APPLICATION

Market-driven modularity: an empirical application in the design of a family of autonomous mobile palletizers

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Abstract

Designing product families is an enabling strategy for mass customization. In general, there are four prevalent classes of problems when designing product families: (i) product family positioning; (ii) customer preferences modeling; (iii) product family modeling; and (iv) product family configuration. Although these classes are interwoven through design problems stemming from marketing, engineering, and economic areas, they are rarely handled together in product family design methods. The lack of a systemic, integrated design perspective may lead to locally optimal solutions and ultimately result in product families not making the economic benefits of customization worthwhile. Over the years, some methods have attempted to overcome this absence of holistic design view. However, because they are restricted to theoretical levels or lack detailed applications, their practical implementation is often not possible. To bridge the pathway between theory and practical implementation, this paper uses the market-driven modularity (MDM) method to design a family of autonomous mobile palletizers economically oriented to market requirements. The empirical application of the method points out the palletizers family as being economically feasible. Furthermore, it also indicates which modules should be developed in successive design phases, as well as reveal the definition of the product family structure as the MDM's outcome that is more sensitive to the variation of parameters/variables composing the configuration model. The main contribution of this work lies in the presentation of practical implementation details of the MDM method, which, to the best of our knowledge, has not been reported since its proposition.

Keywords Product family design · Platform design · Modularity · Collaborative robotics · Autonomous mobile robotics

1 Introduction

Increasing product variety without compromising the efficiency of production systems has been a challenge for many organizations [1]. This issue has been addressed in industry and academia primarily via product family design, which embraces a collection of products sharing a common platform yet having distinct characteristics to fulfill the heterogeneity of customer requirements [2]. Generally, there are four prevalent classes of problems when designing product families [3]: (i) product family positioning; (ii) customer preferences modeling; (iii) product family modeling; and (iv) product family configuration. Although these classes are interwoven through design problems stemming from marketing, engineering, and economic areas [4], they are rarely handled together in most product family design methods [5]. It may seem a natural research move to focus on the specifics of particular classes of design problems. However, from a systemic standpoint, the functioning of a system cannot be entirely understood from an independent evaluation of its parts, just as parts cannot be comprehended without knowing their contribution to the whole [6]. Consequently, the lack of a systemic, integrated design view of the product family may result in local solutions, not optimal global ones [7]. Furthermore, when moderated by certain design criteria, it may result in economically unfeasible families [8].

Few studies have systemically addressed the classes of design problems. As proof, Simpson et al. [3, 9] organized several methods for designing product families and platforms into collections of articles. However, while these

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works allow seeing the methods approaching particular classes of problems in the context of the product family design, they do not explore the interactions or interrelations among the methods within the design process, thus not addressing how the classes of design problems relate to each other. This fact may be restrictive since comprehension of the whole develops through interactions among its parts [10]. In turn, Ferguson et al. [4] proposed a product development framework for mass customization that partially fulfills the role of integrating the classes of design problems. This is because, given the level of granularity used, some design problems, such as product family planning and positioning and building of product family structure, are not addressed. For those design problems considered, their inputs and outputs are not made explicit. Furthermore, in terms of design criteria, the framework overlooks some important ones for assessing the economic viability of product family design, such as market share, demand, and profit [11]. Similarly, Otto et al. [12] organized many strands of research into a logical sequence for developing product platforms. The authors' proposition presents the design problems and the respective inputs and outputs. The design logic is also demonstrated in an empirical application concerning the design of a family of uncrewed ground vehicles. The problem is that the extension of the proposed method is limited to the first three classes, thus not considering the product family configuration. Finally, Gauss et al. [5] connected multiple methods for designing modular product families into a comprehensive functional model. Although the model addresses the four classes of design problems, their inputs and outputs, and the criteria and techniques for their execution, it is essentially theoretical and does not provide an empirical application that attests to its proposition. The cited authors later proposed an integrated method for designing product families economically oriented to the marketplace [13]. As complete as the previous one, the method is evaluated through a series of expert assessments and practical applications. Nevertheless, the level of detail presented in the empirical applications does not favor the method's replication in practical terms.

In summary, on the one hand, the methods that independently or partially address the classes of design problems present empirical applications that favor their adoption but lead to locally optimized solutions. On the other hand, the methods that systematically address the classes of design problems altogether and, consequently, lead to globally satisfactory or optimal solutions, are essentially theoretical or do not provide detailed applications allowing their use in practical terms. Given those above, this study poses the following research question: how to systemically and empirically design product families relying on economically feasible customization? Aiming to answer this question while bridging the gap between theory and practical implementation,

this study uses the market-driven modularity (MDM) method [13] to conceptually design a family of autonomous mobile palletizers economically oriented to market requirements. The empirical application of the method pointed out the palletizers family as being economically feasible. Moreover, it also identified the optimal set of modules that should be developed in subsequent design phases, as well as revealed the definition of the product family structure as the MDM's outcome that is more sensitive to the variation of parameters/variables (i.e., market size and variable cost) composing the configuration model. The main contribution of this work lies in developing practical implementation details of the MDM method, which have not been reported since its proposition. When evaluated in perspective to other works that have addressed palletizer design [e.g., 14–16], this paper brings an economic and market standpoint, complementary to the engineering point of view traditionally adopted by machine manufacturers.

The remainder of this article is organized as follows. Section 2 summarizes the related work on modular product family design, while Sect. 3 provides details of the MDM method. Section 4 describes the empirical application of the method, and Sect. 5 discusses the findings. Finally, Sect. 6 outlines the concluding remarks, limitations, and directions for future research.

2 Related research on modular product family design

Designing product families is an enabling strategy for mass customization [17]. In contrast to developing a single product at a time, the purpose of product family design is to create a modular architecture made up of platforms and modules, from which a multitude of family members are derived [12]. The instantiation of family members is carried out by mixing and matching modules from the platform or scaling the platform variables according to preset configuration rules [18]. There are four prevalent classes of problems when designing product families [3]. The first is product family positioning, where product offerings are optimized based on customer preferences. The second is customer preferences modeling, where the customer choices' influence on product profiles is modeled. The third class is product family modeling, wherein modules and platforms are conceived. Finally, the last one is product family configuration, wherein product family variants are instantiated.

Many methods for designing product families have been developed in the past 20 years [5]. Besides the ones described in Sect. 1 [3, 5, 9, 13], the method by Jiang and Allada [19] also encompasses the four classes of design problems together. However, it presupposes that the modules' set already exists, which makes the method sensitive to

extant modules' ability to meet the customer desired attributes. Other methods covering the first three classes of design problems are also found in the literature [12, 20–27]. However, their fundamental drawback is choosing the modules to make up the product family structure based on individual evaluations rather than combining modules into variants. The problem is that the combination of modules affects the performance of the configured variants [28, 29]. Therefore, there is no guarantee that a local selection will result in global optimized variants.

Further methods focus on modules identification within the product family modeling [30–40]. However, few, if any, methods in this group perform the functional and physical decomposition concurrently, which may result in modular architectures constrained by physical interactions. Furthermore, such methods only measure the quality of the clustering solution on occasion, thus not assuring that the solution found is the most suitable one. Still concerning the product family modeling, some methods combine this class with product family positioning [40–43], whereas others combine it with customer preferences modeling [14, 44–60]. In both cases, although few methods obtain the product desired attributes from the customers themselves, most only guide design decisions in criteria essentially linked to customer preferences. The disadvantage of this strategy is that it may end up in specifications that can barely be achieved in reality [61] or induce economically unfeasible product families [8].

Finally, other methods focus on the product family configuration [7, 29, 62–67]. In this group, most methods solve the optimization problem of combining and parametrizing modules into product family variants through metaheuristics. Among the design criteria used for composing the objective function, cost appears most frequently [5]. Nonetheless, considering it alone, or even in conjunction with utility, may not be enough to justify the investments in a product family design/redesign project [62]. Therefore, some methods combine cost with demand and price to obtain profit. Although profit consists of an adequate criterion for assessing economic viability [11], it assumes the use of fixed costs. Nonetheless, rating fixed costs has shown to be counterproductive in selecting the product mix, as it favors more high-volume variants than those more profitable [68]. With further regard to this group, some methods contemplate the product family modeling and configuration being performed together [17, 28, 69–73]. Nevertheless, as well as the work by Jiang and Allada [19], the assumption that a collection of modules already exists hinders the use of configuration procedures to rationalize the product family structure, which ultimately may result in low-utility configuration spaces.

In summary, the missing integration among the classes of design problems precludes using a single method to conduct the entire design process and leads to local optima.

Furthermore, when combined with profit-related design criteria, this situation may end up in product families that fail to reap the profitability expected from customization. These are gaps that the market-driven modularity method [13], outlined next, sets out to overcome without yet demonstrating detailed empirical applications that would enable its use in practical terms.

3 Market-driven modularity – MDM

MDM is a method for conceptually designing product family structures economically driven to the customers' requirements [13]. Conceived for use in early design stages, the MDM consists of 23 steps organized into 4 classes of design problems that can be executed by an open architecture of techniques. The rationale of the method is to define the target market segments, model the customer preferences for each of them, and then create a modular architecture aiming at covering all segments. From the modular architecture, multiple instances of design parameters are devised and further arranged in a multitude of segment-related variants. Next, established the price and estimated the demand, each segment variant's throughput (sale price minus variable costs) is computed. Finally, the throughputs of the most contributive variants are pooled into the product family throughput, and the design parameter instances comprising them are chosen to make up the final product family structure. The process ceases when the profit exceeds the investment or a pre-determined profit threshold is reached, as seen in Fig. 1. The two primary intended outcomes are (i) ensuring the product family's economic viability and (ii) the product family structure that economically meets the market requirements.

3.1 Product family planning and positioning (Cp$_1$)

In further depth, MDM begins with converting the company strategy into objective measurements for product family design. In step $S_{1.1}$, the potential market size (Mk), the share of market segments (Sms), and investment parameters are estimated. Similarly, the target market segments, $MS \equiv \{ms_i | i = 1, \ldots, I\}$, technological trends, product family leveraging strategy, and complementary elements are defined. The market segmentation is then refined in step $S_{1.2}$, and the resulting specifications trigger the identification of the customer desired attributes, $A \equiv \{a_l | l = 1, \ldots, L\}$, in step $S_{2.1}$, or feedback on the strategic product family planning in step $S_{1.1}$.

