unavoidable during mechanical product development; whereas the avalanche propagation of design change imposes severely negative impacts on the design cycle. To improve the validity of the change propagation prediction, a mathematical programming model is presented to predict the change propagation impact quantitatively. As the foundation of change propagation prediction, a design change analysis model(DCAM) is built in the form of design property network. In DCAM, the connections of the design properties are identified as the design specification, which conform to the small-world network theory. To quantify the change propagation impact, change propagation intensity(CPI) is defined as a quantitative and much more objective assessment metric. According to the characteristics of DCAM, CPI is defined and indicated by four assessment factors: propagation likelihood, node degree, long-chain linkage, and design margin. Furthermore, the optimal change propagation path is searched with the evolutionary ant colony optimization(ACO) algorithm, which corresponds to the minimized maximum of accumulated CPI. In practice, the change impact of a gear box is successfully analyzed. The proposed change propagation prediction method is verified to be efficient and effective, which could provide different results according to various the initial changes.

Keywords Change propagation prediction · Small-world network · Change propagation intensity(CPI) · Design change analysis model(DCAM) · Ant colony optimization(ACO)

1 Introduction

Design changes are very common and unavoidable in product development processes, which determine as much as 70%–80% of the final cost of a product [1]. Additionally, product development schedules and product quality are driven to a large extent by the changes and rework activities. For very different reasons, design changes can be classified into two main categories: *emergent design change* caused by the problems occurring across the internal design project due to solution uncertainty, and *initiated design change* derived from external stakeholders such as new customer requirements, technological innovations and regulation modifications [2]. By analyzing certain change records of original equipment manufacturers, SHANKAR, et al found 77.0% of changes were derived from internal reasons while 23.0% were external, and inferred that 32.4% of the total changes were due to propagated changes [3].

Change propagation is a process in which a change to one part or element of an existing design tends to trigger additional changes to other elements of the design in a cause-effect-cause-effect pattern, even though the triggered changes would not have been required. The propagation will not be completed until the design achieves a new stable status. In other words, such loop-like, dynamic and

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recursive change propagation processes continue until all of the inconsistencies are identified. Consequently, it is possible for the changes even those that were initially thought as simple to propagate uncontrollably, resulting in an avalanche of changes. Change propagation is especially problematic in high-performance products or complex systems designed by large-scale distributed teams, which is composed of tightly coupled elements and functionality. Therefore, it is urgent to propose a technique to predict how a design change may affect the rest of the product, and to evaluate what needs to be modified accordingly.

The design change occurs in complicated products, such as an automobile, an aircraft and a spacecraft, would generate more complex propagations. The complexities are the result of not only from the components explosion, but also from the inter-disciplinary coupling, i.e., the interactions between aerodynamics, thermodynamics, structures and controls. Once a change propagation path planning in the complicated product is inappropriate, plenty of design iterations would be triggered, and the design workload would increase explosively. Change propagation prediction can help to optimize product architecture and robustness by locating the elements that are at high risk to be affected by such changes and determining the propagation behaviours(absorption, buffering, or transmission) of the interested parts. When a change request is raised, the change propagation prediction methodology can be used to support preventive decision-making and project planning in order to isolate expensive elements from such a change request. Furthermore, the prediction can help at the tendering stage to estimate the customization or modification cost of the contracted product.

To predict propagation avalanche and avoid unnecessary changes before the mechanical product redesign, this paper concentrates on predicting the change propagation path triggered by an initial change during the product development process.

In what follows, the related work is investigated and summarized in the next section. The change propagation prediction procedure is overviewed in Section 3. Section 4 introduces DCAM and its characteristics. The details of the change propagation prediction approach are illustrated in section 5 to achieve the precise prediction. Subsequently, section 6 demonstrates an application of the proposed method. The last two sections discuss the methodology and conclude this paper, respectively.

2 Related Work

2.1 Design Change Analysis Model(DCAM)

The engineering change researches can be traced back to the early 1980s with the first publications by DIPRIMA [4]. Limited to less-advanced technologies, the previous work focused on the consistency of change data. Generally, the research of change propagation prediction includes two parts: the DCAM and change propagation prediction algorithm.

In terms of different modelling bases, DCAMs can be categorized into design-process-based model and change-process-oriented model. The design-process-based DCAM is abstracted from the detailed design processes. There were a number of research efforts in this field. For instance, FEI, et al [5], found out design conflicts arising from design changes based on functional structure model, physical interaction model and physical structure model; AHMAD, et al [6], proposed an information structure framework consisting of requirement layer, function layer, component layer, and detail design process layer, in which elements were connected by hyperlinks across layers; HO and LI [7] utilized the bill of materials as a DCAM to evaluate the change likelihood cascading from the top to the bottom of the product structure.

In the meantime, the change-process-oriented DCAMs were directly modelled based on the change processes. CHUA and HOSSAIN [8] built the design structure matrix(DSM) to evaluate the change impact delivering from predecessor activities to successor activities, which is the component of activities, tasks and sub-tasks, to redesign the complex system; WYNN, et al [9], considered the information linkages from the process-oriented perspective and designed a diagram including tasks, deliverables and gateways using Graphic Evaluation and Review Technique; PASQUAL and DE WECK [10] introduced a multilayer network model integrating three coupled layers, namely, the product layer, change layer, and social layer; LI and MOON [11] defined the engineering change management (ECM) as a process and investigated how new product development(NPD) process and ECM process were interrelated, and how these interactions eventually affected the lead time, cost, and quality of an NPD project.

In terms of modelling types, the DCAM research can be divided into matrix-based model and network-based model. The most famous research of the matrix-based DCAM is the contribution from CLARKSON [12]. CLARKSON built the DSM according to the parameter relationships of design components. A further extension by HAMRAZ, et al [13], who modified the DSM to exclude the propagation loop path and self-dependent path; MORKOS, et al [14], added the requirement layer in DSM to control the requirement change propagation; LI and CHEN [15] utilized design dependency matrix(DDM) to organize the dependences between parameter relationships and functions; KOH, et al [16], modelled the effects of potential change propagation brought about by product components, change options and product requirements, which were built on the host of quality; COHEN, et al [17], described product in form of attribute and value and proposed the C-FAR(Change Favourable Representation) matrix to provide comparisons between the attributes of two entities.

