Change Propagation Analysis Considering Design Margins

Arindam Brahma[1], David C. Wynn[2], Ola Isaksson[1].

[1]Department of Mechanical Engineering, Chalmers University of Technology, Sweden
[2]Department of Integrated Design and IRC for Smart Mobility and Logistics, King Fahd University of Petroleum and Minerals, Saudi Arabia

Abstract: Designers add margin to subsystems to absorb engineering changes but deciding how much margin to allocate and where remains poorly supported by existing change propagation methods. This paper presents M-CPM, a modelling approach which addresses this gap by modelling margin as a property that gates whether incoming changes to a component propagate to affect other components. The method is based on CPM, which is preserved as the zero-margin limiting case, and supports a margin-allocation analysis incorporating change source probabilities, costs of margin and DSM structure. A hairdryer example shows that the most valuable location for additional margin is not necessarily the most central subsystem or the most likely source of change as might be expected, but depends on the interaction between existing margin, change source likelihood, cost, and network position. Results demonstrate how M-CPM can support margin allocation considering cost to contain change propagation.

Keywords: Change Propagation, CPM, margin, design margin, risk, uncertainty

1 Introduction

Engineering changes in complex products often propagate beyond their point of origin due to interdependencies between system elements (Eckert et al., 2004). A challenge for teams managing engineering changes is to try to contain them, i.e., to prevent change propagation. One common strategy is to include design margin, such as thermal headroom, structural reserve, packaging space, electrical tolerance, software reconfigurability, or other forms of absorbing capacity (Brahma and Wynn, 2022). Margin can allow a subsystem to accommodate an incoming change without forcing downstream redesign. However, margin may increase cost, mass, volume, complexity, or development effort. Designers therefore face a practical allocation problem: where should limited margin be placed so that likely future changes are absorbed with the greatest system-level benefit?

While methods such as the Margin Value Method (MVM) address this at the parametric level (Brahma and Wynn, 2020), methods considering the component or subsystem level are scant in the literature. This paper addresses this question by extending the Change Prediction Method (CPM) to include margin as a node-level property. The proposed method, termed M-CPM, represents the probability that an incoming change exceeds the available margin of a subsystem and therefore continues to propagate. This models how margin acts as a gate on propagation through the subsystem and is incorporated into the CPM algorithm while preserving classical CPM as the special case of zero margin at all subsystems. The new method can be used not only to assess propagation risk, but also to support margin allocation decisions by combining subsystem margin, source-change probabilities, margin costs, and DSM structure.

The paper contributes in three ways. First, it formalises margin as a subsystem-level gate within CPM. Second, it shows how explicit margins change propagation-risk estimates compared with classical CPM. Third, it demonstrates how M-CPM can support margin allocation considering cost (penalty of applying margins) by identifying where additional margin produces the greatest reduction in expected propagation exposure. The method is illustrated using a previously published hairdryer example and the implications for redesign decision-making are discussed.

2 Background Literature

2.1 Change propagation and its influences

Engineering change propagation refers to the phenomenon in which a modification to one element of a design induces further modifications to other elements, primarily through the dependencies that link them (Eckert et al., 2004; Jarratt et al., 2010). The dependencies along which propagation can occur span multiple domains (Hamraz et al., 2012). Physical and geometric coupling between components is the most commonly modelled (Clarkson et al., 2004), but propagation also occurs along links between other domains such as requirements, functions and the structure that embodies them (Ahmad et al., 2012), through parametric relations between design variables (Yang and Duan, 2011), through the design tasks and information flows of the development process (Wynn et al., 2014), and into manufacturing and supply systems downstream of design (Plehn et al., 2016). Whether propagation actually occurs along a given dependency, however, is shaped by a number of factors (Brahma and Wynn, 2022), several of which are relevant to this paper. First, the type and properties of a connection influence its capacity to transmit change. For example, a spatial interface, an energy flow and a control signal differ in what kinds of change they transmit (Hamraz, 2013; Rutka et al., 2006). Second, the magnitude of an initiating change may have a direct impact on whether a change propagates. Small modifications may often get absorbed without propagation, while larger ones may force redesign (Brahma and Wynn, 2021). Third, the architecture in which subsystems are organised influences how far change may travel. For example, modular architectures with well-defined interfaces may restrict change within subsystems, whereas integral architectures may require it to be propagated across the product due to tight integration (Koh et al., 2015). Fourth, components differ in their sensitivity to change, so that the same incoming change may force redesign in one element and pass through another with no further consequence (Wei et al., 2016). One driver of this sensitivity is the available margin in the element (Eckert et al., 2019). While the first three factors are well represented in literature, the fourth factor (available margin) has received considerably less attention. Methods of change propagation assessment rarely consider margins explicitly, whereas methods of margin allocation and sizing in literature are generally not aimed at change propagation assessment (Brahma and Wynn, 2020).

