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ORIGINAL PAPER

Optimizing module upgrade decisions to maximize profits

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Abstract

With rising market competition, organizations unceasingly strive to improve product offerings by adopting a modular product architecture. Modular product development (PD) is concerned with decisions to upgrade product modules that improve product value by enhancing one or several critical-to-value (CTV) attributes. CTV attributes are, in turn, controlled by the (technical) design decisions made at the module level. Here, an optimization model is presented to help PD managers choose the optimal subset of module upgrades from a large set of potential upgrades to maximize profits. The model is unique in considering the influences of the product architecture and product value on the selection of optimal modular upgrades. While some CTV attributes are discrete in nature, signifying the existence or absence of a product feature, others are continuous over a given range so that the level of desired improvement needs to be specified. The model can be used for both types (discrete and continuous) of attributes. The model is validated using a case study of a small-sized solar water-heating manufacturer. The case study demonstrates the complexity of modular PD decisions, regardless of the size of the investment project, and the effectiveness of the proposed model in the realization of potential profits.

Keywords Product development · Product architecture · Product modules · Module improvement · Product portfolio · Product value

1 Introduction

Customer tastes and market requirements can vary vastly, even within the same market segment, because of several factors including product preference, usage variance, technology advancements, competitive pressure, government regulations, and environmental concerns (Kester et al. 2009). For that reason, companies inevitably face the need to modify and refresh their products to cope with continuously evolving customer demands and emerging requirements (Engel et al. 2017). Industries, such as the automotive, electronics, and aerospace industries, rely on the development of modular, or configurable, product families to proficiently create the variety needed to be competitive in the marketplace (Sanderson and Uzumeri 1995; Aboulafia 2000; Ramdas et al. 2003; Zacharias and Yassine 2008; Paralikas et al. 2011). The alternative approach is called the parametric or scale-based approach to product family design (Simpson et al. 2006, 2014).[1]

It is not a trivial task to create or improve product modules (Kamrad et al. 2013). With limited budgets and scarce resources, companies face the dilemma of prioritizing certain product improvements (and thus modules) over others (Cooper et al. 2001). The goal is to find the subset of modules that provide the most profitable balance between the resources invested and the return on investment. Dependencies among modules make it difficult to determine which modules to change and how to allocate resources among them (Blau et al. 2004). Figure 1 illustrates how the effect of modular improvement on a product family can vary depending on the relationships between the modules and the final products. That complexity necessitates the use of an optimization model that aids in the selection of an optimal set of modules for improvement.

As illustrated in Fig. 1, the modules are the building blocks of the final products. Some modules are designed exclusively for specific products, whereas others are shared

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[1] Scale-based product families are developed by scaling some design variable to stretch or shrink the platform to create the required variety.

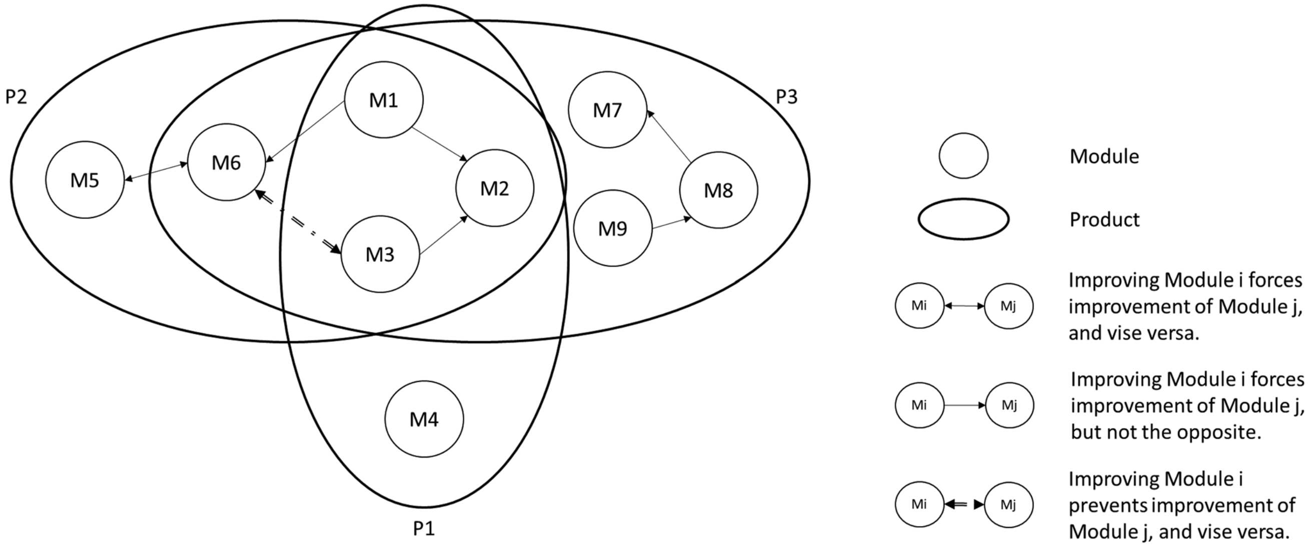

Fig. 1 Venn diagram depicting the interrelationships existing among products and modules

among several products, similar to a product platform. For example, product P1 is composed of four modules: M1, M2, M3, and M4. Module M4 is used only in product P1, whereas modules M1, M2, and M3 are used in products P1, P2, and P3. While the dependencies among the products are based on the sharing of modules, the dependencies among module upgrades are represented by one-way or two-way relationships. In a one-way dependency, the improvement of one module forces the improvement of another module, but not vice versa (i.e., "IF–THEN" relationship). In a two-way dependency, improvement of either module forces (i.e., "AND" relationship) or precludes (i.e., "EITHER–OR" relationship) the improvement of the other.

In the example of Fig. 1, modules M1 and M2 are involved in a one-way relationship (from M1 to M2), meaning that M2 is dependent on M1 but not the opposite. Specifically, if M1 is selected for upgrade, then M2 must also be selected; however, if M2 is selected for upgrade, then it is inconsequential to M1 selection decision. Same argument applies to modules M1 and M6, where M6 is dependent on M1 but the opposite is not true. By contrast, modules M5 and M6 are involved in a two-way "positive" dependency relationship (represented by the solid double-headed arrow). Therefore, the improvement of either module M5 or module M6 forces the improvement of the other, which subsequently affects products P2 and P3. It is worth noting that an improvement of a module can preclude the improvement of another module only if the two modules are involved in a two-way "negative" dependency relationship (represented by the dashed double-headed arrow). That is, selecting any one module for improvement implies that the other cannot be selected. Modules M3 and M6 are an example of a negative two-way dependency relationship, where the improvement of module M3 precludes improvement of module M6, and vice versa. Finally, the improvement of module M4 influences product P1 alone and has no effect on the other modules.

The engineering literature defines a product as a collection of modules and associated design decisions. The marketing literature views a product differently, as a bundle of attributes, or more precisely, critical-to-value (CTV) attributes. CTV attributes are product attributes that are valued by customers and, therefore, associated with the customers' decisions to purchase the product (Cook 1997). In other words, customers value CTV attributes and are willing to pay for them. This paper attempts to bridge the gap between the engineering and marketing perspectives using a mathematical framework for module upgrade decisions that include consideration of product value, price, and demand.

Investment in a module upgrade impacts one or several CTV attributes. In turn, changes in CTV attributes result in changes in the value of products. The interrelation among modules, CTV attributes, and products is illustrated in Fig. 2. Product P1 includes modules M1 and M2. Module M1 contributes to CTV attributes A1 and A2, and module M2 contributes to CTV attribute A3. Therefore, product P1 is valued by customers through CTV attributes A1, A2, and A3. Improvement of module M1 or M2 will result in a change in the value of product P1 in accordance with the change in customer interest (and willingness to pay) towards any of the CTV attributes A1, A2, or A3.

In this paper, the mathematical framework is modeled to optimize the selection of module improvements in the presence of budget limitations, integrating the expected changes in product value, demand, and profits into the decision-making process. While similar module-based optimization

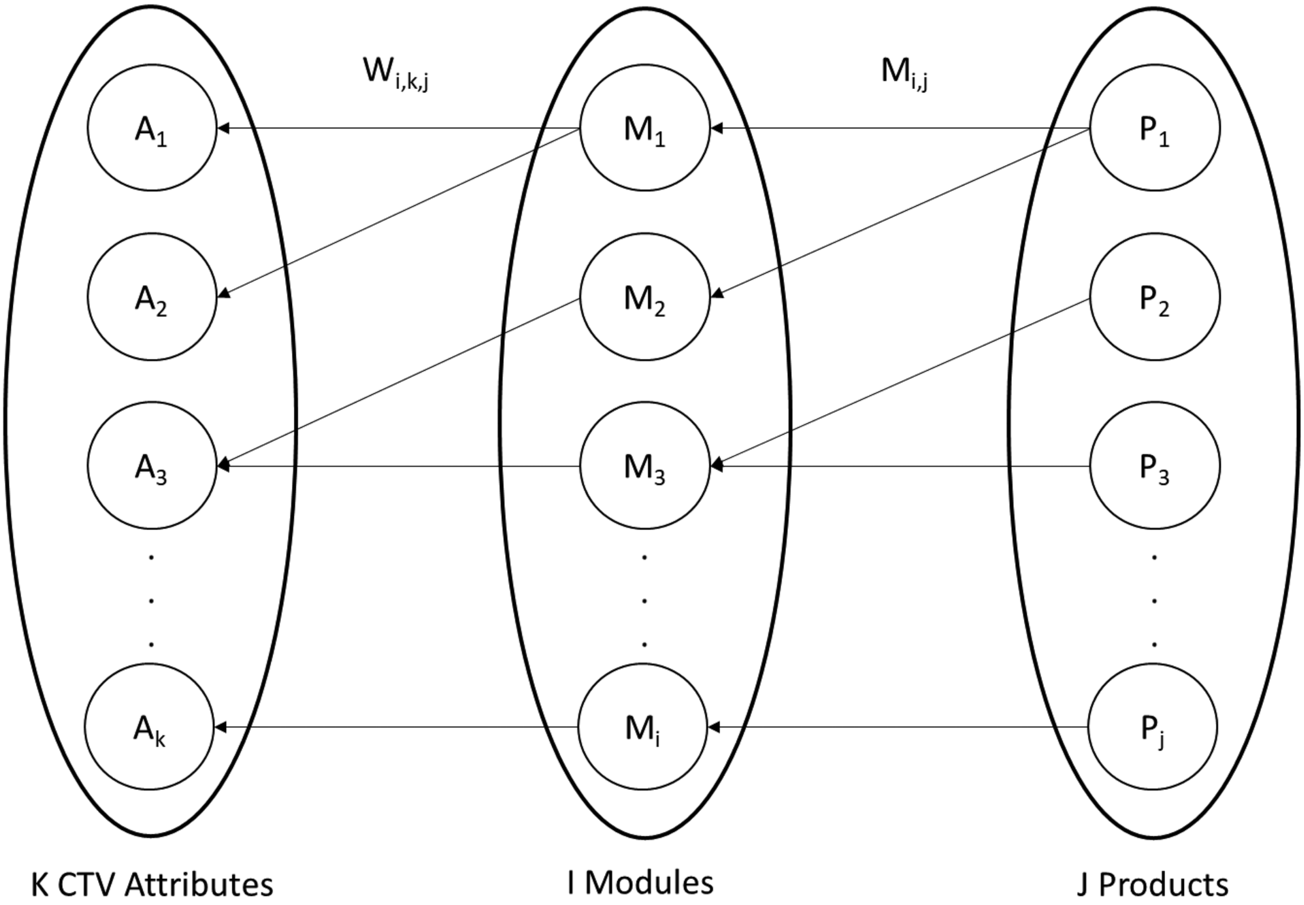

Fig. 2 Mapping among the product, module, and attribute domains

models found in literature focus only on product design and cost (Yassine 2012), this research goes a step further by assessing how each module improvement can affect the products' value, cost and demand, and ultimately, selects the optimal set of module improvements to maximize the overall profits of an organization. Another important benefit of this model is that it does not only specify which module improvements to invest in, but it also specifies the level of improvement that should be invested in for each module, i.e. to maximize the returns of an investment, some modules should be fully improved, some should not, and some should be partially improved. On the contrary, other optimization models follow a binary approach to improvement selection (i.e., the yes/no approach), the model presented here offers both binary and continuous selection, depending on the nature of the modules and CTV attributes. The ability to incorporate product value, cost and demand in the decision-making process for module upgrade design, and also the flexibility to specify the level of modular upgrade under continuous behavior, distinguish this model from similar decision-making tools that exist in the literature.