Currently, the network-based DCAM is a hot spot of the change analysis researches. CHENG and CHU [18] considered the complex product as a weighted network of parts, subassemblies, or subsystems; In order to analyze the quality of characteristic variation propagation, DUAN and WANG, et al [19], built a QCs(Quality Characteristics)-linkage network based on the parameter relationships and constraint relationships; SHIAU and WEE [20] proposed a distributed change control workflow to maintain the consistence among designs in a collaborative design network; LEE, et al [21], introduced the analytic network process(ANP) approach to measure the relative importance of parts and modules in a modular product in terms of design change impacts and propagation; REDDI and MOON [22] developed a system dynamics model to study the complex interrelationships among various members in a collaborative supply chain to achieve effective and efficient engineering change management processes; OUERTANI [23] evaluated the change uncertainty conditions using variability, sensitivity and completeness of the nodes in the data dependencies network.

2.2 Change Propagation Prediction Method

There are at least five factors that affect the change propagation. To be specific, these factors include the transition matrix, degree of initiated change, timing of initiated change, point of initiated change, and redesign duration [8]. These factors vary from project to project based on the characteristics of the design activities and the change source. At the macro level, the effects of change propagation are grasped in three forms: (1) *ripple*, which triggers a small and quickly decreasing volume of changes; (2) *blossom*, a large number of changes which turns to be convergent within expected limits; and (3) *avalanche*, an increasing volume of changes that may not be brought to a conclusion after a given end point (within a certain time or number of changes). CLARKSON [12] predicted the risk of change propagation in terms of the propagation likelihood and the change impact, and built a change prediction method, namely CPM; To evaluate the impact of engineering change effect, MEHTA, et al [24], quantified the important attribute sets by the information entropy that was used for capturing knowledge in the past engineering changes; DUAN and WANG [19] adopted several variation mitigation methods, such as source uncoupling, variation compensation, variation deployment, linkage sensitiveness, linkage principle, superposing effect variation, and propagation path variation.

Change propagation path searching could be abstracted as a travelling salesman problem that is known to be NP-hard. Several optimization algorithms, such as genetic algorithm [25–27], breadth-first search method [28], multi-agent technology [29], have been utilized for searching the change propagation path. Briefly, most of the previous researches modelled the product as a network of elements(i.e., systems, components, or attributes) linked by their dependences(i.e., structural, behavioural, and functional parameters) to provide an available DCAM, and described the change propagation as the spread of knock-on effects along the linkages of this network.

2.3 Current Issues

Although previous methods are powerful tools for analysing change propagation, their ability is limited by the quality of input information used in the analysis. In general, the accuracy of change propagation prediction is mainly impacted by the following two issues.

(1) In most of the previous approaches, the critical inputs such as the propagation likelihood and the change impact are basically measured on a ratio scale based on the judgements of experts. Since such measurements are derived from judgements based on experience and personal understanding, those subjective measurements tend to deviate DCAMs from their real values. Inevitably, this subjectivity decreases the accuracy of change propagation prediction. Taking CPM, the most common change propagation analysis method, for example, the prediction accuracy is only around 30%. In this case, there is a great need for studying the objective measurements in DCAM.

(2) Currently, the principle of change propagation in the fine-grained nature has been seldom studied except for DUAN's work [19]. Generally, some conflicts resulting from the change propagation are not exposed on a large-scale basis, such as at the system level or the component level; while at the property/parameter level, these conflicts would be obvious. One reason for this may be the design margin, which is common in the subsystem and components, and would be a buffer to absorb the design variation. Analyzing the change propagation at the property/parameter level would help to evaluate the design margin of each component and the impact of change propagation objectively and quantitatively. In order to guarantee that the change propagation converges rapidly, the change would be routed purposely along the path with a larger design margin.

3 Procedure Overview

In this section, the change propagation prediction method is overviewed for searching and selecting the optimized change propagation paths. The procedure of this method is illustrated in Fig. 1 and explained as follows.

Step 1: Construct the design model of product as the basis of building DCAM according to the design theory and the relationships of the properties under design. The design model is the core of the whole product design process. Moreover its construction remains the same as the design properties are changing.

Step 2: Construct DCAM for the change propagation analysis on the basis of the design model built in Step 1. In DCAM, each node corresponds to one property in the design model, and accordingly the linkage between nodes corresponds to the relationship between properties. For the preparation of evaluating the change propagation intensity(CPI), the propagation likelihood on linkage and the design margin of node are respectively estimated from the product design change database and the previous design specification.

Step 3: Evaluate the initial CPI of each linkage to quantify the change propagation effects. The initial CPI is the evaluation of propagation intensity before the change is triggered. CPI varies with the design margin and variation in each change routing step.

Step 4: Search the optimal change propagation path with the ant colony optimization(ACO) algorithm, and select the path with the minimized maximum accumulated CPI.

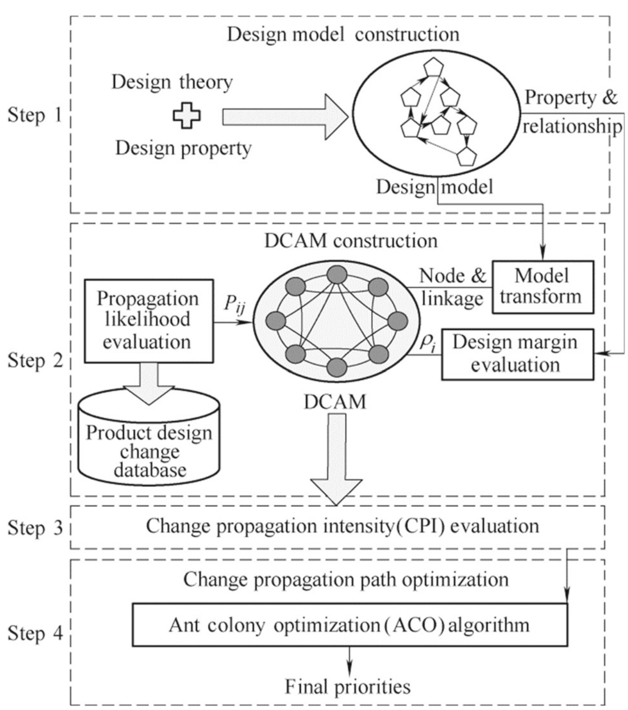


Fig. 1 Change propagation prediction method framework

The design change process could follow the optimal change propagation path to prevent the change avalanche and leaving the hub property unaffected. The change propagation prediction procedure will be detailed in the following sections.

