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ORIGINAL ARTICLE

A two-step methodology for product platform design and assessment in high-variety manufacturing

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Abstract

The delayed product differentiation (DPD) recently rose as a hybrid production strategy able to overcome the main limits of make to stock (MTS) and make to order (MTO), guaranteeing the management of high variety and keeping low storage cost and quick response time by using the so-called product platforms. These platforms are a set of sub-systems forming a common structure from which a set of derivative variants can be efficiently produced. Platforms are manufactured and stocked following an MTS strategy. Then, they are customized into different variants, following an MTO strategy. Current literature proposes methods for platform design mainly using optimization techniques, which usually have a high computational complexity for efficiently managing real-size industrial instances in the modern mass customization era. Hence, efficient algorithms need to be developed to manage the product platforms design for such instances. To fill this gap, this paper proposes a two-step methodology for product platforms design and assessment in high-variety manufacturing. The design step involves the use of a novel modified algorithm for solving the longest common subsequence (LCS) problem and of the k-medoids clustering for the identification of the platform structure and the assignment of the variants to the platforms. The platforms are then assessed against a set of industrial and market metrics, i.e. the MTS cost, the variety, the customer responsiveness, and the variants production cost. The evaluation of the platform set against such a combined set of drivers enhancing both company and market perspectives is missing in the literature. A real case study dealing with the manufacturing of a family of valves exemplifies the efficiency of the methodology in supporting companies in managing high-variety to best balance the proposed metrics.

Keywords Operations and logistics · Industrial plants · Delayed product differentiation · Product platforms · Variety · Make to stock · Make to order

1 Introduction

Nowadays, the huge need of customer personalization forces industrial companies to move from mass production to mass customization, overcoming the 'fordist' strategy of producing a large volume of standardized 'one-fits-all' products toward multiple variants matching single customer needs [1. , 2.]. Several factors drive this trend, from the customer need of new product functionalities to regional requirements. Best managing product variety positively contributes to expanding markets and increasing volumes and revenues. Conversely, these positive effects are not guaranteed when variety is not well-managed along the product life cycle, from design, to manufacturing, distribution, usage, dismantling, and recycling [3.]. The investigation of the effects and consequences of product variety on the production systems is a driver for the success of industrial companies. Several strategies have been developed to cope with the product variety, acting both on the structure of the products and on the production strategies. Indeed, in the mass customization era, traditional production strategies such as make to stock (MTS) and make to order (MTO) show several limitations [4.]. MTS meets customer needs in short lead times, but the larger marketing mixes make this strategy not often economically convenient, while MTO reduces storage costs but customer lead times rise up [5.]. In this context, hybrid production strategies are introduced. The delayed product differentiation (DPD) is among the most relevant and strives to

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join the dual needs of high-variety and quick response time by using the so-called product platforms [6. , 7.]. According to the original definition, a product platform is a set of sub-systems and interfaces forming a common structure from which a set of derivative variants can be produced [8.]. This concept is illustrated in Fig. 1. Products A, B, and C belong to the same product family, and they share common components, in red, that constitute the product platform X. Then, several differentiating components are assembled to the platform to get each product variant.

Product platforms are manufactured and stocked following an MTS strategy. Then, they are personalized into different variants after the arrival of the customer order, following an MTO strategy, through just assembly or combined assembly and disassembly operations [6.]. Among the most important companies that introduced product platforms, Sony deserves mentioning for manufacturing Walkman, in addition to Kodad, Black and Decker, and Hewlett-Packard [9.]. Current literature proposes models and tools for product platforms design by using optimization techniques. However, optimization is usually able to manage and solve in a reasonable amount of time small instances, made of few product variants. This could be a significant limit, especially in the modern competitive industrial scenario, governed by mass customization and by a relevant increase in company production mixes. Hence, efficient algorithms need to be developed to best manage the product platform design for real-size industrial instances, characterized by a wide number of product variants. According to this background, this paper proposes and applies a novel two-step methodology for product platforms design and assessment in high-variety manufacturing.

The first step of the proposed methodology deals with the product platforms design performed combining the longest common subsequence (LCS) and the k-medoids clustering algorithm, which allow to identify common operation sequences in the product variants' technological cycles, i.e. potential product platforms, and grouping the product variants according to their similarity to the identified operation sequences. In the second step, the identified product platforms are globally assessed against a set of industrial and market metrics, i.e. the MTS cost, the variety, the responsiveness to customers, and the product variants' production cost, performing a multi-scenario analysis to identify the best product variants partition. The novelties of the proposed methodology can be summarized as follows: (1) the algorithm for solving the LCS problem [10.] has been modified to take into account technological precedence constraints among operations when designing platforms; (2) a novel similarity index is proposed to group and assign the product variants to the most similar product platforms; and (3) the integration of four relevant industrial and market metrics for platform assessment. To the authors' knowledge, the literature lacks methodologies jointly including these features. The application of the methodology to a real case study dealing with the manufacture of a family of plastic valves showcases its industrial relevance.

Globally, this paper is a research article proposing an innovative two-step methodology for product platforms design and assessment, thus supporting companies in reaching efficiency in the current mass customization era. The main contributions of this paper can be summarized as follows:

1. A methodology for product platforms design and assessment is proposed, which requires the product variants' technological cycle as input, and performs a multi-scenario analysis based on the integration of four different industrial and market metrics.
2. The proposed methodology can also be used to partition of the production mix in product families.
3. The methodology allows solving large-scale problems thanks to the adoption of efficient algorithms (modified LCS and clustering).

According to the introduced background, the remainder of this paper is organized as follows. Section 2 reviews some relevant literature on the topic. Section 3 introduces the novel methodology for product platform design in high-variety manufacturing and the mathematical formulation of the evaluation metrics. Section 4 describes the application of the methodology to a real industrial case study. Finally, Section 5 concludes the paper with final remarks and future opportunities for research.

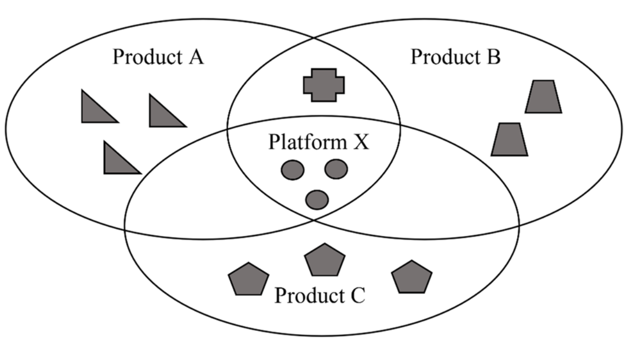


Fig. 1 Reference illustration of a product platform

2 Literature review

A systematic literature review is performed to explore and analyse the literature on the topic. The main findings allow to organize this section into two parts. The former explores the problem of product variety management showing the main strategies and solutions proposed by the literature and implemented by industrial companies, including the DPD, which is deeply analysed in the second part.

2.1 Product variety management

As highlighted by ElMaraghy et al. [3.], the existing variety management strategies can be classified according to three main dimensions, i.e. (1) design, (2) planning, and (3) manufacturing, and applicable at components, products, enterprise, and market levels. The attributes of similarity and commonality within a set of product variants are crucial to successfully manage variety, with the aim to decrease the variety-induced complexity and the related cost. The stream of design for variety (DfV) was recently introduced to integrate customers' needs and their relationship with families of technological solutions [11. , 12.]. In this area, quality function deployment (QFD) is a widespread tool to identify customers' requirements and their relationship to product specifications [13.]. Jose and Tollenaere [14.] stressed the importance of modularity and standardization to help grouping product components in modules. Rizzi and Regazzoni [15.] proposed the concurrent use of design methodologies, such as module interference matrix (MIM), design structure matrix (DSM), and Pugh matrix, applying them to a real reference product from the household appliance field getting significant results in terms of performance. ElMaraghy and AlGeddawy [16.] proposed a novel method for designing product variants based on commonality features and using the concept of co-evolution. Cladistic methods are adopted to identify modules corresponding to common regional market requirements. Finally, algorithms for functional, structural analysis and for variants' generation are proposed. Analytic and optimization models are available in the literature to balance company profit and customer satisfaction within the offered variety [17. , 18.]. In this field, Kumar et al. [17.] expanded the scope of the product family design problem to include the product line positioning, aiming at determining the right market niche for each family variant. The proposed market-driven product family design (MPFD) method analyses the impact of increasing the product variety across different market segments exploring the cost savings associated to commonality decisions. Wu et al. [18.] explored how the diverse consumer evaluation of the product quality affects the company's product variety decisions. At first, the authors considered in the analysis a uniform consumer evaluation distribution (CVD). Then, they tested more complex CVDs as the triangular and Weibull-based functions. The literature recognizes product families, product platforms, modularity, and integration as the top enablers of DfV [3.]. Grouping similar products into families is a key enabler to efficiently design, plan, and produce variants [19. -22.]. A family is a group of products based on a specific design concept or originated from a standard parent' product, similar in design and/or production process. On the other hand, product platforms rose as an important asset of the DPD strategy, representing sub-products made by the most common components within a product family, which can be reconfigured into specific variants after the arrival of the customer order through assembly [23.] or both assembly and disassembly tasks [7. , 19.]. Including modularity and flexibility into product platforms allows industrial companies to face dynamic market needs with a lower increase in complexity and investments. According to modularity, part components can be removed and recombined to form new variants. Hence, each module is functionally independent and contains a set of standard and interchangeable components [14.].

This paper focuses on DPD and product platforms as means to efficiently cope with product variety. Therefore, the next Section 2.2 analyses and discusses some relevant studies exploring these cross-linked topics.