The main objectives of this paper are: (1) to bridge the gap between engineering design decisions and marketing research through CTV attributes and product value, and (2) to formulate and solve a mathematical optimization model that identifies the optimal subset of module upgrades that maximizes profits, while considering both product architecture and changes in product value.

In the next section, a review of similar and relevant models in the literature is presented. In Sect. 3, the relationship among product price, value, and demand is adopted from the literature, paving the path forward into the basis of the optimization model. Section 4 draws out this model explicitly, showing all the assumptions and mathematical formulations behind the decision-making process. In Sect. 5, a demonstrative case study is presented, where the proposed model is applied on a solar energy company product portfolio. Finally, the results and conclusions are summarized in Sect. 6.

2 Literature review

The decision-making process for project selection plays a major role in portfolio management (Cooper et al. 2001). The relevant literature treats that process mainly using financial and optimization techniques to rationally select an optimal product development portfolio that is both profitable and balanced (Kester et al. 2009).

Non-optimization approaches include graphical and charting techniques that visualize a portfolio's balance (Cooper et al. 2001) and also project scoring and ranking techniques that account for multiple perspectives (Henriksen and Traynor 1999). The graphical and charting techniques are usually used to display a trade-off between two relevant criteria, such as risk (e.g., the probability of technical success) and reward [e.g., net present value (NPV)] (Cooper et al. 2001). Another useful criterion used in graphical portfolio management and project selection is the degree of process/product change (Clark and Wheelwright 1993). In that case, projects can be classified as breakthroughs, platforms, or derivatives. It is important to select a portfolio of development projects that is balanced and aligned with the strategy of the organization (Cooper et al. 2001). Although graphical approaches to project selection can provide powerful visual clues by integrating multiple selection criteria into a single picture, they are unable to prioritize projects (Dickinson et al. 2001). On the other hand, project scoring and ranking techniques use a multitude of criteria to score the various projects and then rank them according to different models, such as those based on analytic hierarchy process (AHP) or data envelopment analysis (DEA) approaches (Gabriel et al. 2006; Bitman and Sharif 2008).

A typical optimization approach to project selection is illustrated by the capital budgeting problem, which is built on a (multi-dimensional) knapsack model. The knapsack model usually takes as input the available budget, the cost of selecting each project, and the profit (or NPV) of each project (Koc et al. 2008). The goal is to select the portfolio of projects with the highest total NPV while observing budgetary and other constraints (Marchioni and Magni 2018).

Market, technology, and investment dependencies between projects and products make it difficult to select projects and allocate resources (Blau et al. 2004; Koc et al. 2008). For example, it might be beneficial to invest in a project that is financially unattractive but has the potential to benefit future product development projects. Uncertainty in product demand, customer requirements, and investment requirements exacerbates the difficulty of selecting the optimal portfolio of projects to develop (Chao and Kavadias 2008; Guo et al. 2008). Koc et al. (2008, 2009) introduced an optimization model for the selection of plant capital investments in the nuclear power industry. Their analyses highlighted the importance of hedging against uncertainties in the budget, because deterministic solutions can be unstable with respect to changes in budget values. They, therefore, developed a modified model with an uncertain budget using a two-stage stochastic integer program. Solak et al. (2010) introduced a similar approach to account for uncertainty in project selection.

Dickinson et al. (2001) used a dependency matrix to quantify interdependencies among projects. Using the matrix, they built a non-linear, integer program to optimize project selection for the Boeing Company. In another study, Allada and Lan (2002) presented a model that maximized company profits by systemizing the optimization of module configuration for evolving product families. They used a stage-wise sequential decision process (i.e., dynamic programming) that accounted for interdependencies among modular products. Their optimization model was based on the assumption that product modules have independent effects on the final profits derived from product families.

More recently, van Bommel et al. (2014) introduced an optimization model for the selection of projects from a technological point of view. Their premise was that it is important not only to learn which products yield higher profits but also to decide on the sequence in which the modules should be improved, because the improvement of one module might lead to improvement of other modules or products that share underlying technologies. Technological interdependence among modules within a product family means that improvement of certain modules can increase an organization's technological capabilities, which can lead to improvement of other modules of the portfolio.

3 Proposed optimization framework

The three main pillars that define a product in its market are cost, price, and demand. To develop a market-based optimization framework for this study, it is important to understand how module upgrades affect these three main pillars, and how the latter, in turn, affect the expected profits. Module improvement can reduce the cost of production and ultimately the product price; however, it can also affect the product quality, which means that the product value to customers might change as well. Changes in value and price allow for a change in demand, as shown in the optimization framework of Fig. 3. The aim of the market-based framework is to optimize module upgrades in ways that improve the market characteristics of products and, thus, maximize total profits.

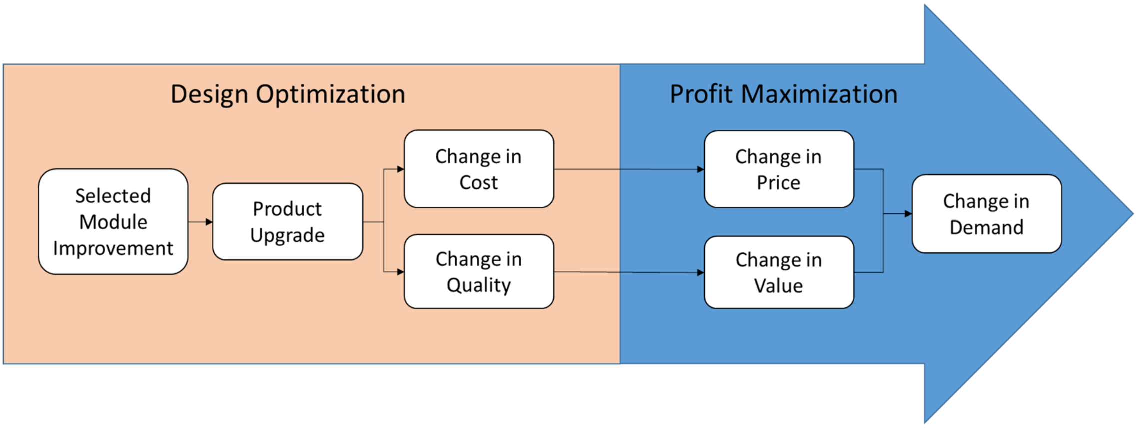

Fig. 3 A market-based optimization framework to maximize profits

3.1 Product demand using the S-model

The relationships among price, value, and demand vary significantly among existing models and different fields of study. For example, according to Fowler (1990), value-engineers define value as worth divided by cost. On the other hand, the quality function deployment literature measures the value of a product on a scale from 0 to 10, representing the product's worth to customers, as descried in Akao (1990). Taguchi and Wu (1980) presented a loss-of-value definition termed "cost-of-inferior-quality" that describes the reduction of a product attribute as the attribute shifts away from its ideal specification. Cook and Wu (2001) unified all three of the aforementioned value definitions under an integrated toolset termed the "S-Model", which is intended to guide the planning, design, and development of new products.

The basic assumption of the S-Model is that the demand d_j for a product j is a linear function of the product's value and price, as expressed by Eq. (1) for a product sold by a monopoly, where μ_j is an empirical constant of product j, v_j is the value of product j, and p_j is the price of product j .[2] A change in value or price yields a change in demand for the product, as expressed by Eq. (2). The δd_j term is the expected change in demand of product j after a shift in its value, δv_j, due to an improvement in some attribute of the product. Finally, δp_j is the change in the price of the product due to the change in value, which can be deduced by market-price benchmarking, consumer willingness to pay, or profit mark-up factor based on product cost (Cook and Wissmann 2007):

$$d_j = \mu_j \times \left(v_j - p_j\right) \tag{1}$$

$$\delta d_j = \mu_j \times \left(\delta v_j - \delta p_j\right). \tag{2}$$

The relationship expressed by Eq. (2) shows that a \$1 increase in value has the same effect on demand as a \$1 decrease in price. An improvement in product value can allow for an equal increase in price for a fixed demand or, alternatively, can yield an increase in demand if the price is kept constant. Those interpretations are graphically represented in Fig. 4, showing that, for small changes in value, the linear model approximates the actual non-linear relationship that exists among demand, value, and price. Furthermore, as described by Cook (1997), the theoretical price of a product that renders the demand to zero is equal to the theoretical value of the product as judged by customers.

3.2 Product value using the S-model

Products are valued by customers based on certain attributes that the products possess and the customers have interest in. The more appealing these attributes are in a product, the more valuable the product becomes in the eyes of the customer. These critical-to-value (CTV) attributes can be of discrete or continuous nature. Discrete CTV attributes signify the existence or absence of a particular product feature (such as an automotive sunroof or a particular color of computer cover). By contrast, continuous CTV attributes vary over a given range (such as the interior noise level in a car or the weight of a cell phone). Continuous CTV attributes can be classified into three categories: smaller is

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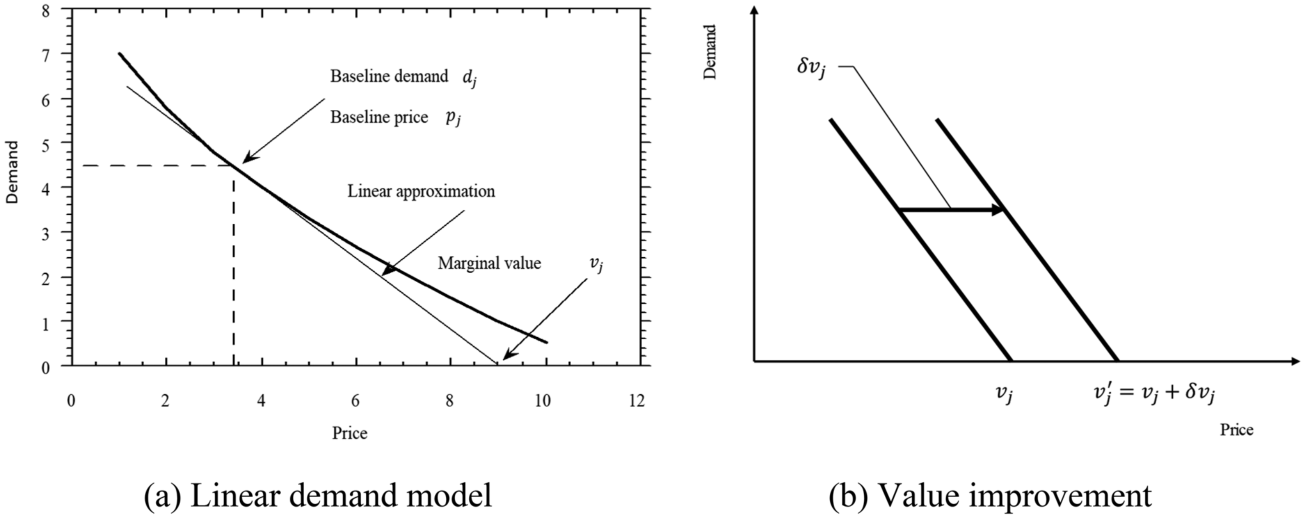
[2] μ can also be expressed as a function of price elasticity of demand (ε) as follows: $\mu = N\left(\bar{D}/\bar{P}\right)\varepsilon$, where $\bar{D}$ and $\bar{P}$ are the average demand and price, respectively, for N competing products in the market. ε is estimated to be less than unity for necessity products, larger than unity for luxury products, and equal to unity for products that are neither necessities nor luxuries. ε is often assumed to be equal to unity if it is unknown (Cook and Wu 2001).