4 DCAM Analysis

4.1 Design Model Construction

A design model is a graphic description of the design specification, which is responsible for organising all the design properties. Fig. 2 shows an elicitation from key design. In Fig. 2, the design properties are represented with circles; the relationships among properties are represented with rectangles. The properties and relationships are connected by lines with direction arrows. The design properties are clustered into a part identified by a dash line.

There are two types of relationships between properties, i.e., parameter relationship and constraint relationship. Generally, the parameter relationship corresponding to the physical law followed in design exists between the parent property and its children. In the design model, a directional linkage is drawn from the child property to the parent property. The arrow of the linkage points to the same direction of specification flow. The constraint relationship occurs between some properties sharing the same physical dimension, which tends to be an artificial rule or condition followed by designers for the purpose of part assembly, interface matching, performance guarantee, or function combination. The constraint relationship is represented by a non-directional link with double arrows in the design model. The parameter relationships could be formulated as $y = f(x_1, x_2, \cdots, x_n)$, where y is the parent property. Correspondingly x_i represents the ith child property, and then f is the principal function for generating the parent property from its child properties. In the parameter relationship, the value of parent property is determined by its child property; that is to say the parent property varies with the changes of each child property according to the physical laws, namely,

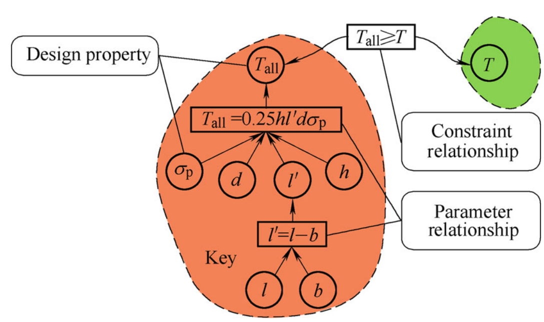


Fig. 2 Graphic description of partial design model

$dy = \partial f / \partial x_i dx_i$. Conversely, the extent of variation of any child property should be made some trade-offs as the parent property changes. Compared with the parameter relationship, the constraint relationship occurs between some properties sharing the same physics dimension, which tends to be artificial rules or conditions during the design process, i.e., $f(x_1, x_2, \cdots, x_n) = 0$. As one property changes, the other properties involved in the same constraint relationship should be altered, and the variation of each property should be identified according to the artificial rule. The construction process is given in detail in our previous article [30] and is not explained here.

Design model shows how the design properties in the bottom layer determine properties in the top layer. Once one property is changed, the other properties involved in the same relationship should be varied, and the variation of each property should be identified according to the relationships.

4.2 DCAM Construction

DCAM is an equivalent to design model in the form of network. Considering the complexity of the relationship to the change propagation analysis, the relationships are simplified as connections. Hence DCAM could be represented as $\boldsymbol{G} = (\boldsymbol{V}, \boldsymbol{E})$ as shown in Fig. 3, where $\boldsymbol{V} = (v_1, v_2, \cdots, v_n)$ is the node set corresponding to the properties, and $\boldsymbol{E}$ is the linkage set corresponding to the relationships. The arrow of the linkage is the direction of specification flow, which points to the successor node (parent property) from its predecessor node (child property). The value on the linkage identifies the corresponding CPI. DCAM has a motley structure.

In DCAM, a change can choose arbitrarily neighbour nodes to propagate. Leaf nodes lie on the bottom of DCAM, including geometry (such as diameter, stroke, thickness, length, and other geometrical parameters), material characteristics (such as elastic modulus, allowable stress, and stiffness), safety factors, and environmental properties (such as pressure, temperature, and air velocity). Root nodes lie on the top of DCAM and represent the design requirements that should be satisfied. The others which have both predecessor nodes and successor nodes are the transition nodes. According to their different roles in DCAM, the nodes have different change propagation patterns. As shown in Fig. 4(a), the initial change on a transition node v_i could choose the path numbered ① to pass its predecessor node, and the path numbered ② to pass its successor node or both. Sequentially, the next change propagation on node v_j would act as the previous step. In Fig. 4(b), the root node v_i could only choose the predecessor nodes to propagate. In contrast, the leaf node v_j shown in Fig. 4(c), could only choose its successor nodes to propagate. Generally, the routing path prefers to pass the predecessor nodes to decrease the change propagation impact. When the change occurs on a non-leaf node, it directly leads to its predecessor nodes to change, and further triggers the influence diffusion if there are coupled nodes on the change routing path. When a non-root node is changed, its influence may cause its upper-level nodes to change. It is necessary to judge whether the change impact can be reduced by the upper-level nodes or the sibling nodes.

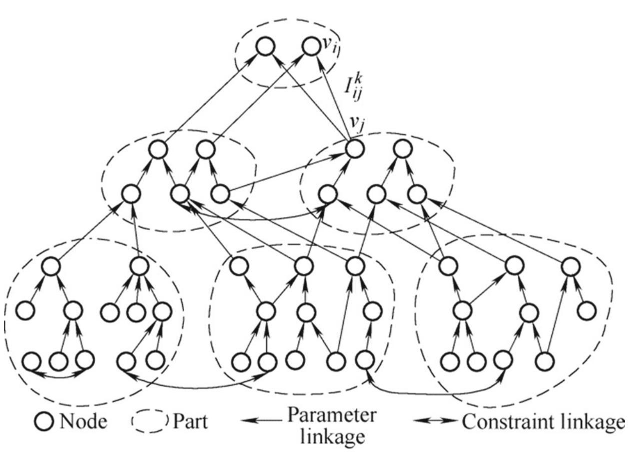


Fig. 3 DCAM in the form of network

Certain research efforts dealing with change propagation choose to tackle the problem by identifying the impacted data. For this purpose, DSM and adjacency matrices are often used in engineering change management. However, DCAM in the form of node-arc diagrams have several advantages over matrix-based visualisations.