2.2 Delayed product differentiation

DPD consists of postponing the final product differentiation point in the supply chain until it is cost-effective [24.]. When postponement occurs at the product shape level, the delayed differentiation is obtained by designing product platforms to develop at the initial manufacturing stages, which will be stored until customers' orders for different product variants are received [2.]. Martin and Ishii [25.] proposed developing product platform architectures to minimize the re-design effort in the case of a significant change in the costumers' needs. They proposed two metrics to support the product platforms design, i.e. the generational variety index, which is a measure of the amount of redesign effort required for future product designs, and the coupling index, which measures the coupling among the product components in case of product platforms redesign. However, their study is qualitative, and product platform architectures are built at the product design level, rather than at a product production level. Moussa and ElMaraghy [2.] introduced a product variety management methodology using median-joining phylogenetic networks (MJPN) for multiple platform design. The methodology allows generating process plans for hybrid, i.e. additive/subtractive, manufacturing technologies for platform customization benefiting from the commonalities between the features of the product family. Similarly, ElMaraghy and Abbas [26.] introduced a co-platforming methodology to map product features platform together with the manufacturing system machines, so that changes in product variants do not lead to significant changes in the platform machines. In this study, the authors proposed an optimization model to design product platforms according to the single variants differentiating features and the manufacturing process.

However, this approach is not suitable with assembly industries, where the similarity is related to the commonality of the product variants technological cycles, rather than to the product features. Galizia et al. [7.] introduced an algorithm for product platforms design, selection, and customization in high-variety assembly industry, considering both assembly and disassembly tasks to get the final variants. The authors proposed two new metrics to evaluate the effort to reconfigure the platform into a variant by considering the required number of assembly and disassembly tasks, i.e. Platforms Reconfiguration Index (PRI), and the ease of assembly and disassembly factors, i.e. Platforms Customisation Index (PCI), which also provide conditions to determine whether it is better to adopt DPD or assemble to order (ATO) strategy for each product variant. Longo et al. [27] proposed a two-stage platform-based optimal design process to support apparel brands in implementing mass customization strategies, validating their methodology in an Italian underwear and lingerie brand. Their methodology considers several factors, including the customer satisfaction and the production and inventory costs to select the best platforms. Ben-Arieh et al. [23.] developed a mixed integer programming model to design product platforms for a given product family to minimize the product platforms production cost, considering the market demand and determining the optimal number of platforms, their optimal configuration, and the assignment of the products to the platforms. Although the authors considered both assembly and disassembly tasks to transform platforms into the final variants, they limited the analysis to a single product family, forcing each component to either belong to a platform or to be a customization component, which is not a realistic assumption. In addition, the objective function does not include the production cost of the product variants not obtained from any platform. Hanafy and ElMaraghy [28] developed a modular product platform configuration model using both assembly and disassembly to get product variants as well as co-planning of platforms and their assembly lines. However, they considered the presence of a single product family, assuming the product family production cost as the unique driver for product platforms selection. Moussa and ElMaraghy [29] developed a non-linear optimization model for designing multi-period product platforms and managing the inventory, providing the optimal product platform design, process plans for customisation, the number of each platform stored as inventory, and the product variant-platform assignment. Zhang et al. [30] proposed a method for product platform planning using the available product data in the product lifecycle management (PLM) database. Their method introduces two key technologies, i.e. pruning analysis and attribute matching. The pruning analysis is used to determine the most common components within different product families, which constitutes the platform. The attribute matching is used to classify product modules into different categories based on their sharing degrees. However, their methodology only includes the product platform design, while any evaluation of the solution is missing.

The analysis of the literature highlights that a methodology for product platforms design and assessment integrating different industrial and market metrics, i.e. MTS cost, production cost, inventory costs, responsiveness, is still missing. Several studies assume to design product platforms for single product families, or that all the product variants belonging to the same product family can be derived by one product platform. Some studies, in addition to the platform design phase, also focus on assigning the best production strategy to each variant, among MTS, MTO, and DPD. However, the selection of the set of platforms to be implemented is guided exclusively by the cost of the variants managed through DPD, at the expense of a global assessment of the production mix, which should also include the remaining products managed through other management strategies [23.]. Finally, many studies use optimization models for designing platforms. However, they usually have a high computational complexity for efficiently managing real-size industrial instances in a reasonable amount of time. On the other hand, existing studies using heuristic algorithms do not consider the technological precedence constraints when designing platforms, which, indeed, is a crucial aspect.

In such a scenario, this paper proposes a novel two-step methodology for the design of potential product platforms and assessment in high-variety manufacturing. In particular, the longest common subsequence (LCS) problem is adopted to identify the set of all the potential product platforms, relaxing any constraints concerning the number of product families under analysis, the number of product platforms designed for each product family, and the components belonging to the product platforms. In addition, the algorithm to solve the LCS problem has been modified to build product platforms that respect the precedence constraints of product variants' technological cycle and to be efficient in managing large-scale industrial instances. This study also proposes a novel similarity index based on the similarities between the product variants and the potential product platforms, and not on the similarities between variants, as in most of the existing studies. In this way, the product variants are not grouped according to the similarity of their technological cycle, but according to their similarity to a specific product platform, guaranteeing that a product variant is assigned to a product platform only if it can be effectively built from it. Hence, the management strategy of each product variant, i.e. MTO or DPD, is also provided by the methodology since a product variant that cannot be built from any product platform is not managed with DPD. Finally, four different industrial and market metrics are proposed to assess the set of solutions that can be obtained from grouping the product variants using a different number of clusters. These metrics consider both the cost associated to the product platforms, i.e. the MTS cost and the variety, and the production cost and the responsiveness of all the product variants, considering those built from the product platforms and those managed with the MTO strategy. The integration of all the above described aspects justifies the novelty of this study as well as the main elements of differentiation compared to the existing methods.

The proposed methodology is introduced and discussed in Section 3.

3 A two-step methodology enhancing delayed product differentiation

Considering a full MTO production environment, the proposed methodology aims at assessing if, and at which degree, adopting the DPD strategy can be beneficial from the industrial and market points of view. In particular, the methodology is able to assign the most suitable production strategy, i.e. MTO or DPD, to each product variant, through the use of product platforms in case of DPD selection. The input of the methodology is the technological cycle of all the product variants manufactured by the company, i.e. ordered sequences of operations in which one component is built on the previous ones. In addition, the variants' demand, the assembly times and costs of each component, their storage cost per unit, and the supply lead times are also required to evaluate possible solutions.

According to the DPD strategy, the main goal of the methodology is to identify the product platforms to realize according to a known demand, where a product platform is intended as an operation sequence common to at least two product variants' technological cycles. As a result, the production process of each product variant is split in two parts: the product platform assembly, which is made to stock, and the customization components assembly, which is made to order to get the requested product variants.

A further relevant issue to consider when designing platforms is their composition in terms of number of components. This characteristic is called 'width' in the following. Hence, each platform can be characterized by few components, i.e. small, or by a high number of components, i.e. wide.

In high-variety manufacturing industries, characterized by a huge production mix, designing and assessing the number of platform types and their width is not trivial. First, the design of the product platforms needs to consider the technological precedence constraints of the original product variants. Second, selecting a specific platform implies to identify a trade-off between a high number of small product platforms or a low number of wide product platforms. Figure 2 shows a reference example of five product variants for which three different platform solutions are proposed. Each solution leads to the presence of a different number of platforms characterized by different width. Such solutions inevitably affect the global number of variants in the production mix managed through the DPD strategy.

Following the standard literature and industrial practice, the proposed methodology lies on the following assumptions, validated by previous studies [2. , 7. , 26. , 29]:

1. The production mix is known, as well as the technological cycles and the bill of materials of each product variant.

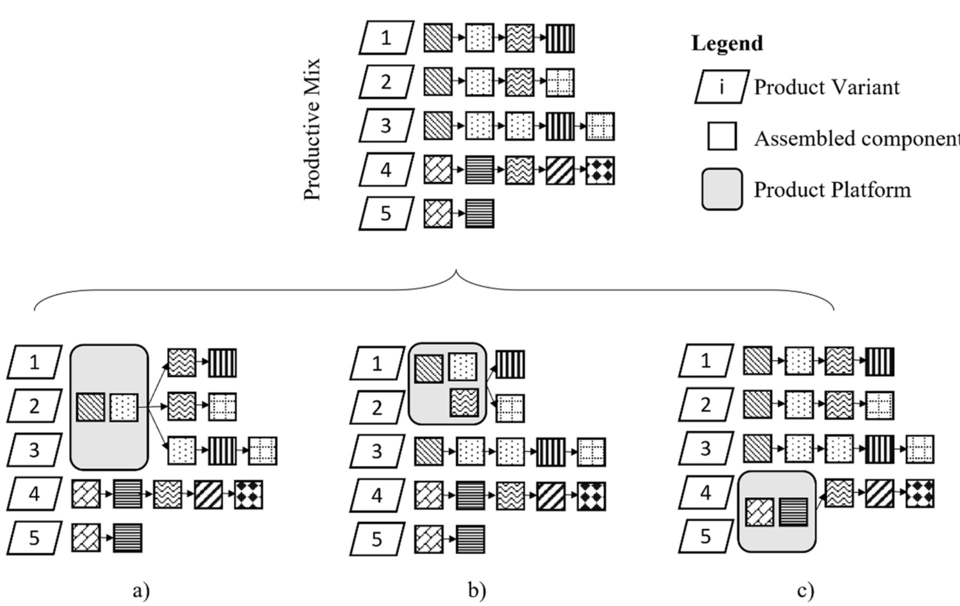


Fig. 2 Product platforms solutions: **a** one product platform made by two components and three DPD variants; **b** one product platform made by three components and two DPD variants; **c** one product platform made by two components, one DPD variant and one MTS variant

2. The product variants and the components are initially managed with an MTO strategy.
3. The demand of each product variant is known and deterministic.
4. The assembly time and cost, and the purchasing cost, of each component are known and deterministic.
5. The product platforms are managed with an MTS strategy and their demand can be derived from the product variants' demand.
6. The components included in at least one product platform are managed with an MTS strategy and their demand can be derived from the bill of materials of each product variant.
7. The components not included in any product platforms, i.e. customization components, are managed with an MTO strategy.
8. Customization of product platforms can only be realized by assembly tasks, i.e. disassembly is not allowed.
9. The cost to assemble a component in a product platform is lower than the assembly cost of the same component if used to customize the platform.
10. Only one component can be assembled in each operation.
11. A product variant can be built on a product platform only if the product variants' technological cycle begins with the platform's technological cycle.

