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Reconciling Platform vs. Product Optimisation by Value-Based Margins on Solutions and Parameters

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Engineering companies face the challenge of optimising margins within product platforms while balancing individual product optimisation and maximising platform commonality. Key obstacles include organizational silos, diverse design variables, design space allocation, and varying time perspectives. This paper proposes a value-based modelling methodology that integrates both internal and external variety within the manufacturer. Using an automotive Head-Up Display (HUD) case study, we demonstrate how to effectively utilise platform margins to maximise technological variety and minimise internal variety, thereby enhancing long-term system value. This approach helps design teams understand the implications of their decisions, optimise platform margins to meet evolving technological demands, reduce costs, and maximise value. Our findings advance the understanding of margin optimisation in product platforms and support informed decision-making for engineering companies facing conflicting objectives.

Keywords: Margin optimisation; Product platforms; Engineering design; Value modelling design margins; Technology integration.

1 Introduction

Engineering companies often face the challenge of balancing two conflicting objectives: 1) optimising individual products for specific customer segments, and 2) maximising the use of standardised components across a product platform. While this standardisation enables cost-efficiency due to economies of scale, it means that the platform often contains components that are 'more capable' than what is requested by many customer segments (Eckert et al. 2020) since the platform is designed for 'worst case' scenarios. While this choice implies some sub-optimisation of individual customer requirements, it can be beneficial as it provides *margins* that provide a useful 'room for growth' if such requirements may arise in the future (Jacobson and Ferguson 2023). For these reasons, margins are added explicitly or implicitly during the development process, often relying on experience and intuition. However, this way of deciding about margins in a platform has some drawbacks. For example, it assumes that *today*, customers would require *tomorrow* a component with a higher capability than what they require. However, this may not always be the case. Some capabilities must be optimised for a certain parameter. For example, the size of a keyboard needs to adapt to the exact anthropometric dimensions of the user's hand (i.e. a larger keyboard size is not always better). In some cases, the capability must avoid a certain parameter (e.g. in the case of resonances; Bertoni, Bertoni, and Isaksson 2018). Also, increasing a capability may come at the expense of other attributes (e.g. cost and weight); therefore, there are several trade-offs involved. These are simple examples that highlight the risk of over-estimating the 'future value' of a margin included in a platform. As it will be further developed in this paper, considering the optimal value of a platform margin is even more complex, owing to the recursive connection among key variables (1) current and future product demand, (2) different cost aspects, such as the cost-efficiency brought by the platform approach, and (3) the maturity of key technologies. Possessing a way to computationally experiment with these nested connections would be helpful and effective to have a clearer visibility of the margin provided by choices made during platform and component selections.

For these reasons, in this paper we focus on the following research question: *"How can decisions about which optimal platform margin to reserve be supported?"*

The result is a modelling approach that aggregates the variables described above in a Net Present Value model, traditionally used in technology evaluation (de Weck 2022).

The outline of the paper is as follows. Section 2 reviews the foundational concepts of design margins within product platforms. Section 3 presents the research methodology and data collection methods employed. Section 4 introduces the value-based margin approach and explains the steps involved in identifying key product properties, platform alternatives, technology options, and scenario variables. Section 5 presents an industrial case study in collaboration with a Swedish car manufacturer on automotive Head-Up Displays (HUD, an advanced optical system to enhance driver safety). Finally, Section 6 discusses the broader implications of the findings, while the last section synthesizes the key takeaways and proposes future research directions to further refine and apply the methodology in diverse industrial contexts.

2 Background: the role of margins in product platforms

2.1 Design margins

Design margins in product development are extra allowances built into the design to handle unexpected issues. These margins provide some *excess* (unused potential) that can be used to adapt to new requirements throughout the product lifecycle (Jones and Eckert 2019; Eckert et al. 2020), as well as a *buffer* to tackle other uncertainties. Design margins are crucial for mitigating the risks and uncertainties inherent in product development, ensuring that the product can withstand variations and unforeseen circumstances (Brahma and Wynn 2020). Unlike safety margins, which specifically address safety considerations, design margins focus on exceeding functional requirements to accommodate uncertainties (Jones, Eckert, and Garthwaite 2020; Eckert and Isaksson 2017).

Excess margins involve intentionally adding more than the necessary allowances to meet functional requirements. However, they can lead to overdesign and inefficiencies in the product (Eckert, Isaksson, and Earl 2019). These margins can result from the independent inclusion of safety and design margins during the design process, thereby contributing to unnecessary redundancy (Eckert and Isaksson, 2017). Despite this, margin management is crucial for effective handling of engineering changes and iterations, allowing for the dynamic exploration of design spaces and influencing constraint satisfaction and performance (Guenov et al. 2018).

In industrial practice, *buffers* are essential for enabling product adaptability, facilitating redesign, and supporting the development of follow-on products (Eckert et al. 2020). While they safeguard against uncertainty and risk, the practice of incorporating margins can sometimes lead to over-engineered solutions (Jones, Eckert, and Gericke 2018), impacting the overall design process by adding costs and delays.

There are different ways to include margins in a product (Eckert et al. 2013).. Given the context of this study, we distinguish between *geometric margins* and *operational or performance margins. Geometric margins* result from the fitting of components within a confined space. *Clearances and empty spaces* are an interesting sub-case of geometric margins, as the empty space can be used to absorb uncertainties during the development process (e.g. changes in the physical placement of neighbouring components) or to include future technologies that will require more space.

In contrast, *operational or performance margins* describe the ability of a component to meet the functional requirements for specific geometries and materials (Isaksson, Lindroth, and Eckert 2014). These margins must be understood in particular configurations and usage scenarios and are challenging to assess owing to the multifaceted functions and interdependencies of components. Extraneous conditions surrounding the operation of a product can dictate the margin consumed or retained within the system. For example, the most efficient performance point may not align with the maximum capability of the product. Thus, after a product begins operations, its usage pattern significantly influences the availability of the margins (Brahma et al. 2023).

2.2 Product platforms

A product platform is a strategic approach that grew from the interest of providing customisation and personalisation to the customer base (i.e. the *external variety* offered) in a cost-efficient manner. Because developing a unique product for each customer segment would dramatically increase the cost, a product platform aims to build a similar architecture so that many products are generated by combining common parts. In this way, *internal variety* is reduced, and a range of diverse products can be produced cost-effectively through economies of scale (Meyer and Lehnerd 1997). Each product generated from a platform is called a *product variant* (van den Broeke, Boute, and Mieghem 2018). Determining the optimal number of variants to be derived from a platform is a challenging task. To aid these decisions, an economic model called Net Present Value (NPV) is often used (De Weck, Suh, and Chang, 2003). NPV is the difference between the cash inflows (i.e. the yearly profit from market share) and the cash outflows (i.e. the yearly costs) considering the current value of a future stream of payments (calculated with a discount rate of money). From a platform optimisation perspective, the challenge is that a platform has complex 'nested' interactions to both the profit and the cost parts of NPV.

First of all, the expected demand and the NPV of the single variants of the platform can be considered cumulative only if one assumes that customers accept product performances 'close enough' to their specific needs (Ofer et al. 2002). This assumption is not always true; therefore, there is a tendency to increase the number of variants more than originally planned, as this increase would increase the likelihood of optimising the variants and accumulating the expected NPV. As observed by de Weck

(2006), the average number of variants per platform has steadily increased. The problem with this is that adapting platforms to individual product requirements involves substantial development efforts (Boute, van den Broeke, and Deneire 2018). Simultaneously, increasing the number of variants must account for the negative effects of increased variety, which can lower the total NPV. These negative effects include reduced sales volume per variant and diminished economies of scale, leading to higher production costs and a lower overall NPV (Randall and Ulrich 2001; Lyons, Um, and Sharifi 2020). Thus, the mere addition of additional variants to a product family does not guarantee greater sales volumes in aggregate. Finding the optimal number of product variants is a complex task that must consider the maximisation of aggregate demand while maintaining low costs due to economies of scale (Tan et al. 2020). To account for these economies of scale, a learning curve scaling rule is often applied to platform cost modelling (Yelle 1979). The learning curve effect suggests that with every doubling of cumulative production, the cost per unit decreases by a constant percentage, owing to increased efficiency, worker proficiency, and process improvements (Argote and Epple 1990). Mathematically, learning curves follow the power function

$$y = kx^n$$

where y = The number of direct labour hours required to produce the Xth unit.

$k =$ The number of direct labour hours required to produce the first unit.

$x =$ The cumulative unit number.

$n = \frac{\log \phi}{\log 2}$ The learning index.

$\phi =$ The learning rate.

$1 - \phi =$ The progress ratio.

This has been demonstrated more recently empirically by comparing two products with different numbers of variants, where the costs related to the differentiation of the one with a greater number of variants were ten-fold those of the lower number of variants (Nørgaard et al. 2024). By leveraging the learning curve, companies can optimise production processes and supply chain decisions based on cumulative experience, thereby enhancing the effectiveness and efficiency of product platforms.

These nested connections among product platform decisions and the total profit and cost contained in an NPV model necessitate a strategic approach to balance component commonality with product distinctiveness. For these reasons, Broeke, Boute, and Mieghem (2018) characterised the optimal platform portfolio strategy that minimises the total cost using an investment versus production customisation trade-off curve.