4.3 DCAM Characteristic Analysis

From the perspective of system engineering, a complex product could be represented as a complex network composed of a number of elements, i.e., subsystems, components, and properties. The elements belonged to the same subsystem are tightly coupled; conversely, the cross-system connections are relatively sparse. In DCAM, each property is expressed as a node, and accordingly the relationship between two properties corresponds to the linkage between two nodes. Then the DCAM is represented as a network graph. After analysing the statistical properties of

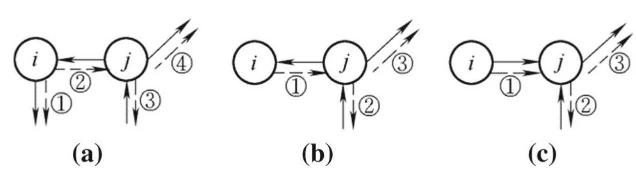


Fig. 4 Three patterns of change propagation

the DCAM's topology, the DCAM is believed to be a small-world network.

The small-world network is an intermediate form between regular network and stochastic network. The small-world network is characterised by two observables, i.e., characteristic path length L and clustering coefficient C. L is defined by the number of linkages on the shortest path between two nodes, averaged over all pairs of nodes as follows:

$$L = \frac{1}{n(n-1)/2} \sum_{1 \le i,j \le n} Dij, \tag{1}$$

where D_{ij} represents the number of linkages along the shortest channel between two nodes. To measure the fraction of connected neighbours of a node, the clustering coefficient is introduced as follows:

$$C = \frac{1}{n} \sum_{i=1}^{n} \frac{2t_i}{d_i(d_i - 1)}, \tag{2}$$

where d_i is the degree of node v_i, i.e., the number of the linkages connecting node v_i; t_i represents all possible connections of the neighbours of node v_i. A small-world network satisfies the following criteria:

$$\begin{cases} C > > C_{\mathrm{r}}, \\ L \ge L_{\mathrm{r}}, \end{cases} \tag{3}$$

where C_{r} and L_{r} represents the clustering coefficient and the mean distance of the stochastic network respectively. This stochastic network has the same number of nodes and degrees with the small-world network. The reason for this is that few long-range short cuts which connect the distant nodes with each other are added in the graph.

BRAHA and BAR-YAM [31, 32] found that the complex product development networks were dominated by some highly centralized nodes, characterized by the uneven distribution of nodal centrality measurements and the asymmetry between incoming and outgoing linkages. Later, They also considered the priority rules based on the in-degree and out-degree of nodes and showed that significant performance improvements could be achieved by focusing efforts on central nodes in the product development network [33]. They proved that if the product design process ran on the top of a stochastic network, a threshold behaviour that depended on the average degree of the network determined whether the product design was stable or not, and how much time it would take. In particular, their research indicates that the dynamics of product development is determined and controlled by the extent of (1) the correlation among neighbouring nodes, and (2) the correlation between the in-degree and out-degree of individual tasks.

The aforementioned characteristics determine the nature of the change propagation, which would be treated as the assessment factors to the prediction method.

5 Change Propagation Prediction

5.1 Change Propagation Intensity Evaluation

In DCAM, once the change is triggered on a certain node, this change would gradually spread to other neighbouring properties. The reachability of node is closely related to the propagation likelihood. Propagation likelihood is the quantification of the change propagation probability between two nodes. Generally, the change prefers the linkage that has greater propagation likelihood to spread.

The propagation likelihood P_{ij} could be estimated and mined from the previous design change recorded in design change database. P_{ij} is measured as the conditional probability of encountering a property v_j given a property v_i in design change database, i.e.,

$$P_{ij} = P(v_j|v_i) = \frac{P(v_i \cap v_j)}{P(v_i)} = P(v_i|v_j)\frac{P(v_j)}{P(v_i)} = P_{ji}\frac{P(v_j)}{P(v_i)}. \tag{4}$$

Normally, P_{ij} and P_{ji} are not equal, since $P(v_i)$ is generally unequal to $P(v_j)$ as shown in Eq. (4). If there is no linkage between the two nodes, P_{ij} equals to 0. Further, the sum of all the propagation likelihood values between node v_i and its neighbours equals to 1:

$$\sum_{j \in \boldsymbol{F}_i} P_{ij} = 1. \tag{5}$$

Except the propagation likelihood, the node degree and the long-chain linkage are both significant assessment factors to the change propagation due to the fact that the DCAM represents the attributes of small-world network. From validation, the node degree drastically affects the change diffusion. That is to say, the variation on the node with large degree would invoke amount of its neighbour nodes to change. To prevent from further spreading, remaining the nodes with great degree unchanged would be more effective than keeping any random node unchanged during the change propagation routing. Meanwhile, considering the specific topological attribute of small-world network, the rewired linkages introduce a few long-chain linkages, which normally connect two disparate design parts. Different from a large proportion of short-chain linkage in DCAM, the long-chain linkage imposes greater influence on the cross-part change propagation, which is not desirable. Then the long-chain linkage is assigned with a penalty coefficient.

Actually, the current value of property is not ideal; it tends to contain some design margin rather than exactly around the limitation. If the target property approximates its permitted value, the change will initialise the negative impact; otherwise, bring the positive impact. When the change in a target property brings a positive or small negative impact, no change propagation occurs and no impact mitigation is needed. On the contrary, when the negative impact is too big to be acceptable, searching for the optimal propagation path to converge the change propagation will be indispensable. The design margin equals to the difference between the permitted value and the current value. The design margin serves as a buffer to absorb a portion of variation and may further raise the next round of change propagation. According to the extent of change absorption, all nodes can potentially become absorbers or carriers or multipliers.

By synthesizing the aforementioned assessment factors, i.e., the propagation likelihood, node degree, long-chain linkage and design margin, CPI is introduced to quantify the intensity of change propagation. In the kth propagation step, CPI is defined as follows:

$$I_{ij}^k = \begin{cases} 0, & \Delta\rho_i^k \le \rho_i, \\ \omega_{\mathrm{s}}\left[\omega_{\mathrm{p}}(1-P_{ij}) + \omega_{\mathrm{d}}\dfrac{d_j}{\sum_{j\in \boldsymbol{F}_i} d_j}\right]\left(1-\dfrac{\rho_i}{\Delta\rho_i^k}\right), & \Delta\rho_i^k > \rho_i. \end{cases} \tag{6}$$

where ρ_i is the design margin of node v_i, and accordingly $\Delta\rho_i^k$ is the design variation of node v_i in the kth propagation step; $\boldsymbol{F}_i$ represents the set of the nodes which are impacted by the kth change propagation; ω_{p} and ω_{d} are the weights of the propagation likelihood and node degree, respectively and $\omega_{\mathrm{p}} + \omega_{\mathrm{d}} = 1$; $\omega_{\mathrm{s}}(\omega_{\mathrm{s}} \ge 1)$ is the penalty coefficient of long-chain linkage, which is used to artificially increase CPI in the cross-part change propagating.