Some of the assumptions, e.g. 1, 3, 4, deal with the availability and knowledge of the data needed to apply the methodology, i.e. production mix, bill of materials (BOM), variant demand, and assembly time and cost. These data can be directly accessible as they are available within industry or can be collected through on-field tests, while assumptions about product platforms (and their components) management strategy, e.g. 5, 6, 7, lie on suggestions and recommendations from the industrial field and evidence of previous studies on product platform design [2. , 7. , 26. , 29].

Following these assumptions, the two-step methodology aims to address two main issues:

1. The platform design, which consists of determining the number and structure, i.e. technological cycle, of the product platforms and, consequently, the number of MTS components, the number of MTO components, and the number of product variants managed through the DPD strategy. First, the sequences of operations common to two or more product variants respecting the precedence constraints of their technological cycle are identified through a modified algorithm (mLCS) to solve the longest common subsequence (LCS) problem (phase 1.A in the following). Then, a novel similarity index is proposed to evaluate the similarity among the product variants and the potential product platforms (phase 1.B in the following). Furthermore, a clustering algorithm is used to group the product variants according to their similarity to the identified platforms. Finally, potential platforms are associated to the clusters, i.e. variant-platform association (phase 1.C in the following).
2. The platform assessment, which consists of evaluating the solution obtained in step 1. Four distinct metrics are integrated for the first time to this aim: the MTS cost and the variety, which derive from the adoption of the MTS strategy for both the product platforms and the components: the responsiveness and the variant production cost, which depend on the management strategy of the product variants, i.e. DPD or MTO. Since the clustering algorithm applied in phase 1.C requires the number of clusters as input, a multi-scenario analysis is performed by iterating phase 1.C and step 2 with different number of clusters.

As shown in Fig. 3, the first step of the methodology is divided into three main phases: the identification of potential product platforms (phase 1.A), the construction of the similarity matrix between the product variants and the potential product platforms (phase 1.B), and the product variants clustering (phase 1.C).

Phase 1.A aims at building the set of potential product platforms by solving the LCS problem to determine the longest common subsequences of components among each couple of product variants. In particular, the traditional algorithm has been modified to consider the precedence constraints imposed by the technological cycles. Phase 1.B involves determining the similarity degree between potential platforms and product variants to define which variants can be potentially derived from which platform(s). In this phase, a novel similarity index is proposed, which assigns a higher similarity score to the couple of variant and platform that shares the higher number of common operations. The novelty of the proposed index is that it is computed between the product variants and the product platforms instead of among product variants. In addition, it is a relative measure, meaning that the similarity of a product variant with a product platform depends on the maximum similarity that the same product variant can have with the other potential platforms. Phase 1.C applies the k-medoids algorithm to group the product variants into k clusters according to their similarity to the potential platforms. Finally, the obtained solution for a given value of k is evaluated in terms of MTS costs, variety, responsiveness, and product variants' production costs (step 2). Since different values of k lead to different partitions of the variant space and, therefore, to different product platforms, phase 1.C and step 2 are iterated for different values of k to perform a multi-scenario analysis to support the decision process.

Before describing each phase of the methodology, the following nomenclature is introduced:

Entities.

Product variants	$i = 1, \ldots, N$	Product variants assembled by the company
Components	$j = 1, \ldots, M$	Components included in at least one product variant
Operations	$s = 1, \ldots, S_i$	Phase of the technological cycle of variant i
Longest common subsequences	$a = (i, i'), a = 1, \ldots, \frac{N(N+1)}{N}$	Potential product platforms
Product platforms	$l = 1, \ldots, L$	Selected product platforms

Parameters.

x_{ijs} The technological cycle of product variant, i defining which component j is assembled in which operation s (binary)

y_{la} The product platform l derived from the LCS a (binary)

z_l The selected product platform l (binary)

z_{il} The product variant i associated with the product platform l (binary)

λ_a The number of operations included in the LCS a

μ_l The number of operations included in platform l

ρ_s The technological cycle of an LCS (binary)

φ_i The management strategy of variant i (binary)

ψ_j The management strategy of component j (binary)

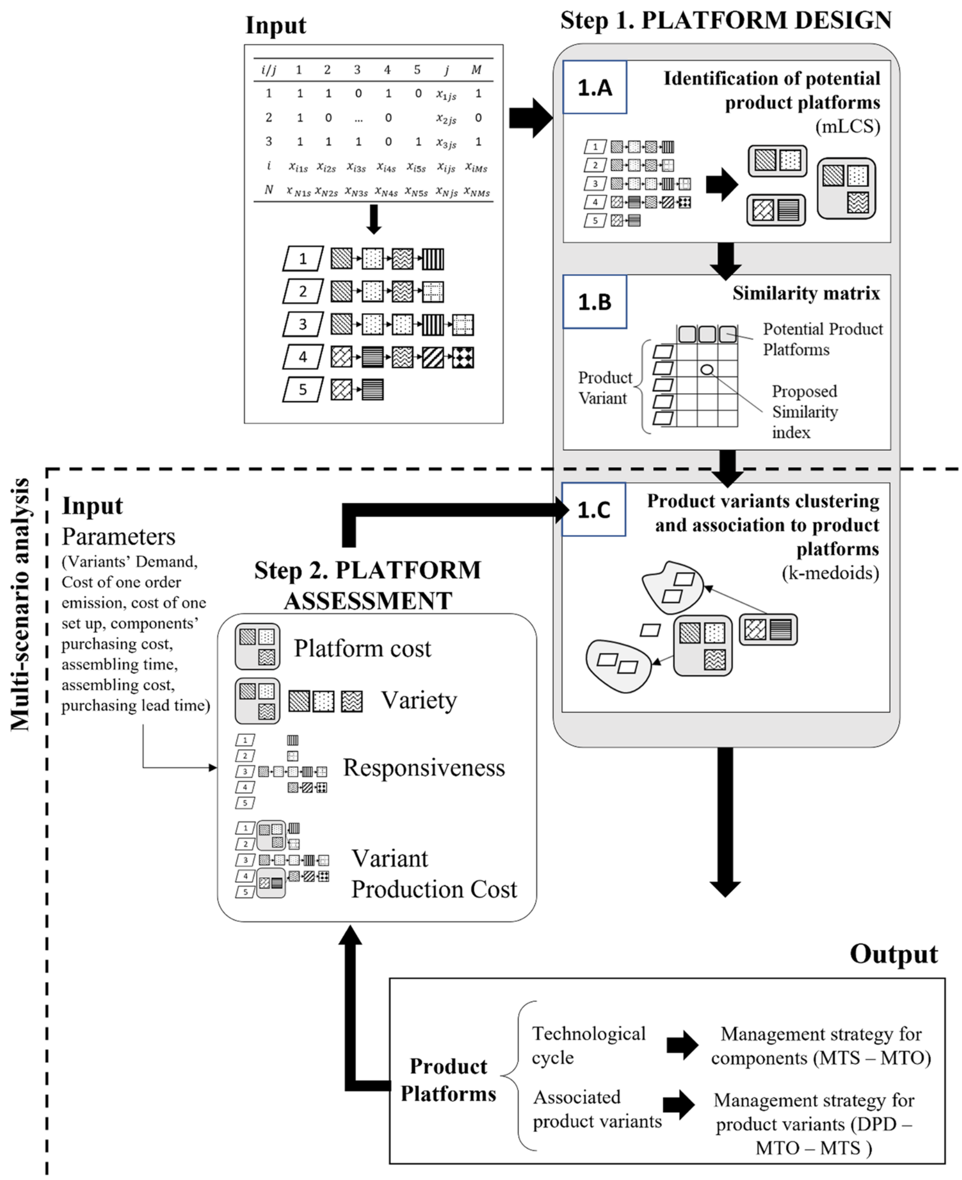


Fig. 3 The proposed methodology

3.1 Step 1: product platform design

3.1.1 Phase 1.A: identification of potential product platforms

This phase aims to identify the potential product platforms by solving the LCS problem. It considers the technological cycle of the product variants as input, computing the longest common subsequence between each couple of product variants and providing as output the list of potential product platforms. In particular, the traceback algorithm, which is widely adopted to find ordered sequence of elements common to two strings [10. , 31.], has been modified to obtain a subsequence that respects the precedence constraints of the variants' technological cycles, i.e. only considers consecutive operations.

Given two product variants i and i' of length S_i and $S_{i'}$, respectively, the goal is to find the vector $\rho = (\rho_0, \rho_1, \dots, \rho_s, \dots, \rho_{\min(S_i, S_{i'})})$ such that $\sum_{s=1}^{\lambda_a} x_{ijs}\rho_s = \sum_{s=1}^{\lambda_a} x_{i'js} = 1 i, i' = 1, \dots, N, j = 1, \dots, M$, where $\lambda_a = \sum_{s=1}^{\min(S_i, S_{i'})} \rho_s$ is the length of the LCS a between the variants i and i', with $a = (i, i')$. About the logical working, the first element of the vector is set to 1. Then, for each operation s, if the previous element is equal to 1 ($\rho_{s-1} = 1$) and if the component j of variant i is equal to the component j of variant i', fill ρ_s with 1. Otherwise, $\rho_s = 0$. The pseudo-code of the algorithm is described in Table 1.

To get the set of the LCSs among all product variants, the mLCS is applied to each couple i, i' of product variants. Therefore, the total number of LCSs is equal to $\frac{N*(N+1)}{2}$. However, two product variants may have no common subsequence, or two couples of product variants may have the same longest common subsequences. To reduce the computational effort of the next phases, a filtering phase is conducted, aimed at removing both empty subsequences and duplicates. Consequently, although the number of potential product platform has an upper limit, their exact number depends on the specific application ($a \leq \frac{N*(N+1)}{2}$).