3.2 Customer preferences modeling (Cp$_2$)

In Cp$_2$, the method continues to model the influence of customer choices on product profiles. It starts in step $S_{2.1}$ by determining the customers' desired attributes. The
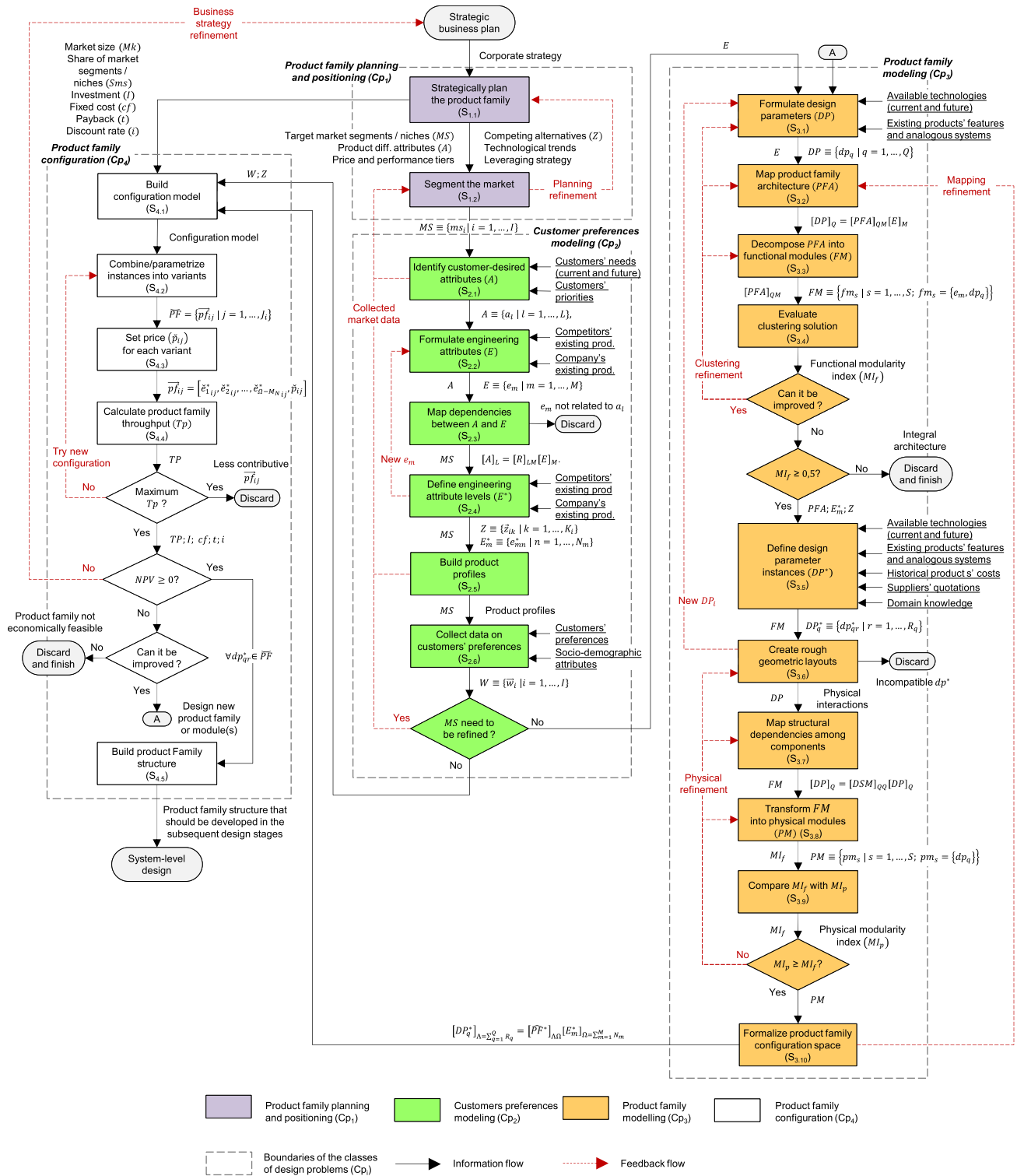
Fig. 1 MDM's diagram (adapted from Gauss et al. [13])

attributes should be derived from existing or future needs, and, in some circumstances, they are also used to refine the market segments established in the preceding step. In step $S_{2.2}$, it is undertaken the translation of customer attributes to engineering attributes, $E \equiv \{e_m | m = 1, \dots, M\}$, followed by the mapping of their relationships in step $S_{2.3}$, which entails that $[A]_L = [R]_{LM}[E]_M$. The customer-related engineering attributes proceed to step $S_{2.4}$, while the unrelated

ones are discarded. Engineering attributes usually have different levels, i.e., $E_m^* \equiv \{e_{mn}^*|n = 1, \ldots, N_m\}$, which are identified in step $S_{2.4}$ from a set of competing alternatives, $Z \equiv \{\vec{z}_{ik}|k = 1, \ldots, K_i\}$, related to the target market segments previously defined (MS).

In other words, the competing alternative is a vector of engineering attribute values ($\breve{e}^*$) and price ($\breve{p}$), $\vec{z}_{ik} = \left[\breve{e}_{1_{ik}}^*, \breve{e}_{2_{ik}}^*, \ldots, \breve{e}_{\Omega-M_{N\,ik}}^*, \breve{p}_{ik}\right]$, from which the levels are inductively defined. From a market-pull standpoint, the competing alternatives may often be obtained from definitions other players assumed or from the company's actual products. In turn, from the technology-push perspective, the alternatives are derived from the company's vision of the future. At this step ($S_{2.4}$), new engineering attributes might arise; when it happens, they serve as feedback for step $S_{2.2}$.

In the following step ($S_{2.5}$), the set of product profiles via which the customers express their preferences is built. Given the possibility of exceptionally high combinations involving engineering attributes $\left(e_m\right)$ and levels $\left(e_{mn}^*\right)$, $\prod_{m=1}^{N} N_m$, the goal of step $S_{2.5}$ is to minimize the number of product profiles while maintaining their significance. The data on customer preferences are then gathered in step $S_{2.6}$. When data is mainly available, the customers are asked to choose a profile from the set, simulating real-world purchase decisions. When data is scarcely known, the experts or the key customers are requested to perform pairwise comparisons involving the customer desired attributes (a), engineering attributes (e), and their respective levels (e^*) hierarchically. Concluding, in step $S_{2.7}$, the importance of engineering attribute levels and the price is computed for each segment, i.e., $\vec{w}_i = \left[w_{1i}, w_{2i}, \ldots, w_{\Omega-M_{N}i}, w_{\Omega+1i}\right]$. If some kind of deviation in market segmentation appears, the process should be repeated until achieving a final solution.

3.3 Product family modeling (Cp$_3$)

Following the customer preferences model, in Cp$_3$, the challenge is to define the product family architecture, break it down into modules, and then generate design parameter instances that might compose the product family structure. In step $S_{3.1}$, the process begins with the formulation of logical entities capable of accomplishing one or more engineering attributes, referred to as design parameters, $DP \equiv \{dp_q|q = 1, \ldots, Q\}$. The formulation of design parameters stems from the available technology, existing product features, technological trends, and analogous systems, as shown in Fig. 1. Once defined, in step $S_{3.2}$, the design parameters and engineering attributes are mapped into a product family architecture covering the target segments altogether, i.e., $[DP]_Q = [PFA]_{QM}[E]_M$. Then, in step $S_{3.3}$, the functional modules are derived from the decomposition of the product family architecture,

$FM \equiv \{fm_s|s = 1, \ldots, S; fm_s = \{e_m, dp_q\}\}$, followed by the evaluation of its clustering solution in step $S_{3.4}$. If the clustering solution succeeds in producing a level of functional modularity higher than or equal to 0.5 (e.g., $MI_f \geq 0.5$), the process continues; otherwise, it ends. After defining the functional modules, the next step ($S_{3.5}$) is to specify the many constructive solutions that a design parameter can assume, referred to as design parameter instances (or building blocks), i.e., $DP_q^* \equiv \left\{dp_{qr}^*|r = 1, \ldots, R_q\right\}$. A design parameter instance consists of a vector formed of engineering attribute values and variable cost, $\overline{dp}_{qr}^* = \left[\hat{e}_{1_{qr}}^*, \hat{e}_{2_{qr}}^*, \ldots, \hat{e}_{\Omega-M_{N\,qr}}^*, \hat{cv}_{\omega\,qr}^*\right]$; therefore, these properties should also be specified in step $S_{3.5}$. Subsequently, preliminary geometric layouts are undertaken in step $S_{3.6}$ to reveal the physical interactions among modules' constituents. At this point of the method, it is possible to delete incompatible design parameter instances, but new design parameters may arise, closing a feedback loop with steps $S_{3.6}$ and $S_{3.1}$. The physical interactions resulting from step $S_{3.6}$ work as inputs for mapping the structural relationships among design parameters in step $S_{3.7}$, i.e., $[DP]_Q = [DSM]_{QQ}[DP]_Q$. In step $S_{3.8}$, the functional modules are converted to physical modules, $PM \equiv \{pm_s|s = 1, \ldots, S; pm_s = \{dp_q\}\}$, and then evaluated in step $S_{3.9}$. If physical interactions do not constraint the modular architecture, i.e., $\left(MI_p \geq MI_f|MI_f \geq 0.5\right)$, the process moves on. Otherwise, physical modularity is refined in successive iterations until achieving the desired threshold. Concluding, the solution space for product family configuration is set in step $S_{3.10}$, $\left[DP_q^*\right]_{\Lambda=\sum_{q=1}^{Q} R_q} = \left[\widehat{PF}^*\right]_{\Lambda\Omega}\left[E_m^*\right]_{\Omega=\sum_{m=1}^{M} N_m}$. Eventually, any required modification may feedback step $S_{3.2}$.

3.4 Product family configuration (Cp$_4$)

Finally, in Cp$_4$, the aim is to pool the market and investment parameters, customer preferences, competing alternatives, product family architecture, and candidate building blocks into a unique model intended to select and parameterize the design parameter instances to constitute the product family structure. This class starts in step $S_{4.1}$ by building the configuration model, as further detailed by Gauss et al. [13]. Then, in step $S_{4.2}$, the design parameter instances are combined and parameterized, yielding a finite group of variants for each target market segment, i.e., $\breve{PF} \subseteq PF$ wherein $PF \equiv \left\{\vec{pf}_{ij}|j = 1, \ldots, J_i\right\}$. In step $S_{4.3}$, the price $\left(\breve{p}_{ij}\right)$ for each variant is determined, $\vec{pf}_{ij} = \left[\breve{e}_{1_{ij}}^*, \breve{e}_{2_{ij}}^*, \ldots, \breve{e}_{\Omega-M_{N}ij}^*, \breve{p}_{ij}\right]$, and the product family throughput (Tp) is calculated in step $S_{4.4}$. The steps from $S_{4.1}$ to $S_{4.4}$ are iteratively undertaken until reaching a satisfactory or optimal throughput. The less

Table 1 MDM's techniques (adapted from Gauss et al. [13])

Steps (S)	Techniques for scarce data	Techniques for abundant data
S$_{1.1}$ – strategically plan the product family	Technology roadmap [74] Aggregate project plan [75] *Market segmentation grid [76]* Delphi [77] Three-point estimate [78] Domain knowledge [20]	 Survey [79] Descriptive statistics [80]
S$_{1.2}$ – segment the market	Delphi [77] Market segmentation grid [76] *Requirements list [82]*	Latent class analysis [81]
S$_{2.1}$ – identify customer desired attributes (*A*)	Qualitative interviews [83] Direct observation [23] Focus group [83] *Content analysis [84, 85]*	Survey [79] Descriptive statistics [80]
S$_{2.2}$ – formulate engineering attributes (*E*)	*Analysis of existing technical systems [82]* *Benchmarking [86]* *Reverse engineering [86]*	
S$_{2.3}$ – map dependencies between *A* and *E*	*Design matrix [87]*	
S$_{2.4}$ – define engineering attributes levels $\left(E_m^*\right)$	*Analysis of existing technical systems [82]* *Benchmarking [86]* *Reverse engineering [86]*	
S$_{2.5}$ – build product profiles		Fractional factorial design [80]
S$_{2.6}$ – collect data on customers' preferences	Qualitative interviews [83] Focus group [83] Analytic hierarchy process [88–90]	Survey [79] Multinomial logistic regression [81]
S$_{3.1}$ – formulate design parameters (*DP*)	*Domain knowledge [20]* *Classification scheme [82]*	
S$_{3.2}$ – map product family architecture (*PFA*)	*Design matrix [87]*	
S$_{3.3}$ – decompose *PFA* into functional modules (*FM*)	*Rank order clustering [91]* *Cluster identification algorithm [92]*	
S$_{3.4}$ – evaluate clustering solution	*Modularity index [93]*	
S$_{3.5}$ – define design parameter instances $\left(DP^*\right)$	*Classification scheme [82]* *Analysis of existing technical systems [82]* *Benchmarking [86]* *Reverse engineering [86]* *Artificial neural network [94]* *Pragmatic approach to product costing [95]* *Request for quotation [96]* *Three-point estimate [78]*	
S$_{3.6}$ – create rough geometric layouts	*Sketching and rendering [97]*	
S$_{3.7}$ – map structural dependencies among components	*Design structure matrix [98]*	
S$_{3.8}$ – transform *FM* into physical modules (*PM*)	*Functional to physical decomposition [13]*	
S$_{3.9}$ – compare MI_f with MI_p	*Modularity index [93]*	
S$_{3.10}$ – formalize the product family configuration space	*Design matrix [87]* *Generic bill-of-material [70]*	
S$_{4.1}$ – build configuration model	*Mathematical modeling [99]* *Data scaling [81]*	
S$_{4.2}$ – combine/parametrize instances into variants	Design heuristic–substitute way of achieving functions [100]	Genetic algorithm [46]
S$_{4.3}$ – set price $\left(\check{p}_{ij}\right)$ for each variant	Trial-and-error [101]	Genetic algorithm [46]
S$_{4.4}$ – calculate product family throughput (*Tp*)	*Throughput accounting [68]*	
S$_{4.5}$ – build product family structure	*Generic bill-of-material [70]*	

contributive variants are then eliminated, and the product family profit is discounted to present value (*NPV*). In step $S_{4.5}$, if $NPV \geq 0$, the most contributive variants are computed, and their design parameter instances become part of the product family structure. Otherwise, the process restarts until reaching the desired value or a final discard, as seen in Fig. 1.