If $\Delta\rho_i^k$ is not larger than ρ_i, the change would be absorbed and I_{ij}^k equals to 0. The greater CPI is, the larger the variation would be transmitted to the successor nodes via this linkage. In other words, there is a much larger extent for the change propagation to impact the other nodes along this linkage.

5.2 Change Propagation Path Optimization

The initial change can be diffused through different paths, even though most of nodes do not connect directly. To prevent an avalanche of changes, there is a need to search the optimal change propagation path before implementing the change.

CPI decreases with P_{ij} or ρ_i getting larger and d_j getting smaller. Actually, the smallest I_{ij}^k belongs to a certain leaf node connecting with only one parent node. This kind of leaf node is generally unchangeable, which presents material characteristics, safety factors, or environmental properties. Then the objective function is defined as the minimized maximum of accumulated CPI of the initial change on a node flowing to another node along the linkages:

$$\begin{array}{ll} \operatorname{argmin}(\max \sum_k I_{ij}^k), & k = 1, 2, \cdots, N, \\ \text{s.t.}(\Delta\rho_j^k - \rho_j) < 10^{-5}, & j \in F^k, \end{array} . \tag{7}$$

When the difference between the design margin and the design variation is under 10^{-5}, the change propagation is considered as converged and no further variation would propagate.

Due to the complexity of DCAM and the volatility of CPI, it is necessary to utilize a heuristic optimization algorithm for routing the change propagation. In this article, ACO algorithm is used to obtain the optimal change propagation path. After each iteration, the pheromone on each linkage is updated as follows:

$$\tau_{ij} = (1-\gamma)\tau_{ij} + \Delta\tau_{ij}, \tag{8}$$

$$\Delta\tau_{ij} = \sum_{l=1}^{N_{\mathrm{a}}} \Delta\tau_{ij}^l, \tag{9}$$

where τ_{ij} is the amount of pheromone deposited for transition from v_i to j; $\gamma(0 < \gamma < 1)$ is the pheromone evaporation coefficient; N_{a} is the ant number and $\Delta\tau_{ij}^l$ is the amount of pheromone deposited by lth ant, typically given for a travelling salesman problem by

$$\Delta\tau_{ij}^k = \begin{cases} QD_l & \text{if ant } l \text{ passes linkage } eij \text{ in its tour,} \\ 0 & \text{otherwise,} \end{cases} \tag{10}$$

where Q is a constant, and D_l is the value of objective function of the lth ant's tour.

Since the variation prefers the neighbour nodes with the maximum CPI to spread, the desirability of state transition η_{ij} is directly related to the CPI. Hence η_{ij} is defined as follows:

$$\eta_{ij} = I_{ij}^k. \tag{11}$$

After each iteration, η_{ij} is updated according to the current CPI. τ_{ij} and η_{ij} represent the attractiveness and trail level for the other possible state transitions. Then the lth ant moves from node v_i to node v_j with the probability

$$\Theta_{ij}^l = \begin{cases} \dfrac{[\tau_{ij}]^\alpha [\eta_{ij}]^\beta}{\sum\limits_{j\in \boldsymbol{F}_i^l} [\tau_{ij}]^\alpha [\eta_{ij}]^\beta}, & j \in \boldsymbol{F}_i^l, \\ 0, & \text{otherwise,} \end{cases} \tag{12}$$

where $\alpha(0 \le \alpha)$ and $\beta(\beta \ge 1)$ are parameters to respectively control the influence of τ_{ij} and η_{ij}. F_i^l is the node set of the allowed neighborhood of the lth ant at node v_i.

6 Case Study

Gear box offers a customized range of reduction ratios for a wide variety of applications in industries. The gear box is characterized by being well fitted to make the parts closely interact with each other. A subtle change in design most probably results in large-scale change propagation. Therefore, designers need to evaluate the impact before implementing the design change.

Different design properties are interdependent according to their geometric dimensions, function, behaviour, material, and other specifications. In order to construct the specification DCAM, the typical parts of a general two-step gear box was catalogued by nine types. There are seven parts (casing, shaft, seal, side cap, bearing, gear and key) in the gear box as shown in Fig. 5 and two extended parts (motor and coupling) which connected the box and affected the relative design parameters. After documenting the general decomposition of the product, the dependency matrix was developed between the main parts and the external parts. Table 1 highlights the long-chain linkages between different parts. For example, in order to design the casing width, the spatial specifications of the shaft, bearing and gear should be defined, such as the span of shaft b_{shaft}, the width of bearing b_{be} and the width of gear b. Conversely, the small variations on these three dimensions impact several properties of the casing.

The DCAM of gear box was constructed as shown in Fig. 6, which contains 91 nodes and 146 linkages (including 137 parameter relationships and 9 constraint relationships). For example, the bi-directional linkage connecting σ_f and σ_F represents a constraint relationship between σ_f and σ_F.