(a) Linear demand model

(b) Value improvement

Fig. 4 The relationship among price, demand, and value [adopted from Cook and Wu (2001)]

better (SIB), larger is better (LIB), and nominal is better (NIB), as defined by Cook and Wu (2001). SIB represents CTV attributes that are disfavored by customers, such as the noise level inside luxury cars. The noisier the car is, the less valued (by customers) the car becomes. Alternatively, LIB represents CTV attributes that are favored by customers, such as the acceleration of a sports car. The faster the car accelerates, the more satisfied are its customers. Finally, NIB represents CTV attributes that are best in moderation, such as the engine size in a family car. A very small engine might not suit customers because it provides too little power, but a very large engine might be equally unsuitable because of its high fuel consumption. The best alternative would be somewhere in between. Figure 5 provides an idealistic representation of the three categories of CTV attributes.

Upgrading modules of a product can affect the related CTV attributes of that product, hopefully to the better. In turn, changes in the CTV attributes can lead to change in the product value. The overall change in product value is estimated by measuring the change in value of the product due to each affected CTV attribute separately, and then combining the results. Depending on the nature of the considered CTV attribute, Cook (1997) developed different methods to measure its individual effect on the overall product value.

For discrete CTV attributes, as described by Cook (1997) and Cook and Wissmann (2007), market surveys based on the direct value method (DVM) are used to draw a discrete value measure for each CTV attribute modification. Customers are asked to choose between the old product at the original price and a product with an improved CTV attribute at an incrementally increasing price. The maximum price the customers are willing to pay for the upgraded product specifies the expected change in value of the product if the decision is made to improve the attribute. For example, in the hypothetical example shown in Fig. 6, the customer is willing to pay \$18,000 for the new version of product P1, which has an improved CTV attribute A1, instead of paying \$16,000 for the unimproved version of product P1. Thus, the market value of product P1 is expected to increase by \$2000 in case CTV attribute A1 is enhanced. Of course, this example considers only one sample survey result, when in fact a large set of responses should be averaged to get the true value change.

For continuous CTV attributes, the product value after an attribute improvement can be expressed as a function of the CTV attribute measure as shown in Eq. (3), where $g_{j,k}$ is the critical magnitude of an attribute k of a product j, at which the value of the product goes to zero, $h_{j,k}$ is the ideal magnitude of the attribute k of product j, at which the value of the product is maximized, $e_{j,k}$ is the baseline magnitude of the

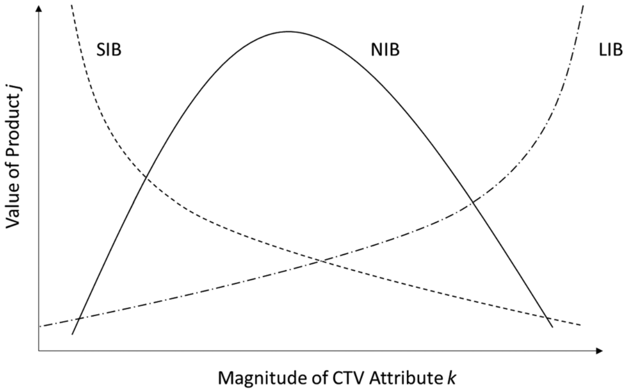


Fig. 5 The relationship between CTV attribute measures and product value for the three attribute categories: smaller is better (SIB), larger is better (LIB), and nominal is better (NIB). [Adopted from Cook (1997)]

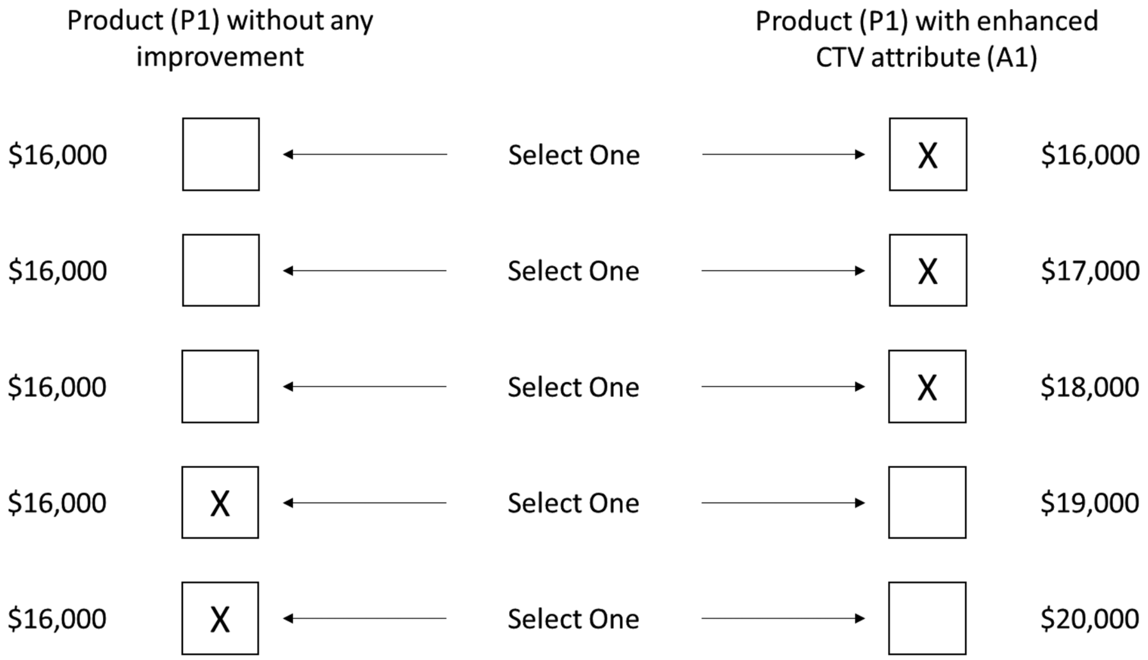
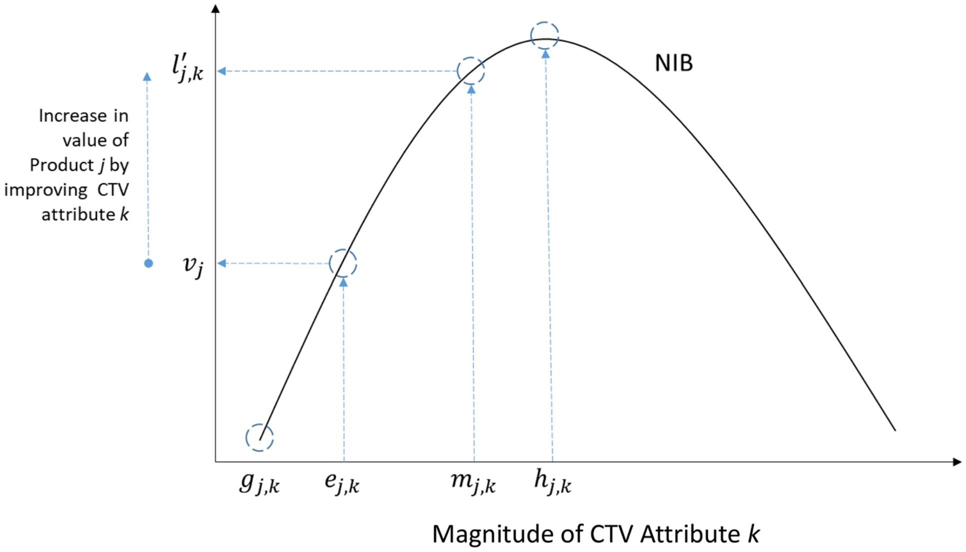


Fig. 6 A hypothetical response to a survey using the Direct Value Method (DVM) to assess the value of product P1 with enhanced CTV attribute A1. [Adopted from Cook (1997)]

Fig. 7 Graphical representation of Cook's model for NIB category



attribute, or the current status of the attribute before any module improvement, at which the product value is known to be v_j, and $m_{j,k}$ is the value of the attribute that yields product value $l'_{j,k}$ (adapted from Cook 1997). The ideal and critical values can be estimated from human factor studies, from intuition, or from surveys, depending upon the nature of the CTV attribute (Cook 1997). The weighting coefficient $\gamma_{j,k}$, which can be deduced from the best-fit curve produced by an empirical study, approximates the magnitude of the influence of the CTV attribute k on a product j. Cook (1997) also noted that $\gamma_{j,k}$ is the fraction of time the attribute k is experienced by the customer when dealing with product j. Figure 7 represents Cook's model graphically for NIB category:

$$l'_{j,k} = v_j \times \left[\frac{\left[g_{j,k} - h_{j,k}\right]^2 - \left[m_{j,k} - h_{j,k}\right]^2}{\left[g_{j,k} - h_{j,k}\right]^2 - \left[e_{j,k} - h_{j,k}\right]^2} \right]^{\gamma_{j,k}}. \tag{3}$$

After the product value is estimated for each CTV attribute improvement separately, the overall change in the product value δv_j, resulting from the combined set of CTV attribute improvements, is computed using the multiplicative value function shown in Eq. (4), where v_j is the current value of product j prior to any modular improvement, and v'_j is the value after implementing the selected product improvements:

$$\delta v_j = v'_j - v_j = v_j \times \left[\prod_k \left(\frac{l'_{j,k}}{v_j} \right) - 1 \right]. \tag{4}$$

4 The model: an optimal module improvement plan

In this section, the details of the proposed optimization model are described. The first step is to define the product portfolio, product architecture, attributes, and modules. The following step is to define the decision variables and their constraints. The expected change in product value based on the selected module improvements is then estimated for every optimized iteration, and consequently, the influence of the change in value on demand is calculated via the relationship between product price, value and demand. Finally, after computing the change in the product price and demand, the expected change in profits is calculated. The selected set of module improvements is optimized to maximize the final change in profits. The model taxonomy and a summary of all the equations introduced in this section can be found in Tables 11 and 12, respectively, in "Appendix A".

4.1 Defining the Portfolio

A product family or portfolio shares common modules, each of which might exist in one or more product. Similarly, CTV attributes that define the value of a product can be influenced by one or more module. Taking the automobile as an example, safety is a major CTV attribute that customers are willing to pay for in all vehicle models. Nevertheless, safety can be achieved by various modules (e.g., an airbag, a seatbelt, a bumper, or brakes). Moreover, each module can influence one or more CTV attribute, and the magnitude of influence can vary depending on the product. For example, the dimensions of a front bumper will influence the safety CTV attribute of an SUV more than it will that of a sports car. The same module, the front bumper, can also affect the weight of the vehicle, which in turn affects the acceleration CTV attribute, albeit to different degrees in an SUV and a sports car. The interrelation among products, modules, and CTV attributes is schematized in Fig. 2.