Note that if no LCS is found, the methodology stops and no product platforms can be designed.

3.1.2 Phase 1. B: the construction of the similarity matrix

The second phase of the methodology consists of building the similarity matrix between the product variants and the potential product platforms. This paper proposes a novel similarity index, which assigns a higher similarity to the product variants and the potential product platform sharing the longest common subsequence. Therefore, the algorithm described in Table 1 is applied to find the length $\lambda_{i,a}$ of the LCS between the product variant i and the potential product platform a. Then, the similarity index is given by Eq. (1):

$$s_{i,a} = \begin{cases} 0 & if\, \lambda_a > \lambda_{i,a} \\ \frac{\lambda_{i,a}}{\max_a \lambda_{i,a}} & otherwise \end{cases} \tag{1}$$

where λ_a is the length of the potential product platform a. As a result, the similarity between a product variant and a potential product platform is equal to zero in two cases: (1) i and a do not share any sequences and (2) the potential product platform is longer than the sequence of operations it shares with the variant. Otherwise, the similarity between the product variant i and the product platforms depends on the maximum length of the LCS between the variant and any product platform for which $\lambda_{i,a} \neq 0$.

Table 2 provides an example including three product variants and three LCSs. For $i = 1$, only two potential product platforms, $a = 1$ and $a = 2$, are included in technological cycle of the product variant ($\lambda_{1,3} = 0$). However, because $\lambda_{1,1} > \lambda_{1,2}$, $\boldsymbol{S}_{11} > S_{12}$. Similarly, for $i = 2$, $\lambda_{2,1} = \lambda_{2,2} = 2$ and $\lambda_{2,3} = 0$. However, $\lambda_1 > \lambda_{2,1}$ and the product variant cannot be built from the potential product platform 1. Therefore, their similarity is equal to zero.

The output of phase B is a matrix of dimensions $N \times a$, in which the generic element $s_{i,a}$ is the similarity index between a product variant i and a potential product platform a, provided by Eq. (1).

Table 1 Algorithm for LCS computation

```
Create a vector ρ of length (min(S_i, S_i') + 1)
Initialize the first position with a 1 (ρ_0 = 1)
For s = 1, …, (min(S_i, S_i') + 1)
    If ρ_{s−1} = 1
        ρ_s = Σ_{j=1}^{M} x_{ijs} * x_{i'js}
    Else
        ρ_s = 0
    End
End
```

Table 2 Example of similarity index between product variants and potential product platforms

Product variant (i)/potential product platforms (a)	$a = 1 \rightarrow (x_{111}, x_{122}, x_{133})$	$a = 2 \rightarrow (x_{111}, x_{121})$	$a = 3 \rightarrow (x_{i41}, x_{i32})$
$i = 1 \rightarrow (x_{111}, x_{122}, x_{133}, x_{144})$	$\lambda_{1,1} = 3, \max_a \lambda_{1,a} = 3$ $S_{11} = 1$	$\lambda_{1,2} = 2, \max_a \lambda_{1,a} = 3$ $S_{12} = 0.67$	$\lambda_{1,3} = 0,$ $S_{13} = 0$
$i = 2 \rightarrow (x_{211}, x_{222}, x_{243}, x_{234})$	$\lambda_{2,1} = 2, \lambda_1 = 3$ $S_{21} = 0$	$\lambda_{2,2} = 2, \max_a \lambda_{2,a} = 2$ $S_{22} = 1$	$\lambda_{2,3} = 0,$ $S_{23} = 0$
$i = 3 \rightarrow (x_{311}, x_{322}, x_{333})$	$\lambda_{3,1} = 3, \max_a \lambda_{3,a} = 3$ $S_{31} = 1$	$\lambda_{3,2} = 2, \max_a \lambda_{3,a} = 3$ $S_{32} = 0.67$	$\lambda_{3,3} = 0,$ $S_{33} = 0$

3.1.3 Phase 1. C: product variants clustering

After computing the similarity matrix, the product variants are grouped according to their similarity to the potential product platforms to determine the product variants that can be built from the same product platform.

An exemplar-based clustering model, i.e. k-medoids, is used to this aim. It divides a set of observations into k clusters minimizing the sum of distances between an observation and a cluster centre, named medoid. The reader could refer to reference [32] for a deep explanation of k-medoids.

The clustering algorithm provides as output a set of k clusters, each including a certain number of product variants considered the most similar to the same potential product platform. However, it does not directly provide the product platform associated to each cluster. The association between product platforms and clusters is made by checking which potential product platform is included in all the variants within a cluster. In particular, the longest platform is chosen in case different product platforms could be assigned to the same cluster. On the contrary, no platform is assigned to a cluster if there is no potential product platform included in the technological cycle of the product variants grouped in the same cluster.

At the end of clustering, the first step of the methodology is concluded, providing all the parameters listed at the beginning of this section, which can be extracted as follows:

$$L = \sum_l z_l \tag{2}$$

$$z_l = \begin{cases} 1 & if \sum_{i=1}^{N} z_{il} > 1 \\ 0 & otherwise \end{cases} \quad \forall l = 1, \dots, L \tag{3}$$

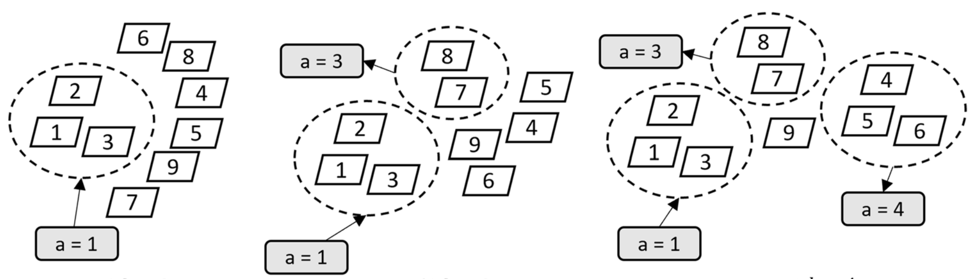
$$\mu_l = \sum_a y_{la} \lambda_a \quad \forall l = 1, \dots, L \tag{4}$$

$$\varphi_i = \begin{cases} 1 & if \sum_l z_{il} > 0 \\ 0 & otherwise \end{cases} \quad \forall l = 1, \dots, N \tag{5}$$

$$\psi_j = \begin{cases} 1 & f \sum_{i=1}^{N} \sum_{l=1}^{L} \sum_{s=1}^{\mu_l} z_{il} x_{ijs} > 0 \\ 0 & otherwise \end{cases} \quad \forall l = 1, \dots, M \tag{6}$$

where L is the total number of the selected product platforms. If $\varphi_i = 1$, the product variant i is managed through the DPD strategy. Otherwise, it is managed through the MTO strategy. If $\psi_j = 1$, the component j is managed through the MTS strategy. Otherwise, it is managed through the MTO strategy.

Because the obtained solution depends on the number of clusters k, running the k-medoids for different values of k provides a range of possible solutions that will be evaluated in step 2 to perform a multi-scenario analysis. Consider the example of clustering through k-medoids shown in Fig. 4. For $k = 2$, the variant space is divided into two non-homogeneous groups. It means that the three variants in the little cluster have a higher similarity with the same product platform, while the other variants are less similar to a specific platform. For this reason, no product platform is assigned to that cluster. Similarly, for $k = 3$, only two clusters can be associated to a product platform. Finally, for $k = 4$, one cluster includes only one variant, and, for this reason, it is not convenient to assign a product platform to it.



a) $k = 2$ b) $k = 3$ c) $k = 4$

Fig. 4 Clustering process and product platform association, with a. $k = 2$, b. $k = 3$, c. $k = 4$. In this figure, the representation of product variants, i.e. white parallelograms, and product platforms, i.e. grey rectangles, coherently follows the legend introduced in Fig. 2

Table 3 Example of the solution provided by the k-medoids and step 1 of the methodology with different values of k

Input of clustering		Output of clustering					Output of step 1	
Product variants	Potential product platforms	k	$a : y_{la} = 1$	$i : z_{il} = 1$	L	μ_l	$i : \varphi_i = 1$	$j : \psi_j = 1$
$x_{111}, x_{122}, x_{133}, x_{143}$	$a = 1 : x_{111}, x_{122}$	2	1	1,2,3	1	2	1,2,3	1,2
$x_{211}, x_{222}, x_{243}, x_{234}$	$a = 2 : x_{311}, x_{322}, x_{333}$	3	1,3	1,2,3,7,8	2	2,2	1,2,3,7,8	1,2,4,5
$x_{311}, x_{322}, x_{333}$	$a = 3 : x_{741}, x_{752}$	4	1,3,4	1,2,3,7,8,4,5,6	3	2,2,2	1,2,3,7,8,4,5,6	1,2,4,5,8
$x_{421}, x_{482}, x_{493}, x_{474}$	$a = 4 : x_{421}, x_{482}$							
$x_{521}, x_{582}, x_{533}, x_{544}$	$a = 5 : x_{521}, x_{582}, x_{532}$							
$x_{621}, x_{682}, x_{633}, x_{674}$								
$x_{741}, x_{752}, x_{763}, x_{774}$								
$x_{841}, x_{852}, x_{863}$								
$x_{971}, x_{922}, x_{933}$								

The set of solutions obtained from this example is shown in Table 3, where the input and output of clustering with different k are summarized, together with the output of the step 1 of the methodology.

3.2 Step 2: product platform assessment

The last phase of the methodology aims at evaluating and selecting one of the solutions provided by the clustering phase with different values of k. Each solution is evaluated through four distinct metrics, which can be divided into company and customer drivers. The MTS costs, variety, and variant production costs belong to the first category. Responsiveness is the market driver. The parameters needed to compute each metric are listed in Table 4.

The following subsections provide the mathematical formulations of each metric.