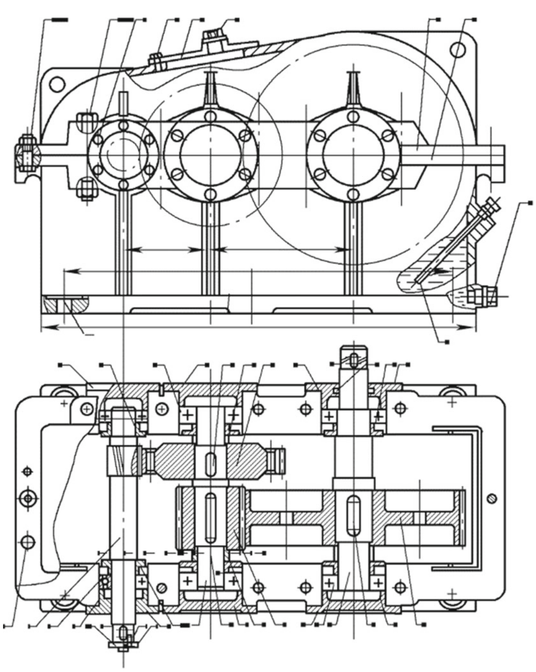


Fig. 5 Structure of a general two-step gear box

Table 1 Dependency matrix of gear box in part scale

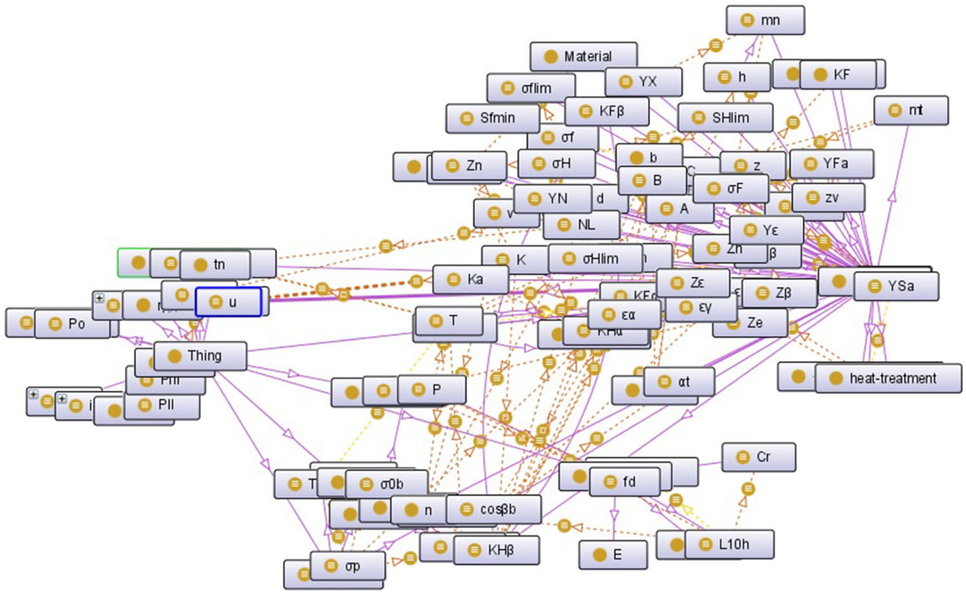
		1	2	3	4	5	6	7	8	9
1	Key	–		d_{shaft}						
2	Casing		–	b_{shaft}			b_{be}	b		
3	Shaft			–					P_0, n	
4	Seal		d_{ca}		–					
5	Side-cap		d_{ca}			–	d_{be}			
6	Bearing			T, n			–			
7	Gear							–	P_0, n	
8	Motor						η_{be}	η_{ge}	–	η_{co}
9	Coupling								P_0, n	–

Propagation likelihood supplies the direct change propagation assessment, which could be estimated using the data mining technology in the design change database. The propagation likelihood matrix of gear box's properties is shown in Fig. 7. The lightness of each element (i, j) is proportional to the magnitude of P_{ij} between node v_i and v_j (i.e., the darker elements represent the larger propagation probability). As shown in Fig. 7, most of the design properties are independent of others. According to the various lightness of the propagation likelihood matrix, the critical design properties could be judged. The change propagation path should choose the design properties which are less critical in DCAM to keep the premise of the same performance and functions.

Table 2 lists the node degree of gear box's DCAM. For example, the degree of σ_f (bending stress) is 10, where its out-degree is 1 and the in-degree is 10. According to Table 2, σ_f, σ_h and β all have the maximum degree. These three have tight connection to the gear design, and significantly influence the shaft, key, and bearing design, which causes the most out-degree and the minimum changeability. In other words, a small change of the gear's property may result in the variations of the shaft, key, even the casing and side cap.

Design margin is an additional impact assessment factor. In DCAM, the design properties with large design margins have enough tolerance to absorb most of the design variation, for example the stress correction factor of gear (currently the design margin of α is 0.41) in Table 2. During the design process, the shafts transform energy from the motor to the gear by rotating. Furthermore, the span between the driving and the driven shafts restricts the design parameters of the coupling, side cap and gear and their assembly location. Therefore, the strength of the shaft

Fig. 6 DCAM of a gear box



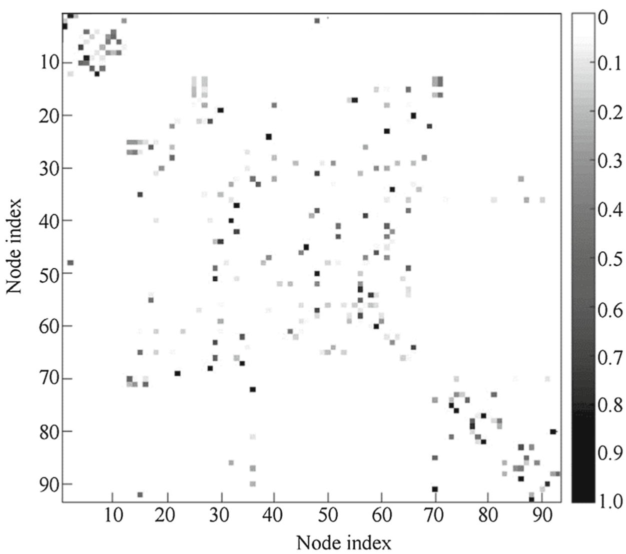


Fig. 7 Matrix of propagation likelihood P_{ij} between two nodes

has also high design margin in the initial model ($\alpha < 1$). Accordingly, the changes of many properties, such as the rotation speed, torque and centre distance, are weakened for the further propagation as the propagation passing the shaft. The shaft may be changed due to the receipt of large variation.

Synthesizing the above four factors, the assessment of a property's changeability is defined as CPI. The initial I_{ij}^0 matrix is shown in Fig. 8. If I_{ij}^k is large, the successor node v_j has low changeability and is recommended to be blocked to the propagation. For example, the element on line 90 column 36 has the largest CPI ($I_{ij}^0 = 0.784$) in Fig. 8. In the test product, the change of T (Tangential transmitted load) at node v_{36} has a strong effect on the whole product design.