To introduce this relationship into the optimization model, it is necessary to first define the available products J, the CTV attributes K that define the market value of the products, and the modules I that are available for upgrade. It is then required to define the contribution of each module to each shared CTV attribute in each product separately. The matrix $W_{i,j,k}$ defines the contribution of module i, in product j, to CTV attribute k. The magnitudes of all elements of the matrix are fractions between zero and 1. A magnitude of zero means that module i either does not exist in product j or has no effect on CTV attribute k in that product, whereas a magnitude of 1 means that module i exists in product j and, if fully upgraded, can by itself enhance the CTV attribute k in that product to its ideal measure.

4.2 Defining the decision variables

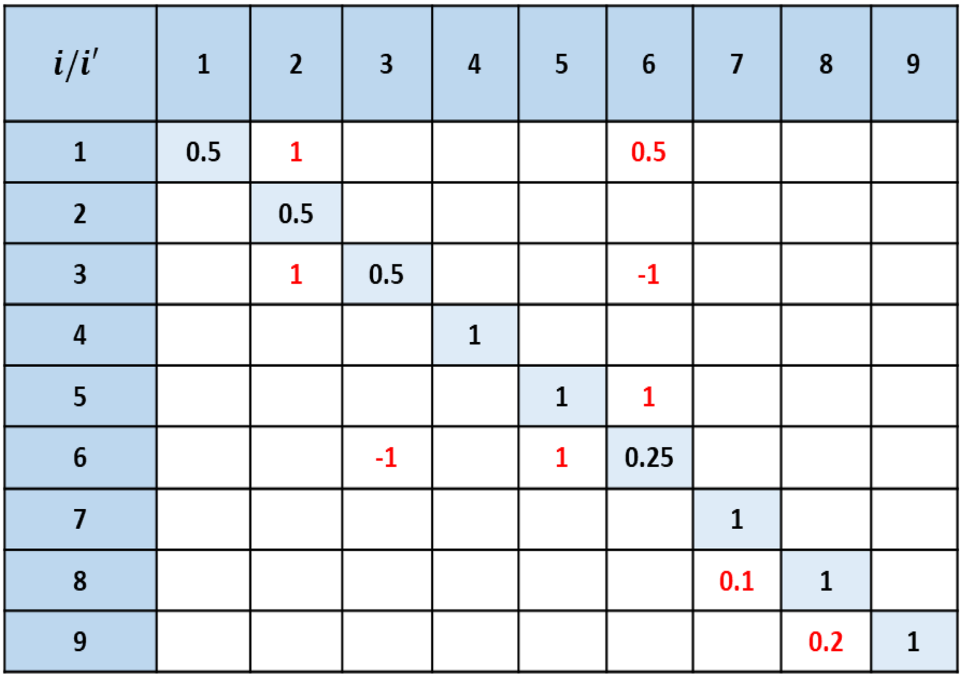
As in other portfolio selection models, the decision variable vector X determines which modules should be improved and which should not. Element $x_i \in X$ indicates whether or not to invest in the improvement of module i. The model presented here goes a step further, however, by expressing the optimal level of improvement as a fraction of the total possible improvement for each module. Vector element x_i is a positive integer that ranges from zero to 1 and, expressed as a percentage, indicates the optimal percentage of improvement that should be invested in module i; $x_i = 0\%$ means that module i should not be improved at all, whereas $x_i = 100\%$ means that module i should be upgraded fully. A linear relation is assumed between the cost of improvement and the level of improvement. For example, a 50% improvement of module i will require investing in 50% of the defined cost of module i full improvement. The decision to upgrade some modules may be discrete in nature. Those modules can either be completely improved for the full cost or not improved at all. The type of module improvement is defined as continuous or discrete through vector N as expressed in Eq. (5):

$$n_i = \begin{cases} 0, & \text{indicating a continuous modular improvement} \\ 1, & \text{indicating a discrete modular improvement} \end{cases}. \tag{5}$$

Vector X^* is an adjustment of the decision variable matrix X, which incorporates the type of modular improvement (i.e., continuous or discrete) using Eq. (6):

$$x_i^* = \begin{cases} 0, & x_i = 0 \\ x_i, & x_i > 0 \text{ and } n_i = 0 \\ 1, & x_i > 0 \text{ and } n_i = 1 \end{cases}. \tag{6}$$

Allowing for partial module improvement makes this model flexible to portray practical budget allocation problems, however, increases the complexity of the problem due



i/i'	1	2	3	4	5	6	7	8	9
1	0.5	1				0.5			
2		0.5							
3		1	0.5			-1			
4				1					
5					1	1			
6			-1		1	0.25			
7							1		
8							0.1	1	
9								0.2	1

Fig. 8 Example of module improvement interdependency using matrix Y

to expanding the solution space. The complexity of the problem is derived from the relationships that exist among the decision variables, profits that are related to product demand, price and value, interdependencies between products, modules and CTV attributes, as well as directional interdependencies among modules. Accordingly, an optimization-based approach is the most effective strategy to facilitate our search of the desired optimal solution.

4.3 Defining the product architecture

Based on the product architecture, there might exist a dependency relationship among the modules considered for upgrade. The decision to modify one module might be dependent on or have an impact on other modules. We assume that the decision to improve one module can either force improvements to other modules, have no effect on any decision to improve another module, or prevent the improvement of other modules.

To define the relationships between the available module improvements, the square matrix Y is introduced, the size of which is equal to the number of modules available. The elements of this matrix, $y_{i,i'}$, indicate the directional dependency of upgrade decisions and also define the minimum level of upgrade required to satisfy the existing dependency. For every $y_{i,i'}$, a value of 1 indicates a unidirectional relationship between modules i and i' such that improvement of module i requires 100% improvement of module i' as a prerequisite. On the other hand, a value of zero indicates that improvement of module i does not require any improvement of module i'. Element $y_{i,i'}$ can take any value between zero and 1 only in the case where module i' is continuous. In that case, the assigned value indicates the minimum level of improvement of module i' that is required for module i to be improved. In the case where $y_{i,i'} > 0$ and $y_{i',i} > 0$, the dependency between the two modules is bidirectional, meaning that selection of either module for improvement requires the selection of the other module. By contrast, when $y_{i,i'} = -1$ and $y_{i',i} = -1$, the improvement of one module absolutely precludes improvement of the other module, and the constraint is always bidirectional.[3] Finally, it is important to note that for every $y_{i,i'}$ where $i = i'$ (i.e., the diagonal of the matrix), the elementary value should be equal to the minimum allowed improvement of module i. Thus, the minimum level of improvement allowed for module i is expressed by the element $y_{i,i}$. For a discrete module i, element $y_{i,i} = 1$.

Figure 8 shows a matrix that describes the directional dependencies among the module improvements shown in Fig. 1. For example, the matrix specifies that if module 1 is

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[3] For example, and assuming that modules i' and i'' cannot be improved in case module i is improved, the related elementary values are expressed by $y_{i',i} = y_{i,i'} = y_{i'',i} = y_{i,i''} = -1$. This expression prevents the improvement of any of the modules i' and i'' in case module i is selected for improvement, or it prevents the improvement of module i in case any of the other two modules are selected for improvement. However, the hypothetical expression allows the improvement of module i' if module i'' is improved, or vice versa. In the case where selecting any one of the three modules for improvement prevents the improvement of any of the other two modules, the mathematical expression becomes $y_{i',i} = y_{i,i'} = y_{i'',i} = y_{i,i''} = y_{i',i''} = y_{i'',i'} = -1$.

Table 1 Calculation of constrains on module 6 improvement in the absence of module 3 improvement (in reference to Fig. 8)

i'	Module i' upgraded?	$\alpha_{i'}$	$y_{i',6}$	$\alpha_{i'} \times y_{i',6}$	Trial $x_6^* = 1$	Equations
1	Assumed yes ($x_1^* > 0$)	1	0.5	0.5	$1 \geq 0.5 \rightarrow$ OK	(7)
2	Assumed no ($x_2^* = 0$)	0	0	0	$1 \geq 0 \rightarrow$ OK	(7)
3	Assumed no	0	− 1	0	$1 \geq 0 \rightarrow$ OK	(7)
4	Assumed no	0	0	0	$1 \geq 0 \rightarrow$ OK	(7)
5	Assumed yes	1	1	1	$1 \geq 1 \rightarrow$ OK	(7)
6	Trial $x_6^* = 1$	1	0.25	0.25	$1 \geq 0.25 \rightarrow$ OK	(7)
7	Assumed yes	1	0	0	$1 \geq 0 \rightarrow$ OK	(7)
8	Assumed no	0	0	0	$1 \geq 0 \rightarrow$ OK	(7)
9	Assumed no	0	0	0	$1 \geq 0 \rightarrow$ OK	(7)

selected for improvement, then module 6 must be improved by at least 50% of the total possible upgrade. The relationship is unidirectional between modules 1 and 6, because $y_{1,6} = 0.5$ and $y_{6,1} = 0$. A bidirectional relationship exists between modules 5 and 6, however, because $y_{5,6} = y_{6,5} = 1$, meaning that either both modules can be completely improved or neither module can be improved at all. Element $y_{6,6} = 0.25$, meaning that the smallest upgrade possible for module 6 is 25% of the total possible upgrade defined for that module. Finally, elements $y_{3,6} = y_{6,3} = -1$ indicate that modules 3 and 6 cannot both be selected for improvement. Upgrading module 3 prohibits module 6 from being upgraded, and vice versa.

To mathematically express the unidirectional and bidirectional relationships introduced by matrix Y, and to ensure that the minimum required level of improvement is respected, the set of constraints represented by Eq. (7) must be satisfied:

$$x_i^* \geq \alpha_{i'} \times y_{i',i} \quad \forall i' \in I, \tag{7}$$

where, $\alpha_{i'}$ belongs to vector A and indicates whether module i will be improved or not, as shown in Eq. (8):

$$\alpha_{i'} = \begin{cases} 0, & x_{i'}^* = 0 \\ 1, & x_{i'}^* > 0 \end{cases} \tag{8}$$

In Eq. (7), the right side of the inequality ($\alpha_{i'} \times y_{i',i}$) defines the set of constraints that the decision variable x_i^* must satisfy. For example, referring to Fig. 8, improvement of module 6 is influenced by the improvement decisions for modules 1, 3, and 5. If module 1 is selected for improvement, module 6 will have to be improved by at least 50% of the total possible upgrade. If module 3 is selected for improvement, module 6 cannot be improved at all. Lastly, if module 5 is selected for improvement, then module 6 will have to be upgraded fully. Assuming modules 1, 5 and 7 are selected for improvement, as well as module 6 for a 100% improvement, Eq. (7) is expressed mathematically as described in Table 1. Equations (7), (8), and (9) for Fig. 8 are expanded in "Appendix B".