The *total MTS cost* arises because the MTS strategy is adopted for the product platforms and the components included in at least one product platform. According to the

Table 4 List of parameters

Component parameters			**Platform parameters**		
Symbol	Description	Unit	Symbol	Description	Unit
c'	Cost of one order emission	€/order	c	Cost of one set up	€/setup
D_j	Demand	Unit/year	D_l	Demand	Unit/year
EOQ_j	Economic order quantity	Unit/lot	EOQ_l	Economic order quantity	Unit/lot
h_j	Inventory cost	€/unit	H_l	Inventory cost	€/unit
MTS_C	Cost of component' MTS policy	€	MTS_L	Cost of platforms' MTS policy	€
$p'_j(q_j)$	Price	€/unit	p_l	Production cost	€/unit
q_j	Order quantity	unit	χ	Production rate	Unit/year
γ_j	Assembling cost	€/unit			
τ_j	Assembling time	min/unit			
δ_j	Purchasing lead time	days/unit			

Global parameters		
Symbol	Description	Unit
MTS	Total cost of MTS entities	€
P	Total Production cost	€
P_{DPD}	Production cost of product variants $i : \varphi_i = 1$	€
P_{MTO}	Production cost of product variants $i : \varphi_i = 0$	€
R_{DPD}	Responsiveness of product variants $i : \varphi_i = 1$	Min
R_{MTO}	Responsiveness of product variants $i : \varphi_i = 0$	Min
R	Total responsiveness	Min
V	Number of SKUs in the warehouse	Unit
Y_i	Demand of variant i	Unit/year
ξ_1	Reduction of platforms' inventory costs	%
ξ_1	Reduction of platforms' production costs	%

Harris's model [33, 34], the total cost of the MTS policy depends on whether a product is bought from a supplier or is manufactured by the company. In the first case, the total cost of the buy policy includes the purchasing cost, the order emission cost, and the storage cost. In the second case, the total cost of the make policy includes the production cost, the setup cost, and the storage cost. In the case under analysis, components are bought from suppliers, while the product platforms are assembled internally by the company.

The total cost provided by the Harris's model for the buying lot is given by Eq. (7):

$$MTS_c = \sum_{j=1}^{M} \left(p_j'(q)D_j + \frac{c'D_j}{EOQ_j} + h_j \frac{EOQ_j}{2} \right) \psi_j \tag{7}$$

where the buying lot size EOQ_j and the demand of the component j D_j are given Eqs. (8) and (9), respectively, while and p_j' depends on the relationship between the resulting EOQ_j and q_j.

$$EOQ_j = \sqrt{\frac{2c'D_j}{h_j}} \tag{8}$$

$$D_j = \sum_{i=1}^{N} Y_i x_{ijs}, j = 1, \ldots, M, s = 1, \ldots, S_i \tag{9}$$

The total cost provided by Harris's model for the production lot is given by Eq. (10):

$$MTS_L = \sum_{l=1}^{L} \left(p_l D_l + \frac{D_l}{EOQ_l} + H_l \frac{EOQ_l}{2} \frac{\chi - D_l}{\chi} \right) z_l \tag{10}$$

where the manufacturing lot size EOQ_l the demand d_l, the storage cost H_l, the production rate χ, and the production cost p_l of each product platform are given by Eqs. (11, 12, 13, 14, 15), respectively.

$$EOQ_l = \sqrt{\frac{2cD_l}{H_l}} \sqrt{\frac{\chi}{\chi - D_l}} \tag{11}$$

$$D_l = \sum_{i=1}^{N} Y_i z_{il} \tag{12}$$

$$H_l = \xi_1 \textstyle\sum_{i=1}^{N} \sum_{j=1}^{M} \sum_{s=1}^{\mu_l} h_j x_{ijs} z_{il} \;\; \xi_1 \in \{0, 1\} \tag{13}$$

$$\chi = \sum_{i=1}^{N} \sum_{l=1}^{L} 2D_l z_{il} \tag{14}$$

$$p_l = \xi_2 \textstyle\sum_{i=1}^{N} \sum_{j=1}^{M} \sum_{s=1}^{\mu_l} \gamma_j x_{ijs} z_{il} \;\; \xi_2 \in \{0, 1\} \tag{15}$$

Finally, the total MTS cost is given by Eq. (16):

$$MTS = MTS_c + MTS_L \tag{16}$$

Variety arises because of product platforms and MTS components introduced in the warehouse. According to the most adopted definition of product variety, i.e. the number of stock-keeping units (SKUs) [35.], the variety can be computed as the number of product platforms and the number of components included in at least one product platform, as indicated by Eq. (17):

$$V = \sum_{j=1}^{M} \psi_j + L \tag{17}$$

Responsiveness is defined as the order fulfilment cycle time, i.e. the time needed to realize a finished product from the arrival of a customer's order [36]. In this context, because the product platforms are made to stock, regardless the existence of a specific customer order, responsiveness depends on the product variant's management strategy. In the case of DPD, the responsiveness of a product variant i only considers the time to assemble the customization components to the product platform from which the product variant is derived. For these components, two cases can be distinguished: the customization component is managed through the MTS strategy, i.e. $\exists l, i' \neq i : z_{i'l} = 1 \wedge \exists s \in [1, \ldots, \mu_l] : x_{i'js} = 1$, or the customization component is managed through the MTO strategy. In the first case, the component j is in the warehouse when the customer order arrives and the responsiveness only includes the assembling time. In the second case, the component has to be ordered, and the responsiveness also includes the supplying lead time.

Therefore, if a product variant is managed through a DPD strategy, the total time needed to personalize all platforms to get all DPD variants is given by Eq. (18):

$$R_{DPD} = \sum_{i=1}^{N} Y_i \left(\sum_{j=1}^{M} \sum_{s=(\mu_l+1)}^{S_i} \tau_j x_{ijs} z_{il} \psi_j + \sum_{j=1}^{M} \sum_{s=(\mu_l+1)}^{S_i} (\delta_j + \tau_j) x_{ijs} z_{il} (1 - \psi_j) \right) \varphi_i \tag{18}$$

where the first term corresponds to the assembly time of customization components managed with the MTS strategy ($j : \psi_j = 1$) and the second term corresponds to the lead time and assembly time of the customization components managed with the MTO strategy ($j : \psi_j = 0$). Note that Eq. (18) also applies to product variant managed with the MTS strategy. Indeed, in these cases, the structure of the product variant is equal to the structure of the product platform, and its responsiveness is equal to zero.

If products variants cannot be built from any product platform, they are managed with the MTO strategy. Therefore, in this case, the responsiveness considers all components in the product variant's technological cycle (Eq. (19)). Similarly to the case of DPD strategy, MTS components and MTO components have to be considered separately.

$$R_{MTO} = \sum_{i=1}^{N} Y_i \left(\sum_{j=1}^{M} \sum_{s=1}^{S_i} \tau_j x_{ijs} z_{il} \psi_j + \sum_{j=1}^{M} \sum_{s=1}^{S_i} (\delta_j + \tau_j) x_{ijs} z_{il} (1 - \psi_j) \right) (1 - \varphi_i) \tag{19}$$

Therefore, the total responsiveness of all product variants is given by Eq. (20):

$$R = R_{DPD} + R_{MTO} \tag{20}$$

About the *variants production cost*, as demonstrated by [36], the MTO strategy is more expensive than the MTS strategy in terms of production costs due to the higher complexity of operational activities. Indeed, the cost of assembling one component to an existing product platform when an order is released is higher than the cost of assembling the same component within a product platform. Therefore, the product variants' production costs change depending on whether they are managed through a DPD or MTO strategy. In the first case, the production cost is given by the platform's production cost and the customization cost. In the second case, the product variant is managed with the MTO strategy, and only the customization cost is considered. Like responsiveness, the customization cost depends on the components' management strategy in both cases. For MTS components, only the components' assembly cost is considered since the component is available in the warehouse. In the case of MTO components, the production cost also includes the components' buying cost.

In the DPD context, the production cost of a product variant is given by Eq. (21):

$$P_{DPD} = \sum_{i=1}^{N} Y_i \left(p_l z_{il} + \sum_{j=1}^{M} \sum_{s=(\mu_l+1)}^{S_i} \gamma_j x_{ijs} z_{il} \psi_j + \sum_{j=1}^{M} \sum_{s=(\mu_l+1)}^{S_i} (p'_j(q_j) + \gamma_j) x_{ijs} z_{il} (1 - \psi_j) \right) \varphi_i \tag{21}$$

where the first term corresponds to the product platform production cost, given by Eq. (14), the second term corresponds to the assembly cost of the customization components managed through the MTS strategy, and the third term corresponds to the assembly cost of the customization components managed through the MTO strategy.

In the MTO context, the production cost of a product variant is given by Eq. (22):

$$P_{MTO} = \sum_{i=1}^{N} Y_i \left(\sum_{j=1}^{M} \sum_{s=1}^{S_i} \gamma_j x_{ijs} z_{il} \psi_j + \sum_{j=1}^{M} \sum_{s=1}^{S_i} (p'_j(q_j) + \gamma_j) x_{ijs} z_{il} (1 - \psi_j) \right) (1 - \varphi_i) \tag{22}$$

Therefore, the total production cost is given by Eq. (23):

$$P = P_{DPD} + P_{MTO} \tag{23}$$

4 Industrial application

This section applies the proposed methodology to an Italian industrial case study, representative of a company producing a family of 38 plastic valve variants involving 93 different operations. In the past years, the company handled 5 different valve models. Subsequently, an increasing number of customers asked for novel customization elements in the product, e.g. in the colour, shape, and insertion of their brand. All these requests led to increase complexity in the product operations and the product mix management because of the number of different models to design, produce, and schedule rose to 38. Hence, the company had to face this complexity, investigating the possibility of implementing new production logics and strategies to streamline the production, storage, and delivery phases. Great attention is paid to DPD, rising as a novel strategy able to support companies in better managing the production mix.