In this case study, the initial change was supposed to be triggered on the shaft diameter (i.e. d_{shaft} in node v_{81}). Since the initial change is invoked, the most possible propagation path routes from the shaft via the key to the gear and subsequently to the bearing respectively, as highlighted by the red arrows in Fig. 9. Accordingly, the minimized maximum accumulated CPI is $0.599\,1 + 0.537\,1 + 0.628\,0 + 0.590\,5 + 0.608\,0 + 0.728\,1 = 3.690\,8$. The predicted propagation path corresponding to the minimized maximum accumulated CPI coincides with the actual change propagation path. This small variation impacts the key, gear, bearing and even side cap through the direct parametric relationships- and consequently impacts the whole gear box. The absorption range and alterative value of the change impacted property is shown in Table 3. As shown in Table 3, the variation is buffered or even absorbed by the properties with design margin. Even the shape of the shaft (i.e., shaft diameter d_{shaft} at node v_{81}) with modest degree is not very central in DCAM; the whole gear box would be changed when it varies.

7 Discussion

Except for the change propagation impact assessment, the prediction indices can be a guide to the design process. For example, the properties not passing the change propagation paths are the datum in design. Additionally, the properties with a large degree are usually the main undetermined parameters, because they provide more specification for the product functions. The seal and side cap are the most changeable from the degree perspective, because they are auxiliary parts in the gear reducer; their variations are

Table 2 **Degree d_j and design margin ρ_i on each node**

v_i	Property	d_i	ρ_i
1	Low-speed train value i_{low}	2	
2	Train value i_{total}	3	
3	High-speed train value i_{high}	1	
4	Power I P_{I}/kW	4	
5	Power II P_{II}/kW	4	
6	Power III P_{III}/kW	3	
7	Total power P_0/kW	3	100
8	Overall efficiency η_{total}	4	
9	Bearing efficiency η_{be}	3	
10	Coupling efficiency η_{co}	4	
11	Gear efficiency η_{ge}	1	
12	Motor version V_{mo}	2	
13	Coefficient A	4	
14	Coefficient B	4	
15	Face width b/mm	7	
16	Coefficient C	4	
17	Base circle helix angle β_{b}/(°)	3	
18	Pitch diameter d/mm	6	
19	Whole tooth depth h/mm	2	
20	Heat treatment	1	
21	Bending load factor K	5	
22	Overload factor K_{A}	2	
23	Contact load factor K_{F}	1	
24	Load-distribution factor $K_{\mathrm{F}\alpha}$	1	
25	Load-distribution factor $K_{\mathrm{F}\beta}$	5	
26	Load-distribution factor $K_{\mathrm{H}\alpha}$	3	
27	Load-distribution factor $K_{\mathrm{H}\beta}$	7	
28	Dynamic factor K_{v}	3	
29	Gear material	5	
30	Normal module m_{n}/mm	7	
31	Transverse module m_{t}/mm	3	
32	Rotation speed $n/(\mathrm{r} \bullet \mathrm{min}^{-1})$	4	
33	Number of load cycles N_{L}	5	
34	Min. bending safety coefficient S_{Fmin}	2	
35	Min. contact Safety coefficient S_{Hmin}	4	
36	Tangential transmitted load $T/(\mathrm{N{\cdot}m})$	8	12
37	Total working time t_{h}/h	1	10^4
38	Train value u	2	
39	Load-distribution factor $K'_{\mathrm{F}\alpha}$	4	
40	Speed $v/(\mathrm{mm} \bullet \mathrm{s}^{-1})$	3	
41	Geometry coefficient $Y_{\mathrm{F}\alpha}$	2	
42	Bending reliability coefficient Y_{N}	2	
43	Stress correction coefficient $Y_{\mathrm{S}\alpha}$	2	
44	Size coefficient Y_{X}	3	
45	Helix angle factor Y_{β}	4	
46	Min. helix angle factor $Y_{\beta\mathrm{min}}$	2	
47	Contact ratio coefficient Y_{ε}	3	
48	Number of teeth z	7	
49	Elastic coefficient Z_{E}	2	
50	Pitch point coefficient Z_{H}	3	
51	Contact reliability coefficient Z_{N}	3	
52	Equivalent teeth number z_{v}	4	
53	Helix angle factor Z_{β}	2	
54	Contact ratio factor Z_{ε}	4	
55	Transverse pressure angle α_{t}/(°)	2	
56	Helix angle β/(°)	10	
57	Equivalent transverse contact ratio $\varepsilon_{\alpha\mathrm{v}}$	5	
58	Transverse contact ratio ε_{α}	4	
59	Overlap ratio ε_{β}	8	
60	Total contact ratio ε_{γ}	2	
61	Bending stress σ_{f}/MPa	10	281
62	Allowable bending stress σ_{F}/MPa	5	
63	Bending fatigue limit σ_{Flim}/MPa	3	
64	Allowable contact stress σ_{H}/MPa	3	
65	Contact stress σ_{h}/MPa	10	243
66	Contact fatigue limit σ_{Hlim}/MPa	5	
67	Single tooth meshing num. per cycle N_{sc}	1	
68	Motor working condition	1	
69	Meshing precision	1	
70	Working condition	6	
71	Check standard	3	
72	Manufacturing accuracy	1	
73	Allowable transmitted load $T_{\mathrm{all}}/(\mathrm{N} \bullet \mathrm{m})$	3	100
74	Allowable bearing stress σ_{p}/MPa	3	26
75	Key version	1	
76	Key material	1	
77	Stress correcting factor α	2	0.41
78	Equivalent alternating stress $\sigma_{-1\mathrm{b}}$/MPa	3	
79	Equivalent midrange stress $\sigma_{0\mathrm{b}}$/MPa	2	
80	Shaft Span b_{shaft}/mm	1	15
81	Shaft diameter d_{shaft}/mm	3	1
82	Shaft material σ_{B}/MPa	2	
83	Basic dynamic load C_{r}/N	2	4180
84	Determination factor e	1	
85	Impulsive load coefficient f_{d}	2	
86	Basic rating life $L_{10\mathrm{h}}$/h	4	2910
87	Equivalent dynamic load P/N	3	
88	Bearing version	2	
89	Bearing overload/N	2	
90	Coupling version	1	
91	Allowable lifetime/h	3	
92	Shell width/mm	2	
93	Bore diameter/mm	1	