2.3 The role of margins in product platforms

Design margins are a critical aspect of product platform development (Eckert et al. 2020). However, platform margins have a contrasting ‘dual’ role in fulfilling the goals of platform planning and product development. From a product development point of view, margins are seen as an opportunity to meet the specific customer requirements in each market segment by deriving many product variants (often through parametric design) and therefore increase the likelihood of increasing the cumulative NPV coming from each individually optimised variant. This, however, may come at the expense of the original intent of the platform strategy, which is to decrease the number of variants, consolidating production around fewer, high-volume components and assemblies, to gain economies of scale through volume (Eckert et al. 2020). At the same time, platform developers focus on margins related to solution principles rather than specific continuous parameters. This involves working with discrete alternatives (i.e. that can have a value within a set of options) as opposed to the continuous (i.e. that can have any value within a range) optimisation parameters commonly used in product development. As discrete alternatives are difficult to manipulate and assess computationally (André and Elgh 2018), there is a risk that product developers will attempt to optimise a product that is already severely overdesigned during the platform planning stages.

How to compromise this dual role can be difficult to be discerned, especially since the true value of platform margins for specific components often becomes apparent later in the design process (Eckert et al. 2020). In the next sections, we further explore this difficulty by looking at a case study in automotive platform design.

3 Research Methodology

In this study, we adopted an interactive research approach, a form of coproductive research characterised by close collaboration between researchers and practitioners to co-create knowledge that is both scientifically robust and practically relevant (Lindhult and Axelsson 2021). Unlike traditional quantitative and qualitative methods, which often maintain a distance between researchers and the subjects of their study, the interactive research approach emphasises continuous interaction and mutual learning.

This participatory method enables deeper engagement with the research context, ensuring that the knowledge generated is immediately applicable and beneficial to the stakeholders involved (Engström et al. 2022). Comparatively, traditional research approaches, such as surveys or experiments, might provide quantitative data or controlled insights, but they often lack the practical applicability that comes from direct engagement with industry stakeholders. On the other hand, purely qualitative approaches might capture rich, contextual data, but can fall short in driving actionable change within organisations. The interactive research approach combines the strengths of both by enabling a collaborative environment in which theoretical and practical knowledge intersect. By engaging practitioners throughout the research process, from data collection to the application of the findings, we ensure that our theoretical models and methodologies are grounded in actual industrial practices and constraints. This close interaction enhances the relevance and applicability of our findings (Lindhult and Axelsson 2021), supporting better decision-making in engineering design and product platform development.

The data collection for this study took place both during physical and online meetings, interviews, and workshops, conducted in 2022-2023. Twelve semi-structured one-hour-long interviews were conducted with nine industry professionals (listed in Table 1) at two automotive Original Equipment Manufacturers (OEMs). One OEM manufactures and markets luxury cars, whereas the other participates in the development of trucks distributed in more than 190 markets worldwide by different brands. The roles of the interviewees varied from platform planning (for example, System Architects and Modular Product Architecture Strategists) to product development (such as developers of the electrical infrastructure). The average years of experience in the sector of the interviews was 20 years, with a minimum of 9 years and a maximum of 35.

Table 1 Case study interview participants

ID	Role	Experience	Interactions
P1	Product Owner – Electrical Infrastructure	14 years	Interview
P2	Architecture Design Leader	15 years	Interview
P3	Product Owner	9 years	Interview (2)
P4	Mechanical Integration – Interior Room	20 years	Interview Workshop
P5	Modular Product Architecture Strategist	24 years	Interview (2)
P6	Base Product Development – Electrical Infrastructure	22 years	Interview
P7	Mechanical Integration Coordinator	21 years	Interview
P8	Team Leader - Mechanical Architecture and Integration	20 years	Interview
P9	Architecture Development	35 years	Interview (2)

			Workshop

Additionally, four workshops were organised, each lasting for three hours and attended on average by seven participants (some of which also participated in the interviews). Information from the workshops was collected through questionnaires and field notes. These sessions provided firsthand insights from industry professionals and offered empirical evidence to support the theoretical constructs. Furthermore, the authors attended weekly system integration meetings and biweekly project coordination meetings with practitioners for a year. This empirical study emphasised the importance of evaluating the 'value' of platform margins. These margins are influenced by various combinations of platform options and new technologies. These insights led to the development of a value-based margin methodology, which is presented in the next section. The methodology was then applied to a case study related to automotive Head-Up Displays (HUDs). Digital experiments using the approach were conducted to showcase the application of the approach to industrial partners.

4 Overview of the value-based margin methodology

The objective of our study is to quantify the advantages (or value) of incorporating platform margins by analysing the net lifetime value of a system. This endeavour is complex, as it necessitates the integration of perspectives from both platform and product development, involving a multitude of characteristics.

The overall approach is shown in Figure 1, represented using an IDEF0 diagram.

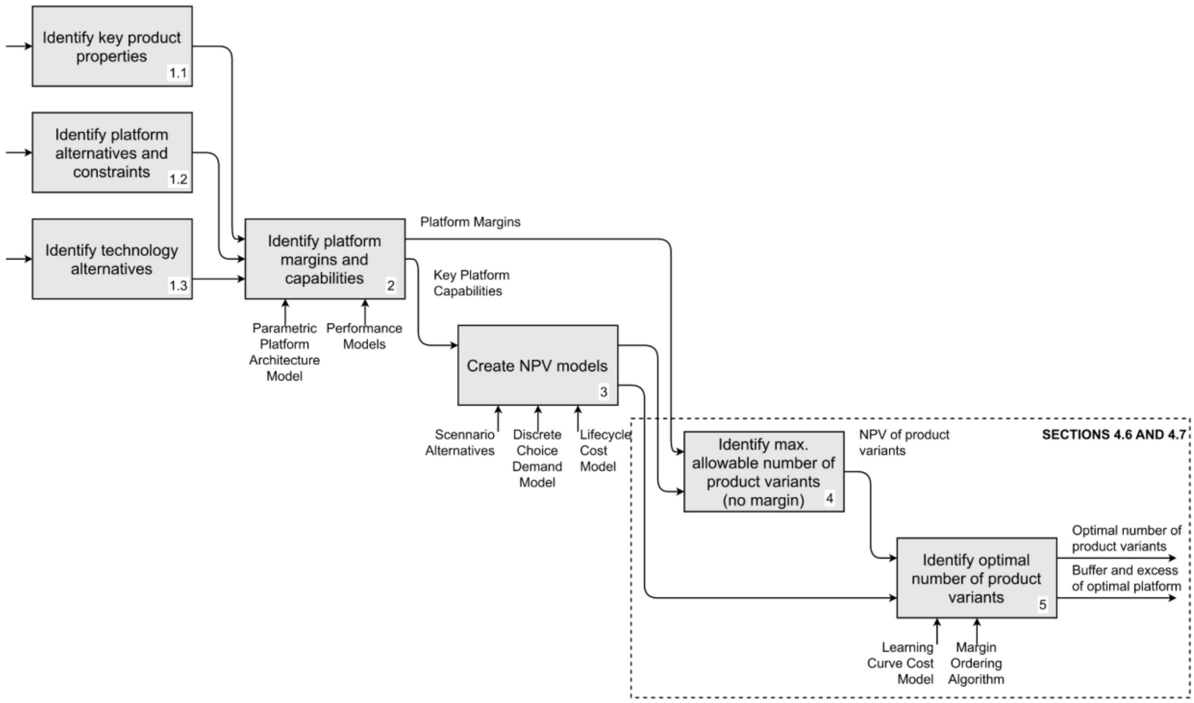


Figure 1 Overall value-based margin approach using the IDEF0 representation.

The overall steps, main models, and methods used are briefly summarised below.

4.1 Step 1.1: Identify key product properties

Customers and users of a product have expectations about the behaviour and properties of the product. Likewise, other stakeholders involved in the lifecycle of a product have their expectations and needs (e.g. regarding the sourcing of raw materials, the assembly of components, or the disposal of units at their end of life).

4.2 Step 1.2: Identify platform alternatives and constraints

This step involves considering factors such as available resources, technical capabilities, market requirements, and organisational goals and constraints to determine the available platform alternatives and to identify any constraints that may impact the implementation of these alternatives.

4.3 Step 1.3: Identify technology alternatives

This step involves considering factors such as the technical capabilities, compatibility, scalability, and cost of different technology solutions to determine the available technology alternatives that can support the goals and requirements of the product platform.

4.4 Step 2. Identify platform margins and performance capabilities

We consider platform margins as a variable influenced by decisions regarding platform design constraints and the integration of new technologies, enabling the exploration of various configurations by adjusting platforms, technologies, and margins concurrently. Therefore, the combination of technologies and platform alternatives determines both the margins and performance capabilities of the platform. To model these combinations, the approach emphasises the use of 'parametric platform architecture models', using idealised models of the unit and the surrounding components (because in a preliminary design, it is often not possible to possess a detailed CAD model of the platform). The approach uses the concept of 'space envelope', a shape model based on a boundary description (Hoover, Goldgof, and Bowyer 1998). The space envelope represents a three-dimensional volume that encapsulates the allowable spatial region within which components can exist. Instead of modelling each component individually, the space envelope encloses the volume of empty space around the components. This method provides a flexible and robust way to manage and optimise spatial allocations without the need for detailed models of each component.

The main components in the architecture are described by their position in three-dimensional space and the dimensions of their basic shape (e.g. box, cylinder). Conceptual three-dimensional models of the space allocations for each of the design solutions and their margins positioned within the constraints of the platform can then be generated. These space envelopes can then be used to understand and control the spatial constraints and interactions of various components within the product platform.

Such parametric models allow us to identify the geometrical margins (Isaksson, Lindroth, and Eckert 2014) provided by technology-platform combination alternatives. At the same time, they can be used by dedicated tools to simulate the different product properties that determine the level of capability (or performance) given by the combinations. This will also allow us to determine the performance margins (Isaksson, Lindroth, and Eckert 2014) or operational margins (Brahma et al. 2023) of technology-platform combination alternatives.