Lastly, Table 1 complements the functional description of MDM by providing an open architecture of techniques. The left and the right-hand side techniques are respectively more suitable for scarce and abundant data availability. Techniques in the middle part of the table serve to be used for both situations.

4 Empirical application

The empirical execution of MDM in the conceptual design of a family of autonomous mobile palletizers is presented in this section. The application was carried out by the first author of this work with the assistance of two engineers from the Brazilian machine manufacturer (referred to here as to company) who provided data for this study. The data stem from 35 palletizing projects quoted by the company during 5 years and the websites of five leading players. Such a situation configures a scarce data availability scenario.

Palletizing consists of stacking products onto a pallet, whereas a palletizer is equipment that executes this operation

[102]. In general, palletizers can be of two types [14]: (i) conventional or (ii) robotic. A traditional palletizer is preferred for long production runs handling non-variable stock-keeping units (SKU) and size packages. In turn, robotic palletizers are best suited in conditions that require palletizing of multiple SKU pallets with different package sizes and short production cycles [102]. In today's economic scenario, retailers and distribution centers use fewer single SKU pallets and more mixed-load ones. Thus, the adoption of robotic palletizers is expected to overtake conventional ones shortly [103]. Following this direction and considering industrial robotics as an enabling technology for advanced manufacturing [104], the company defined collaborative and autonomous mobile robotics as technological trends for product family design in step $S_{1.1}$. The roadmap in Fig. 2 aided this definition by depicting the relationships among technology, product, and market layers, as reasoned by Paul and Muller [74]. The technology layer shows the evolution of industrial robotics in terms of morphology, control, and payload capacity. In turn, the product layer indicates how technological progress might support the emergence of new intermediate goods (e.g., collaborative robots (COBOT), autonomous mobile robots (AMR), autonomous mobile cobots (AMC), and unmanned aerial vehicles (UAV)) to compose future production systems. Lastly, the market layer suggests upcoming opportunities from the two bottom ones.

Two potential product families were identified based on future opportunities, as illustrated in Figs. 2 and 3. The first
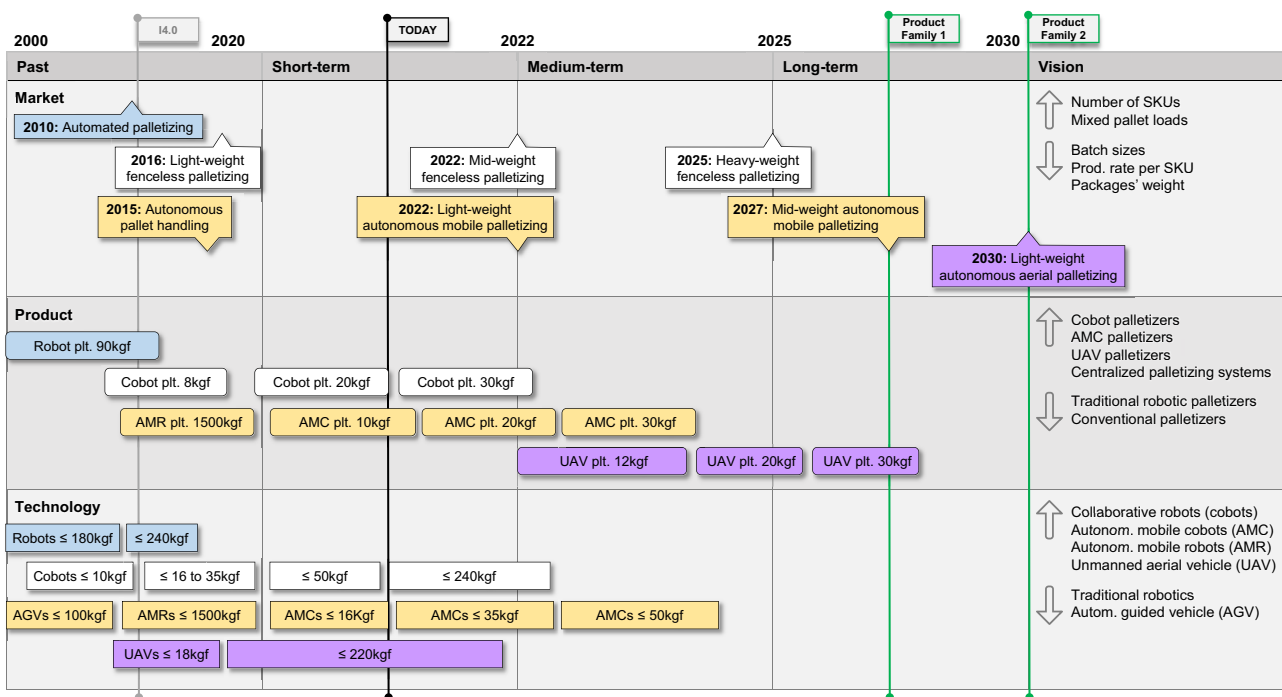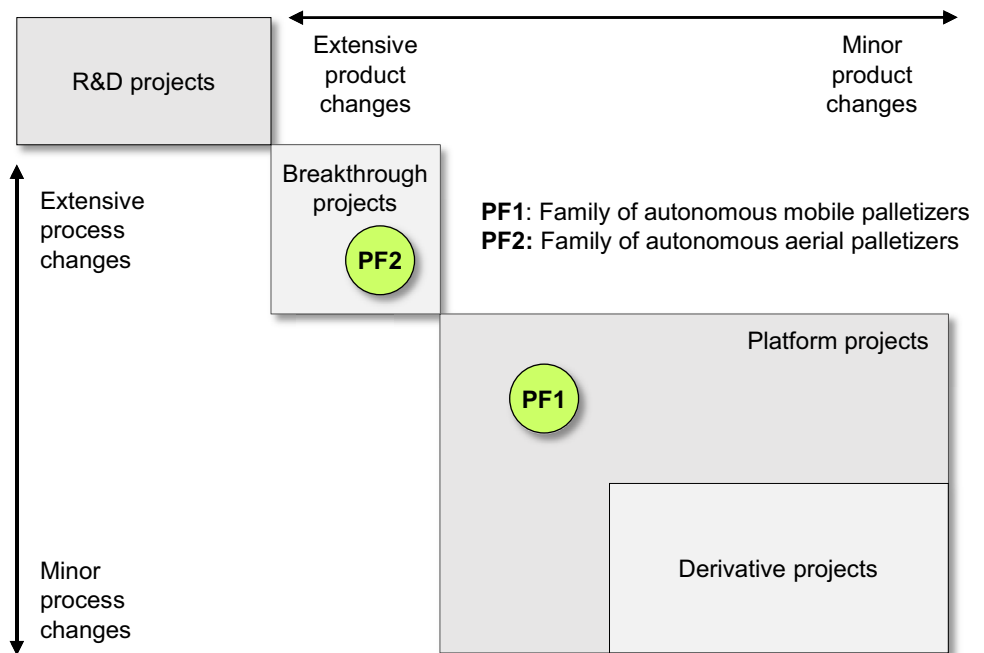

Fig. 2 Technology roadmap for autonomous mobile palletizers

Fig. 3 Aggregate project (adapted from Wheelwright and Clark [75])

refs to a family of autonomous mobile palletizers (PF1), whereas the other consists of a family of aerial palletizers (PF2). Given that PF2 can potentially be developed from the PF1 platform, the company chose first to develop product family PF1, which comprises the scope of this study.

Estimate the potential market size (Mk) is another activity to be done in step $S_{1.1}$. In this case, such action was assisted by the existing market data, in conjunction with experts' knowledge [20]. According to Fortune Business Insights [105], the global palletizer market reached USD 1.6 billion in 2019 and possibly must surpass USD 2.2 billion by 2027. Regarding the Brazilian market, based on the experience of engineers who supported this work and the company's historical sales data, Brazil accounts for less than 5% of the global demand, with an average price per stacking position equal to USD 120,000.00. Assuming the global palletizer market size as a uniform distributed variable $U(1.63.10^9, 2.16.10^9)$, the Brazilian market size as a constant fraction (5%) of the global demand, and the price per stacking position as a normally distributed variable $N(120.10^3, 20.10^3)$, the average market size was estimated as 814 stacking positions a year from 2021 to 2027.

Coupled with this arose the necessity to determine the target market segments and the product family leveraging strategy. To this end, the market segmentation grid (MSG)

was employed multidimensionally, as depicted in Fig. 4. The MSG axis represents the key customer desired attributes and their respective performance tiers. The markers, in turn, consist of palletizing projects quoted by the company for different markets and package types. The bars on the left and the upper left of Fig. 4a represent the competing alternatives, whereas their length suggests how they span the corresponding axis. In Fig. 4b, the red, green, and blue areas show the design frontiers of product family PF1, set based on cobots and AMC's payload capacity and production rate. The markers dropping in these areas indirectly point out the target market segments of PF1, while the bars on the left and the upper left of Fig. 4b depict its working principle and leveraging strategy to reach the intended attribute levels.

The last activity of step $S_{1.1}$ was to estimate the investment parameters required to develop the product family. So, the company estimated an investment of USD 4,000,000.00 that would be possible to launch the product family PF1 in up to two years, i.e., $I = 4,000,000.00[USD]$. In addition, the company argued that for the project to be viable, the payback period should not exceed 2 years, $t \leq 2[years]$, considering a discount rate of 12% a year, i.e., $i = 12[\%/year]$.