2.2 Design margins in change propagation

The notion that margins significantly influence propagation is well represented in the change propagation literature. Eckert et al. (2004) observed that components with substantial margin can absorb incoming changes without forcing further redesign, and that such components consequently behave differently in propagation networks than their topology alone would suggest. Giffin et al. (2009), in an empirical study of change events in a complex industrial dataset, classified components into roles using Eckert et al. (2004)'s terminology: absorbers, multipliers, carriers, and constants, which captures this behavioural difference. An absorber receives change without transmitting it; a multiplier receives change and amplifies the output; a carrier transmits change without itself being modified; a constant does neither. Eckert et al. (2019) develop a conceptual framework distinguishing two constituents of a margin: buffer and excess and discuss how margin accumulates and is consumed across the product lifecycle. A smaller body of work has incorporated margin more explicitly into models of propagation. Brahma and Wynn (2021) study the mechanisms by which margins shape propagation in mechanical design. Long and Ferguson (2020) develop a margin-based formulation in which absorbing capacity is tracked through the direct change likelihoods themselves: each modification consumes excess by progressively increasing the edge weights of the affected components, allowing the analysis to forecast how propagation behaviour evolves over a system's lifecycle as multiple successive modifications are made. The method, however, looks at margin as a property of the dependency (the edge) rather than the subsystem (the node). This is contrary to the view of this paper as stated earlier. These contributions establish margin as an important attribute of the design elements which influence change propagation within the literature and provide partial mechanisms for representing it.

A separate strand of literature focuses on margin as a property of a design which is to be sized or allocated in order to mitigate uncertainties or to achieve design objectives. Margin allocation methods address questions such as how much margin should be placed on each parameter or subsystem to achieve a given level of robustness, reliability, or future flexibility (Thunnissen and Tsuyuki, 2004). Margins may also be allocated to mitigate uncertain future requirements, manufacturing variation, or operational loads (Helton, 2011). These methods primarily support margin sizing and trade-off under uncertainty, but they do not model whether a specific engineering change initiated in one component will be absorbed or propagated through a product's dependency structure. Brahma and Wynn (2020) propose the Margin Value Method (MVM) that quantifies the design value of margin held in particular parameters, supporting decisions about where to allocate additional margin and where existing margin can be safely removed. MVM operates at the parameter level and evaluates the value of excess margin for design improvement, but it does not predict component- or subsystem-level change propagation. Al Handawi et al. (2024) extend MVM for design-space exploration, ranking concepts by trading change absorption capability against performance impact. This supports concept evaluation but does not predict component-level propagation paths and risks. Jacobson and Ferguson (2023) similarly relate margins to change absorption, but at the decision-variable level, using Complete Flexibility Ranges to show how far a variable can change before requirements or constraints are violated. This supports identifying local change absorbers but does not model multi-step propagation through a product. The margin allocation and trade-off approach of Guenov et al. (2018) introduces a margin space analogous to design space and trades margins against design parameters. This approach supports exploration of feasible margin and design combinations, but it is not formulated to calculate propagation likelihoods or risks arising from dependencies between components. Multidisciplinary optimisation approaches have also been used to size margins under parameter uncertainty (Bianchi et al., 2018; Takamatsu et al., 1974), and Monte-Carlo and probabilistic methods have been used to determine margin requirements for specific systems (Pagani, 2004). The optimisation-based methods address robustness and feasibility, rather than the containment or mitigation of change as it propagates through a product architecture. A recent review of margin literature can be found in Brahma et al. (2023).

In summary, margin is recognised as a strong influence on change propagation, yet no propagation method represents it as a node-level property and no margin allocation method predicts propagation through the dependency structure.

2.3 Position of the present work

The present work addresses the gap between the recognised influence of design margin on change propagation and the methods by which propagation is most commonly analysed. We introduce M-CPM, a margin-aware change propagation assessment method that builds on the likelihood, impact, and risk logic of Clarkson et al. (2004)'s CPM, while explicitly representing the capacity of subsystems to absorb incoming change. In M-CPM, each subsystem carries a margin threshold, and the magnitude of incoming change is treated as a random variable. The resulting node-level gate represents the probability that the incoming change exceeds the available margin. Dependencies therefore define the possible routes of propagation, while subsystem margins determine whether change is likely to continue through those routes.