4.5 Step 3: Create NPV models

Future scenarios that have an impact on the value and cost of the alternatives, such as fluctuating demand for specific customer attributes and other time-dependent exogenous variables, are used.

For system value, we adopt a modified model that aggregates product demand over time and lifecycle costs, in line with the Decision-Based Design framework (Hazelrigg 1998; Donndelinger and Ferguson 2019). This synthesis is financially quantified through Net Present Value (NPV) analysis, a method previously applied in studies exploring the introduction of new technologies in product platforms (Suh et al. 2009; Suh, de Weck, and Chang 2007).

The proposed model has two key features.

(1) Product demand depends on product variety, represented by the different performance levels of key product properties. This variety is generated through

the introduction of new technologies and parametric differentiation within existing technologies to maximise the external variety available to customers.

(2) Lifecycle costs are affected by the internal variety generated during the manufacturing process. An increase in internal variety typically results in diminished economies of scale and elevated costs, including development and production expenses. Consequently, the goal is to reduce internal variety. Moreover, lifecycle costs are contingent on the necessity of redevelopment when platform constraints are exceeded, forcing platform modifications.

Product demand is estimated based on specific customer attributes (the percentage coverage of delivered FoV and the product price) using Discrete Choice Analysis (DCA) (Hensher and Johnson 1981; Haghani, Bliemer, and Hensher 2021). DCA collects quantitative choice data for the proposed designs versus alternative options. From this data, demand can be estimated using a multinomial logit model (Wassenaar et al. 2005). This model allowed us to estimate the demand for a product with specific key product properties and prices.

Our lifecycle simulation model computes the system costs and values over time, placing significant emphasis on the allowed platform margin as a pivotal variable. In the model, the allowed platform margin plays a crucial role in providing maximum external variety with minimal internal variety and needs to be traded off considering these two goals. Another important parameter in this model is the cost of platform redesign. This represents a penalty cost for redesigning the platform if the spatial constraints are violated by introducing a new technology.

4.6 Step 4: Identify the maximum allowable number of product variants

This step focuses on applying a product-development perspective to platform margins

(Isaksson, Lindroth, and Eckert 2014). From a product development point of view, margins are seen as a method to increase the number of variants in the platform (often through parametric design) so that precise requirements from customers can be met (and therefore, NPV can be increased by 'summing' the revenues made in each customer segment). Therefore, there is a need to 'segment' the product into variants so that the precise requirements for the product attributes can be met. In this method, all the allowable margin is used to create variants, by dividing the platform margin into 'bins', representing potential product segments. In each bin, the frequency of the design points and their average NPV were calculated. A threshold value of NPV was selected to calculate the number of variants. Above this threshold, a different variant is created (considering that product demand is sufficient to justify a dedicated segment). For 'bins' with an average NPV below the threshold value, a single segment is considered (assuming that the product demand is not sufficient to justify a dedicated segment).

4.7 Step 5: Identify the optimal number of product variants and the maximum allowable reserved platform margin

This step focuses on adjusting the maximum number of product variants by considering the original objectives of the platform designers. From a platform perspective, margins are considered a method to reduce the number of variants in the platform to gain economies of scale through volume (Eckert et al. 2020). Increasing the number of variants by assuming that the expected demand (and, therefore, the NPV) of individually optimised variants can be cumulative has two negative effects, thereby lowering the total NPV:

- Greater variety reduces the sales volume of individual variants (from the total sales volume potential).

- Greater variety reduces economies of scale owing to lower sales volumes. This results in higher production costs and, therefore, a lower NPV.
- Utilising all allowable platform margins to generate product variants limits the ability to reserve part of the margin for 'unknown unknowns' (e.g. new emerging technologies) or for the expansion of neighbouring components.

Therefore, this step focuses on selecting the optimal number of variants to be developed and introduced in the market by 1) considering the effect of economies of scale using a learning curve scaling rule (Argote and Epple 1990) and 2) applying a margin optimisation-focused ordering.

The application of these steps is illustrated in an industrial case study in the next section.

5 Case Study - Space Reservation for Head-Up Display Technologies

The case study presented here concerns the integration of a new technology with an OEM manufacturer in the automotive sector. Head-up displays (Hosking and Blackham 1974) have been steadily gaining traction in the automotive sector. Automotive HUDs project information, such as speed and navigation prompts, directly into the line of sight of the driver via an optical combiner, commonly a windshield. This functionality enhances safety and comfort by allowing the driver to maintain focus on the road, mitigating the need to alternate attention between the road and instrument panel. The HUD case study was chosen by the manufacturer because it represents the concerns of both the platform and product developers.

5.1 Step 1.1: Identify key product properties

The HUD unit is placed behind the dashboard and instrument panel (IP) above the steering column, which is surrounded by heating, ventilation, and air conditioning

(HVAC) components. Its primary performance attribute is the field-of-view (FoV, Figure 2), which represents the maximum image size that can be projected on the windshield in the vertical and horizontal dimensions (for simplicity, the FoV variables are combined as the percentage of the windshield used when presenting the results of this case study).

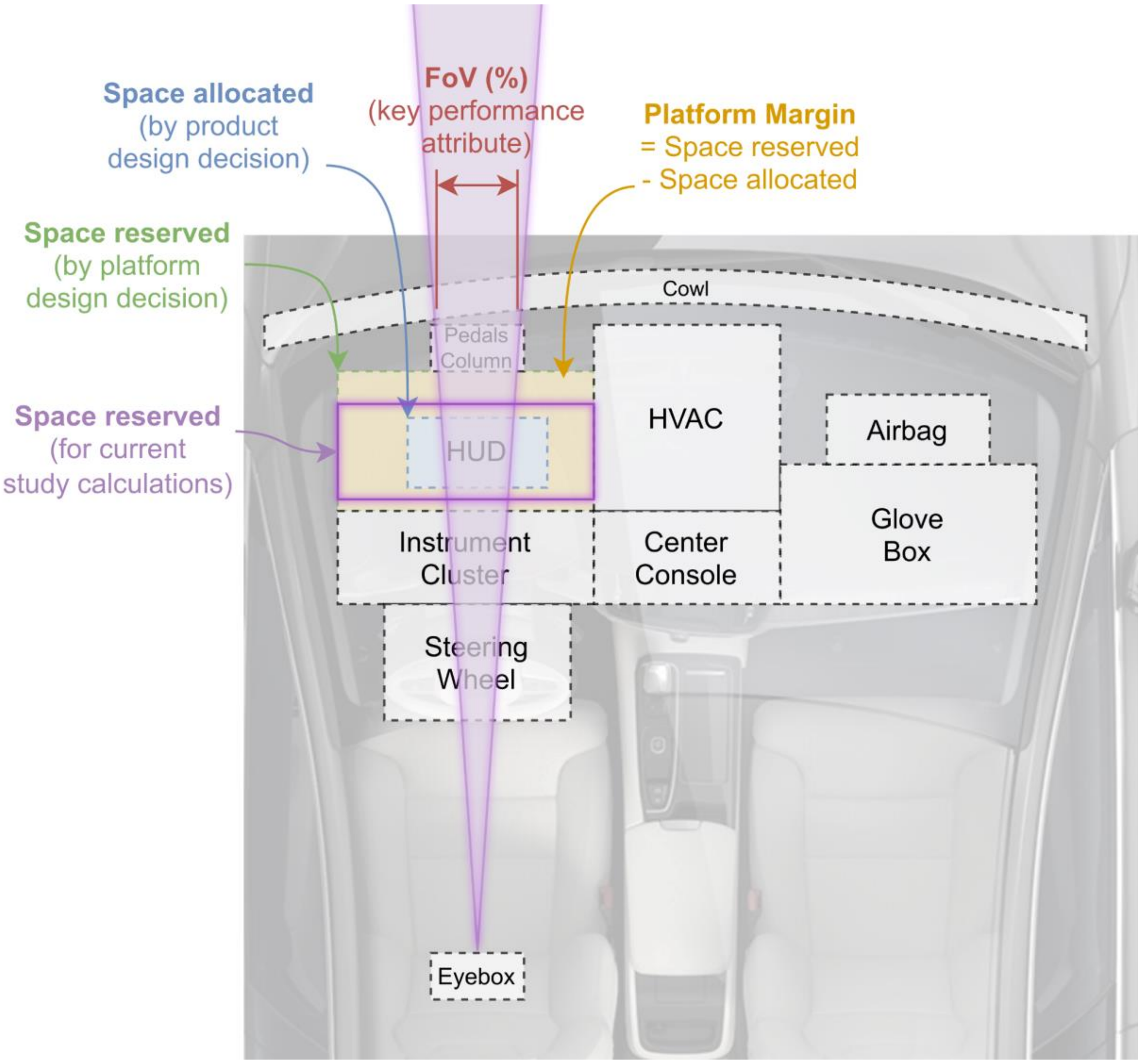


Figure 2 Head-Up Display within its context. The simplification of the reserved space (in litres) of the case study (i.e. the purple rectangle) from the actual reserved space in the real-world industrial scenario (yellow area) is also shown.