With the product family strategically planned, the next step ($S_{1.2}$) was to define the share of market niches (Sms). This task started with a change in segmentation perspective,
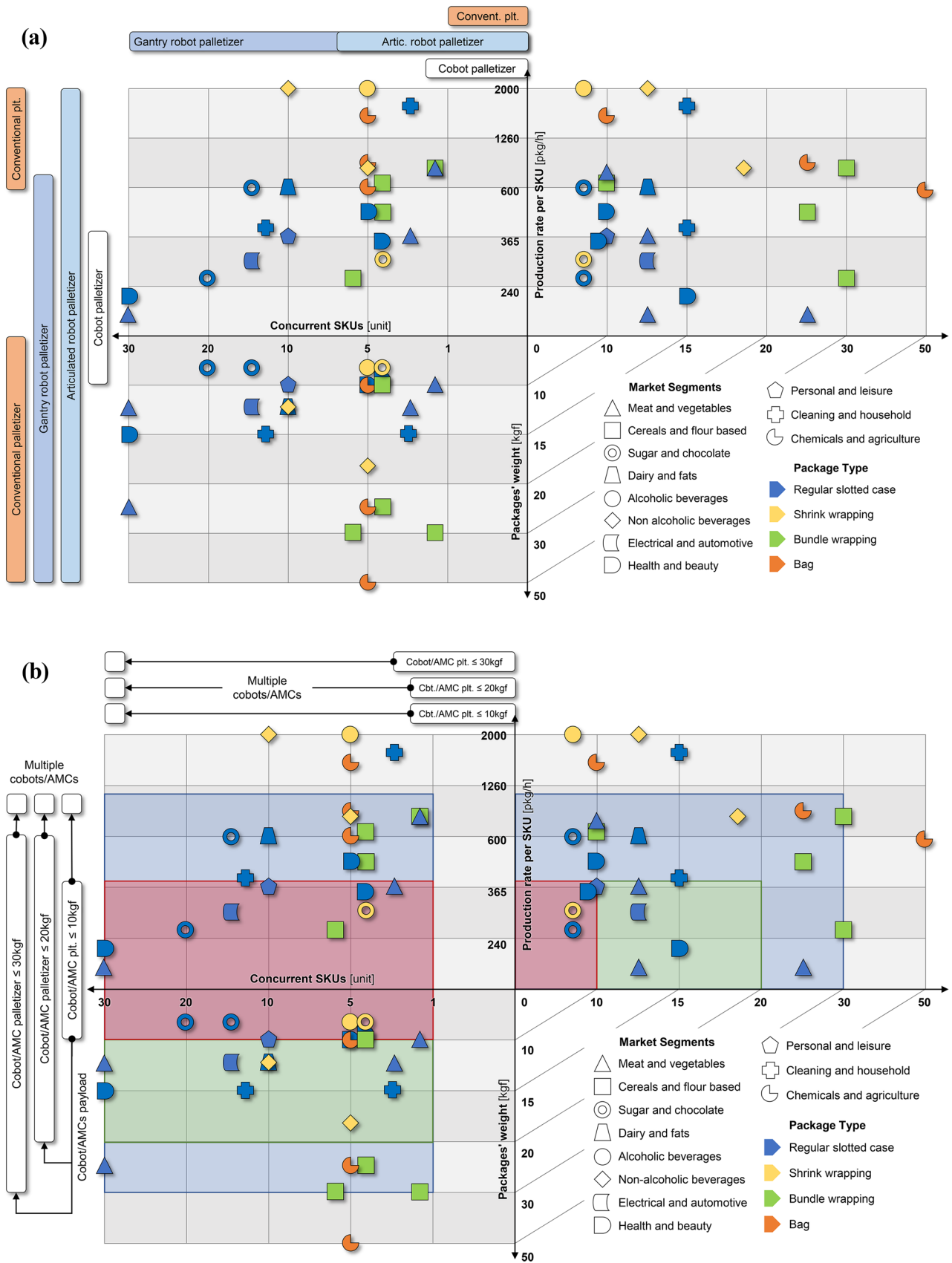
Fig. 4 Market segmentation grid: **a** market segmentation; **b** leveraging strategy

which shifted from "sector" to "package type." Then, based on the projects quoted, nine market niches and their respective shares were defined. Of these niches, six in line with the working principle and leverage strategy of PF1 were considered targets, as illustrated by Fig. 5. At the end of this first class of design problems (Cp_1), the information generated was aggregated into a requirements list, as recommended elsewhere [82].

Next, the issue was to model the customer preferences for each target market niche. It was undertaken in class Cp_2 and began with the identification of customer-desired attributes (A) in step $S_{2.1}$. In this case, 9 customers' desired attributes were derived from a content analysis performed on the 35 projects quoted by the company, as reasoned by Bardin [84]. After identifying, the customer desired attributes were analyzed as to the possibility of still existing in 2027. There was a consensus among the company engineers that, regardless of their relative importance might change, they would nonetheless reflect the customer needs shortly. Finally, each attribute was linked to its respective niche, as illustrated in Table 2.

Subsequently, in step $S_{2.2}$, 27 engineering attributes (E), including price, were formulated from five competitors' product portfolios in the palletizing market. This task was undertaken through the analysis of existing technical systems combined with benchmarking, as proposed by Pahl et al. [82] and Thevenot and Simpson [86]. Then, in step $S_{2.3}$, the customer desired attributes were mapped to engineering attributes, as depicted in the upper part of Table 2 and reasoned by Suh [87]. Table 2 also shows the preferred direction of engineering attributes, resembling quality function deployment [106].

The engineering attributes often have different levels $\left(E_m^*\right)$. In order to identify these levels, the competing alternatives $(\vec{z}_{ik})$ covering all target niches and their respective engineering attribute values ($\check{e}^*$) and price ($\check{p}$) were captured in step $S_{2.4}$, i.e., $\vec{z}_{ik} = \left[\check{e}_{1_{ik}}^*, \check{e}_{2_{ik}}^*, \ldots, \check{e}_{\Omega-M_{N\,ik}}^*, \check{p}_{ik}\right]$. This activity used the same techniques and data sources of step $S_{2.2}$ and resulted in the identification of 50 engineering attribute levels (e^*) retrieved from 10 competing alternatives divided into six market niches, as presented in Tables 2 and 3.
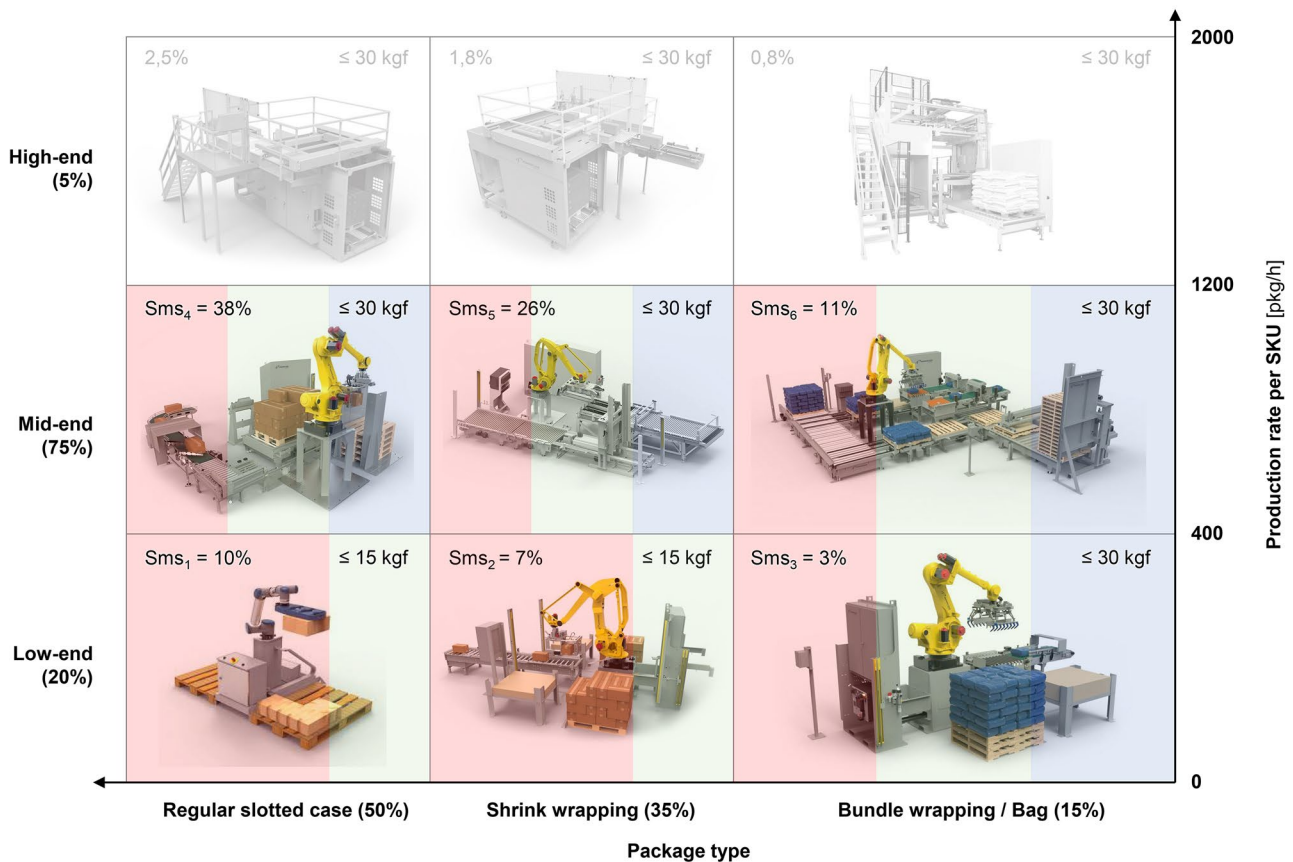

Fig. 5 MSG (adapted from Meyer and Lehnerd [76])

Table 2 Product family attributes deployment

		Preferred direction	=		=	-	Mkt. niche (MS)		
		Engineering attributes (E)	Type of palletizer	…	Type of labeler	Price per stk. loc. [USD]	RSC/L/ ≤ 15 kgf	…	BW/B/M/ ≤ 30 kgf
			e_1	…	e_{26}	$\check{p}$	ms_1	…	ms_6
Customer desired attributes (A)	a_1	Palletizing technology	1	…			1	…	1
	a_2	Production capabilities		…			1	…	1
	a_3	Package handling		…			1	…	1
	…	…	…	…		…	…	…	…
	a_8	Traceability		…	1		1	…	1
	a_9	Price		…		1	1	…	1
Competing alternatives (Z)	$z_{1.1}$	Collaborative robotic palletizer (A1)	Articulated robot	…	None	40,000.00	1		
	$z_{1.2}$	Robotic pick'n place palletizer (B1)	Gantry robot	…	None	125,000.00	1		
	$z_{1.3}$	Low infeed palletizer (C1)	Conventional	…	None	90,000.00	1		
	$z_{1.4}$	Robotic palletizer (D1)	Articulated robot	…	None	35,000.00	1		
	$z_{1.5}$	Robotic palletizer (D2)	Articulated robot	…v	None	135,000.00	1		
	…	…	…	…	…	…	…	…	
	$z_{6.1}$	Hybrid robotic palletizer (B3)	Articulated robot	…	Side label	260,000.00			1
	$z_{6.2}$	Low infeed palletizer (C2)	Conventional	…	Side label	160,000.00			1
	$z_{6.3}$	Robotic palletizer (D4)	Articulated robot	…	Side label	185,000.00			1
Engineering attribute levels (E*)			Articulated robot	…	Side label	≤ 260,000.00			
			Gantry robot	…	Corner label				
			Conventional	…	None				

Given the scenario of scarce data availability, in step $S_{2.5}$, the customer-desired attributes, engineering attributes, and respective levels were organized in a three-level hierarchy. Then, in step $S_{2.6}$, the two company engineers and the first author of this work independently performed a set of pairwise comparisons between elements of the same hierarchical level, for each target market niche. The technique employed was the analytical hierarchy process [88], with preference aggregation being performed through geometric mean [89]. The outcomes of steps $S_{2.5}$ and $S_{2.6}$ are summarized in Table 3, with all cases presenting consistency ratios lower than 0.1.

At the end of Cp_2, it was found no deviation from the market niches established in step $S_{2.1}$. Therefore, the next challenge was determining the modular product family architecture and creating the design parameter instances that might compose the product family structure. These activities happen in class Cp_3 and began with the formulation of design parameters (DP) in step $S_{3.1}$. The formulation of DP was assisted by the classification scheme by Pahl et al. [82], wherein the working principles (WP) related to engineering attributes were identified and cataloged, as illustrated in Table 4 and

further detailed in Supplementary Material. Then, the logical entities underlying the working principles with the same physical effect were inductively derived. For instance, in Table 4, the working principles wp_{15}, wp_{16}, and wp_{17}, though differing morphologically, they share the same physical effect of gripping packages. Concerning the robotic palletizers, the logical entity executing that function is the end-effector; thus, it was defined as the design parameter number seven (dp_7).

Following this reasoning and supported by the company engineers, 17 design parameters stem from the 37 working principles recorded in Table 4.