An example of a reference product variant is shown in Fig. 5, while the technological cycles of the product variants and the demand data are in Appendix 1. Appendix 2 details the values of the parameters listed in Table 4, e.g. the cost of one-order emission and the holding costs of the components adopted in the case study. The methodology has been coded in MATLAB and executed on a PC with 16 GB of RAM and Intel(R) Core(TM) i7-8565U CPU @ 1.80 GHz. The execution time of the methodology depends on the number of iterations needed to find the best number of clusters k. Considering 38 product variants and 93 components, each iteration is executed in less than 2 s on average.

According to the proposed methodology, the first step consists in identifying the set of the longest common subsequences among all the product variant couples that correspond to the potential product platforms. The application of the mLCS and the subsequent filtering step led to identifying 25 non-identical subsequences, summarized in Table 5. Then, the similarity matrix between the product variants and the potential product platforms is built using the similarity index in Eq. (1). Finally, the clustering algorithm is applied to the similarity matrix for $k = 2, \ldots, 25$ and, at each iteration, the four metrics described by Eq. (16), Eq. (17), Eq. (20), and Eq. (23) are computed.

Table 6 shows the clusters created at each iteration, the product platforms associated to each cluster, and the total similarity among the elements in the new cluster, computed as the sum of the similarity indexes of all the product variants with the product platforms.

For $2 \leq k \leq 14$, the number of product platforms equals the number of clusters k minus one because there is always a partition to which a product platform cannot be associated. For $15 \leq k < 21$, the number of product platforms does not change. However, wider platforms

Component ID.	Component name
1	Handle
2	Pin O-ring gasket
3	Pin
4	Body
5	PTFE gasket
6	Ball
7	Gasket supporting 5
8	Radial sealing O-ring gasket
9	Bush

Fig. 5 Example of a valve variant and its components

Table 5 Components included in the technological cycle of the identified potential product platforms

a	λ_a	Technological cycle	a	λ_a	Technological cycle	a	λ_a	Technological cycle
1	2	c_{10}, c_{15}	10	6	$c_{78}, c_{79}, c_{84}, c_{86}, c_{87}, c_{88}$	19	8	$c_{13}, c_{40}, c_{41}, c_{42}, c_{43}, c_{44}, c_{45}, c_{46}, c_{47}$
2	3	c_{10}, c_{15}, c_{16}	11	2	c_1, c_2	20	5	$c_2, c_7, c_{10}, c_{13}, c_{15}$
3	4	$c_{10}, c_{15}, c_{16}, c_{17}$	12	3	c_1, c_2, c_4	21	9	$c_2, c_7, c_{10}, c_{13}, c_{15}, c_{16}, c_{18}, c_{20}, c_{21}$
4	3	c_{10}, c_{15}, c_{25}	13	7	$c_1, c_2, c_4, c_7, c_8, c_9, c_{10}$	22	9	$c_2, c_7, c_{10}, c_{13}, c_{15}, c_{25}, c_{27}, c_{29}, c_{30}$
5	4	$c_{10}, c_{15}, c_{25}, c_{26}$	14	3	c_2, c_6, c_7	23	9	$c_{13}, c_{34}, c_{35}, c_{36}, c_{37}, c_{38}, c_{39}, c_{40}, c_{41}$
6	7	$c_{10}, c_{15}, c_{78}, c_{79}, c_{80}, c_{81}, c_{82}$	15	4	c_2, c_6, c_7, c_{10}	24	2	c_1, c_3
7	8	$c_{10}, c_{15}, c_{78}, c_{79}, c_{80}, c_{81}, c_{82}, c_{84}$	16	5	$c_2, c_6, c_7, c_{10}, c_{16}$	25	2	c_{10}, c_{50}
8	2	c_{78}, c_{79}	17	3	c_{13}, c_{40}, c_{41}			
9	3	c_{78}, c_{79}, c_{84}	18	9	$c_{13}, c_{40}, c_{41}, c_{48}, c_{49}, c_{50}, c_{51}, c_{52}, c_{53}$			

replace some product platforms selected in previous iterations. Consequently, the number of product variants managed with the DPD strategy increases until $k \leq 14$, representing the iteration in which the maximum number of product variants is associated to product platforms. Then, for $15 \leq k < 21$, the number of product variants subject to the DPD strategy decreases. Conversely, the number of components managed with the MTS strategy at each iteration is equal to or greater than the number of components included in the same set in the previous iteration. Indeed, a component may be part of one or more product platforms. Therefore, their number depends on the platform width rather than the platform number.

The relationships between the number of clusters and the three involved entities, i.e. product platforms, product variants managed with the DPD strategy, and MTS components, is shown in Fig. 6.

Because disassembly operations are not allowed to derive a product variant from a product platform, the wider the platforms, the less the number of product variants that can be derived from it. The k-medoids algorithm groups the product variants that provide the higher total intra-cluster similarity index. In general, the higher similarity value corresponds to product platforms of middle-length. Indeed, when a small platform is selected, the number of associated product variants is high, but their total similarity to the platform decreases. Conversely, when a product platform is wider, the number of associated product variants is low, but their total similarity is high. Therefore, the selected product platforms depend on (1) the number of

Table 6 Clustering process

k	Product variants (i)	Associated product platforms (a)	Intra-cluster similarity
2	$I = \{25, 26, 29, 30\}$	$A = \{6\}$	3.625
3	$I \cup \{2, 5, 6\}$	$A \cup \{15\}$	2.600
4	$I \cup \{24, 35, 38\}$	$A \cup \{4\}$	2.500
5	$I \cup \{23, 34, 37\}$	$A \cup \{2\}$	2.500
6	$I \cup \{28, 31, 32\}$	$A \cup \{9\}$	2.000
7	$I \cup \{8, 11\}$	$A \cup \{21\}$	2.000
8	$I \cup \{9, 12\}$	$A \cup \{22\}$	2.000
9	$I \cup \{7, 10\}$	$A \cup \{13\}$	2.000
10	$I \cup \{15, 18\}$	$A \cup \{19\}$	2.000
11	$I \cup \{14, 17\}$	$A \cup \{18\}$	2.000
12	$I \cup \{13, 16\}$	$A \cup \{23\}$	2.000
13	$I \cup \{20, 21\}$	$A \cup \{25\}$	2.000
14	$I \cup \{22, 33\}$	$A \cup \{24\}$	2.000
15	I	A	-
16	$I - \{28\}$	$A - \{9\} \cup \{10\}$	2.000
17	$I - \{37\}$	$A - \{2\} \cup \{3\}$	2.000
18	$I - \{38\}$	$A - \{4\} \cup \{5\}$	2.000
19	$I - \{6\}$	$A - \{15\} \cup \{16\}$	2.000
20	$I - \{25\}$	$A - \{6\} \cup \{7\}$	3.000
21 –25	I	A	

product variants belonging to a cluster and (2) the similarity indexes between variants and platforms. In general, the methodology looks for product platforms providing the best trade-off between the number of product variants and their similarity to the product platform.

Finally, the clusters with feasible platforms created for a certain value of k are retained in the subsequent run for $k \leq 14$. Hence, the algorithm first tries to cover the whole space by balancing the number of product variants and their similarity index with the corresponding platform. Then, it replaces existing platforms with wider platforms, preferring a high similarity index to the number of product variants exploiting the DPD strategy.

Figure 7 shows the trend of each metric against the number of clusters. The values of each metric are detailed in Appendix 3.

The platform cost, which includes the management cost of platforms (MTS_p) and MTS components (MTS_c), increases as the number of clusters increases. In particular, MTS_c increases both when a higher number of platforms is selected (for $k < 14$) and when wider platforms are selected (for $k > 14$). Conversely, MTS_p decreases when the algorithm replaces existing platforms with wider platforms (for $k > 14$). This trend occurs because of the lower number of product variants built from the platform and, therefore, the lower platform demand. However, the total platform cost increases when more platforms are selected because the MTS_c has a more significant impact.

As in the case of the platform cost, the variety increases when the number of clusters increases. In particular, the number of product platforms naturally increases by one as a new platform is selected. Conversely, the number

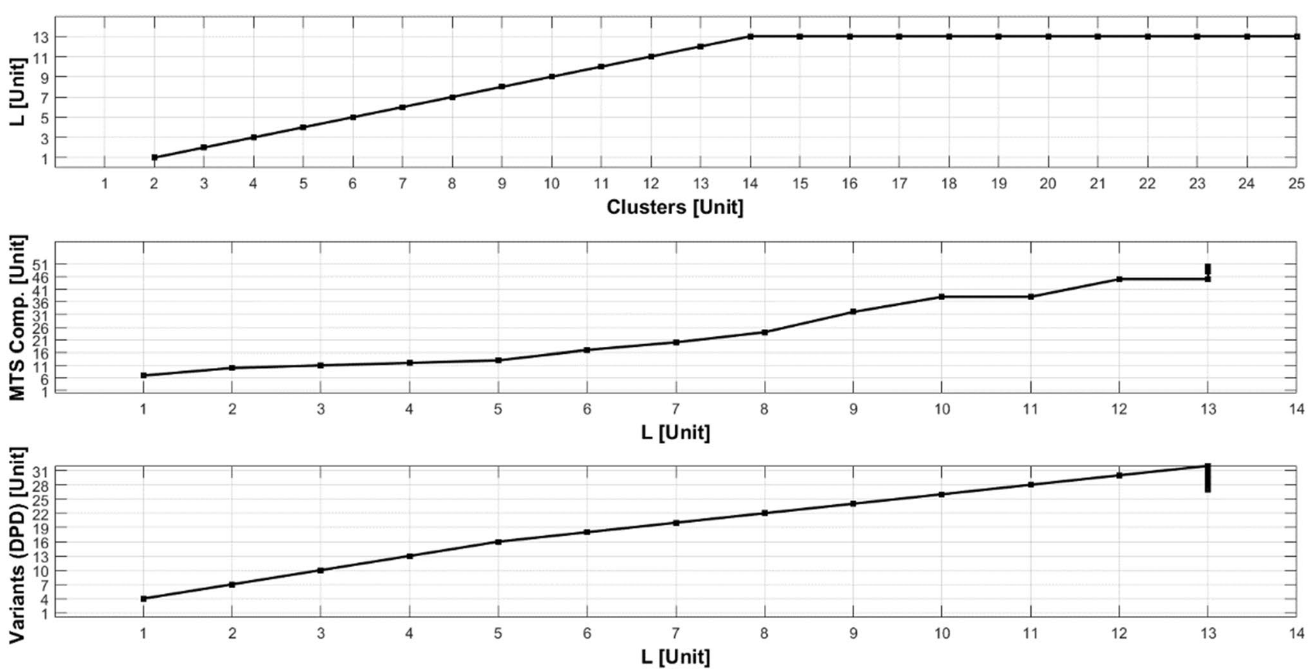


Fig. 6 Relationships between the number of clusters and the number of product platforms, variants managed with the DPD strategy, and the number of MTS components