This formulation is important because absorption is a property of the subsystem receiving change, not only of the dependency through which change arrives. Two subsystems may have similar dependency structures but different available margins, and therefore different tendencies to absorb, carry, or amplify change. By representing margin explicitly, M-CPM allows propagation risk to be assessed as a function of both product architecture and the distribution of design margin within that architecture.

The remainder of the paper develops the formalism (Section 3), illustrates it on the hairdryer example used in several articles on change propagation, such as by Clarkson et al. (2004) and Hamraz et al. (2012) in Section 4, and discusses implications for redesign decision-making in Section 5.

3 Change Propagation Method with Margin (M-CPM)

In M-CPM, the first step is to elicit the dependencies between subsystems using a design structure matrix. As in Clarkson et al. (2004)'s CPM, each dependency is assigned a direct likelihood and a direct impact value, where columns denote the subsystem in which a change originates and rows denote the subsystem affected by that change. Thus, $l_{j,k}$ represents the direct likelihood that a change initiated in subsystem k affects subsystem j, while the impact value $i_{j,k}$ represents the relative redesign effort in j if that propagation occurs. In CPM, the corresponding direct risk $r_{j,k}$ representing the risk that a change initiated in subsystem k directly forces redesign of subsystem j, is defined as:

$$r_{j,k} = l_{j,k} i_{j,k} \qquad (1)$$

Clarkson et al. (2004) then calculate combined likelihood, combined risk and combined impact by tracing change through feasible direct and indirect propagation paths in the dependency network. The combined likelihood $L_{b,a}$ represents the probability that a change initiated in subsystem a eventually affects subsystem b. The combined risk $R_{b,a}$ is calculated as:

$$R_{b,a} = 1 - \prod_u (1 - r_{b,u}) \qquad (2)$$

where the product is taken over the relevant penultimate subsystems u in the propagation chains from a to b, and:

$$r_{b,u} = s_{u,a} l_{b,u} i_{b,u} \qquad (3)$$

Here, $s_{u,a}$ is the likelihood that change reaches subsystem u from the initiating subsystem a, $l_{b,u}$ is the direct likelihood of change propagating from u to b, and $i_{b,u}$ is the direct impact of such propagation. The combined impact is then obtained as:

$$I_{b,a} = \frac{R_{b,a}}{L_{b,a}} \qquad (4)$$

M-CPM uses the same DSM convention and the same interpretation of risk in terms of likelihood and impact but introduces a node-level quantity representing each subsystem's capacity to absorb incoming change before passing it onward. For each subsystem u, let m_u in [0,1] denote a margin threshold, interpreted as the largest relative change that the subsystem can absorb without further propagation. Let δ denote the magnitude of the change arriving at that subsystem, treated as a random variable on [0,1]. The probability that the arriving change exceeds the available margin is defined as the margin gate:

$$g_u = P(\delta > m_u) \qquad (5)$$

This quantity expresses the likelihood that subsystem u does not absorb the incoming change locally. When g_u is close to 1, the available margin is small relative to typical change magnitudes, and change is likely to continue propagating. When g_u is close to 0, the subsystem is likely to absorb the change.

In the present implementation, δ is assumed by default to follow a truncated normal distribution on [0,1], with mean μ and standard deviation σ. The choice of truncated normal here is only for demonstration; any other bounded distribution may be substituted if it better reflects knowledge of change magnitudes. Under this assumption, the gate for subsystem u is calculated as:

$$g_u = \frac{\left\{\Phi\left(\frac{1-\mu}{\sigma}\right) - \Phi\left(\frac{m_u-\mu}{\sigma}\right)\right\}}{\left\{\Phi\left(\frac{1-\mu}{\sigma}\right) - \Phi\left(\frac{0-\mu}{\sigma}\right)\right\}} \qquad (6)$$

where $\Phi(.)$ is the standard normal cumulative distribution function. The same formulation can also be used with other bounded distributions if they better reflect expectations about change magnitude in the system under study. For example, a uniform distribution represents the case in which all change magnitudes within a specified range are considered equally likely;

$$g_u = max\left(0, \frac{b - m_u}{b - a}\right), for\ m_u \in [a, b] \qquad (7)$$

The margin gate is then incorporated as a subsystem-level modifier on propagation through intermediate subsystems. The direct likelihood $l_{c,u}$ describes the dependency from subsystem u to subsystem c, while $g_u$describes whether the incoming change exceeds the margin available in u, as defined in Eq. 1. Thus, for paths passing through u, the continuation term is attenuated by g_u, without redefining the direct likelihood or impact values.