In step $S_{3.2}$, the design parameters and engineering attributes were mapped into the product family architecture, i.e., $[DP]_Q = [PFA]_{QM}[E]_M$. Then, through the ranking order clustering [91], the rows and columns of $[PFA]_{QM}$ were rearranged leading to the identification of functional modules (FM) in step $S_{3.3}$. Lastly, in step $S_{3.4}$, the clustering solution was evaluated via functional modularity index (MI_f) [93]. In this application, steps from $S_{3.1}$ to $S_{3.4}$ were iteratively performed until the clustering solution, composed of seven functional modules, reached the $MI_f = 0.63$, as shown in Table 5.

Table 3 Importance of engineering attribute levels

A	Customer desired attributes	E	Engineering attributes	Type	Dir	E*	Engineering attributes levels	w_1	w_2	w_3	w_4	w_5	w_6
a_1	Palletizing technology	e_1	Type of palletizer	chr	=	$e^*_{1.1}$	Articulated robot	0.195	0.195	0.189	0.188	0.188	0.189
						$e^*_{1.2}$	Gantry robot	0.035	0.035	0.034	0.034	0.034	0.034
						$e^*_{1.3}$	Conventional	0.031	0.031	0.031	0.030	0.030	0.031
		e_2	Type of end-effector	chr	=	$e^*_{2.1}$	Vacuum style	0.043	0.009	0.008	0.042	0.007	0.006
						$e^*_{2.2}$	Mechanical style	0.009	0.043	0.042	0.008	0.043	0.044
		e_3	Load building strategy	chr	=	$e^*_{3.1}$	Traditional (one SKU per pallet)	0.020	0.020	0.020	0.019	0.019	0.020
						$e^*_{3.2}$	Mixed (multiple SKU per pallet)	0.003	0.003	0.003	0.003	0.003	0.003
a_2	Production capabilities	e_4	Production per stacking location [pkg/h]	double	+	$e^*_{4.1}$	≤1,920	0.073	0.073	0.076	0.069	0.069	0.076
		e_5	No. of SKUs palletized concurrently [un.]	int	+	$e^*_{5.1}$	≤4	0.060	0.060	0.063	0.056	0.056	0.063
		e_6	Max. package dimension [mm]	double	+	$e^*_{6.1}$	≤737	0.007	0.007	0.007	0.006	0.006	0.007
		e_7	Max. package height [mm]	double	+	$e^*_{7.1}$	≤457	0.006	0.006	0.007	0.006	0.006	0.007
		e_8	Max. package weight [kgf]	double	+	$e^*_{8.1}$	≤50	0.016	0.016	0.017	0.015	0.015	0.017
		e_9	Min. pallet/load size [mm]	double	−	$e^*_{9.1}$	≥700	0.007	0.007	0.008	0.007	0.007	0.008
		e_{10}	Max. pallet/load size [mm]	double	+	$e^*_{10.1}$	≤1,300	0.007	0.007	0.007	0.007	0.007	0.007
		e_{11}	Max. load height [mm]	double	+	$e^*_{11.1}$	≤2,134	0.015	0.015	0.016	0.014	0.014	0.016
		e_{12}	Max. load weight [kgf]	double	+	$e^*_{12.1}$	≤2,000	0.015	0.015	0.015	0.014	0.014	0.015
a_3	Package handling	e_{13}	Type of package accumulation conveyor	chr	=	$e^*_{13.1}$	Modular belt	0.016	0.016	0.016	0.019	0.019	0.016
						$e^*_{13.2}$	Chain-driven live roller	0.008	0.008	0.008	0.009	0.009	0.008
		e_{14}	Length of package accumulation [m]	double	+	$e^*_{14.1}$	≤3.0	0.020	0.020	0.021	0.024	0.024	0.021
		e_{15}	Type of package turner	chr	=	$e^*_{15.1}$	Cushioned turn	0.001	0.001	0.001	0.001	0.001	0.001
						$e^*_{15.2}$	Turn table	0.003	0.003	0.003	0.003	0.003	0.003
						$e^*_{15.3}$	Soft turn	0.004	0.004	0.004	0.004	0.004	0.004
						$e^*_{15.4}$	Robotic pick-up tool	0.001	0.001	0.001	0.001	0.001	0.001
		e_{16}	Package rotating angle [deg]	int	+	$e^*_{16.1}$	≤180	0.009	0.009	0.009	0.011	0.011	0.009
a_4	Pallet handling	e_{17}	Type of pallet dispenser	chr	=	$e^*_{17.1}$	Standalone	0.020	0.020	0.019	0.022	0.022	0.019
						$e^*_{17.2}$	Robotic pick-up tool	0.008	0.008	0.008	0.009	0.009	0.008
						$e^*_{17.3}$	Manual	0.003	0.003	0.003	0.004	0.004	0.003
		e_{18}	Pallet hopper capacity [pallet]	int	+	$e^*_{18.1}$	≤20	0.010	0.010	0.010	0.012	0.012	0.010
a_5	Sheet handling	e_{19}	Type of sheet dispenser	chr	=	$e^*_{19.1}$	Standalone	0.016	0.016	0.015	0.011	0.011	0.015
						$e^*_{19.2}$	Robotic pick-up tool	0.039	0.039	0.037	0.027	0.027	0.037
						$e^*_{19.3}$	None	0.007	0.007	0.006	0.005	0.005	0.006
		e_{20}	Sheet hopper capacity [sheet]	int	+	$e^*_{20.1}$	≤167	0.021	0.021	0.020	0.014	0.014	0.020
a_6	Load handling	e_{21}	Type of load conveyor	chr	=	$e^*_{21.1}$	Chain-driven live roller	0.009	0.009	0.012	0.016	0.016	0.012
						$e^*_{21.2}$	Two/three-strand chain	0.009	0.009	0.012	0.016	0.016	0.012
						$e^*_{21.3}$	AGV	0.015	0.015	0.007	0.010	0.010	0.007
						$e^*_{21.4}$	None (Floor stacking)	0.002	0.002	0.002	0.002	0.002	0.002
		e_{22}	Load buffer capacity [pallet]	int	+	$e^*_{22.1}$	≤4	0.011	0.011	0.011	0.015	0.015	0.011

Table 3 (continued)

A	Customer desired attributes	E	Engineering attributes	Type	Dir	E*	Engineering attributes levels	w_1	w_2	w_3	w_4	w_5	w_6
a_7	Stretch wrapping	e_{23}	Type of stretch wrapper	chr	=	$e^*_{23.1}$	Turntable	0.019	0.019	0.023	0.021	0.021	0.023
						$e^*_{23.2}$	Rotating arm	0.011	0.011	0.014	0.013	0.013	0.014
						$e^*_{23.3}$	Robotic	0.008	0.008	0.010	0.009	0.009	0.010
						$e^*_{23.4}$	None	0.002	0.002	0.002	0.002	0.002	0.002
		e_{24}	Film pre-stretch [%]	double	+	$e^*_{24.1}$	≤400	0.013	0.013	0.016	0.015	0.015	0.016
a_8	Traceability	e_{25}	Type of reader	chr	=	$e^*_{25.1}$	Image-based	0.007	0.007	0.006	0.009	0.009	0.006
						$e^*_{25.2}$	Laser-based	0.003	0.003	0.003	0.004	0.004	0.003
						$e^*_{25.3}$	RFID	0.001	0.001	0.001	0.002	0.002	0.001
						$e^*_{25.4}$	None	0.001	0.001	0.001	0.001	0.001	0.001
		e_{26}	Type of labeler	chr	=	$e^*_{26.1}$	Side label	0.006	0.006	0.005	0.007	0.007	0.005
						$e^*_{26.1}$	Corner label	0.006	0.006	0.005	0.007	0.007	0.005
						$e^*_{26.1}$	None	0.002	0.002	0.002	0.002	0.002	0.002
a_9	Price	$\check{p}$	Price per stacking location [USD]	chr	–	$\check{P}^*$	≤260,000.00	0.147	0.147	0.146	0.155	0.155	0.146

The next issue was to define the constructive solutions (i.e., building blocks) that a design parameter might take, which MDM refers to as design parameter instances, i.e., $DP^*_q \equiv \left\{ dp^*_{qr} | r = 1, \ldots, R_q \right\}$. Given that a design parameter instance is a vector of engineering attribute values and variable cost, $\overrightarrow{dp}^*_{qr} = \left[\widehat{e}^*_{1_{qr}}, \widehat{e}^*_{2_{qr}}, \ldots, \widehat{e}^*_{\Omega - M_{N\,qr}}, \widehat{cv}^*_{\omega\,qr} \right]$, these elements were also determined in step $S_{3.5}$. In this context, the constructive solutions were derived from the classification scheme presented in Table 4, while the engineering attribute values were abductively defined based on Tables 2 and 3.

Finally, the variable cost was estimated through a linear arrangement of cost-related design features (CDF)[1], based on Gauss et al. [13]. In this sense, the mean coefficients were obtained through artificial neural networks, with no hidden layers, after 30 replications. The activation function used was linear, and the algorithm employed to calculate the coefficients was the resilient backpropagation [94]. This approach requires the existence of historical cost data, which, when not available, was bypassed by requesting quotes from suppliers [96]. In total, 134 design parameter instances were specified, as illustrated in Table 6. Besides the direction, this table also shows the case associated with each engineering attribute level, as recommended elsewhere [13]. Further details on CDFs are disposed of in Appendix (Fig. 10).
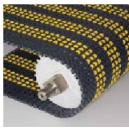
Next, in step $S_{3.6}$, 12 geometric layouts were created to identify the physical interactions among the design parameters, as shown in Fig. 6. In the end, no incompatible design parameter instances were found, and the resulting interactions were mapped using a design structure matrix in step $S_{3.7}$ (Table 7), as reasoned by Browning [98].

Then, in step $S_{3.8}$, the physical modules (PM) were established by joining together the design parameters belonging to the corresponding functional modules, e.g., $pm_1 \subset fm_1 = \left\{ dp_7, dp_6, dp_{15} \right\}$, as presented in Table 7. Afterward, the clustering solution was again evaluated, but at this time from a constructive perspective, by using the physical modularity index $\left(MI_p \right)$ in step $S_{3.9}$. The result was $MI_p = 0.94$, indicating that the product family PF1 had a modular architecture physically unconstrained. Finally, in step $S_{3.10}$, the configuration space, composed of 7 modules (functional/physical), 17 design parameters, 134 design parameter instances, and able to generate billions of variants, was formalized in tabular (Table 6) and graphical form (Fig. 8a).

In product family configuration (Cp_4), the goal is to pool the market and investment parameters, customer preferences (Table 3), competing alternatives (Table 2), product family architecture (Table 5), and candidate

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Table 4 Classification scheme

DP	Design parameters	wp$_1$	...	wp$_{15}$	wp$_{16}$	wp$_{17}$	...	wp$_{37}$
dp$_1$	Package accumulation conveyor	1	...				...	
dp$_2$	Package break conveyor		...				...	
dp$_3$	Package turner		...				...	
dp$_4$	Package singulation conveyor		...				...	
dp$_5$	Package reader		...				...	
dp$_6$	Pick and place		...				...	
dp$_7$	End-effector		...	1	1	1	...	
...	...		...	...	...	...	...	...
dp$_{17}$	Load labeler		...				...	1

building blocks (Table 6) into a mathematical model intended to choose the design parameter instances to constitute the product family structure. This routine started in step $S_{4.1}$ by formulating the configuration model, as detailed in Gauss et al. [13]. The design parameter instances were then instantiated in step $S_{4.2}$, yielding one variant for each target market niche. In step $S_{4.3}$, the price of variants was set, succeeded by the computing of the overall product family throughput (Tp) in step $S_{4.4}$. In this work, steps from $S_{4.2}$ to $S_{4.4}$ were performed using a genetic algorithm (GA), as reasoned by Jiao and Zhang [107] and illustrated in Fig. 7.