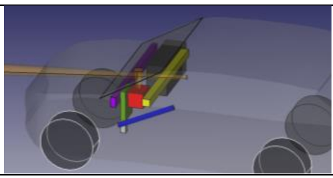
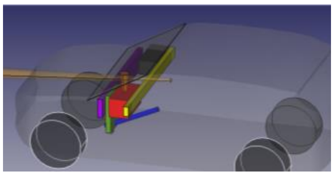
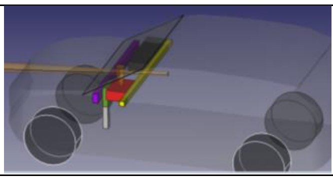
From a performance perspective, a clear objective is to increase the FoV such that more information can be displayed. However, the current and future desires for larger FoVs are still unclear. One strategy for a company could be to maximise its FoV by exceeding what is requested by most of the customer base today (Eckert et al. 2020). This performance margin (Isaksson, Lindroth, and Eckert 2014) would allow flexibility if higher demands for FoVs occur. Therefore, there is a request for product planners to increase the space reserved for HUD technologies, represented by a rectangular design space within which the HUD team can innovate without compromising the platform's integrity. However, the actual realisation of this performance margin is not without consequences. First, providing a higher FoV assumes that customers who are satisfied with less FoV will appreciate that more information is projected onto the windshield. Because the FoV interferes with the sight of the driver, it could be perceived as distracting. Therefore, it is likely that customers desire an FoV that exactly meets their requirements. Also, realising an increase in the FoV would mean an increase in the actual dimensions of the HUD 'box' unit (which would increase the weight, size and cost of the vehicle and therefore lower the demand for HUD technologies).

For these reasons, there is a need to vary the actual (allocated) HUD unit sizes to keep the FoV to the actual FoV requests from the customers by creating variants. From a margin perspective, this need for variation creates an interesting 'clearance' between the reserved space and the actual dimensions of the HUD 'box' unit in a product-variant design. This clearance represents a case of a geometric margin (Isaksson, Lindroth, and Eckert 2014) that can be used 1) as a buffer to handle uncertainties in the desire of FoV (Eckert et al. 2020) or 2) as an excess (Long and Ferguson 2020) to allow for future expansions of the FoV unit or neighbouring components (such as the HVAC). Therefore, increasing this clearance is another objective of the platform team.

5.2 Step 1.2: Identify platform alternatives and constraints

The main components of the architecture are described by their position in three-dimensional space and the dimensions of their basic shapes (e.g. box and cylinder). Table 2 lists the three platforms considered. The key components included in the model were the HUD, the Cross-Car Beam (CCB), Pedal Column Frame (PCF), Windscreen (WS), Steering System, and the Heat, Ventilation, and Air Conditioning System (HVAC) system. The table also reports the space reserved for the HUD (i.e. the platform constraints on the size of the HUD; other platform constraints might have been an energy budget or a weight limit).

Table 2 Platform alternatives.

	CAD Image of the space reservations for the components of interest	**Space reserved (constraint from platform architecture choice)**	**Simplified space reserved (considered in the case study)**
Platform A (in production) High maturity		13.8 litres ($300x230x200\ mm^3$)	2.5 litres
Platform B (under development) Medium - High maturity		48 litres ($400x400x300\ mm^3$)	13.16 litres
Platform C (conceptual) Low maturity		31.5 litres ($350x360x250\ mm^3$)	9.59 litres

Owing to the difficulties in visualising the three-dimensional intricacies of the selectable technologies (presented in Section 4.1), the reserved space (in litres) in the case study is reduced from the actual reserved space in the industrial case (i.e. the violet rectangle). This simplification does not undermine the main purpose of this study (which is to show how the value of a platform margin can be modelled).

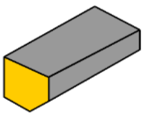
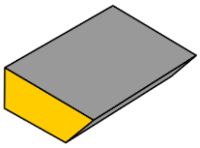
5.3 *Step 1.3: Identify technology alternatives*

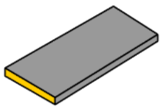
A three-dimensional analysis of the selectable technologies was performed using the parametric architecture model and dedicated performance models.

Table 2 shows that the three platforms included in this study are at different levels of maturity. Platform A is the most mature platform considered; therefore, it has a more constrained space for the HUD. Changes to increase its volume would propagate further and with greater impact, whereas changes to reduce its volume would not be easily taken advantage of by the surrounding components. Platform B is an evolution of Platform A, but with a larger space reservation for the HUD. Platform C is the least mature, and it considers the introduction of a different architecture in this area of the car, which is enabled by a Steer-by-Wire (SbW) system.

The three technological alternatives considered in this study are listed in Table 3. The technologies differ in terms of allocated volume (crucial for determining the platform margin), provided customer attributes (FoV percentage), and cost and maturity (crucial for determining technology uncertainty).

Table 3 Technology alternatives.

	Volume (litres)	**FoV as percentage of windshield used**	**Current Maturity (TRL)**	**Cost (relative)**
Technology 1 (2G) HUD 	~1-8	~0.75-3%	TRL 9	Modest
Technology 2 (2G) AR-HUD 	~6-20	~1.5-8%	TRL 9	High

Technology 3 (3G) Holographic Wave Guide AR-HUD 	~1-33	~3-15%	TRL 7-8	High

The first alternative technology considered is a traditional windscreen HUD based on a mirror assembly and an image generated by a display (for example, Thin-Film Transistor, TFT). This alternative embodies a mature technology for moderate cost and space requirements, but has limited performance in terms of image size, field of view, and distance to the virtual image. A second alternative is an Augmented Reality (AR) HUD, which enables variable dimensionality of the projection (in contrast to a fixed position in the traditional HUD) and features a Digital Light Processor (DLP) projector as the image source. This alternative has a higher cost of acquisition, as well as much greater space requirements, as it still requires the same kind of optical mirror arrangement as traditional HUDs but is scaled up to accommodate larger image sizes and fields of view. The third alternative is a laser-based projector with holographic waveguides (Skirnewskaja and Wilkinson 2022). This third alternative is the least mature option, with lower space requirements for image size and field of view comparable to those of the second alternative (together with other benefits such as lower energy use and high luminance).

5.4 Step 2. Identify platform margins and performance capabilities

By using the data gathered in Steps 1.2 and 1.3, it is possible to model the performance of the component using the different technologies while within the boundaries defined by each platform under study. In Figure 3, the relationship between the volume of the component and its performance in terms of FoV(%) is compared to the limits set by the platforms on the volume of the component.

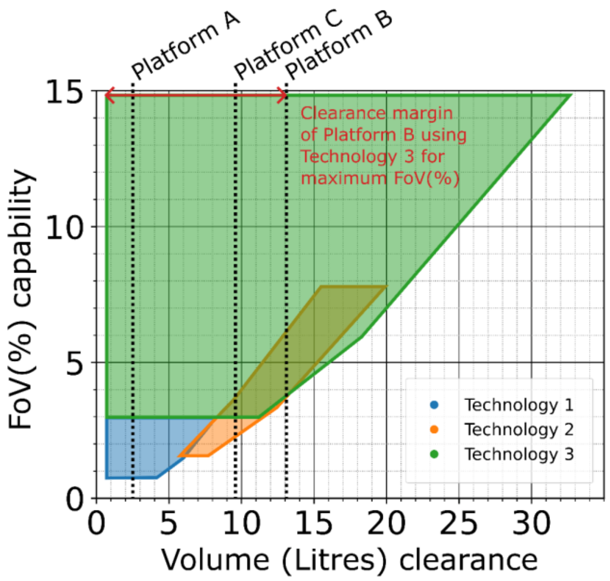


Figure 3 Platform constraints and associated performance in terms of FoV(%)

The areas represented correspond to designs with different levels of other performance parameters (e.g. the distance to the virtual image). Table 4 summarises the values of the FoV (%) and clearance (i.e. the geometrical platform margin) for designs optimised to maximise either the FoV or clearance. Note that even in the most favourable cases, it is inevitable to have considerable margins (1.801 litres), given the limitations of the technologies considered.

Table 4 Values of FoV (%) and clearance (in litres) for each combination of technology and platform

	Technology 1 (2G) HUD		**Technology 2** (2G) AR-HUD		**Technology 3** (3G) Holographic Wave Guide AR-HUD	
	FoV (capability maximized)	**Clearance (margin maximized)**	**FoV (capability maximized)**	**Clearance (margin maximized)**	**FoV (capability maximized)**	**Clearance (margin maximized)**
Platform A (in production) High maturity	FoV = 2.985 Clearance = 1.801	FoV = 2.985 Clearance = 1.801	N/A	N/A	FoV = 14.925 Clearance = 1.801	FoV = 14.925 Clearance = 1.801

Platform B (under development) Medium - High maturity	FoV = 2.985 Clearance = 12.4556	FoV = 2.985 Clearance = 12.4556	FoV = 6.2 Clearance = 0	FoV = 5.763 Clearance = 7.3926	FoV = 14.925 Clearance = 12.4556	FoV = 14.925 Clearance = 12.4556
Platform C (conceptual) Low maturity	FoV = 2.985 Clearance = 8.8904	FoV = 2.985 Clearance = 8.8904	FoV = 3.7 Clearance = 0	FoV = 5.763 Clearance = 3.8274	FoV = 14.925 Clearance = 8.8904	FoV = 14.925 Clearance = 8.8904

5.5 Step 3: Create NPV models

The profit for the company (in terms of Net Present Value), which is determined by the revenues generated from demand minus product costs, varied in time depending on the sensitivity of the customers to the attributes (for example, FoV versus price) given by the platform-technology combinations and exogenous variables outside the control of the company that are defined as scenarios (following an approach similar to the ones by Hazelrigg 1998; Suh et al. 2009).

Three scenarios are considered for the future, encompassing changes to the manufacturing costs of the components (e.g. the cost of the main optical elements, such as mirrors in conventional HUDs), the levels of performance expected from customers, and the possibility of large architectural changes to the platform.