To make the recursive notation explicit, let $L^m(u, b)$ denote the combined likelihood that a change currently present at subsystem u eventually reaches subsystem b, once margin is taken into account. For each direct successor c of u, $L^m(c, b)$ is the same quantity evaluated from c to b. It is not an additional input parameter, but the recursively calculated likelihood over the remaining propagation paths from c to b. The recursion terminates when the target subsystem b is reached; paths with no admissible route to b, or paths beyond the selected path length, do not contribute to the combined likelihood.

In the recursive implementation, if u is an intermediate subsystem on a path from a to b, the continuation term associated with each child branch is modified from the classic CPM form by multiplying it by g_u. Combined likelihood is therefore written as:

$$L^m(u, b) = 1 - \prod_c \left[1 - g_u l_{c,u} L^m(c, b)\right], \qquad (8)$$

and the combined risk is written as:

$$R^m(u, b) = 1 - \prod_c \left[1 - g_u l_{c,u} R^m(c, b)\right]. \qquad (9)$$

Here, $l_{c,u}$ denotes the direct likelihood of change propagating from subsystem u to subsystem c, while L^m and R^m denote the combined likelihood and combined risk with margin taken into account. The gate is applied only at intermediate subsystems, because the present formulation is intended to represent whether a subsystem passes change onward rather than whether the initiating or final affected subsystem absorbs it.

A consequence of the formulation is that when all margins are zero (g_u = 1) for every subsystem, the modified recursion reduces directly to the original CPM calculation. M-CPM therefore generalises CPM as it incorporates margin information when available and returns classical analysis when it is not.

For interpretation, the method produces a margin-incorporated combined risk matrix R^m, from which incoming and outgoing change propagation probabilities may be summarised exactly as in CPM. The practical purpose, however, is different: by varying the margin thresholds m_u, the analysis can reveal which subsystems most strongly restrict downstream propagation and therefore where additional margin is most valuable. This supports targeted margin allocation and reduces overdesign. A modelling choice in this formulation is that m_u is a property of the subsystem alone, independent of the type or source of the incoming change. In practice, absorption capacity may vary with change type; extending the gate accordingly, for example by defining m_u per change type. This is left for future work.

4 Illustrative Example

4.1 Product model and dependency structure

The hairdryer, a generic illustration of which is shown in Figure 12, is decomposed into six subsystems: fan (1), motor (2), heating unit (3), casing (4), control system (5), and power supply (6). The direct change likelihood matrix l and direct change impact matrix i (Table 6) capture the strength of pairwise design dependencies as elicited from designers; entries in row j, column k represent the likelihood (or impact) that a change initiated in subsystem k forces a redesign of subsystem j. Both matrices use values in the unit interval [0,1] and are taken as published in Hamraz et al. (2012).

Figure 12. Generic illustration of a hairdryer.

Table 6. Direct likelihood l (left) and direct impact i (right) for the hairdryer DSM. Empty cells denote absent dependencies.

	Element	1	2	3	4	5	6
1	Fan		0.6	0.9	0.9		0.3
2	Motor	0.6			0.6	0.3	0.9
3	Heating	0.6			0.6	0.3	0.9
4	Casing	0.9	0.9	0.6			0.3
5	Control	0.6		0.3	0.3		
6	Power		0.3	0.3			

	Element	1	2	3	4	5	6
1	Fan		0.6	0.6	0.3		0.3
2	Motor	0.3			0.3	0.3	0.9
3	Heating	0.3			0.3	0.3	0.6
4	Casing	0.9	0.6	0.6			0.3
5	Control	0.3		0.3	0.3		
6	Power		0.9	0.9			

The interconnection pattern is dense and asymmetric. The casing has incoming dependencies from every other subsystem, reflecting its physical role as a structural and thermal interface that must be locally redesigned whenever an internal component changes shape, mass, position, or thermal output. The power supply, by contrast, is the dominant outgoing source: a change to it has a direct likelihood of 0.9 and an impact of at least 0.6 on both the motor and the heating unit, since both depend on its electrical specifications. The control system is comparatively decoupled from the rest of the structure, with relatively few outgoing dependencies and a modest set of incoming dependencies. This reflects that changes to the control system are assumed to have limited effects on the physical subsystems, while changes elsewhere require only slight changes to the control subsystem.