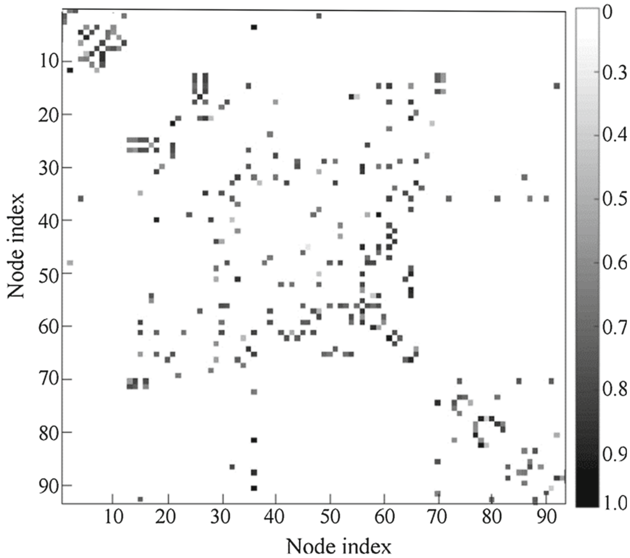


Fig. 8 Change propagation intensity I_{ij}^{0} before the initial change

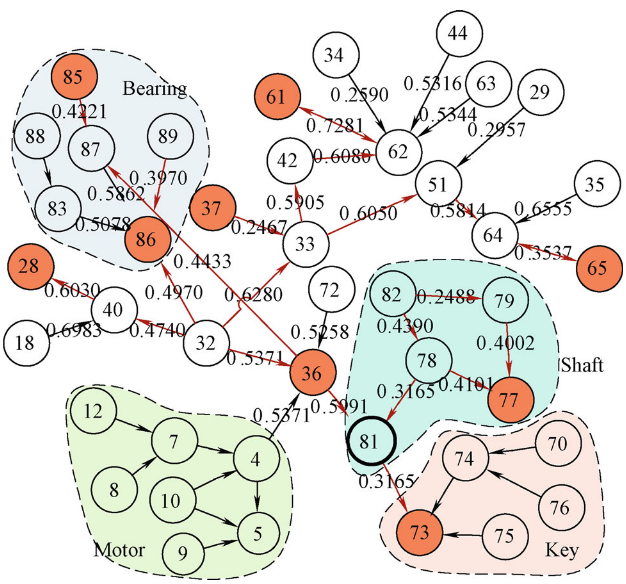


Fig. 9 Change propagation path with the initial change triggered on node v_{81}

usually determined by other related properties but less likely to impact the others. The designers can choose the properties that have less impact on the product to redesign or change on the premise of the same performance and functions.

In the change propagation prediction research, an important issue is how to deal with product-level requirements, such as output power. In this paper, the product-level performances are treated as possible external constraints on one or more properties of the product. Generally, these constraints are directly represented as the linkages between nodes in DCAM and translated into different specifications of the properties. The constraints should be so clear that the dependencies caused by those constraints are determined undoubtedly.

The proposed CPI is merely defined from the perspective of design, rather than from the product life cycle. The cost of change and the time consumption are essentially important to search for the optimal change propagation path. The evaluations of change cost involve the data from process and manufacture. The cost may come from material, energy, equipment, human resource and other related factors. All of these consumptions for producing a certain property should be converted into the corresponding cost. This conversion is complex in that it involves adequate knowledge of statistics, management and manufacture. Since the conversion of change cost varies with the technological conditions, it should be implemented for every original equipment manufacturer. The same is true for the evaluations of the time consumption of change.

The future work will focus on how the cost and time consumption of change influence the change propagation path planning. If change and time consumption costs are considered, the change propagation path planning is equivalent to a multi-objective optimization problem with the minimized maximum of accumulated CPI, cost and time consumption.

8 Conclusions

(1) The quantitative change propagation prediction approach is proposed to prevent propagation avalanche and determine the change propagation path for the mechanical product development before implementing the initial change.

(2) DCAM is organized on the level of detail design properties, which is characterized by the small-world network theory. Moreover, DCAM built on the design property network, which cuts down the man-made factors, provides the foundation to the objective and precise prediction.

(3) CPI as mathematical impact assessment metric is defined and verified, which includes propagation likelihood, node degree, long-chain linkage and design margin. This definition quantifies the change propagation effects and improves the precision of change propagation prediction.

(4) The application demonstrates the effectiveness of the proposed method. The proposed method can

Table 3 Change impacted properties and their variation absorption range

v_i	Property	Initial value	Absorption limit	Alterative value	Changed value	Change status
81	d_{shaft}/mm	35	1	−5	30	Invoked
73	T_{all}/(N • m)	596.8	−100	−85.3	511.5	Absorbed
78	$\sigma_{-1\text{b}}$/MPa	60	0	27.4	87.4	Amplified
77	α	0.59	0.41	0	0.59	Absorbed
82	σ_{B}/MPa	650	0	325	975	Amplified
79	$\sigma_{0\text{b}}$/MPa	102.5	0	45	147.5	Amplified
36	T/(N • m)	138.0	12	18.8	156.8	Buffered
87	P/N	3500	0	10	3510	Amplified
85	f_{d}	1.1	±0.1	0	1.1	Absorbed
33	N_{L}	5.76×10^8	0	-0.72×10^8	5.04×10^8	Amplified
37	t_{h}/h	33600	40 880	5200	38 400	Absorbed
42	Y_{N}	0.95	0	0.02	0.97	Amplified
62	σ_{F}/MPa	464	0	11	473	Amplified
61	σ_{f}/MPa	183	281	0	183	Absorbed
51	Z_{N}	1.19	0	0.14	1.25	Amplified
64	σ_{H}/MPa	816	0	41	857	Amplified
65	σ_{h}/MPa	595	221	0	595	Absorbed
32	n/(r • min^{-1})	200	0	–25	175	Amplified
40	v/(m • s^{-1})	0.94	0	–0.12	0.82	Amplified
28	K_{v}	1.08	0.01	0	1.08	Absorbed
86	$L_{10\text{h}}$/h	96 882	83 082	12 897	109 779	Absorbed

automatically generate a different result since the initial change varies, which can be widely used in the design of mechanical products.

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