In Table 5, the scenario variables are described, and the levels or values considered in this study are listed. For example, for each scenario, a subset of the three technologies (T1, T2, and T3) may be available.

Table 5 Scenario variables for the HUD case.

Scenario variable	Levels	Description
x) Technology available	T1, T2, T3	Sub-set of [T1, T2, T3]
y) Demand by Year	2022-2030	Composite variable that combines the trends in

		consumer expectation of performance and price sensitivity
z) Unit cost	Percentage of cost versus baseline technology	Driven by the main components of the technology

The combination of scenario variables into the plausible scenarios of interest is presented in Table 6.

Table 6 Description of scenarios.

Scenario	Description	Vector of variables
S1 Current status	Currently common technologies available, low preference for FoV	([T1, T2], 2022-2024, 100%)
S2 Greater performance desire from users	Expectations regarding FoV from customers rise (e.g. due to the alternatives from competitors), and procurement costs decrease	([T1, T2], 2024-2026, 80%)
S3 New technology available, even greater desire from users	A radically new technology is mature, with even greater preferences for higher FoV	([T1, T2, T3], 2026-2028, 80%)

For example, the first scenario considers the current situation in which only technologies T1 and T2 are available, with market adoption for HUD technologies being low (only early adopters) and at 100% of the current cost. One important parameter that has been modelled is that preferences for higher performance progressively increase for Scenarios 2 and 3 (due to alternatives from competitors and HUD technologies maturing in the technology adoption lifecycle).

The comparative results for all three platforms are shown in Figure 4. For confidentiality reasons, all value data were normalised in the results from the underlying monetary NPV figures.

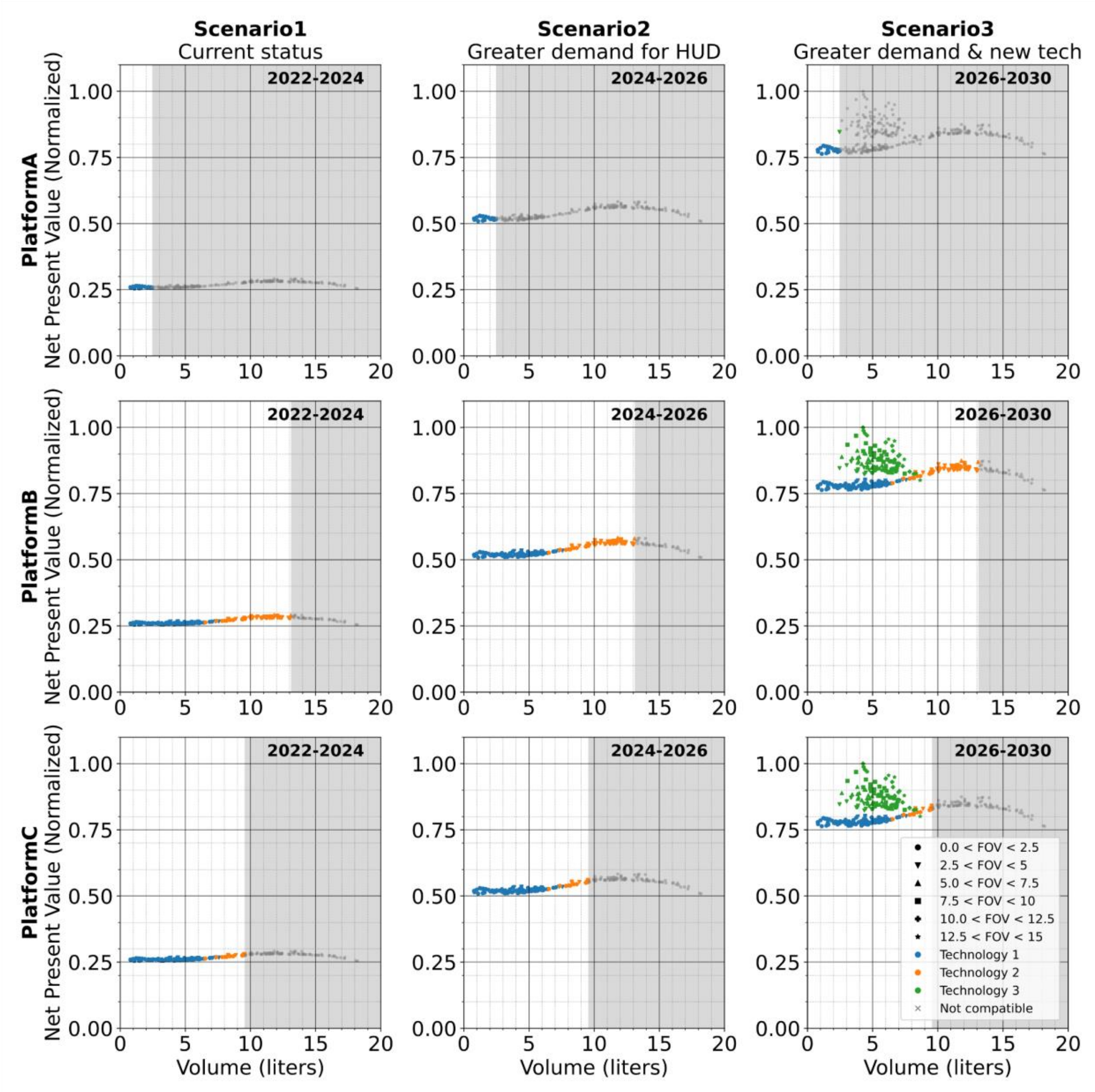


Figure 4 Results for the three platforms for the three technologies in the three scenarios.

Figure 4 shows the Net Present Value (normalised) for different HUD volumes (in litres) provided by the three different technologies. Each HUD design provides a different FoV that impacts product demand depending on the scenario. Demand is calculated as the probability of purchase from the total potential sales volume, and constants are set for all FoV values allowed by the HUD designs. In addition, the figure shows a grey area indicating HUD designs that fall outside the volume constraint set by the reserved platform space (for example, approximately 13 litres for Platform B). The

NPV for these incompatible designs progressively decreases, indicating the effect of the cost of the platform redesign if the HUD volume exceeds the reserved volume. As a minor detail, the volume constraint is shown as a clear cut-off value, although some incompatible designs may still exist within the reserved volume owing to incompatibility along the three-dimensional space. However, this did not affect the core results of the study. Table 7 indicates for each scenario the design that yields the highest NPV and the specific technology enabling this optimal configuration.

Table 7 Designs with the maximum NPV (normalized) for each platform and scenario

	Scenario 1	**Scenario 2**	**Scenario 3**
Platform A	Max NPV = 0.264 Volume = 2.461 L Technology = 1	Max NPV = 0.527 Volume = 2.461 L Technology = 1	Max NPV = 0.846 Volume = 2.459 L Technology = 3
Platform B	Max NPV = 0.291 Volume = 13.101 L Technology = 2	Max NPV = 0.583 Volume = 13.101 L Technology = 2	Max NPV = 1 Volume = 8.644 L Technology = 3
Platform C	Max NPV = 0.280 Volume = 9.558 L Technology = 2	Max NPV = 0.561 Volume = 9.558 L Technology = 2	Max NPV = 1 Volume = 8.644 L Technology = 3

Determining the value of these ‘platform-technology introduction roadmaps’ can provide insights into the margins that can be used in the later design phases. This can be observed when looking at a given platform when transitioning from Scenario 2 to Scenario 3 (Figure 5).