4.2 Classic CPM analysis

We first apply the classic CPM algorithm to this DSM with 6 propagation steps, which is sufficient for convergence for a six-node graph. Increasing the path-length limit beyond this yields negligible additional contribution. The combined risk matrix R is shown in Table 2.

Table 7. Combined risk matrix R from classic CPM. The table to the right shows the aggregated incoming and outgoing risks based on the row and column averages, respectively and the ratio between the two averages.

#	Element	1	2	3	4	5	6
1	Fan		0.73	0.74	0.69	0.39	0.89
2	Motor	0.60		0.62	0.62	0.24	0.92
3	Heating	0.56	0.57		0.54	0.23	0.80
4	Casing	0.93	0.83	0.91		0.45	0.96
5	Control	0.43	0.56	0.51	0.47		0.73
6	Power	0.64	0.59	0.60	0.63	0.30	

Incoming	Outgoing	Ratio
0.57	0.53	1.07
0.50	0.55	0.91
0.45	0.56	0.80
0.68	0.49	1.38
0.45	0.27	1.66
0.46	0.72	0.64

Aggregating the matrix for each of the subsystems yields the following average incoming risk (mean of row entries) and the average outgoing risk (mean of column entries). This provides a compact view of each subsystem's role in the propagation network. Under classic CPM, the casing has the highest incoming risk, 0.68, and is therefore the most susceptible subsystem, while the power supply has the highest outgoing risk, 0.72, and is therefore the most influential change source.

The incoming to outgoing risk ratio gives a first indication of absorber or multiplier behaviour. Under classic CPM, this ratio ranges from 0.64 for the power supply to 1.66 for the control system. However, this distinction arises only from the DSM topology, since CPM has no explicit representation of subsystem margin. Two components with identical dependency patterns would receive identical CPM analyses, even if one were a heavily over-designed structural element with substantial absorption capacity and the other an optimised part with no margin to spare.

4.3 Margin specification

To apply the margin gate in the hairdryer case, we associate with each subsystem a margin threshold $m_u \in [0,1]$, representing the fraction of the subsystem's design that can absorb a change without forcing a downstream redesign. The change magnitude δ is modelled as a truncated normal distribution on [0,1] with mean $\mu = 0.30$ and standard deviation $\sigma = 0.15$, representing typical incoming changes of moderate magnitude with realistic spread; the truncation handles the boundary conditions that δ cannot be negative or exceed unity. The margin gate $g_u = P(\delta > m_u)$, i.e., the probability that an incoming change exceeds u's available margin and therefore propagates onward, is computed analytically from the truncated normal using Eq. 6. For example, with $m_1 = 0.20$ for the fan, this evaluates to $g_1 = 0.76$.

This reflects that a fan with only 20% design margin will almost certainly fail to absorb a typical incoming change of mean magnitude 0.30. Conversely, for the control system with $m_5 = 0.60$, the same calculation yields $g_5 \approx 0.02$, which is a near-fully-closed gate, reflecting that 60% of the control subsystem design can absorb almost any plausible incoming change before redesign is required. The margin values used here are illustrative. They are summarised in Table 8 alongside the resulting margin gates. In a production application of the method, m_u would be elicited from designers in the same way as the direct likelihood and impact values: through structured interviews and potentially from historical change records, with appropriate uncertainty representation if the available information is limited.

Table 8. Margin specification and resulting gate values.

	Subsystem	m_u	g_u
1	Fan	0.20	0.76
2	Motor	0.40	0.26
3	Heating unit	0.55	0.05
4	Casing	0.50	0.09
5	Control system	0.60	0.02
6	Power supply	0.30	0.51

The fan, with the smallest assumed margin, has a near-fully-open gate (0.76); the control system, with the largest assumed margin, has a near-fully-closed gate (0.02). The heating unit, casing, and motor sit at progressively more closed gates owing to their thermal, structural, and mechanical absorption capacities. Note that the gates are not monotonic in the margin values alone: g_u depends jointly on m_u, μ, and σ, and the rapid drop from $g_6 = 0.51$ at $m_6 = 0.30$ to $g_3 = 0.05$ at $m_3 = 0.55$ reflects the steep tail of the truncated normal beyond $\mu + \sigma$.

4.4 Analysis of propagation results considering margins in subsystems

Application of the CPM algorithm considering margin in the nodes, with the parameters of Section 4.3, produces the combined risk matrix R^m shown in Table 4. The aggregated incoming and outgoing risks for each component, alongside the classic CPM values, are summarised in Table 5.