The GA hyperparameters were determined using sensitivity analysis, wherein four population sizes were considered

Table 5 Modular product family architecture

	Price per stacking location [USD]	Production per stacking location [pkg/h]	Max. package weight [kgf]	Type of palletizer	Load building strategy	Type of end-effector	Max. package dimension [mm]	Max. package height [mm]	Min. pallet/load size [mm]	Max. pallet/load size [mm]	Package rotating angle [deg]	Max. load height [mm]	Load buffer capacity [pallet]	No. of SKUs palletized concurrently [un.]	Type of sheet dispenser	Type of pallet dispenser	Pallet hopper capacity [pallet]	Length of package accumulation [m]	Type of package turner	Type of package accumulation conveyor	Type of load conveyor	Max. load weight [kgf]	Type of stretch wrapper	Film pre-stretch [%]	Sheet hopper capacity [sheet]	Type of labeler	Type of reader
		e_4	e_8	e_1	e_3	e_2	e_6	e_7	e_9	e_{10}	e_{16}	e_{11}	e_{22}	e_5	e_{19}	e_{17}	e_{18}	e_{14}	e_{15}	e_{13}	e_{21}	e_{12}	e_{23}	e_{24}	e_{20}	e_{26}	e_{25}
End-effector dp$_7$	1	1	1	1	1	1	1	1																			
Pick and place dp$_6$	1	1	1	1	1				1	1	1	1	1	1													
Sheet dispenser dp$_{15}$	1	1			1									1													
Pallet hopper dp$_8$	1	1							1	1						1	1										
Pallet dispenser dp$_9$	1	1							1	1						1	1										
Pkg. singulation conveyor dp$_4$	1		1		1	1												1									
Package turner dp$_3$	1		1		1						1							1	1								
Pkg. accumulation conveyor dp$_1$	1		1		1													1		1							
Pkg. break conveyor dp$_2$	1		1		1													1		1							
Stretch wrapper dp$_{16}$	1								1	1		1									1	1	1	1			
Pallet station dp$_{10}$	1								1	1		1									1	1					
Pallet/load shuttle car dp$_{11}$	1								1	1		1									1	1					
Load discharge. conveyor dp$_{12}$	1								1	1		1									1	1					
Load turntable dp$_{13}$	1								1	1		1									1	1					
Sheet hopper dp$_{14}$	1								1	1					1										1		
Load labeler dp$_{17}$	1																					1				1	
Package reader dp$_5$	1																										1

to set up the experiments: 100, 300, 400, and 600. Likewise, four crossover rates (0.6, 0.7, 0.8, and 0.9) and five mutation rates (0.005, 0.01, 0.05, 0.1, and 0.2) were also used. These values were defined based on the rule-of-thumb from previous GA applications [108]. Then, 16 experiments were generated through fractional factorial design [80]. After 160 replications, ten for each experiment, the parameters were selected based on the highest average fitness value, as reasoned by Jiao et al. [109]. Considering a population size of 300 variants, a crossover rate equivalent to 0.8, and a mutation rate equal to 0.1, the GA found the results in Table 8 after 400 generations.

The bottom row of Table 8 shows the results of PF1 comprising all target niches, in which the maximum throughput reached was $Tp = 16,162,788.81\left[USD/\text{year}\right]$. Considering a fixed cost (cf) around 2.10^6 [USD/year], a payback period (t) of 2 [years], a discount rate (i) equals 12 [%/year], and an investment (I) equivalent to 4.10^6 [USD], the net present value was calculated as $NPV = 7,290,488.53[USD]$. The result indicated that it would be worth investing in PF1.

In step $S_{4.5}$, with the family considered economically feasible, the design parameter instances making up the most profitable variants (second column of Table 8) were chosen to constitute the final structure of PF1. The solution comprises 7 physical modules, 17 design parameters, and 49 design parameter instances. It is able to generate 25,194,240 variants. Figure 8b shows it. Following the original proposal, it is the product family structure that economically meets the market requirements. Thus, it is the one that should proceed to the following developing stages, an issue not covered in this work.

5 Discussion

The primary MDM outcomes are (i) the product family's economic viability and (ii) the respective structure that economically meets the market requirements. In managerial terms, the first outcome supports the decision to invest or not in the product family. In the case of feasibility, the second outcome indicates which building blocks should be

Table 6 Design parameter instances

Engineering attributes key (columns e^*):
e_1 Type of palletizer — $e^*_{1,1}$ Articulated robot, $e^*_{1,2}$ Gantry robot, $e^*_{1,3}$ Conventional; e_2 Type of end-effector — $e^*_{2,1}$ Vacuum style, $e^*_{2,2}$ Mechanical style; e_3 Load building strategy — $e^*_{3,1}$ Traditional, $e^*_{3,2}$ Mixed; e_4 Prod. per stk. loc. [pkg/h] — $e^*_{4,1} \le 1{,}920$; e_5 No. SKUs pelt. cncr. [un.] — $e^*_{5,1} \le 4$; e_6 Max. pkg. dim. [mm] — $e^*_{6,1} \le 737$; e_7 Max. pkg. height [mm] — $e^*_{7,1} \le 457$; e_8 Max. pkg. weight [kgf] — $e^*_{8,1} \le 50$; e_9 Min. plt./load size [mm] — $e^*_{9,1} \ge 700$; e_{10} Max. plt./load size [mm] — $e^*_{10,1} \le 1{,}300$; e_{26} Type of labeler — $e^*_{26,1}$ Side label, $e^*_{26,2}$ Corner label, $e^*_{26,3}$ None; cv^* Variable cost [USD].

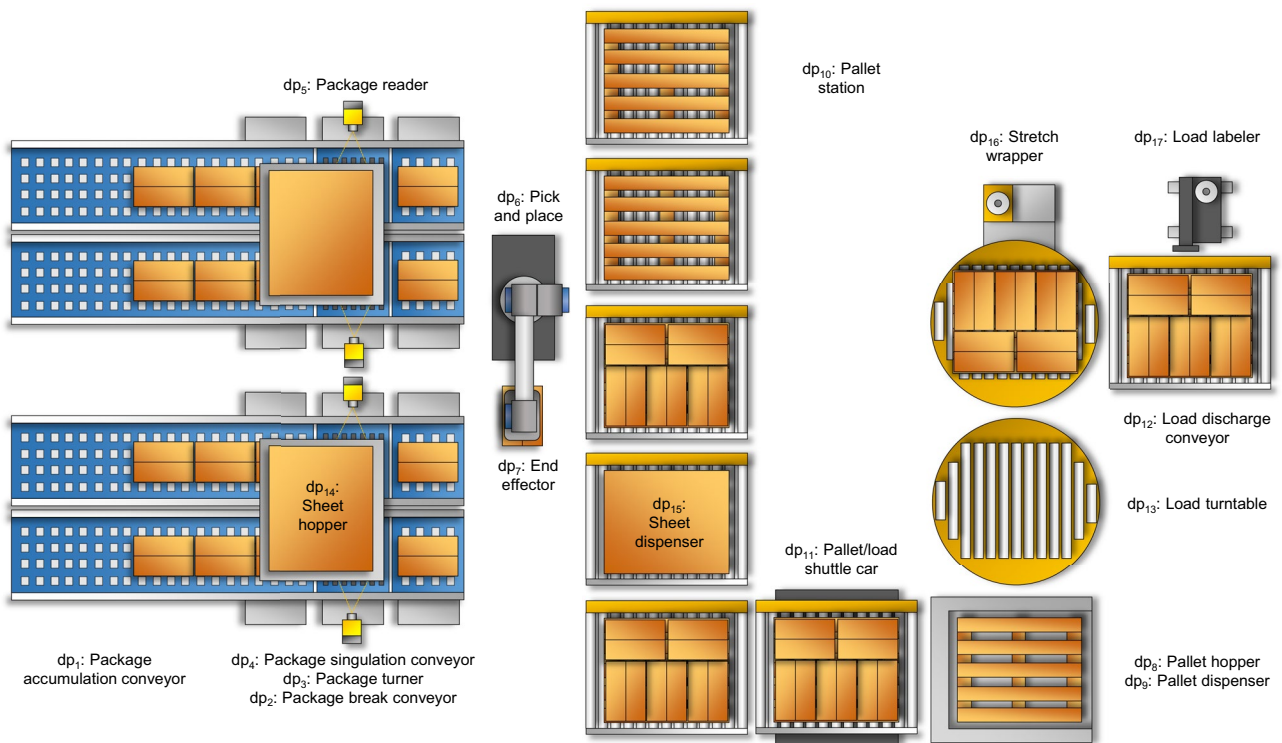| FM / Functional modules	DP / Design parameters	DP* / Design parameter instances	$e^*_{1,1}$	$e^*_{1,2}$	$e^*_{1,3}$	$e^*_{2,1}$	$e^*_{2,2}$	$e^*_{3,1}$	$e^*_{3,2}$	$e^*_{4,1}$	$e^*_{5,1}$	$e^*_{6,1}$	$e^*_{7,1}$	$e^*_{8,1}$	$e^*_{9,1}$	$e^*_{10,1}$	...	$e^*_{26,1}$	$e^*_{26,2}$	$e^*_{26,3}$	cv^*
Dir. Case			= / +	/ +	+ / +	= / =	/ +	= / x	/ x	+ / x	+ / +	+ / +	- / --	- / --	- / ++	+ / --	...	= / +	/ +	/ +	- / +
fm_1 Palletizer	dp_7 End-effector	$dp^*_{7.1}$ Vacuum style - surface pad - 400 x 600 mm - 1 x 8 $\le$ 8kgf	1	1	0	1	0	1	1	1		600	450	8							3,485.00
		...	...	...	...	...	...	...	...	...		...	...	...							...
		$dp^*_{7.40}$ Finger style - 400 x 300 mm - 2 x 15 $\le$ 30kgf	1	1	0	0	1	1	0	2		600	450	15							17,948.72
	...	...																			...
	dp_{15} Sheet dispenser	$dp^*_{15.1}$ Vacuum style - Suction cups				0	1			0.78											2,564.10
		$dp^*_{15.2}$ Vacuum style - Surface pad				1	0			0.78											0.00
		$dp^*_{15.3}$ None				1	1			1											0.00
fm_2 Pallet dispenser	dp_8 Pallet hopper	$dp^*_{8.1}$ Hopper - 15 pallets								1					800	1300					681.82
		$dp^*_{8.2}$ Hopper - 20 pallets								1					800	1300					909.09
		$dp^*_{8.3}$ None								1					800	1300					0.00
	dp_9 Pallet dispenser	$dp^*_{9.1}$ Lift and separate								1					800	1300					13,636.36
		$dp^*_{9.2}$ Screw style								1					1000	1200					9,090.91
		$dp^*_{9.3}$ None								0.74					800	1300					0.00
... ...	... ...	... ...								...	...				...	...					...
fm_4 Pallet handling	dp_{16} Stretch wrapper	$dp^*_{16.1}$ Self-propelled robot $\le$ 250%													800	1300	250				8,727.27
		...													...	...	...				...
		$dp^*_{16.7}$ None													700	1300	0				0.00
	... ...	...													...	...					...
	dp_{13} Load turntable	$dp^*_{13.1}$ Turntable - CLRC - load weight $\le$ 2.000 kgf													800	1300					7,500.00
		$dp^*_{13.2}$ Turntable - TCC - load weight $\le$ 2.000 kgf													800	1300					8,250.00
		$dp^*_{13.3}$ None													800	1300					0.00
fm_5 Sheet hopper	dp_{14} Sheet hopper	$dp^*_{14.1}$ Hopper - 100 sheets													800	1300					363.64
		$dp^*_{14.2}$ Hopper - 200 sheets													800	1300					545.45
		$dp^*_{14.3}$ None													800	1300					0.00
fm_6 Load labeler	dp_{17} Load labeler	$dp^*_{17.1}$ All-electric automated labeling																1	0	0	11,250.00
		$dp^*_{17.2}$ None																0	0	1	0.00
fm_7 Package reader	dp_5 Package reader	$dp^*_{5.1}$ An image-based barcode reader (1D and 2D)																			3,750.00
		$dp^*_{5.2}$ Laser barcode scanner (1D and 2D)																			2,500.00
		$dp^*_{5.3}$ None																			0.00

Fig. 6 Example of the geometric layout

kept or removed from the product structure, or still, which ones should be further developed.