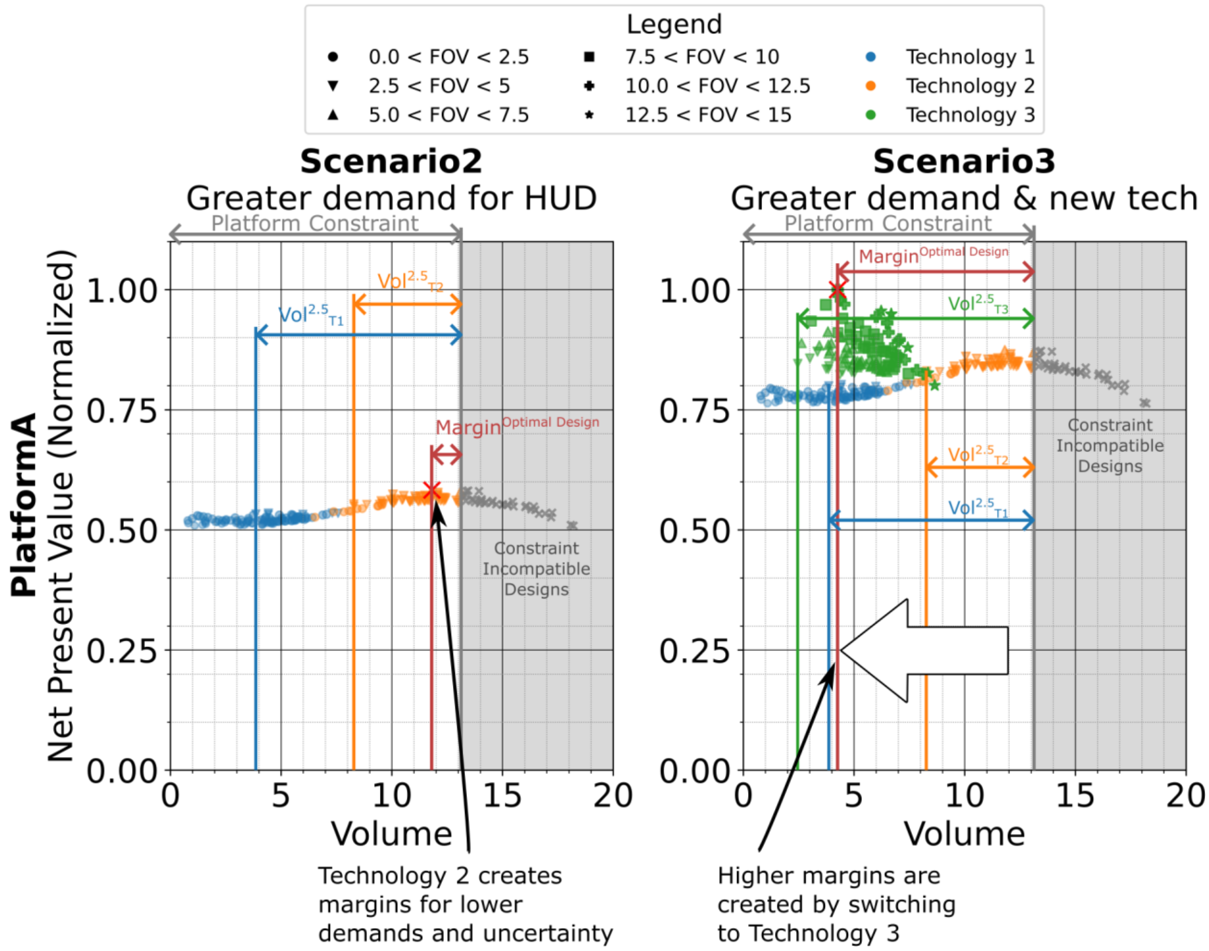


Figure 5 Net Present Value versus HUD volume for Platform B when transitioning from Scenario 2 to Scenario 3.

The figure also shows the margins (in terms of space in litres) that can be generated by adopting different design solutions. For example, the figure shows the margins generated when choosing the designs that provide an FoV for a size of 2.5% of the projection on the windshield (as an example of the minimum requirement that could be set by customers) for each technology. However, from a platform point of view, it would be more intuitive to select the design that provides the highest NPV (i.e. the highest profit with the least number of manufactured designs). For this platform in Scenario 2, this optimal design is provided by Technology 2 with a HUD of 11.8 litres (which corresponds to an FoV of 2.69%). However, the NPV provided by the different designs of Technologies 1 and 2 are not significantly different (although there is an optimal point for Technology 2). This result suggests the first benefit of the margins provided by Technology 2 over Technology 1. Because higher FoV values can be provided (for example, 2.69%), the demands for a lower FoV (for example, 2.5%) can still be satisfied because of this buffer. At the same time, allowing the introduction of Technology 2 in the platform provides a buffer for product developers in cases in which the optimal designs should be different in the future (e.g. due to uncertainties in the demand model).

Considering Scenario 3 in Figure 5, another impact of the technology roadmap on the margins can be visualised. In this scenario, Technology 3 has matured, potentially providing a higher FoV while occupying a smaller volume. In this scenario, the demand for a higher FoV increases, and the optimal point shifts to the left (at 4.3 litres with 7.87% FoV). This indicates that higher margins were created. Additionally, the ‘cloud’ of designs enabled by Technology 3 never surpasses 9 litres (Figure 5). This means that even if the optimal design should shift in the future (even going down to 2.5% of the FoV at 8 litres), there will always be approximately 4 litres of ‘room for growth’ (Eckert et al. 2020) for neighbouring components or even for completely new components if new technologies emerge.

5.6 Step 4: Identify the maximum allowable number of product variants

In this step, the analysis shifts towards enhancing the external variety of the product platform within the constraints of the previously defined platform margin. This phase aims to create a diverse range of product variants through parametric modifications, thereby increasing the product's appeal and differentiation in the market without compromising the efficiency and cost-effectiveness established by the optimal platform margin. The results of this study are shown in Figure 6.

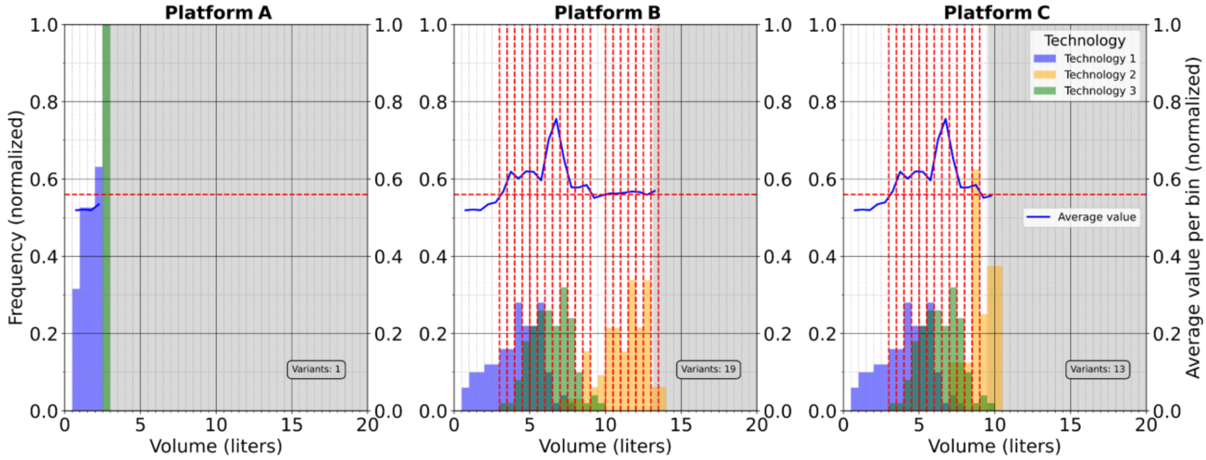


Figure 6 Results for the three platforms to identify the maximum allowable number of product variants given the platform margin.

This study used the same design points, as shown in Figure 4, however, the platform margin was divided into 'bins' of 0.5 litres each, representing potential product segments. In each bin, the frequency of the design points (from Figure 4) and their average NPV were calculated. A threshold value of NPV (corresponding to 0.56 in normalized terms) is selected to calculate the number of variants. Above this threshold, a different variant is created (considering that product demand is sufficient to justify a dedicated segment). For 'bins' with an average NPV below the threshold value, a single segment is considered (assuming that the product demand is not sufficient to justify a dedicated segment).

These findings indicate that a deeper understanding of margins enables product developers to maintain a wide range of offerings without the need to expend effort to optimise configurations that are unlikely to be successful (Isaksson, Lindroth, and Eckert 2014). This can be seen in Platforms B and C, where the designs from 9.5 to 10.5 litres are merged into one single variant (instead of two). However, looking at the platform margin from a pure product optimisation perspective may lead to the risk of product development teams *misusing* margins. This can be visible in Platform B.

Because a larger margin is allowed (and the designs after 2 litres offer an average NPV per design above the threshold), the HUD product development team may find it beneficial to 'use' all the reserved platform margins for a granular segmentation of HUD components (allowing for 19 variants). Thus, a larger total NPV can be obtained because of this variety. However, this assumption must consider the original considerations of platform planners when designing platforms. Increasing the total number of variants has a profound impact on the economies of scale that can be obtained in production, which in turn affects the total NPV that can be obtained from each variant. These considerations were examined in the final step of the approach.

5.7 Step 5: Identify the optimal allowable number of product variants and the maximum allowable reserved platform margin

This step builds upon Steps 3 and 4, but incorporates a platform-centric view of variety. This perspective emphasises the strategic reduction of product variants to capitalise on economies of scale. The goal is to optimise the balance between offering sufficient external variety to meet market demands and maintaining a streamlined production process that maximises economic and operational efficiencies by minimising internal variety. There is an *optimal point* for the number of variants where the positive effects of external variety (the cumulative NPV derived by the sale of individually optimised variants) are counterbalanced by the negative effects brought about by a reduction in economies of scale. In terms of margin, identifying this optimal number of variants allows us to reserve part of the margin for *unknown unknowns* or the growth of other neighbouring components (e.g. the HVAC).

To perform this step, the same 'clouds' of design points as in Figure 4 were used but in this case, we considered only the designs that provide the highest NPVs for each 'bin' of HUD designs incrementally increasing by 0.5 litres. To select the optimal number variants, two additions are made to the NPV model created in Step 3: 1) a learning curve scaling rule (Argote and Epple 1990) applied to the production cost and 2) a margin-optimisation-focused ordering of the design variants. The results of these two additions are shown in Figure 7.