Table 9. Combined risk matrix R^m from CPM with margin on subsystems.

	Element	1	2	3	4	5	6
1	Fan		0.39	0.56	0.32	0.04	0.20
2	Motor	0.20		0.26	0.29	0.09	0.82
3	Heating	0.21	0.19		0.31	0.10	0.58
4	Casing	0.83	0.73	0.75		0.08	0.44
5	Control	0.19	0.11	0.23	0.22		0.08
6	Power	0.05	0.27	0.30	0.08	0.03	

Table 10. Average incoming and outgoing risk per subsystem, classic CPM and M-CPM, with absorber/multiplier ratios.

#	Subsystem	Incoming			Outgoing			Ratio In/Out	
		CPM	M-CPM	Δ	CPM	M-CPM	Δ	CPM	M-CPM
1	Fan	0.57	0.25	**-56%**	0.53	0.25	**-53%**	1.09	1.02
2	Motor	0.50	0.28	**-45%**	0.55	0.28	**-49%**	0.91	0.98
3	Heating	0.45	0.23	**-49%**	0.56	0.35	**-38%**	0.80	0.66
4	Casing	0.68	0.47	**-31%**	0.49	0.20	**-58%**	1.38	2.30
5	Control	0.45	0.14	**-69%**	0.27	0.06	**-79%**	1.67	2.40
6	Power	0.46	0.12	**-73%**	0.72	0.35	**-51%**	0.64	0.35

The method reduces to CPM at zero margin. Every entry of R^m is smaller than or equal to the corresponding entry of R, and the two become equal as m_u becomes 0. We confirmed this in a separate run with all margins set to zero (not reported here). The M-CPM matrices match the classic CPM values exactly. The proposed method adds a margin dimension to the CPM algorithm.

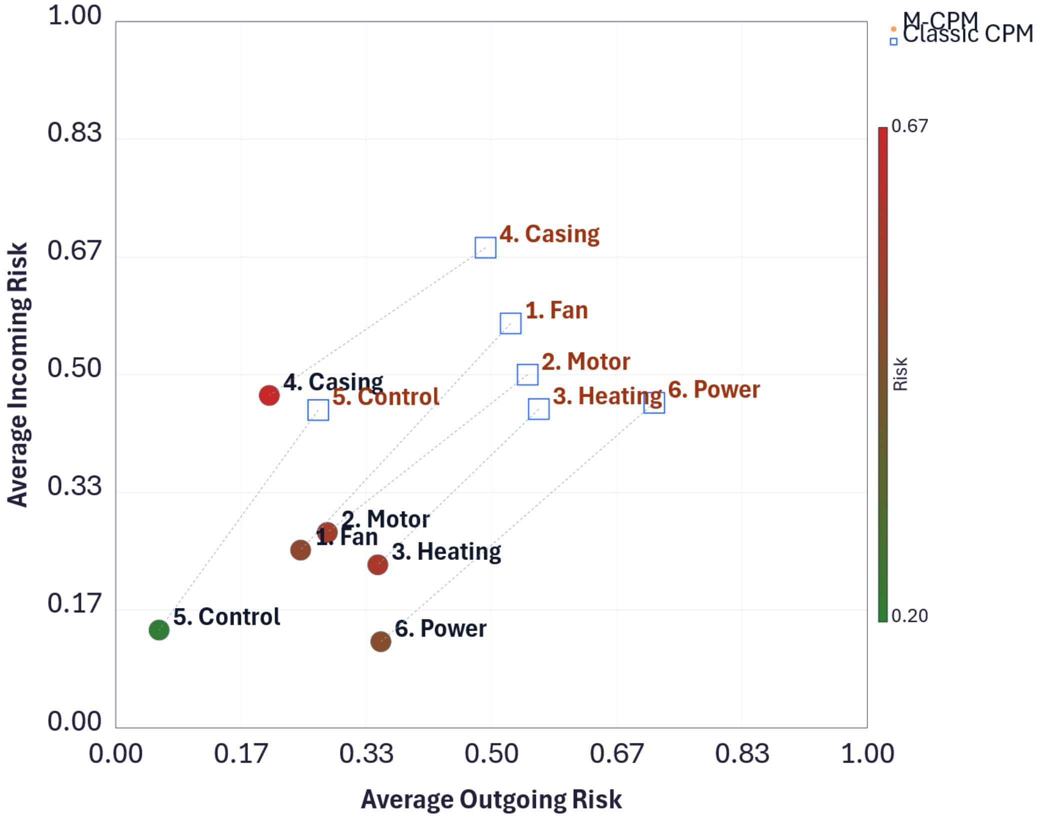

Figure 13. The average incoming risk and outgoing risks plotted for both CPM and M-CPM algorithms.