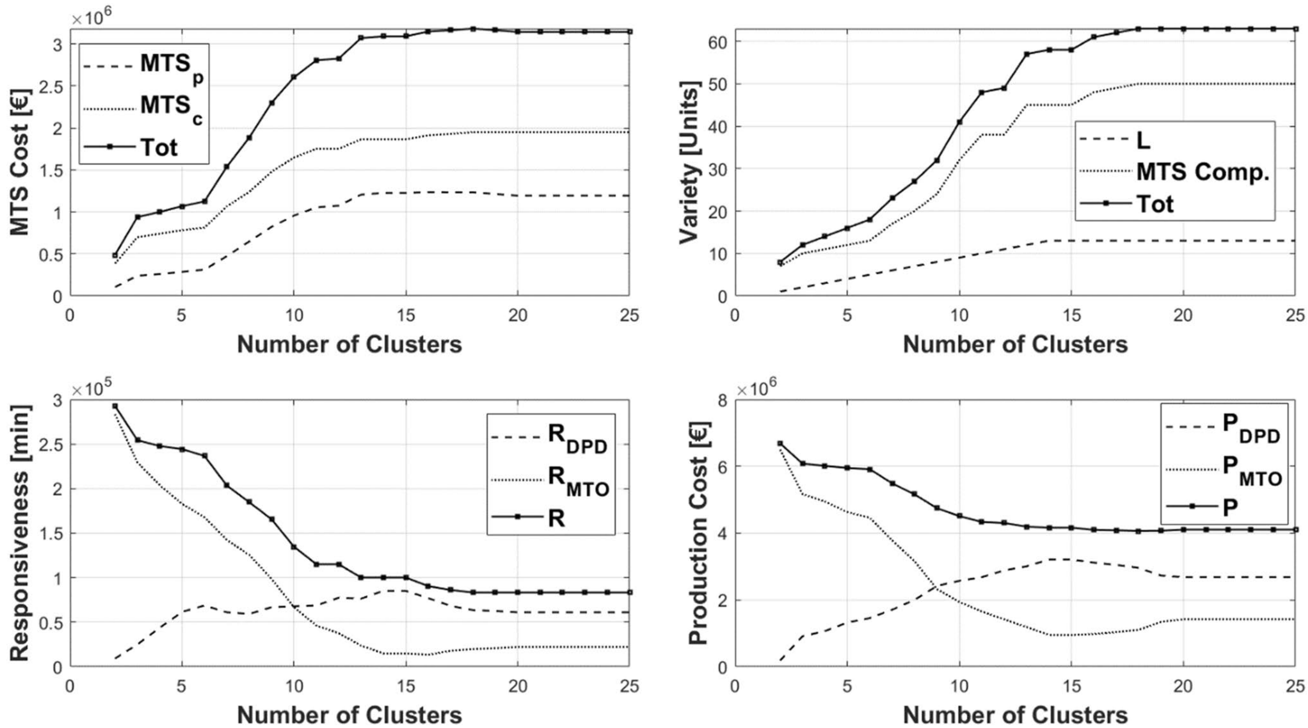


Fig. 7 Metrics' trend against the number of clusters

of MTS components grows rapidly at the beginning to remain almost the same when wider platforms are selected because of the possibility that the components added to the wider platform are already managed with the MTS strategy.

Responsiveness and production cost trends depend on two factors: the number of platforms and their width, which both determine the number of product variants managed with the DPD strategy. Indeed, as mentioned above, the number of platforms increases until the number of clusters is lower than 14. During these iterations, the number of variants associated to the product platforms increases because more platforms are selected. Therefore, responsiveness decreases because of the time saved to assemble the components that, in the DPD strategy, belong to a product platform. Similarly, the production cost decreases due to the lower production cost of product platforms compared to the assembly cost of the same components according to the MTO strategy. In addition, both the responsiveness and the production cost of a product variant managed through the DPD strategy decrease because of the presence of some customization components that are managed through the MTS strategy (since they belong to another product platform) and do not have buying lead time nor buying cost. As in Fig. 7, for $k > 14$, the number of platforms does not change, while more wide platforms, i.e. characterized by a high number of components, are selected. For instance, as highlighted in Table 6, when $k = 16$ the platform $a = 9$ is replaced with platform $a = 10$, which has 3 more components (see Table 5) and from which 2 product variants can be built instead of 3. As a result, the number of product variants associated to a product platform slightly decreases and both responsiveness and production cost increase.

Because of the conflicting trends, finding a trade-off between the metrics is crucial to select the best number and type of product platforms. Therefore, each metric is first normalized in the range [0,1] through the min–max normalization method, where 0 represents the best case and 1 the worst case. Then, the total value is computed as the weighted sum of the normalized values of all metrics, and the solution providing the minimum value is selected. When all metrics have an equal weight, at the two extremes, $k = 2$ and $k = 25$, the total normalized function assumes the value 0.5, and the solution characterized by 9 clusters provides the minimum value of 0.4401. Compared to the solution obtained with 2 clusters and one only product platform, at this point:

- The MTS cost increases from 487,333 to 2,300,094 euros (+371.9%)
- The variety increases from 8 to 32 units (+300.0%)

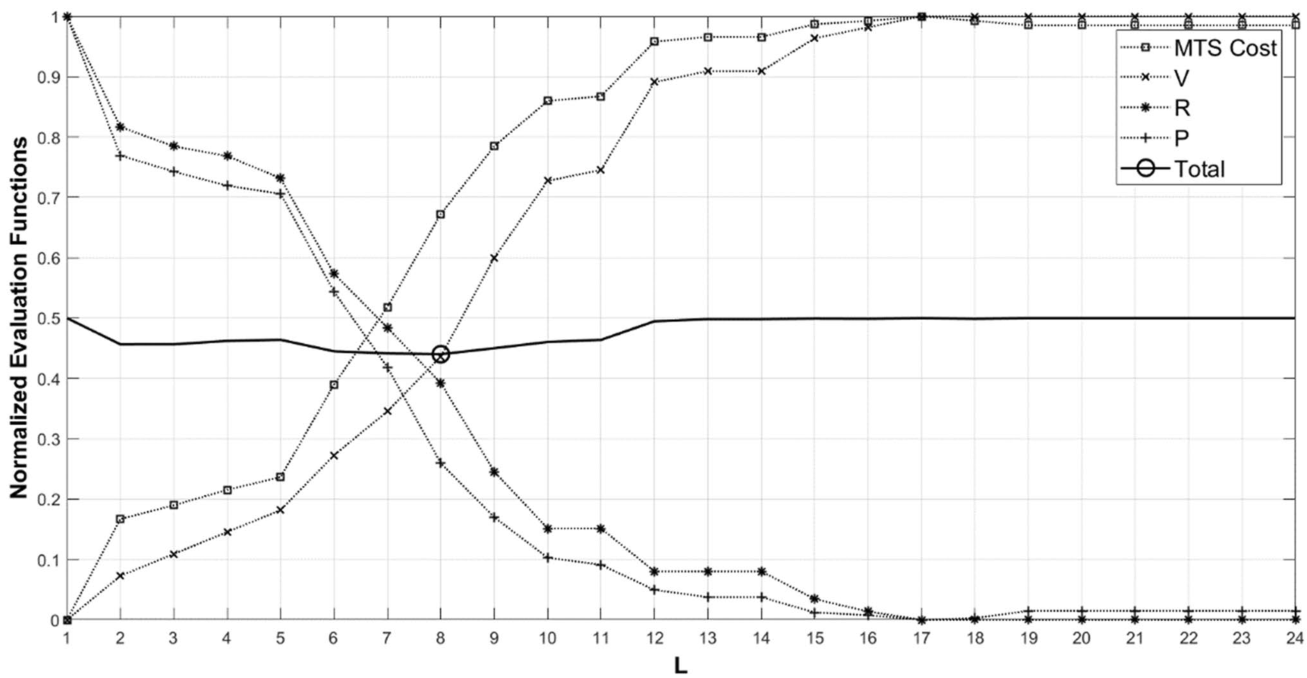


Fig. 8 Normalized metrics' trend at each iteration

- The responsiveness decreases from 292,811 to 165,486 min (−76.9%)
- The production cost decreases from 6,685,558 to 4,743,619 euros (−40.9%)

Figure 8 shows the normalized values of the four metrics against the number of clusters. Table 7 shows the product platforms and the associated product variants corresponding to the selected solution, while Fig. 9 shows the system configuration corresponding to the best solution. Twenty-two product variants are managed with the DPD strategy, while the remaining 16 with the MTO strategy. The number of MTS components is equal to 24, and the number of product platforms is equal to 8.

To highlight the impact of the proposed methodology on the industrial field, an alternative widespread method for product platform design is used as benchmark, i.e. the bio-inspired MJPN algorithm. By applying this method to the above presented industrial case study, a set of 15 platforms rises covering the whole production mix. On the other hand, the application of the methodology proposed in this paper leads to the creation of 7 platforms able to manage 22 variants, while the remaining 16 are managed through a more suitable production strategy, i.e. MTO. Table 8 shows the values of the four metrics, i.e. the MTS cost, the variety, the responsiveness, and the production cost, computed for the solution obtained with the MJPN algorithm and the solution selected in this paper.