In the same example, assuming now that module 3 was selected as well for improvement, then module 6 can no longer be selected for improvement. Equation (9) generalizes that constraint mathematically. For the case when $y_{i',i} \geq 0$, the inequality in Eq. (9) is always true for all possible values of x_i^*. However, when $y_{i',i} = -1$, the only feasible solution for the inequality is to set $x_i^* = 0$; i.e. module i is not selected for improvement. Therefore, the constraints given by Eqs. (7) and (9) should all be satisfied for every module upgrade decision variable x_i^*:

$$y_{i',i} \times x_i^* \geq 0 \quad \forall i' \in I. \tag{9}$$

Table 13 in "Appendix C" combines Eqs. (7) and (9) for illustration. The trial value of $x_6^* = 1$ is invalid, because not all constraints for module 6 improvement decision are satisfied (since $y_{3,6} = -1$). The only value for x_6^* that will satisfy constraint (9) is zero (i.e., module 6 is not selected for improvement when module 3 is improved). Table 14 in "Appendix C" assumes for the same example that module 6 is not improved, however, the constraints are again not fully met because modules 1 and 5 are selected for improvement, and thus module 6 is a must to improve. The only solution for improving module 3 is not to improve any of modules 1, 5 and 6.

4.4 Defining the budget

With a fixed budget available for modular improvement, it is necessary to consider all direct and indirect costs related to the modules under consideration. Equation (10) sums up the expected costs of developing the selected modules, expressed by matrix R, where $r_i \in R$. In addition, each proposed modular improvement should be tested and verified for compatibility with the final products. The testing and verification costs are expressed by matrix S, where $s_{i,j} \in S$, which must be included in the available budget B. Additional costs, represented by O, will also be required regardless of the selected portfolio. Such costs are related to market assessment, module and product analysis, and various other studies and overheads. All of those costs should be within the available budget, as shown in Eq. (10):

$$\sum_i \left[x_i^* \times \left(r_i + \sum_j s_{i,j} \right) \right] + O < B. \tag{10}$$

4.5 Optimizing value to maximize profit

In this section, the profits before and after upgrading the modules are calculated. Matrix element $t_i \in T$ introduced by Eq. (11) gives the profit share of product j based on the price $p_j \in P$, cost $c_j \in C$, and demand $d_j \in D$ prior to any module improvement. Equation (12) sums up the profit generated by all the products under study to yield the total current profits π.

$$t_j = \left[p_j - c_j \right] \times d_j \tag{11}$$

$$\pi = \sum_j t_j. \tag{12}$$

To estimate the increase (or decrease) in profits generated by the selected module upgrades, the modified price of the upgraded products should be calculated, as well as the cost of their production (or assembly), and the expected demand for the upgraded products based on market assessment. To begin with the price calculation, there are several pricing techniques available. The model presented here uses the cost-plus method, where profits are determined by adding an appropriate mark-up to the costs incurred (Ulrich and Eppinger 2008). The cost-plus method assumes a percentage profit on each module cost based on the overhead costs, profit margins, and demand levels. The mark-up factors are represented by matrix U, where $u_{i,j}$ assigns the mark-up factor of module i in product j. Equation (13) gives the expected price of the modified product j after the selected module improvements are implemented. The equation adds to the initial price of each product the change in the cost of each related product that is improved multiplied by $u_{i,j}$. The defined cost $z_i \in Z$ is the cost of module i prior to its improvement, while $z_i' \in Z'$ is the expected cost of module i when the model is fully upgraded (i.e., when $x_i^* = 1$):

$$p_j' = p_j + \sum_i \left[x_i^* \times u_{i,j} \times \left(z_i' - z_i \right) \right]. \tag{13}$$

Equation (14) estimates the modified cost of producing (or assembling) product j by adding to the initial product cost the change in the cost of each module i in product j that is subjected to an upgrade level x_i^*, where $c_i \in C$ and $c_i' \in C'$ are the cost of product j before and after the selected module improvement, respectively:

$$c_j' = c_j + \sum_i \left[x_i^* \times \left(z_i' - z_i \right) \right]. \tag{14}$$

After calculating the price and cost of the upgraded products, Eq. (15) can be used to estimate the modified demand $d_j' \in D'$ for each product j based on the optimized selection of module improvements. Equations (16) and (18) are thoroughly developed in Sect. 3, and Eq. (17) is deduced from Eq. (13). Note that Eq. (18) is the same as Eq. (4):

$$d_j' = d_j + \delta d_j, \tag{15}$$

where,

$$\delta d_j = \mu_j \times \left(\delta v_j - \delta p_j \right) \tag{16}$$

$$\delta p_j = p_j' - p_j = \sum_i \left[x_i^* \times u_{i,j} \times \left(z_i' - z_i \right) \right] \tag{17}$$

$$\delta v_j = v_j \times \left[\prod_k \left[\frac{l_{j,k}'}{v_j} \right] - 1 \right]. \tag{18}$$

To estimate the product value per CTV attribute after module improvements, as defined by matrix V', where $v_j' \in V'$, it is important to understand how module upgrades affect the CTV attributes and thus the product value. Similar to module upgrades, which can be discrete or continuous [as in Eq. (5)], CTV attributes can also be discrete or continuous as explained in Sect. 3. Equation (19) defines the CTV attribute as continuous or discrete through matrix Q, where $q_k \in Q$. The method used to evaluate the effect of each CTV attribute on the final product value differs for continuous and discrete CTV attributes. The value of the final product after its modules are upgraded is dictated by the influences of all the CTV attributes that are affected by the module upgrades:

$$q_k = \begin{cases} 0, & \text{indicating a continuous CTV attribute} \\ 1, & \text{indicating a discrete CTV attribute} \end{cases}. \tag{19}$$

There are two conditions for the modules affecting discrete CTV attributes: the decision variables for the modules have to be discrete, and all required modules must either be selected together or not selected at all, which should be reflected in matrix Y.[4] By contrast, in the case of continuous CTV attributes, the related modules can have a mix of discrete and continuous decision variables and can be selected for upgrade independently, without additional constraints and as specified by matrix Y. Equation (20) summarizes the

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[4] For example, in an automobile, the chassis of the vehicle as well as the windows must be upgraded to provide a convertible model. There will be no sense in upgrading one without the other, nor will there be sense in partially upgrading the two modules.

method to calculate the elements of matrix V', in reference to Sect. 3:

$$v'_{j,k} = \begin{cases} v_j & \sum_i \left(w_{i,j,k} \times x_i^*\right) = 0 \\ \text{Survey based value,} & \sum_i \left(w_{i,j,k} \times x_i^*\right) > 0 \text{ and } q_k = 1 \\ v_j \times \left[\frac{\left[g_{j,k}-h_{j,k}\right]^2-\left[m_{j,k}-h_{j,k}\right]^2}{\left[g_{j,k}-h_{j,k}\right]^2-\left[e_{j,k}-h_{j,k}\right]^2}\right]^{\gamma_{j,k}} & \sum_i \left(w_{i,j,k} \times x_i^*\right) > 0 \text{ and } q_k = 0 \end{cases}. \tag{20}$$

where,

$$m_{j,k} = \begin{cases} \sum_i \left(w_{i,j,k} \times x_i^*\right) \times \left(f_{j,k} - g_{j,k}\right) + g_{j,k}, & \sum_i \left(w_{i,j,k} \times x_i^*\right) \le 1 \\ f_{j,k}, & \sum_i \left(w_{i,j,k} \times x_i^*\right) > 1 \end{cases}. \tag{21}$$

In Eq. (20), $g_{j,k} \in G$ is the least favorable magnitude of CTV attribute k that drops the value of product j to zero; $h_{j,k} \in H$ is the ideal magnitude of CTV attribute k; $e_{j,k} \in E$ is the current magnitude of CTV attribute k that yields value v_j for product j; and $f_{j,k} \in F$ is the optimal magnitude for CTV attribute k that can be achieved (for product j) with the given (or selected) set of module upgrades. Noting that the modules considered for improvement might not be sufficient to yield the most ideal magnitude of the CTV attribute even when fully upgraded, it can be deduced that $f_{j,k} \le h_{j,k}$. It is worth noting that $f_{j,k}$ can get to $h_{j,k}$ only if all the modules that contribute to attribute k are taken into consideration. In this case, $\sum_i \left(w_{i,j,k} \times x_i^*\right) > 1$ and $f_{j,k} = h_{j,k}$.

An important feature of the proposed model is that it does not only optimize the selection of modules for improvement, but also indicates the best level for these improvements as a percentage of the maximum possible upgrade for a module. The term $\left[\sum_i \left(w_{i,j,k} \times x_i^*\right) \times \left(f_{j,k} - g_{j,k}\right) + g_{j,k}\right]$ in Eq. (21) assumes that the expected magnitude of a CTV attribute varies proportionally with the level of investment made towards all the modules that constitute the attribute.[5] An alternative value for $m_{j,k}$ is $f_{j,k}$ in the case where $\sum_i \left(w_{i,j,k} \times x_i^*\right) > 1$. The inequality $\sum_i \left(w_{i,j,k} \times x_i^*\right) > 1$ can exist in the case where $\sum_i w_{i,j,k} > 1$, meaning that the CTV attribute can reach its maximum magnitude by means of more than one set of module upgrades. For example, an acceleration target for a sports car can be achieved in full by increasing the engine power alone; however, reduction of the weight of the car can also help to achieve the desired acceleration. In this case, $w_{i,j,k}$ is larger than 1. The optimization model ensures that the best combination of modular improvements is selected to reach the optimal acceleration. That might mean limiting costly investment in an engine upgrade and focusing more on reducing the weight of the car, which would produce the same desired increase in acceleration.

To calculate the expected profits after the module improvement, matrix element $t'_j \in T'$ defined by Eq. (22) gives the expected profit generated by product j, and the sum of all profits generated by the upgraded products under study can be summed up using Eq. (23).

Finally, the model aims at maximizing the percent increase in total profits as calculated by Eq. (24). A summary of the full optimization model is given in "Appendix A":

$$t'_j = \left[p'_j - c'_j\right] \times d'_j. \tag{22}$$

$$\pi' = \sum_j t'_j \tag{23}$$

$$\text{Maximize} \frac{\pi' - \pi}{\pi} \times 100\%. \tag{24}$$

The optimization model introduced in this section is a non-linear integer program. The goal is to maximize the expected increase in profits (for an organization) due to the selected set of modular upgrades subject to budgetary and dependency constraints. The model was implemented and solved using Microsoft Excel Premium by Frontline Systems.

5 Case study

To demonstrate the usefulness of the proposed model, the model was applied to a product portfolio upgrade analysis for a local solar water-heating manufacturer. The company offers customers a wide range of complete solar water-heater systems. The main system modules, such as hot water tanks, solar collectors, chassis, and insulation, are manufactured in-house using raw materials purchased on the local market. Other functional modules, such as electric heaters, pocket sensors, and controllers, are procured from external suppliers as semi-finished products and assembled in the company's warehouse. The company produces four different types of solar water-heater systems, each composed of a combination of manufactured and procured modules. Table 2 summarizes the product portfolio, matching each module to its associated products.

An upgrade proposal is available for each of the modules described in Table 2. The upgrade proposals are presented in Table 3. The proposed modular upgrades were analyzed from a financial and value-based perspective to estimate their potential impacts on cost and demand. The rest of this section describes the selection process for which modular improvements the solar company should implement and

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[5] It is important to note, however, that other non-linear relationships might exist between the modular improvement investment ratio x_i^* and the CTV attribute magnitude. The proposed model can easily accommodate such nonlinear relationships.