Reductions are uneven across subsystems. The drop in incoming risk ranges from 31% for the casing to 73% for the power supply. The pattern reflects the gates of the intermediate subsystems on the paths leading to each affected component. Paths arriving at the power supply pass through several heavily margined intermediates, such as the heating unit, control system and casing, which absorb most of the propagating change before it arrives. Paths arriving at the casing pass through fewer absorbing intermediates, since the casing sits at the end of most chains rather than in their middle. The casing's own gate does not affect the probability of change reaching the casing in this formulation; it affects the probability that change continues beyond the casing when the casing is an intermediate subsystem.

The absorber/multiplier effect amplifies. Under classic CPM, the incoming-to-outgoing risk ratios fall in a narrow band from 0.64 (power) to 1.67 (control). Under M-CPM, the band widens to 0.35 (power) to 2.40 (control), and the casing joins the control system as a clear absorber at 2.30. The power supply emerges as a sharper multiplier because incoming change is heavily filtered by the intermediates while its own outgoing paths are filtered only by its own moderate gate. This matches the engineering intuition that components carrying substantial design margin should appear as absorbers rather than as transmission paths, a distinction classic CPM cannot make because it has no node-level description.

The susceptibility ranking changes. Under classic CPM, the order of incoming risk is *Casing* > *Fan* > *Motor* > *Power* > *Heating* ≈ *Control*. Under M-CPM it becomes *Casing* > *Motor* ≈ *Fan* > *Heating* > *Control* > *Power*. The power supply moves from fourth place to last, because most paths that reach it pass through the most strongly margined intermediates, i.e., it is protected not by its own margin but by absorbing margin between it and the rest of the product. The outgoing-risk ranking, by contrast, stays the same under both analyses (*Power* > *Heating* > *Motor* > *Fan* ≈ *Casing* > *Control*), which is consistent with the M-CPM gate-at-intermediate formulation. In other words, outgoing rankings depend mainly on a subsystem's own gate and the topology of its outgoing dependencies, not on what gates lie further downstream.

4.5 Implications for redesign decisions

Adding consideration of margin leads to more nuanced redesign recommendations than classic CPM.

Under classic CPM, both the casing and the power supply appear as priority concerns. The casing because change is likely to reach it, the power supply because change initiated there is likely to spread. Classic CPM offers no basis for choosing between them, because it does not represent the existing physical robustness of either component.

Under M-CPM the picture is more nuanced. The casing's apparent exposure to change is largely absorbed by its own margin: with $g_f = 0.09$, roughly 91% of arriving change is absorbed before redesign is needed. The priority therefore shifts to the power supply and the motor, which combine high outgoing risk with limited absorbing capacity, and therefore act as the main carriers of change into the rest of the product. A customer requirement targeting the power supply, say, due to a new voltage standard, is identified by both analyses as a high-impact change, but only M-CPM indicates which downstream consequences are already absorbed by margin and which are not, and therefore where redesign effort should actually go. The analysis also identifies the control system, casing, and heating unit as the natural absorbers in the architecture. This suggests two complementary courses of action. Where additional margin can be added at modest cost, these are the components where the investment will produce the largest reduction in propagated risk. Where margin already exists, it should be recognised and preserved, since optimising these subsystems for cost or weight may remove the buffering on which the rest of the product depends to absorb uncertainties.

5 Margin Allocation Using Source Probabilities and Cost

The preceding analysis shows how a given margin vector changes propagation risk. In practice, however, designers face an allocation problem: given limited resources for adding margin, which subsystem should receive additional margin to reduce expected future propagation most effectively? To illustrate how M-CPM can support this decision, we extend the hairdryer example by assigning each subsystem a source-change probability and a relative cost of adding margin. The source-change probabilities represent the expected frequency with which future changes originate in each subsystem. The cost values represent the relative design penalty of increasing margin, such as additional mass, volume, material cost, development effort, or reduced performance. The expected propagation exposure of the system was then computed by weighting each source column of the M-CPM risk matrix by the corresponding source probability. For each subsystem, we increased its margin by 0.10 while holding all other inputs constant, recomputed M-CPM, and recorded the reduction in expected propagation exposure. Dividing this reduction by the relative cost gives a cost-adjusted margin value.