These outcomes stem from integrating the four prevalent classes of design problems, as shown in Fig. 9. The integration of classes is one of the contributions of MDM, and it naturally leads to globally satisfactory solutions. This is because the solution space is conceived based on customer preferences and the selection of alternatives considers the economic impact of the building blocks (local solution) on the configured variants (global solution), a different

perspective if compared to the methods presented in Sect. 2. Another contribution of MDM that amplifies the ability to obtain globally satisfactory solutions is the use of throughput as a performance measure for configuring the product family variants. This strategy overcomes the profit limitation in favoring the configuration of higher volume variants rather than most contributive ones, which has to do with the fact that throughput does not consider the fixed costs and apportionment [68].

Table 7 Physical modules

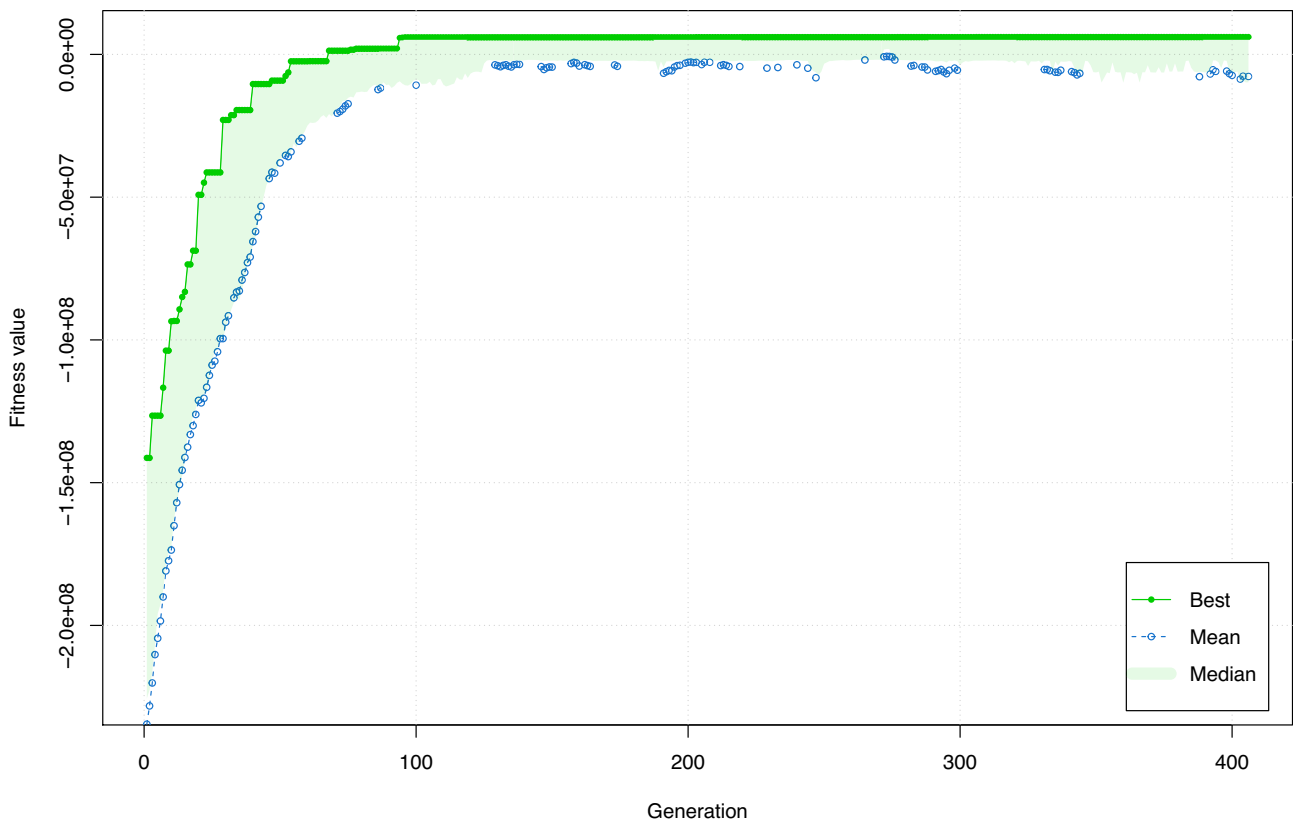|	dp_7	dp_6	dp_{15}	dp_8	dp_9	dp_4	dp_3	dp_1	dp_2	dp_{16}	dp_{10}	dp_{11}	dp_{12}	dp_{13}	dp_{14}	dp_{17}	dp_5
End-effector dp_7	1	1	1				1										
Pick and place dp_6		1															
Sheet dispenser dp_{15}	1	1	1														
Pallet hopper dp_8				1	1												
Pallet dispenser dp_9				1	1												
Pkg. singulation conveyor dp_4						1									1		
Package turner dp_3							1								1		
Pkg. accumulation conveyor dp_1								1	1								
Package break conveyor dp_2								1	1								
Stretch wrapper dp_{16}										1	1	1	1	1			
Pallet station dp_{10}					1					1	1	1					
Pallet/load shuttle car dp_{11}										1	1	1		1			
Load discharge conveyor dp_{12}										1			1				
Load turntable dp_{13}										1		1		1			
Sheet hopper dp_{14}															1		
Load labeler dp_{17}													1			1	
Package reader dp_5																	1

Fig. 7 Results of genetic algorithm for the market niche ms_4

The MDM provides an open architecture of techniques, and depending on which one is used in the configuration process; it is possible to obtain optimal solutions. Besides the techniques, the MDM outcomes are also influenced by the parameters and variables making up the configuration model. Table 9 adds a sensitivity analysis in which parameters/variables were modified independently until one of the MDM outcomes changed. The variation of parameters/variables was accounted for in relative terms concerning the

results obtained in the previous section, referred to as baseline in Table 9.

In a closer look, although the decision variable price $\left(\check{p}_{ij}\right)$ has a negative influence on the choice probability $\left(Pr_{i\pi}\right)$, the model tended to increase it to maximize throughput (Tp). The unintended effect was that the model did this for variants of shallow utility $\left(U_{i\pi}\right)$ and variable cost $\left(\check{C}v_{ij}\right)$, a pattern incompatible with reality. This occurred for the reason that the marginal increase in throughput reached from the price

Table 8 Configuration results

| MS	Product family variants $\left(\overrightarrow{pf}_{ij}\right)$	Mk [stk. loc./yr.]	Sms_i [%]	$Pr_{i\pi}$ [%]	Q_i [un./yr.]	$\check{C}v_{ij}$ [$/stk. loc.]	$\check{p}_{ij}$ [$/stk. loc.]	Tp [$/yr.]
ms_1	[dp*$_{1.3}$, dp*$_{2.2}$, …, dp*$_{17.2}$]	814	10%	24.1%	20	65,644.46	125,000.00	1,187,110.80
ms_2	[dp*$_{1.1}$, dp*$_{2.1}$, …, dp*$_{17.2}$]	814	7%	26.3%	15	103,678.00	125,000.00	319,830.00
ms_3	[dp*$_{1.3}$, dp*$_{2.2}$, …, dp*$_{17.2}$]	814	3%	22.6%	6	99,185.20	135,000.00	214,888.80
ms_4	[dp*$_{1.1}$, dp*$_{2.1}$, …, dp*$_{17.2}$]	814	38%	24.5%	76	80,130.59	160,000.00	6,070,075.16
ms_5	[dp*$_{1.4}$, dp*$_{2.2}$, …, dp*$_{17.2}$]	814	26%	26.4%	56	122,962.80	245,000.00	6,834,083.20
ms_6	[dp*$_{1.1}$, dp*$_{2.1}$, …, dp*$_{17.2}$]	814	11%	18.5%	17	94,599.95	185,000.00	1,536,800.85
PF1	[dp*$_{1.1}$, dp*$_{1.3}$, dp*$_{1.4}$, dp*$_{2.1}$, dp*$_{2.2}$, …, dp*$_{17.2}$]	814	-	23.3%	190	-	-	16,162,788.81
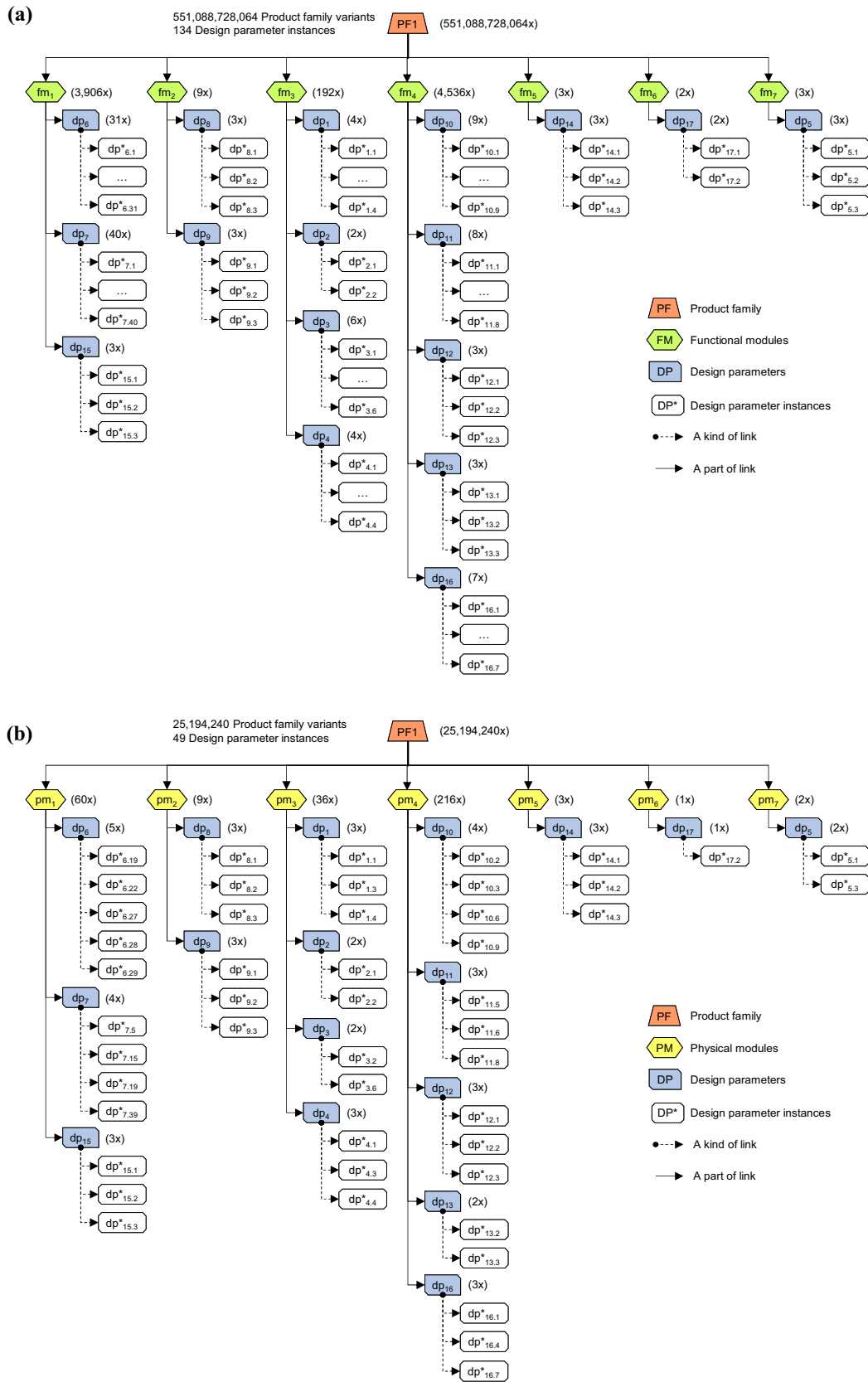
Fig. 8 Final configuration: **a** solution space; **b** product family structure
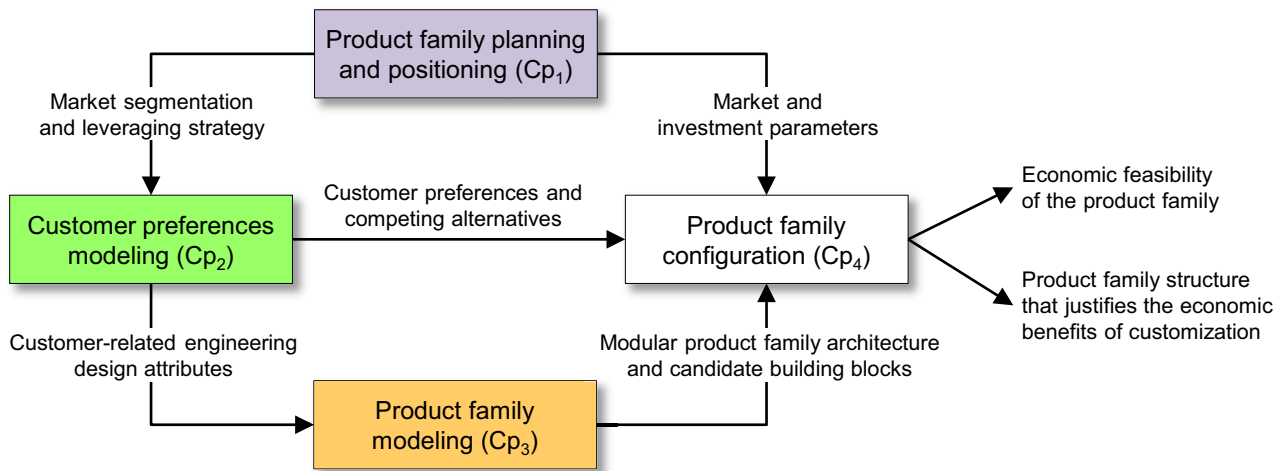
Fig. 9 Conceptual framework of MDM