Table 2 List of the products and their respective modules

Module # (i)	Module definition	Design variable	CTV attributes	Product # (j)			
				1	2	3	4
				Non-Pressurized compact system	Pressurized compact system	Non-pressurized split system	Pressurized split system
1	Pressurized horizontal Tank	Material and thickness	Longevity and working pressure		X		
2	Non-pressurized horizontal tank	Material and thickness	Longevity	X			
3	Pressurized vertical tank	Material and thickness	Longevity and working pressure				X
4	Non-pressurized vertical tank	Material and thickness	Longevity			X	
5	Pressurized flat plate	Reflective coating technology	Efficiency				X
6	Non-pressurized flat plate	Reflective coating technology	Efficiency	X	X	X	
7	Steel chassis	Paint	Longevity and aesthetics	X	X	X	X
8	Circulation pump station	Pump quality	Function			X	X
9	Safety valves	Replace by higher quality	Safety and function		X		X
10	Heat transfer fluid	Include glycol	Efficiency and function				X
11	Plumbing accessories	Quality	Function, longevity and aesthetics	X	X	X	X

estimates the increase in profits expected after the selected upgrades are made.

The selection of modules for improvement involves directional constraints that must be satisfied. For example, if one of the solar tanks is upgraded to stainless steel, all of the tanks must be upgraded to stainless steel, because the manufacturing line that produces all of the solar tanks will be shifted from steel to stainless steel. A unidirectional selection constraint exists between modules 5 and 6. Because most of the flat plates installed are non-pressurized, it would be very expensive to import only the pressurized collectors; it would be more economical to import all of the flat plates from the same supplier. The opposite does not apply, because the non-pressurized flat plates can be economically imported alone. The constraints on the module upgrades are summarized in Fig. 9. The discrete modules, for which the related matrix elements must be either zero or 1, are highlighted in the figure.

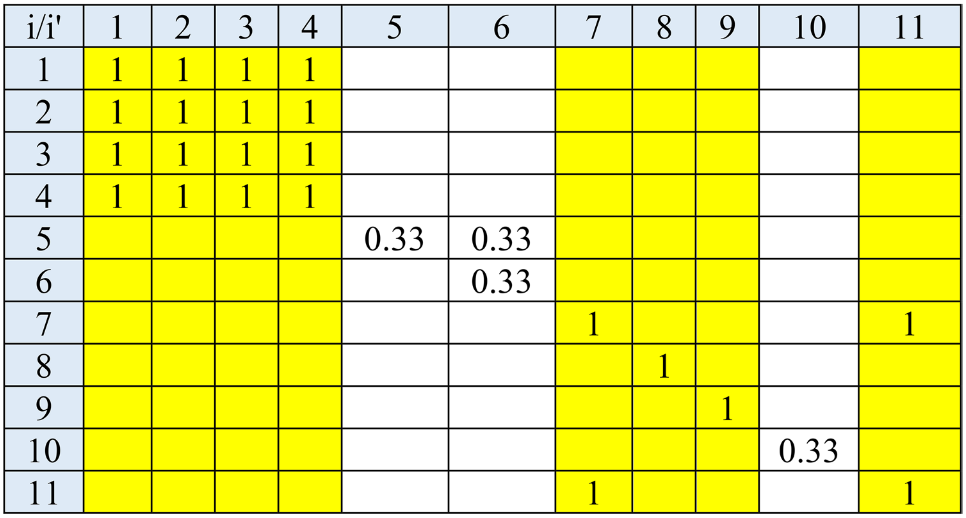
Because modules 1, 2, 3, 4, 7, 8, 9, and 11 in Fig. 9 are discrete, their diagonal elements in the matrix are unity, meaning that if they are selected for improvement, they have to be improved completely. For the remaining modules, the values on the matrix diagonal are calculated on the basis of the range of possible improvement, as described in Table 3. For example, module 5 can be improved by applying a coat of reflective paint that can vary in thickness between 100 and 300 µm. To translate that range of possible improvement into percentages, simple linear scaling is applied that transforms the 300 µm maximum thickness to 100%, making the 100 µm minimum thickness 33%. Finally, the module improvements affect discrete and continuous CTV attributes. Table 4 shows detailed descriptions of the CTV attributes mentioned in Table 2, specifying their nature as discrete or continuous.

After the existing products, their constituent modules, and the related CTV attributes are defined, the market parameters of the products must be described. According to Cook and Wu (2001), the constant μ is calculated using Eq. (25):

$$\mu = \frac{\text{Number of Competitors} \times \text{Price Elasticity of Demand} \times \text{Average Demand}}{\text{Average Price}}. \tag{25}$$

Table 3 Module improvement options

Module # (i)	Existing module	Proposed improvement	Module nature (n_i)
1	Horizontal tank made of 4 mm steel and enamel painted	Horizontal tank upgraded to 1.8 mm stainless steel	Discrete
2	Horizontal tank made of 2 mm steel and enamel painted	Horizontal tank upgraded to 0.8 mm stainless steel	Discrete
3	Vertical tank with coil made of 4 mm steel and enamel painted	Vertical tank with coil upgraded to 1.8 mm stainless steel	Discrete
4	Vertical tank with coil made of 2 mm steel and enamel painted	Vertical tank with coil upgraded to 0.8 mm stainless steel	Discrete
5	Pressurized flat plate with standard reflective layer (produced in-house)	Highly selective coating with variable thickness ranging from 100 to 300 µm (must be imported from external supplier)	Continuous
6	Non-pressurized flat plate with standard reflective layer (produced in-house)	Highly selective coating with variable thickness ranging from 100 to 300 µm (must be imported for external supplier)	Continuous
7	Steel chassis made of galvanized steel (unpainted)	Galvanized steel coated with hammer paint (slows rusting and enhances aesthetics)	Discrete
8	Circulation pump station assembled using medium quality pumps (serviced every 2–3 years)	Circulation pump station assembled using higher-quality pumps for longer life span and lower failure rates (5-year warranty)	Discrete
9	Safety valves of medium quality (replaced almost annually)	Higher-quality safety valves (replaced every 3 years expected)	Discrete
10	Heat transfer fluid	Glycol solution added in variable amounts ranging from 5 to 10% to heat transfer fluid to prevent overheating and freezing. This will slightly reduce efficiency	Continuous
11	PPR pipes and accessories used and insulated on site with masking tape protection cover	Shift to pre-insulated, UV-resistant PEX pipes and accessories	Discrete



i/i'	1	2	3	4	5	6	7	8	9	10	11
1	1	1	1	1							
2	1	1	1	1							
3	1	1	1	1							
4	1	1	1	1							
5					0.33	0.33					
6						0.33					
7							1				1
8								1			
9									1		
10										0.33	
11							1				1

Fig. 9 Module improvement interdependency matrix Y

Assuming that the price elasticity of the four products is equal to 1, the value of μ is calculated for each product as shown in Table 5. Table 6 summarizes the cost, price, demand, and value of the products prior to the implementation of any improvement plan.

Initially, the model was solved with an unlimited budget as a benchmark. As shown in Table 7, the optimal solution does not improve all of the modules under the unlimited budget, despite the fact that each modular improvement yields an increase in product values.[6] The explanation for

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[6] Online Appendix D contains a check of all the constraint calculations for the optimal solution shown in Table 10 using Eqs. (7), (8), and (9), in reference to the module interdependency matrix presented in Fig. 9.

Table 4 CTV attributes and their related modules

CTV attribute (k)	CTV attribute	Definition as shared with customers	CTV attribute (q_k)	Related modules	Modules type
1	Longevity	Extended warranty on system between 5 and 10 years (current warranty is 3 years)	Continuous	1, 2, 3, 4, 7, 11	Mixed
2	Working pressure	Increased working pressure from 4 to 6 bar	Discrete	1, 3	Discrete
3	Efficiency	Boost efficiency between 10 and 25%	Continuous	5, 6, 10	Continuous
4	Aesthetics	Color coated chassis that does not rust	Discrete	7, 11	Discrete
5	Function	Reduced sudden breakdowns from 2 per year to between 0.5 and 1 per year	Continuous	8, 9, 10, 11	Mixed
6	Safety	Prevent uncomfortably high water temperatures on end users, and protect system tanks from exploding because of overpressure	Discrete	9	Discrete

Table 5 Competitive market study

Product	Number of competitors	Price elasticity of demand	Average demand	Average price	μ
1	4	1	382	$1545.00	0.99
2	4	1	474	$1878.00	1.01
3	5	1	499	$2450.00	1.02
4	5	1	580	$2950.00	0.98

Table 6 Market parameters of the products prior to any modular improvement

Product	Value (v_j)	Price (p_j)	Cost (c_j)	Demand (d_j)
1	$2036.00	$1485.00	$850.00	551
2	$2343.00	$1745.00	$950.00	598
3	$2990.00	$2645.00	$1500.00	345
4	$3765.00	$3445.00	$1750.00	320

that unintuitive result is that the added product value gained from upgrading module 8 is outweighed by increases in product cost and price, which cause the demand to drop to a point where the new profit made by selling the upgraded product is lower than the profit prior to the upgrade. This example illustrates the complexity of decisions regarding modular upgrades, because even as some variables improve, such as the product value, changes in other variables, such as the price versus demand relationship, might have a negative impact on profits.

As shown in Table 7, modules 8, 9, and 10 are completely upgraded in the optimal solution; however, modules 5 and 6 are only partially upgraded. In comparison with Table 6, the demand for products 2, 3, and 4 increases, whereas that for product 1 decreases. These results also highlight the difference between managing a portfolio of projects and managing a collection of individual projects. Because the profit margin is kept the same for all products before and after improvement, the profits resulting from sales of product 1 decrease in the optimal solution. However, the same modules that cause the decrease in profits from product 1 yield a much greater increase in profits for the other products, and thus the optimal increase in total profits is achieved (see Table 8). The total cost of the optimal module improvements is 1,789,299 USD. It is important to note that the cost of the optimal solution is much less than the cost of improving all the modules. Hence, the trivial decision to improve all of

Table 7 Optimal solution under an unlimited budget

Product#	V'	P'	C'	D'	Project summary	
1	$2091	$1569	$915	522	Budget	Unlimited
2	$2517	$1849	$1030	668	Project cost	$1,789,299
3	$3580	$2866	$1670	715	%ΔT	66%
4	$4373	$3695	$1942	678	ROI (years)	1.5

Module#	1 (%)	2 (%)	3 (%)	4 (%)	5 (%)	6 (%)	7 (%)	8 (%)	9 (%)	10 (%)	11 (%)
Optimal sol.	0	0	0	0	93	86	0	100	100	100	0

Table 8 Profits before and after implementation of the optimal upgrade solution

Product#	t	t'	$t' - t$
1	$ 349,885.00	$341,828.25	$(8056.75)
2	$ 475,410.00	$547,389.33	$71,979.33
3	$ 395,025.00	$854,786.36	$459,761.36
4	$ 542,400.00	$1,187,715.05	$645,315.05
Total	$1,762,720.00	$2,931,718.99	$1,168,998.99

Table 9 Effects of module upgrades on total profits

Modules	Scenario 1 (optimal)	Scenario 2 (opt.−mod. 10)	Scenario 3 (mod. 10 alone)
1	0%	0%	0%
2	0%	0%	0%
3	0%	0%	0%
4	0%	0%	0%
5	93%	93%	0%
6	86%	86%	0%
7	0%	0%	0%
8	100%	100%	0%
9	100%	100%	0%
10	100%	0%	100%
11	0%	0%	0%
Project cost	$ 1,789,298.72	1,689,299	$350,000.00
%Increase in profit	66%	59%	− 31%

Table 10 Budget sensitivity analysis of the optimal solution

Modules	Budget			
	$2,000,000	$1,500,000	$1,000,000	$500,000
1	0%	0%	0%	No solution
2	0%	0%	0%	
3	0%	0%	0%	
4	0%	0%	0%	
5	93%	93%	85%	
6	86%	67%	36%	
7	0%	0%	0%	
8	100%	100%	100%	
9	100%	100%	100%	
10	100%	100%	71%	
11	0%	0%	0%	
Project cost	$1,789,299	$1,499,998	$1,000,000	–
%Increase in profit	66%	64%	49%	–
ROI	1.53	1.32	1.16	–

the modules whenever the budget allows is not always the wisest, even if the module improvements increase the value of all the products. The reason behind that observation is that the cost of producing the modules increases with each improvement, potentially making the price of the resulting products less appealing to customers despite the better value promised, leading to reduced demand and profits.