In this illustrative example, the source probabilities and cost coefficients are assumed values chosen to demonstrate the calculation. In an industrial application, source probabilities could be estimated from historical engineering change records, warranty data, requirement volatility, supplier-change frequency, or expert elicitation. Cost coefficients could similarly be derived from design constraints or business priorities.

Let q_j be the probability that the next engineering change originates in subsystem j, and m is the margin vector denoting the margin in all the subsystems; the expected system-level propagation exposure is then:

$$E(m) = \sum_{j=1}^{n} q_j \sum_{\substack{i=1 \\ i\neq j}} R_{ij}^{m}(m) \qquad (10)$$

Where $R_{ij}^{m}(\mathbf{m})$ is the M-CPM combined risk that a change originating in subsystem j affects subsystem i under margin vector $\mathbf{m}$. To evaluate the value of adding margin to subsystem u, we define a perturbed margin vector m^{+u}:

$$m^{+u} = (m_1, m_2, \ldots m_u + \Delta m, \ldots, m_n) \qquad (11)$$

Where Δm is a small candidate margin increment. The marginal propagation reduction from adding margin to the subsystem u is:

$$B_u = E(m) - E(m^{+u}) \qquad (12)$$

If c_u is the relative cost of adding margin to subsystem u, the cost-adjusted margin value is:

$$V_u = \frac{B_u}{c_u} \quad (13)$$

Table 11. Cost-adjusted ranking of candidate margin allocations based on expected reduction in weighted propagation exposure.

Rank	Subsystem	Source probability q_s	Cost	Margin tested	Risk reduction	Benefit/cost
1	Fan	0.12	1.00	0.20 to 0.30	0.1120	0.1120
2	Motor	0.14	1.30	0.40 to 0.50	0.0851	0.0655
3	Power	0.32	1.50	0.30 to 0.40	0.0265	0.0177
4	Casing	0.12	2.00	0.50 to 0.60	0.0280	0.0140
5	Heating	0.22	1.80	0.55 to 0.65	0.0233	0.0130
6	Control	0.08	0.50	0.60 to 0.70	0.0010	0.0021

Table 6 shows that the fan gives the highest return for an additional 0.10 margin, adjusted for cost, followed by the motor. The ranking is not explained by DSM position or change probability alone. For example, the power supply has the highest source probability and remains the strongest outgoing driver, but additional margin there gives a lower return because much of its downstream propagation is mitigated by other subsystems. Conversely, the control subsystem is cheap to add margins to, but is already weakly coupled and well protected, so adding any further margin, adds little benefit.

Thus, the most valuable location for additional margin is not simply the most central subsystem, nor the subsystem most likely to change. Margin value emerges from the interaction between source-change probability, existing margin, margin cost, and the subsystem's position in the DSM. This is the main practical advantage of M-CPM: it transforms CPM from a propagation assessment method into a method which could be used for allocating margins, keeping both its absorption capability and cost in mind.

The ranking should be interpreted as a local marginal ranking for the specified increment $\Delta m = 0.10$, rather than as a globally optimal margin allocation. Because the margin gate is nonlinear, the value of additional margin depends on the current margin level of each subsystem and may change after one or more increments have already been allocated. The table, therefore, supports a practical screening question: where is the next unit of margin most valuable, given the present design? Allocation decisions beyond one step of $\Delta m = 0.10$ could be made by repeating this calculation iteratively or embedding M-CPM in an optimisation procedure.

6 Conclusion

Change propagation analysis supports designers in anticipating how engineering changes may spread through a product's constituent elements. This paper has shown that explicitly considering margin in such analysis changes both the magnitude and interpretation of propagation risk. The margin-allocation analysis showed that the most valuable location for additional margin is not necessarily the most central subsystem, nor the subsystem most likely to initiate change. Instead, margin value depends on the interaction between existing margin, source-change probability, margin cost, and position in the DSM. The approach therefore is a way to inform the designer about the nature of the architecture and its elements, in relation to potential cost performance, as a part of either a component and architecture design, or even a sizing and optimisation study. Future work should validate the approach in industrial case studies, improve estimation of margin and cost parameters, and examine cases where repeated changes progressively consume available margin during development.

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Contact: A. Brahma, Department of Mechanical Engineering, Chalmers University of Technology, Chalmersplatsen 1, 412 96, Göteborg, Sweden, +46-31-772-40-37, brahma@chalmers.se, https://www.chalmers.se/en/persons/brahma/