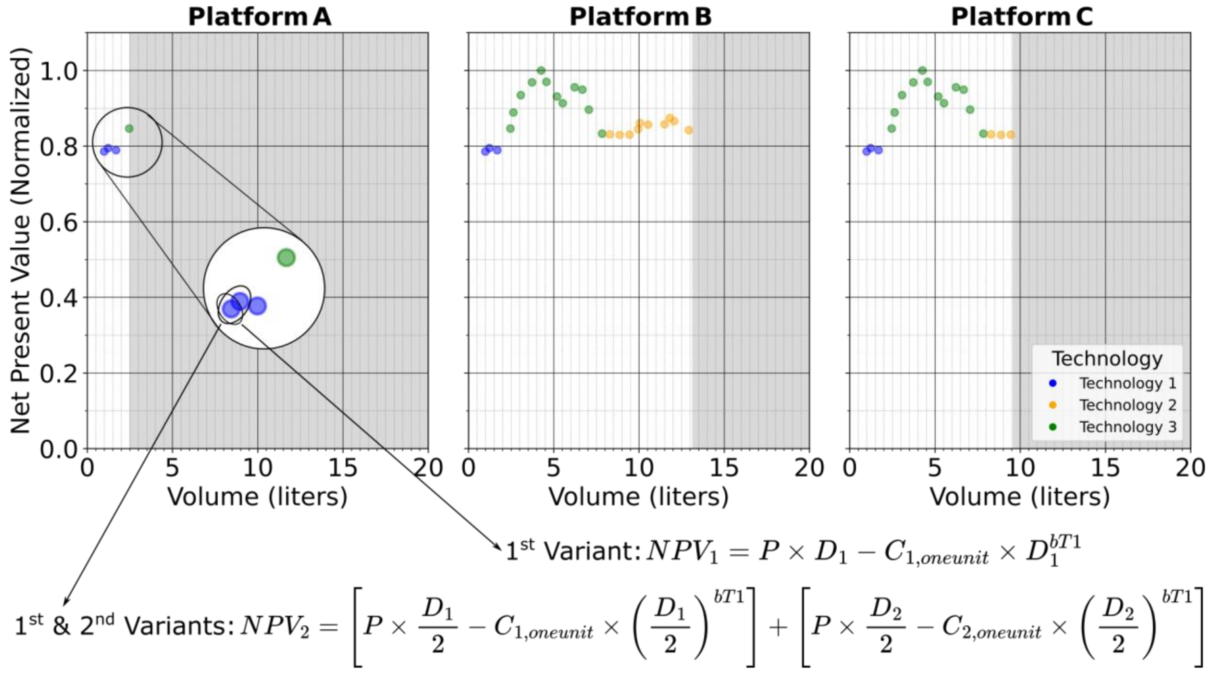


Figure 7 Margin-optimisation-focused ordering of variants.

The idea behind this margin optimisation-focused ordering is that while in Step 3 the NPVs for the designs have been obtained by modelling customer preferences (Figure 6), there could still be some uncertainties (e.g. in the technology or market conditions) that have not been modelled. Therefore, there is a need to select design variants that maximise the summed total NPV given by all selected variants while maintaining the highest possible margin. Therefore, the first variant selected was the one that allowed for the maximum margin. For Platform A in Figure 7, this is represented by the blue dot on the far-left side of the figure. Therefore, the NPV is given by the price (P), demand D_1, and cost C_1 (comprising the production costs). The learning curve rule used to adjust cost C_1 is dependent on the cost of producing a single unit of the variant on the production line ($C_{1,\ ONE\ UNIT}$) and a learning factor depending on the technology chosen *bT1*. The second variant was chosen by considering the blue dot immediately to the right, as it is the design that allows the second-largest margin. However, the combined NPV of producing these two variants must consider the following: 1) the potential demands D_1 and D_2 (if only that variant is produced) are now divided in half, and 2) the variant costs C_1 and C_2 are now much higher (because the production volume has been roughly halved). The same rule is applied when the production of a third variant is considered (the blue dot immediately on the right, which divides the potential demand by three) and the production of a fourth variant (the green dot immediately on the right, which divides the potential demand by four). In addition, this technology has a different learning rate, *bT3*). The sorting-by-value algorithm, by definition, will always have a higher value for the first variants. The advantage of the sorting-by-margin algorithm is that at a certain point, it is possible to achieve both high value and high margin, while using the sorting-by-value algorithm, many margins are sacrificed too early.

Applying this sorting procedure to all three platforms allowed us to obtain the results shown in the top row (a) of Figure 8, while the sorting-by-value of each additional variant is represented in the bottom row (b). The graphs represent the cumulative NPV for sets of variants for each platform on their left axis and the remaining margin available for that set of variants on the right axis. The stacked bars represent the contribution to the total NPV of each variant (with its unique colour) in the set.

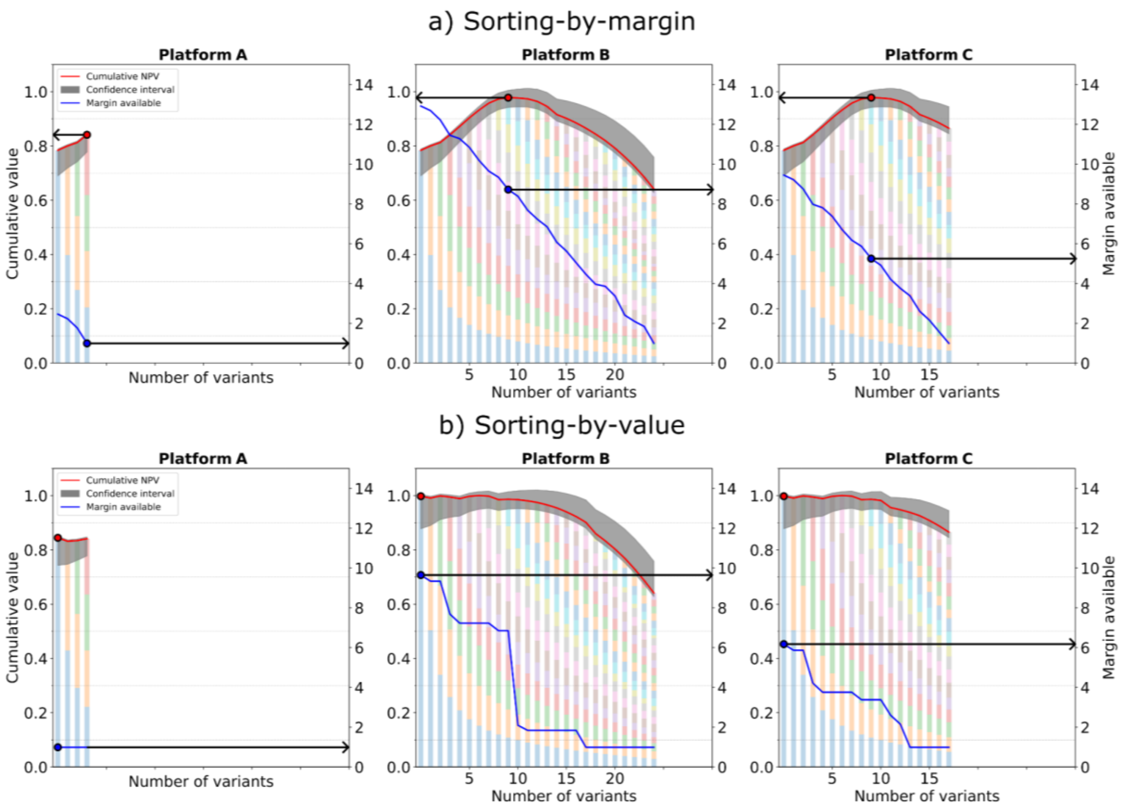


Figure 8 (a) Sorting-by-margin and (b) sorting-by-value of variants.

The focal point of the figure is to show how the platform margin is ‘consumed’ to create product variants that adhere to precise customer preferences (e.g. following a product-focused view). However, the figure shows that there is an optimal point after which creating margins to create many product variants is not beneficial from a platform perspective (because the NPV from each variant becomes low owing to the loss of economies of scale). Merging the platform and product perspectives allows us to obtain a more balanced perspective on margins. Powered by a model such as the one shown in Figure 8, the design teams may decide not to ‘consume’ all the margins to create variants for the HUD, but to reserve part of the margin as a buffer. To determine this optimal margin, Figure 8 intersects the point of the highest NPV with the available margin. The results show that the number of variants for each platform tends to be lower than that calculated in Step 4 for platforms with high margins (Platform B fluctuates from 19 to 9 and Platform C from 12 to 9).

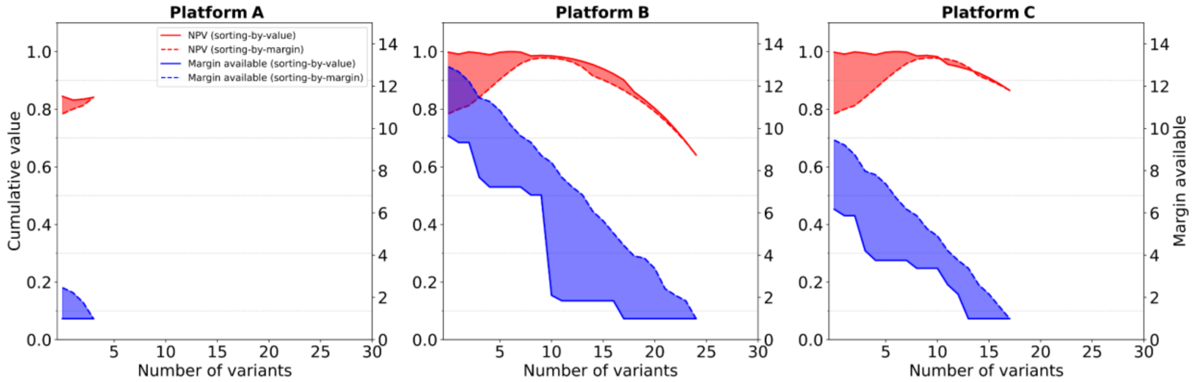


Figure 9 Comparison of NPV and margins for the two sorting algorithms

In Figure 9, both the NPV and margins for the two sorting algorithms are represented for each platform (in blue for the difference in margins and red for the difference in NPV). For low external variety, optimisation in terms of single products is advantageous (resulting in high NPV and some margin), but as soon as high external variety is desired, prioritising the margins of the selected variants leads to NPV close to that from the previous approach, but with a much better margin still available.