To further illustrate the hidden effects of cost, price, demand, and value on the optimization model, a simple example is shown in Table 9, in which the optimal solution is compared with the scenario where module 10 is excluded from the solution (Scenario 2) and the scenario where only the effect of upgrading module 10 is considered (Scenario 3). The results show that although upgrading module 10 is part of the optimal solution, upgrading module 10 alone leads to a 31% reduction in overall profits. Removing module 10 from the overall improvement plan also yields a suboptimal solution. Therefore, the sum of the effects of Scenarios 2 and 3 does not yield the same effect as the optimal solution. The reason for this result is that improving module 10 alone would increase the cost of the related products without justifiably affecting the overall value of the products. However, when module 10 is improved along with the other modules selected in the optimal solution, the overall increase in the value of the products can be maximized.

To assess how changes in the budget affect the increase in total profits resulting from the optimal solution, the optimal solution was recalculated with incremental decreases in the available budget. Because the decision variables for some of the modules selected for improvement were continuous, the model yielded optimal solutions with total costs equal to the specified budget whenever possible. The results are summarized in Table 10.

For a budget of 2 million USD, the optimal solution yielded an increase in profit of 66% with a return on investment (ROI) of 1.5 years, which is the maximum possible increase for the project under study. Reduction of the budget to 1.5 million USD yielded an increase in profit of 64% with an ROI of 1.3 years, which might be a better option than the solution for the higher budget, because the increase in profit was nearly the same but with a much lower initial investment. For a budget of 1 million USD, the increase in profit dropped to 49% with an ROI of 1.2 years. For budgets lower than 1 million USD, there was no solution that yielded any increase in profits. It is notable that the choices of the optimal levels of improvement of continuous design variables were complex. Referring to Table 10, reduction of the budget from 2 million USD to 1.5 million USD resulted in a decrease in the level of improvement of module 6 from 86 to 67% without any change in the levels of other modular improvements. When the budget was reduced further to 1 million USD, the level of improvement of module 6 decreased to 36%, accompanied by a decrease in the level of improvement of module 5 from 93 to 85% to meet the budget. The model was thus able to combine reductions in the levels of improvement of different modules rather than reduce the level of a single module to meet the specified budget, thus ensuring optimality.

6 Conclusion

It is not a trivial task to find the optimal subset of modules to upgrade in a product portfolio, as demonstrated by the case study despite its relatively small size. Having continuous decision variables and interdependencies among modules, products, and CTV attributes on the one hand, and the relationships that exist among the various parameters of cost, price, value, and demand on the other hand, allow the model presented here to pose real-life module improvement decision-making problems, however, magnifies the complexity in finding the optimal solution. The complexity can increase exponentially as the range of products and modules increases. This draws the need for an effective decision support framework based on mathematical optimization formulation.

The practicality of the proposed mathematical model is that it bridges the gap between engineering design decisions and market research, and allows for high flexibility in the magnitude of module improvement. Additionally, as evidenced in the case study, the optimized solution required only part of the assigned budget, which means that the model not only gives an optimal solution for a given budget but also helps to determine the required budget for improvement. The proposed model can, therefore, be used for budget assignment as well as for budget allocation on optimal module upgrades.

The model proposed in this paper can be improved in several ways, which would constitute interesting avenues for future research and extensions. First, the demand for a product is modelled as a linear function of the product value and price, using the S-Model. However, there is a strong underlying assumption, that is, consumers know the exact value of the new products to them, even when there are different combinations of modules that lead to different attributes. In other words, there is no uncertainty in valuation when consumers face different new products. Future research would investigate relaxing this assumption as an extension to the model using uncertain valuation of product improvements. In that way, the model can be made to portray more realistic business scenarios.

Additionally, since we assume that customers value attributes (as shown in Figs. 6, 7), then there could be interdependencies across attributes. That is, some attributes and their combinations could be available in multiple modules. For ease of setup and explanation, this situation is not being addressed directly by the proposed model. Instead, we assume that these attributes are assessed and valued, by customers, one at a time using Cook's DVM and value curves (Cook 1997). However, Cook's method for discrete CTV attributes can be used for several CTV attributes at a time using conjoint DVM. In this paper, DVM was used for one CTV attribute at a time to estimate the effect of each CTV attribute on the product value separately.

Finally, the proposed model is designed to optimize in a linear manner, because it assumes that the costs of improvements and module upgrades are linearly related. Other more complex relationships might exist between investments and the levels of module upgrade and product cost, however. Future work can develop the model presented here to include predefined mathematical relationships between the proposed investments and the level of upgrades for continuous modules.

In spite of these limitations, the proposed model remains very useful by providing product development (PD) managers with easy-to-use computer-based decision support tool that can be easily implemented by PD managers without the need to explicitly formulate or solve a different mathematical optimization model every time they face such a product upgrade decision. As explained throughout this paper and illustrated in the case study, such module improvement decision-making problems are highly sensitive and dependent on the initial data provided. Any change in the initial data can alter the optimal solution and magnitude of module improvements, which may require reassessment of all the interrelated variables and tedious equations to find the revised optimal solution. However, using the proposed model, the PD manager can simply change any of the input data at any time, and the revised optimal solution is automatically and immediately presented.

Appendix A: Summary of variables, parameters, and equations used in the model

See Tables 11 and 12.

Table 11 Summary of all indices, variables, and parameters used in the model

Indexes	Description
i	Module index $i \in (1, \ldots i, \ldots I)$; where I is the total number of modules considered for improvement
i'	Another module index $i' \in \left(1, \ldots i', \ldots I\right)$; where I is the total number of modules considered for improvement
j	Product index $j \in (1, \ldots j, \ldots J)$; where J is the total number of products under consideration
k	Critical-to-value (CTV) attribute index $k \in (1, \ldots k, \ldots K)$; where K is the total number of CTV attributes under consideration

Variables	Description
α_i	Binary variable $\alpha_i \in A\left(\alpha_1, \ldots \alpha_i, \ldots \alpha_I\right)$, indicates whether module i will be improved or not
x_i	Decision variable $x_i \in X\left(x_1, \ldots x_i, \ldots x_I\right)$, indicates the percentage of improvement made on module i; where $0 \leq x_i \leq 100\%$
x_i^*	Adjusted decision variable $x_i^* \in X^*\left(x_1^*, \ldots x_i^*, \ldots x_I^*\right)$, adjusts x_i for modules with a discrete nature

Input parameters	Description
B	Total available budget for modules improvement
c_j	Variable $c_j \in C\left(c_1, \ldots c_j, \ldots c_J\right)$, indicates the cost of product j prior to improving any module
c'_j	Variable $c'_j \in C'\left(c'_1, \ldots c'_j, \ldots c'_J\right)$, indicates the cost of product j after improving the selected modules
d_j	Variable $d_j \in D\left(d_1, \ldots d_j, \ldots d_J\right)$, indicates the demand for product j prior to improving any module
d'_j	Variable $d'_j \in D'\left(d'_1, \ldots d'_j, \ldots d'_J\right)$, indicates the expected demand for product j after improving the selected modules
$e_{j,k}$	Variable $e_{j,k} \in E\begin{pmatrix} e_{1,1} & \cdots & e_{1,K} \\ \vdots & e_{j,k} & \vdots \\ e_{J,1} & \cdots & e_{J,K} \end{pmatrix}$, defines the current magnitude of CTV attribute k of product j; i.e. prior to any module improvement
$f_{j,k}$	Variable $f_{j,k} \in F\begin{pmatrix} f_{1,1} & \cdots & f_{1,K} \\ \vdots & f_{j,k} & \vdots \\ f_{J,1} & \cdots & f_{J,K} \end{pmatrix}$, defines the magnitude of CTV attribute k of product j that will be achieved if all considered modules that affect CTV attribute k are 100% improved
$g_{j,k}$	Variable $g_{j,k} \in G\begin{pmatrix} g_{1,1} & \cdots & g_{1,K} \\ \vdots & g_{j,k} & \vdots \\ g_{J,1} & \cdots & g_{J,K} \end{pmatrix}$, defines the magnitude of CTV attribute k that drops the value of product j to zero
$\gamma_{j,k}$	Variable $\gamma_{j,k} \in \theta\begin{pmatrix} \gamma_{1,1} & \cdots & \gamma_{1,K} \\ \vdots & \gamma_{j,k} & \vdots \\ \gamma_{J,1} & \cdots & \gamma_{J,K} \end{pmatrix}$, defines the fraction of time attribute k is experienced by a customer of product j
$h_{j,k}$	Variable $h_{j,k} \in H\begin{pmatrix} h_{1,1} & \cdots & h_{1,K} \\ \vdots & h_{j,k} & \vdots \\ h_{J,1} & \cdots & h_{J,K} \end{pmatrix}$, defines the most ideal magnitude CTV attribute k can have to maximize the value of product j
$l'_{j,k}$	Variable $l'_{j,k} \in L'\begin{pmatrix} l'_{1,1} & \cdots & l'_{1,K} \\ \vdots & l'_{j,k} & \vdots \\ l'_{J,1} & \cdots & l'_{J,K} \end{pmatrix}$, defines the value of product j after changing the magnitude of CTV attribute k to $m_{j,k}$
$m_{j,k}$	Variable $m_{j,k} \in M\begin{pmatrix} m_{1,1} & \cdots & m_{1,K} \\ \vdots & m_{j,k} & \vdots \\ m_{J,1} & \cdots & m_{J,K} \end{pmatrix}$, defines the magnitude of CTV attribute k of product j after the selected modules are improved
n_i	Binary variable $n_i \in N\left(n_1, \ldots n_i, \ldots n_I\right)$, indicates the nature of module i improvement; continuous or discrete
O	Other overheads incurred during the module improvement process
p_j	Variable $p_j \in P\left(p_1, \ldots p_j, \ldots p_J\right)$, indicates the selling price of product j prior to improving any module

Table 11 (continued)