increment was greater than the one retrieved from the raise in choice probability. To inhibit this behavior, a constraint between price and the variable cost was added to the model, i.e., $\frac{\breve{p}_{ij}}{\breve{c}v_{ij}} \leq \xi$, as further detailed in Gauss et al. [13]. In practical terms, for the case presented in Sect. 4, the company indicated this relationship as being $\xi \leq 2$. Concerning the price variation, by exceeding the limits given in Table 9, the viability of the product family was maintained while the product family structure changed.

In terms of demand variation, it may be associated with errors in the estimation of market size (Mk) or the share of segments/niches $\left(Sms_i\right)$. Regardless of the source of error, given the relationship between these two parameters, the

variation is perceived in the demand of each market segment/niche, i.e., $Q_i = Mk.Sms_i$. Thus, for parsimony, the sensitivity analysis only considered variations in market size (Mk), which, when outpacing the limits of Table 9, primarily induced changes in the product family structure. This slight variation in Mk (-1.5%) was noticed in the segment/niche ms_3 where the demand is the lowest, i.e., $Q_3 \approx 24$, a pattern that did not occur in the others.

Two other parameters influence the outputs of the proposed method; the engineering attributes values ($\breve{e}^*$) and the variable cost of design parameter instances $\left(\widehat{c}v_{qr}^*\right)$. Although these parameters stem from the same construc-

Table 9 Sensitive analysis

Parameter/variable	Δ [%]	Tp [$/yr.]	NPV [$]	ΔNPV [$]
Baseline	–	16,162,788.81	7,290,488.53	–
Price $\left(\breve{p}_{ij}\right)$	−3.5%	14,965,438.81	6,335,968.44	−13.1%
	+0.2%	16,231,208.81	7,345,032.53	+0.7%
Market size (Mk)	−1.5%	15,775,311.81	6,981,594.24	−4.2%
	+0.0%	16,162,788.50	7,290,488.28	+0.0%
Engineering attribute values ($\breve{e}^*$)	−20.0%	16,162,788.81	7,290,488.53	−0.0%
	+3.0%	16,162,788.81	7,290,488.53	+0.0%
Variable cost of design parameter instances $\left(\widehat{c}v_{qr}^*\right)$	−0.2%	16,198,882.22	7,319,261.97	+0.4%
	+2.8%	15,657,465.35	6,887,647.76	−5.5%
Overall weight of the attribute: palletizing technology $\left(wa_1\right)$	−12.0%	16,444,564.83	7,515,118.65	+3.1%
	+10.3%	15,754,797.94	6,965,240.70	−4.5%
Overall weight of the attribute: production capabilities $\left(wa_2\right)$	−4.5%	16,162,788.81	7,290,488.53	−0.0%
	+0.8%	16,162,788.81	7,290,488.53	+0.0%
Overall weight of the attribute: price $\left(wa_9\right)$	−3.6%	15,754,797.94	6,965,240.70	−4.5%
	+1.2%	16,162,788.81	7,290,488.53	+0.0%

tive solution $\left(dp_{qr}^{*}\right)$, they might be independently affected by errors arising from the techniques used to obtain them. For this reason, they were evaluated separately in the sensitivity analysis. As shown in Table 9, the engineering attribute values and the variable cost of design parameter instances induced changes in the product family structure before altering decisions related to its economic feasibility. In this context, the $\hat{cv}_{qr}^{*}$ appeared to be the most influential product parameter. It is essential to mention that errors associated with the engineering attribute values of competing alternatives $\left(\vec{z}_{ik}\right)$ might also influence the MDM outcomes. However, since they are revealed parameters and not estimated by the proposed method, they were not evaluated in this work.

Whether in a configured variant $\left(\overrightarrow{pf}_{ij}\right)$ or a competing alternative $\left(\vec{z}_{ik}\right)$, a factor that moderates the effects of the resultant engineering attribute values $\left(\breve{e}_{\omega ij}^{*}\right)$ and price $\left(\breve{p}_{ij}\right)$ is the customer preference. In MDM, this preference is modeled using a weight vector for each market segment/niche, $W \equiv \left\{\overline{w}_i | i = 1, \ldots, I\right\}$, as depicted in Table 3. Of the nine customer desired attributes $\left(a_l\right)$ identified in this research, the three most influential ones $(a_1, a_2, \text{and } a_9)$, accounting for 68.4% of W, were considered in the sensitivity analysis. In all three cases, variations exceeding the limits expressed in Table 9 induced changes in the product family structure and not in the decisions related to its economic viability.

In short, the economic viability of the product family is verified by all trials in Table 9, i.e., $NPV \geq 0$. This means that the MDM outcome that is most sensitive to changes in the parameters/variables comprising the configuration model is the definition of the product family structure. Concerning the parameters/variables themselves, the market size (Mk) was the most relevant, as the relative fluctuations of -1.5% and $+0.0\%$ required the configuration of new structures.

Finally, although the MDM considers the rationale of platforming through the constructive solutions shared across different product family variants, this is done passively. In other words, no mutual exclusion constraints between cross-segment/niche compatible building blocks are considered in the model. This pattern was noticed after the engineers who supported this work critically analyzed the product family structure presented in Fig. 8b. On this occasion, they identified the possibility of communalizing instances belonging to design parameters DP_1, DP_2, DP_3, DP_4, and DP_9. However, despite reducing the quantity of design parameter instances $\left(DP_q^{*}\right)$ from 49 to 43, the proposed solution decreased the throughput from

16,162,788.81 [USD] to 13,895,896.61 [USD], which shows that communality is not always associated with obtaining better results. Having discussed the results, attention is now turned to the main concluding remarks of this work.

6 Concluding remarks

Aiming at systemically and empirically designing product families that economically meet the market requirements, this paper carried out an in-depth application of the MDM method in the conceptual design of a family of autonomous mobile palletizers. This work made it possible to understand how integrating classes of design problems, combined with the use of throughput in the configuration process, supported the investment decision in the product family design and defined which building blocks should be developed, maintained, or removed from the product structure. Furthermore, this work allows visualizing the method in use and assessing the sensitivity of its results regarding the uncertainty of the model's parameters and variables.

In addition to the main contribution of this paper, which lies in a detailed empirical application of the MDM method, limitations prompting future research directions were also found. The first refers to not exploring the adequate number of variants per segment/niche, which, combined with a pricing strategy, could result in complementary positionings, thus influencing the throughput. The second is that the MDM did not consider the company's resource capabilities in accomplishing the potential demand, which could be seen as a moderator of NPV and, consequently, project viability. The third has to do with the passive way the MDM considered platform identification, which could potentially be exploited by evaluating the impacts of cross-segment/niche commonality constraints on throughput. Finally, given the sensitivity to the parameters/variables composing the configuration model, the definition of product family structures in contexts of uncertainty could also be explored in future studies. Further studies should include the relationship of module-based design with the concept of open innovation, which represents a change in developing innovative solutions and doing business within companies [110]. Open innovation includes sharing intellectual property, joint search for innovative solutions, and creative potential outside the company aiming at providing a competitive edge not only by new products but also by new methods to support decision-making processes [111].
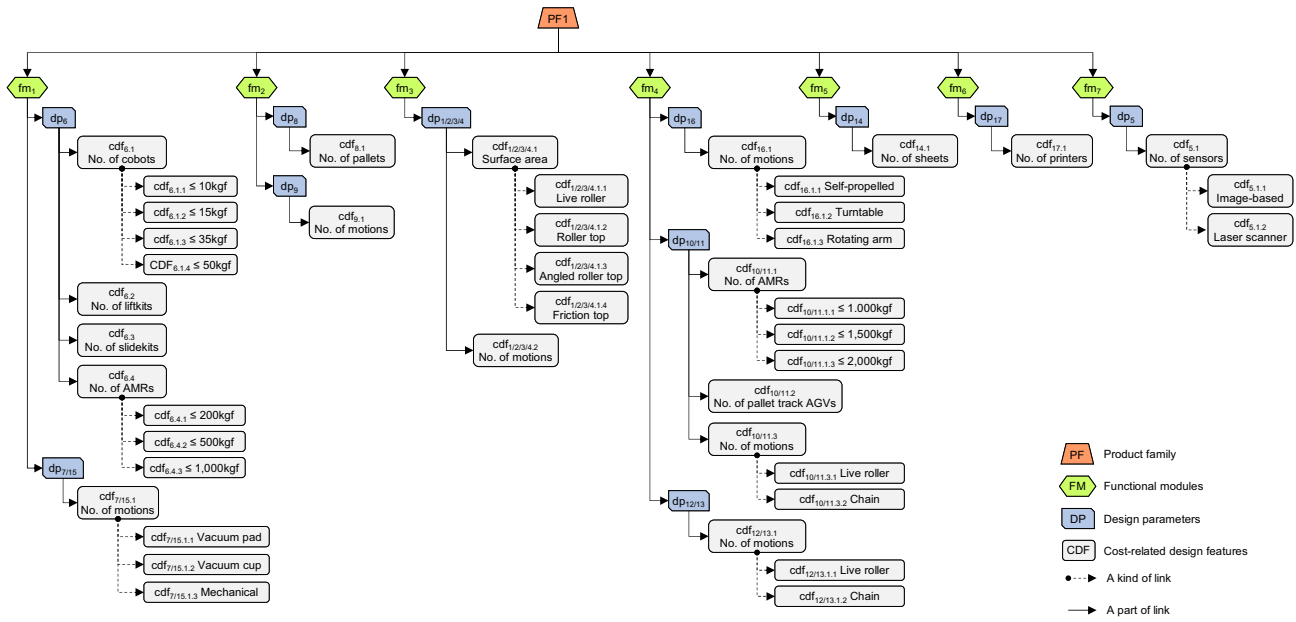
Appendix

Fig. 10 Cost-related design features (*CDF*)

Declarations

Competing interests The authors declare no competing interests.

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