In this model, the effects of uncertainties can also be considered to determine the optimal margin. We consider uncertainties following this assumption: if only one variant is produced, there is a greater change in the NPV that is lower than that calculated considering a *nominal* scenario (because the variant does not adhere to the precise preferences of the entire customer base). If two variants are produced, the possibility of a lower NPV is reduced (because the two variants are close to the preference of the two customer segments). If many variants are produced, the possibility of worst-case scenarios is reduced, and there is a greater possibility of the actual NPV being greater than that calculated for a nominal scenario. In Figure 8, this is visible by the gray area (the confidence interval) being skewed from the nominal scenario (the red line), considering more optimistic scenarios when the variety increases (until a certain point, where the NPV starts to decay due to the loss of economies of scale). This skewed confidence interval shows how the margin can be partially consumed to allow for variants that ‘absorb’ the possibility of worst-case scenarios. This means that the optimal margin is slightly reduced from the nominal scenarios, thus allowing for a minor increase in the NPV. For Platform B, the optimal residual platform margin is 8.7 litres, and for Platform C, it is 5.3 litres. For Platform A, all margins were consumed with a much lower NPV than those of the other two platforms. This result indicates that Platform A did not provide high overall flexibility because of its overly constraining limitations. In terms of design margins, this platform does not provide valuable margins for its product variants, allowing for the useful evolution of the platform considering the technology path.

In contrast, Platform B enables a considerable number of variants, but many of them do not increase the value of the system. Under-constraining the platform causes, in this case, a waste of reserved space, impacting the options of the neighbouring components to utilise that space. This means that this platform, compared to Platform A, suffers from the opposite imbalance: the margin provided allows for the evolution of the platform, yet not always in valuable ways.

Finally, Platform C shows that with balanced margin delimitation, a high value can be achieved by offering adequate variety for the HUD without restricting the freedom to address uncertainties. In this platform, the margin level assigned to the platform was carefully selected by considering the following:

(1) The need for technological evolution (which may increase the available margin, as shown in Step 3).

(2) The need to provide adequate variety that adheres to the precise preferences of the customer base (while not undermining the possibility of achieving

economies of scale). In addition, providing such an adequate variety can absorb the uncertainties related to the customer base itself and the value model used to calculate the cost-revenue profiles expected from each variant.

(3) Cost of violating platform constraints.

The results from this step highlight how the understanding of margins can be the key to diversifying product offerings while mitigating the need for exhaustive optimisation of configurations with anticipated low sales volumes.

6 Discussion

To address the research question, *"How can decisions about which optimal platform margin to reserve be supported?"*, the study proposes a value-based modelling methodology that integrates Net Present Value (NPV) assessments with a comprehensive understanding of both discrete and parametric variables. This model helps evaluate and allocate platform margins by considering the balance between external variety (meeting diverse customer preferences) and internal variety (maintaining production efficiencies). The methodology includes steps to identify key product properties, platform alternatives, technology options, and scenario variables, which collectively inform the optimal margin reservation by incorporating the potential impact of uncertainties and technological evolution. The results presented in the previous section demonstrate that optimal margin reservation is achieved by strategically balancing the highest NPV and flexibility necessary for future technology integration.

The research presented in this paper highlights the utility of value-modelling approaches in assessing platform margins to balance individual product optimisation against platform commonality. The value model demonstrated in this study provides a novel methodology that integrates both discrete and parametric variables, offering a comprehensive way to evaluate platform margins. An industrial case study on automotive Head-Up Displays (HUDs) showcases the practical application and implications of the proposed methodology. It highlights the trade-offs involved in balancing platform and product optimisation, illustrating the varying outcomes across different platforms (A, B, and C) based on their margin allocations and technological adaptability.

Eckert et al. (2013) and Eckert and Isaksson (2017) have extensively explored the concept of design margins, emphasizing their critical role in managing uncertainties and enabling design flexibility. Their work underscores that while margins are essential for accommodating unexpected variations and future technological requirements, they also pose a risk of overdesign if not managed properly. Our study builds on this foundation by providing a structured approach to optimise these margins, ensuring that they are neither excessively generous nor insufficiently allocated. By integrating value modelling, we offer a more nuanced understanding of how to balance these margins effectively to maximise the overall system value.

Our findings contribute to the existing body of literature on product platform optimisation. Previous studies, such as those by Isaksson, Lindroth, and Eckert (2014), have emphasised the challenges of balancing individual product optimisation with platform commonality. The dual-level representation of margins in our study extends the work of Brahma and Wynn (2020) on mitigating risks and uncertainties through design margins. Additionally, the methodology aligns with the strategic insights provided by Meyer and Lehnerd (1997) on leveraging common components to achieve economies of scale. Our approach further supports the arguments of Suh, de Weck, and

Chang (2007) on the economic benefits of flexible product platforms by providing a more detailed and actionable methodology for margin allocation.

This study highlights that platform margins are crucial for accommodating external variety and ensuring long-term system value. Using a holistic approach that merges platform planning and product development perspectives, the proposed model offers a balanced and integrated way for optimising margins. This integration is critical for preventing suboptimal use of margins and ensuring that they are preserved for future technological advancements and market shifts.

An industrial case study on automotive Head-Up Displays (HUDs) demonstrates the practical application and implications of the methodology. This underscores the importance of carefully selecting margin levels to accommodate both current and future needs, thereby enabling a more resilient and adaptable product platform. For example, it provides a clearer picture for design teams to renegotiate when the design team of another component (e.g. the HVAC) wants to claim the 'use' of 'some' platform margin originally reserved for one component (e.g. the HUD). The findings show that balanced margin delimitation can achieve a high value by offering adequate product variety without compromising the ability to address uncertainties.

Furthermore, Eckert, Isaksson, and Earl (2019) highlight the hidden issues in industry related to design margins, particularly the tendency towards overdesign which can lead to inefficiencies and increased costs. Our case study on automotive HUDs demonstrates this risk, particularly with Platform B, which, while flexible, risks inefficient use of space owing to poor margin optimisation. Our findings suggest that by adopting a value-based approach, companies can mitigate the risk of overdesign highlighted by Eckert et al. (2020), ensuring that margins are used judiciously to support both current and future needs using buffers without unnecessary excess.

Although the presented value model contains significant insights, it also has limitations. One limitation is the simplification of technology trajectories and the three-dimensional complexity of selectable technologies. While these simplifications are necessary for the feasibility of the model, they may not fully capture the intricacies of real-world applications. Additionally, the case study's focus on HUDs, although illustrative, limits the generalisability of the findings to other product types. Mitigations to these limitations include further refinement of the model to incorporate more detailed technological projections and extending the application of the methodology to diverse industrial contexts to test its robustness.

Another potential drawback is the model's reliance on Net Present Value (NPV) as a primary metric for decision-making. While NPV is useful for projecting financial performance, some authors claim that it does not fully incorporate future risk and strategic flexibility. Critics suggest that NPV-based approaches may overlook managerial flexibility in adapting to unforeseen changes, potentially leading to suboptimal decisions. Du and Jiao (2022) proposed integrating real options theory into value-driven models to better capture strategic flexibility and operational uncertainty, thus enhancing the model's robustness and applicability in diverse engineering contexts. However, this study addresses these concerns by introducing the concept of design margins, particularly platform design margins, which encompass strategic flexibility.

The implications of our findings are significant for engineering companies that aim to optimise platform margins in a dynamic market environment. The proposed model provides a holistic methodology that supports informed decision-making, helping design teams balance immediate product requirements with long-term system value. Moving forward, companies should consider adopting value-modelling approaches to enhance strategic and tactical alignment in platform planning and product development. Recommendations for both researchers and practitioners include the following:

(1) Further Refinement and Validation: Continued development of the value model to include more comprehensive technological and market scenarios.
(2) Broader Application: Testing the methodology in various industrial settings to validate its applicability across different product platforms.
(3) Training and Implementation: Providing training for design teams on using value-modelling tools to ensure a thorough understanding of margin optimisation and its implications.
(4) Integration with Existing Processes: Seamlessly integrating the value model into existing product development and platform planning processes to enhance decision-making efficiency.

7 Conclusion

This paper presents a value-based modelling approach to optimise platform margins, addressing the dual objectives of individual product optimisation and platform commonality. The proposed methodology integrates discrete and parametric variables, offering a comprehensive way to effectively evaluate and allocate platform margins. This dual-level representation of margins, coupled with a value model, has not been explored previously and provides a significant contribution to the field of engineering design and product platform optimisation.

This study advances state-of-the-art research by introducing a new platform margin representation methodology. This work extends the current research in margins of 1) increasing the traceability of the reasons behind the ‘use’ of a platform margin during the design process and 2) representing the ability of margins to absorb changes in both discrete variables (e.g. technology types) and parametric variables.

Furthermore, this work extends the state-of-the-art in platform modelling by simultaneously considering alternative platform designs instead of the prevailing research work on the optimisation of the architecture of a single platform at a time. However, industrial reality (as reported by participants in the HUD case study) suggests that multiple platforms are designed simultaneously, and the work of platform planners is to assess how long a particular platform design can last before changes in the technology landscape make it more profitable to introduce a new platform. Our approach has this ability (for example, Platform A in the case study provides a satisfactory NPV in Scenarios 1 and 2 compared to the other two platforms, while being severely suboptimal in Scenario 3).

In conclusion, this research advances the understanding of platform margin optimisation by providing a methodology that supports informed decision-making. The insights gained from this study can guide design teams in optimising platform margins to meet evolving technological demands, reduce costs, and maximise the overall system value. This approach is essential for engineering companies that aim to balance conflicting objectives in a dynamic market environment. Future research should focus on further refining this methodology and exploring its applications in diverse industrial contexts to enhance its robustness and applicability.

Acknowledgements

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