Input parameters	Description
p'_j	Variable $p'_j \in P'\left(p'_1, \dots p'_j, \dots p'_J\right)$, indicates the selling price of product j after improving the selected modules
π	Total profits before improving any module
π'	Expected total profits after improving the selected modules
q_k	Binary variable $q_k \in Q\left(q_1, \dots q_k, \dots q_K\right)$, indicates the nature of CTV attribute k; continuous or discrete
r_i	Variable $r_i \in R\left(r_1, \dots r_i, \dots r_I\right)$, defines the research and development costs required to develop module i
$s_{i,j}$	Variable $s_{i,j} \in S\begin{pmatrix} s_{1,1} & \cdots & s_{1,J} \\ \vdots & s_{i,j} & \vdots \\ s_{I,1} & \cdots & s_{I,J} \end{pmatrix}$, defines the validation and verification costs for compatibility of modular improvement i with final product j
t_j	Variable $t_j \in T\left(t_1, \dots t_j, \dots t_J\right)$, indicates the profits related to product j prior to improving any module
t'_j	Variable $t'_j \in T'\left(t'_1, \dots t'_j, \dots t'_J\right)$, indicates the expected profits related to product j after improving the selected modules
$u_{i,j}$	Variable $u_{i,j} \in U\begin{pmatrix} u_{1,1} & \cdots & u_{1,J} \\ \vdots & u_{i,j} & \vdots \\ u_{I,1} & \cdots & u_{I,J} \end{pmatrix}$, defines the profit mark-up factor on the cost of module i in product j
μ_j	Variable $\mu_j \in \varphi\left(\mu_1, \dots \mu_j, \dots \mu_J\right)$, defines the market elasticity of product j
v_j	Variable $v_j \in V\left(v_1, \dots v_j, \dots v_J\right)$, indicates the value of product j prior to improving any module
v'_j	Variable $v'_j \in V'\left(v'_1, \dots v'_j, \dots v'_J\right)$, indicates the expected value of product j after improving the selected modules
$w_{i,j,k}$	Variable $w_{i,j,k} \in W\left(w_{1,1,1}, \dots, w_{i,j,k}, \dots, w_{I,J,K}\right)$, indicates the contribution of module i in defining CTV attribute k for product j
$y_{i,i'}$	Binary variable $y_{i,i'} \in Y\begin{pmatrix} y_{1,1} & \cdots & y_{1,I} \\ \vdots & y_{i,i'} & \vdots \\ y_{I,1} & \cdots & y_{I,I} \end{pmatrix}$, defines the upgrade relationship among the existing modules; where Y is a square matrix, and $i' \in \left(1, \dots i', \dots I\right)$ is a module index
z_i	Variable $z_i \in Z\left(z_1, \dots z_i, \dots z_I\right)$, indicates the cost of module i prior to improving it
z'_i	Variable $z'_i \in Z'\left(z'_1, \dots z'_i, \dots z'_I\right)$, indicates the expected cost of module i after a 100% improvement

Table 12 Summary of all equations used in the model

Equations in each model subsection	References
Defining the decision variables	Equation (5)
$n_i = \begin{cases} 0, & \text{indicating a continuous modular improvement} \\ 1, & \text{indicating a discrete modular improvement} \end{cases}$	Equation (6)
$x_i^* = \begin{cases} 0, & x_i = 0 \\ x_i, & x_i > 0 \text{ and } n_i = 0 \\ 1, & x_i > 0 \text{ and } n_i = 1 \end{cases}$	Figure (7)
	Equation (7)
Defining the product architecture (i.e. modular interdependencies) Matrix ***Y***	Equation (8)
$x_i^* \geq \alpha_{i'} \times y_{i',i} \forall i' \in I$	Equation (9)
$\alpha_{i'} = \begin{cases} 0, & x_{i'}^* = 0 \\ 1, & x_{i'}^* > 0 \end{cases}$	
$y_{i',i} \times x_i^* \geq 0 \forall i' \in I$	
Defining the budget	Equation (10)
$\sum_i \left[x_i^* \times \left(r_i + \sum_j s_{i,j} \right) \right] + O < B$	
	Equation (11)
Optimizing value for best profit	
$t_j = \left[p_j - c_j \right] \times d_j$	Equation (12)
$\pi = \sum_j t_j$	
	Equation (13)
$p_j' = p_j + \sum_i \left[u_{i,j} \times x_i^* \times \left(z_i' - z_i \right) \right]$	
	Equation (14)
$c_j' = c_j + \sum_i \left[x_i^* \times \left(z_i' - z_i \right) \right]$	
	Equation (15)
$d_j' = d_j + \delta d_j$	
$\delta d_j = \mu_j \times \left(\delta v_j - \delta p_j \right)$	Equation (16)
$\delta p_j = \sum_i \left[u_{i,j} \times x_i^* \times \left(z_i' - z_i \right) \right]$	Equation (17)
$\delta v_j = v_j \times \left[\prod_k \left[\frac{l_{j,k}'}{v_j} \right] - 1 \right]$	Equation (18)
$q_k = \begin{cases} 0, & \text{indicating a continuous CTV attribute} \\ 1, & \text{indicating a discrete CTV attribute} \end{cases}$	Equation (19)
$v_{j,k}' = \begin{cases} v_j, & \sum_i \left(w_{i,j,k} \times x_i^* \right) = 0 \\ \text{Survey based value}, & \sum_i \left(w_{i,j,k} \times x_i^* \right) > 0 \text{ and } q_k = 1 \\ v_j \times \left[\frac{\left[g_{j,k} - h_{j,k}\right]^2 - \left[m_{j,k} - h_{j,k}\right]^2}{\left[g_{j,k} - h_{j,k}\right]^2 - \left[e_{j,k} - h_{j,k}\right]^2} \right]^{\gamma_{j,k}} & \sum_i \left(w_{i,j,k} \times x_i^* \right) > 0 \text{ and } q_k = 0 \end{cases}$	Equation (20) Equation (21) Equation (22)
$\omega_{j,k} = \begin{cases} \sum_i \left(w_{i,j,k} \times x_i^* \right) \times \left(f_{j,k} - g_{j,k} \right) + g_{j,k}, \sum_i \left(w_{i,j,k} \times x_i^* \right) \leq 1 \\ f_{j,k}, \sum_i \left(w_{i,j,k} \times x_i^* \right) > 1 \end{cases}$	Equation (23)
$t_j' = \left[p_j' - c_j' \right] \times d_j'$	Equation (24)
$\pi' = \sum_j t_j'$	
Maximize $\frac{\pi' - \pi}{\pi} \times 100\%$	

Appendix B: Expansion of constraints in Eqs. (7) and (9) for Fig. 8

$$x_i^* \geq \alpha_{i'} \times y_{i',i} \forall i' \in I \tag{26}$$

$$\alpha_{i'} = \begin{cases} 0, & x_{i'}^* = 0 \\ 1, & x_{i'}^* > 0 \end{cases} \tag{27}$$

$$y_{i',i} \times x_i^* \geq 0 \forall i' \in I \tag{28}$$

Constraint Eq. (7)	Constraint Eq. (9)
$x_1^* \geq \alpha_1 \times y_{1,1}$	$y_{1,1} \times x_1^* \geq 0$
$x_1^* \geq \alpha_2 \times y_{2,1}$	$y_{2,1} \times x_1^* \geq 0$
$x_1^* \geq \alpha_3 \times y_{3,1}$	$y_{3,1} \times x_1^* \geq 0$
…	…
$x_1^* \geq \alpha_I \times y_{I,1}$	$y_{I,1} \times x_1^* \geq 0$
$x_2^* \geq \alpha_1 \times y_{1,2}$	$y_{1,2} \times x_2^* \geq 0$
$x_2^* \geq \alpha_2 \times y_{2,2}$	$y_{2,2} \times x_2^* \geq 0$
$x_2^* \geq \alpha_3 \times y_{3,2}$	$y_{3,2} \times x_2^* \geq 0$

Constraint Eq. (7)	Constraint Eq. (9)
…	…
$x_2^* \ge \alpha_I \times y_{I,2}$	$y_{I,2} \times x_2^* \ge 0$
$x_3^* \ge \alpha_1 \times y_{1,3}$	$y_{1,3} \times x_3^* \ge 0$
$x_3^* \ge \alpha_2 \times y_{2,3}$	$y_{2,3} \times x_3^* \ge 0$
$x_3^* \ge \alpha_3 \times y_{3,3}$	$y_{3,3} \times x_3^* \ge 0$
…	…
$x_3^* \ge \alpha_I \times y_{I,3}$	$y_{I,3} \times x_3^* \ge 0$
.	.
.	.
.	.
$x_I^* \ge \alpha_1 \times y_{1,I}$	$y_{1,I} \times x_I^* \ge 0$
$x_I^* \ge \alpha_2 \times y_{2,I}$	$y_{2,I} \times x_I^* \ge 0$
$x_I^* \ge \alpha_3 \times y_{3,I}$	$y_{3,I} \times x_I^* \ge 0$
…	…
$x_I^* \ge \alpha_I \times y_{I,I}$	$y_{I,I} \times x_I^* \ge 0$

Appendix C: Calculation of constraints on module 6 improvement

See Tables 13 and 14.

Table 13 Calculation of constraints on module 6 improvement when module 3 is also improved [demonstrating Eqs. (7) and (9) in reference to Fig. 8]

i'	Module i' upgraded?	$\alpha_{i'}$	$y_{i',6}$	$\alpha_{i'} \times y_{i',6}$	$y_{i',6} \times x_6^*$	Trial $x_6^* = 1$	Equations
1	Assumed yes ($x_1^* > 0$)	1	0.5	0.5	0.5	$1 \ge 0.5$ → OK $0.5 \ge 0$ → OK	(7) (9)
2	Assumed no ($x_2^* = 0$)	0	0	0	0	$1 \ge 0$ → OK $0 \ge 0$ → OK	(7) (9)
3	Assumed yes	1	-1	-1	-1	$1 \ge -1$ → OK $-1 \ge 0$ → NO	(7) (9)
4	Assumed no	0	0	0	0	$1 \ge 0$ → OK $0 \ge 0$ → OK	(7) (9)
5	Assumed yes	1	1	1	1	$1 \ge 1$ → OK $1 \ge 0$ → OK	(7) (9)
6	Trial $x_6^* = 1$	1	0.25	0.25	0.25	$1 \ge 0.25$ → OK $0.25 \ge 0$ → OK	(7) (9)
7	Assumed yes	1	0	0	0	$1 \ge 0$ → OK $0 \ge 0$ → OK	7(7) (9)
8	Assumed no	0	0	0	0	$1 \ge 0$ → OK $0 \ge 0$ → OK	(7) (9)
9	Assumed no	0	0	0	0	$1 \ge 0$ → OK $0 \ge 0$ → OK	(7) (9)

Table 14 Calculation of constraints on module 6 improvement when all other modules are improved except for modules 1 and 5 [demonstrating Eqs. (7) and (9) in reference to Fig. 8]

i'	Module i' upgraded?	$\alpha_{i'}$	$y_{i',6}$	$\alpha_{i'} \times y_{i',6}$	$y_{i',6} \times x_6^*$	Trial $x_6^* = 0$	Equations
1	Assumed yes ($x_1^* > 0$)	1	0.5	0.5	0	$0 \ge 0.5$ → NO $0 \ge 0$ → OK	(7) (9)
2	Assumed no ($x_2^* = 0$)	0	0	0	0	$0 \ge 0$ → OK $0 \ge 0$ → OK	(7) (9)
3	Assumed yes	1	-1	-1	0	$0 \ge -1$ → OK $0 \ge 0$ → OK	(7) (9)
4	Assumed no	0	0	0	0	$0 \ge 0$ → OK $0 \ge 0$ → OK	(7) (9)
5	Assumed yes	1	1	1	0	$0 \ge 1$ → NO $0 \ge 0$ → OK	(7) (9)
6	Assumed no (Trial $x_6^* = 0$)	0	0.25	0	0	$0 \ge 0$ → OK $0 \ge 0$ → OK	(7) (9)
7	Assumed yes	1	0	0	0	$0 \ge 0$ → OK $0 \ge 0$ → OK	(7) (9)
8	Assumed no	0	0	0	0	$0 \ge 0$ → OK $0 \ge 0$ → OK	(7) (9)
9	Assumed no	0	0	0	0	$0 \ge 0$ → OK $0 \ge 0$ → OK	(7) (9)

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