The proposed methodology leads to significantly lower values of the MTS cost and the variety and higher values of the responsiveness and the production cost. However, the last two metrics are computed not considering the precedence

Table 7 Output of the methodology at $k=9$

$a: y_{la}=1$	Product platforms' technological cycle	l	μ_l	$i: z_{il}=1$	$\sum_i \varphi_i = 1$	$\sum_j \psi_j = 1$
2	$\{c_{10}, c_{15}, c_{16}\}$	1	3	$\{23, 34, 37\}$	22	24
4	$\{c_{10}, c_{15}, c_{25}, c_{26}\}$	2	3	$\{24, 35, 38\}$		
6	$\{c_{10}, c_{15}, c_{78}, c_{79}, c_{80}, c_{81}, c_{82}\}$	3	7	$\{25, 26, 29, 30\}$		
9	$\{c_{78}, c_{79}, c_{84}\}$	4	3	$\{28, 31, 32\}$		
13	$\{c_1, c_2, c_4, c_7, c_8, c_9, c_{10}\}$	5	7	$\{7, 10\}$		
15	$\{c_2, c_6, c_7, c_{10}\}$	6	4	$\{2, 5, 6\}$		
21	$\{c_2, c_7, c_{10}, c_{13}, c_{15}, c_{16}, c_{18}, c_{20}, c_{21}\}$	7	9	$\{8, 11\}$		
22	$\{c_2, c_7, c_{10}, c_{13}, c_{15}, c_{25}, c_{27}, c_{29}, c_{30}\}$	8	9	$\{9, 12\}$		

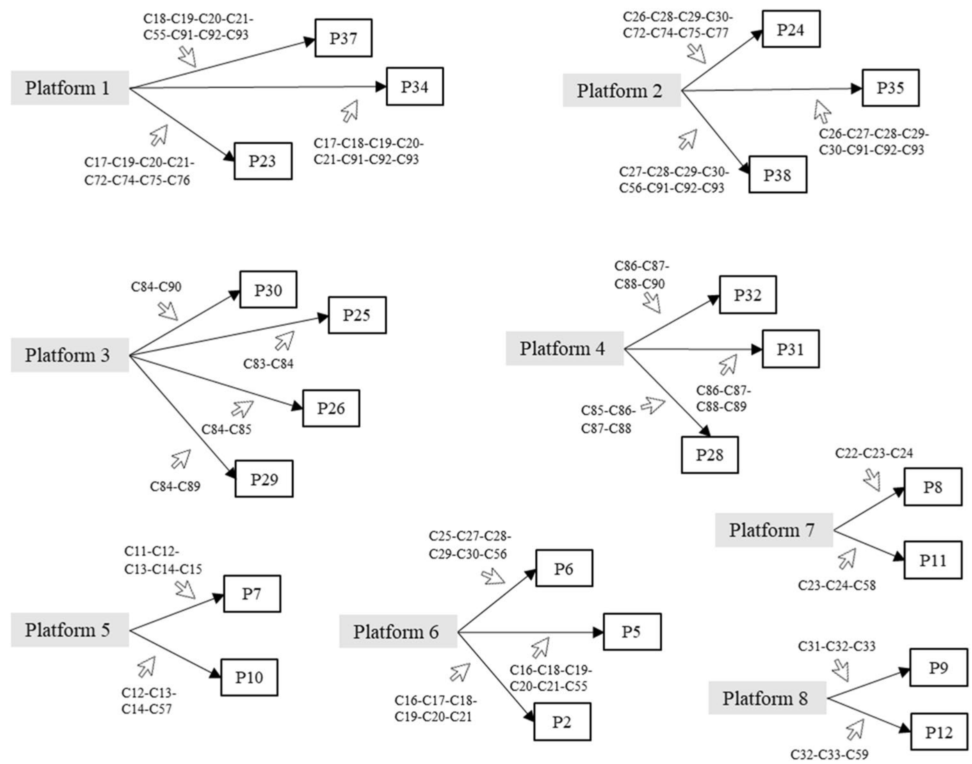


Fig. 9 System configuration corresponding to the best solution

constraints, rising as a significant limitation of the MJPN. In fact, according to the hypothesis of the MJPN algorithm, an assembling/disassembling task is performed regardless the position of the component in the technological cycle. Hence, both platforms and product variants are considered as ensembles of components, in which a component is added or removed without disassembling and re-assembling other components. Therefore, in real-word scenarios, both responsiveness and production costs would be higher.

For comparison, the normalized values of each metric and total normalized value are shown in Table 9. The proposed solution, considering both DPD and MTO strategies, leads to a reduction of this value. On the contrary, the solution obtained through the MJPN algorithm, including only the DPD strategy, leads to an increase in the total normalized value.

Globally, the proposed methodology overcomes some drawbacks of the MJPN:

- Existing studies applying MJPN lie on the assumption that all the product variants included in the production mix are managed with the same production strategy. This could be not realistic in the industrial practice, where different strategies coexist.
- MJPN allows disassembly operations, in addition to assembly, to derive final variants from platforms. While this aspect is useful to further delay the differentiation point, the presence of disassembly operations rises complexity in manufacturing industries due to reverse logistics activities connected to disassembled components, e.g. in terms of time and costs, so that, it must be avoided, if possible.
- Existing MJPN-based applications allow the creation of platforms according to the similarity of components located in any part of the product variant production cycle, neglecting the respect of the precedence constraints. In this study, a variant can be derived from a

Table 8 Comparison between metrics obtained with the MJPN algorithm and with the proposed methodology

Method	MTS Cost (€)		V (unit)		R (min)		P (€)	
	MTS_p	MTS_c	L	$\lvert C_{MTS}\rvert$	R_{DPD}	R_{MTO}	$Prod_{DPD}$	$Prod_{MTO}$
MJPN	2,251,300	2,267,100	15	63	50,029	0	3,198,710	0
Proposed methodology	822,033	1,478,061	8	24	66,874	98,612	2,419,218	2,324,401

Table 9 Comparison between results obtained with the MJPN algorithm and with the proposed methodology

Method	MTS Cost		V		R		P		Total normalized value
	€	Norm	Unit	Norm	Min	Norm	€	Norm	
MJPN	4,518,440	1.495	78	1.273	50,029	−0.159	3,198,710	−0.330	**0.5700**
Proposed methodology	2,300,094	0.672	32	0.436	165.486	0.392	4,743,619	0.259	**0.4401**

Bold represent the main result of the paper

platform only if the variant and the platform technological cycles share the initial part.

All these elements prompted the company to prefer applying the proposed methodology to designing platforms, as it collapses some constraints rose by other methodologies, allowing to assign the most suitable production strategy to each product variant and to manage production and storage processes in a streamlined way.

4.1 Discussions and implications for industrial companies

The case study analysed in the previous section leads to three main considerations that can strongly affect industrial decisions.

First, the mLCS proposed in this paper provides a sequence of operations satisfying the precedence constraints imposed by the technological cycle of the product variants. The advantage of this method is that the product variants can be directly built from the platforms, with no disassembly activities. From the industrial point of view, this advantage implies an easier production management and an improved resource exploitation.

The second consideration concerns the advantage of considering metrics of a different nature. Indeed, considering only responsiveness and production costs would lead to selecting the maximum number of platforms, i.e. 13, obtained at the 18th iteration, in which both responsiveness and production cost are minimal. However, both metrics increase if wider platforms are selected, meaning that both responsiveness and production costs depend on the platform width rather than the platform number. Conversely, platform costs and variety depend on the platform number and are obviously minimal at the first iteration because they arise from the introduction of the DPD strategy. Therefore, all the aspects need to be considered.

Finally, the last consideration concerns the possibility of performing a global analysis of the production mix. Indeed, although the longest common subsequences identified through the mLCS are non-identical, it is possible to identify some pattern among groups of subsequences. Several groups of subsequences can be identified, in which a sequence represents a root, and the other subsequences can be created by adding components to the root sequence. Hence, the introduced methodology also allows dividing the production mix into product families that can be analysed separately.

In the case under analysis, nine (9) product families can be identified. Each of them can have different levels of differentiation. For instance, consider the subsequences $a = 1, \dots, 7$ in Table 5. The potential product platform $a = 1$ represents the root sequence from which all the others can be derived. In particular, it identifies a product family, within which the differentiation point can be delayed at three levels: if $a = 1$ is selected as product platform, all the product variants within the product family can be built by assembling the customization components. If $a = 2$, $a = 4$, and $a = 6$ are selected, they can be used to derive ten product variants out of eleven. Finally, If the widest platforms of the product family are selected, i.e. $a = 5$ and $a = 7$ are selected, only seven variants would exploit the DPD strategy. Therefore, the step 1 of the methodology allows grouping the product variants into product families and identifying different delayed product differentiation points within each product family. The relationship between the platform width and the four metrics is linear in this case. Figure 10 shows the trend of the four metrics against the level of differentiation for the six product families generated in the case under analysis, where

$$PF1 = \{a : a = 1, \dots, 7\}, PF2 = \{a : a = 8, \dots, 10\}, PF3 = \{a : a = 11, \dots, 13\}, PF4 = \{a : a = 14, \dots, 16\}, PF5 = \{a : a = 17, \dots, 19\}, PF6 = \{a : a = 20, \dots, 22\}$$

The MTS cost increases as the differentiation point is delayed because of the storage cost of both product platforms and components. Similarly, the variety increases when the product platforms contain more components because of a higher number of component managed with the MTS strategy On the contrary, responsiveness and production cost decrease if the product platform's width increases.

The analysis performed at a product family level will always lead to platforms of medium length and to select one product platform for each product family. Conversely, the solution provided by the global analysis consists of three platforms belonging to $PF1$ and two platforms belonging to $PF6$. In addition, no product platforms are selected for family $PF5$. Therefore, the proposed methodology not only addresses the product platforms' design and selection issue, but also supports the decision on which strategy, among MTO and DPD, in more convenient considering the whole productive mix.

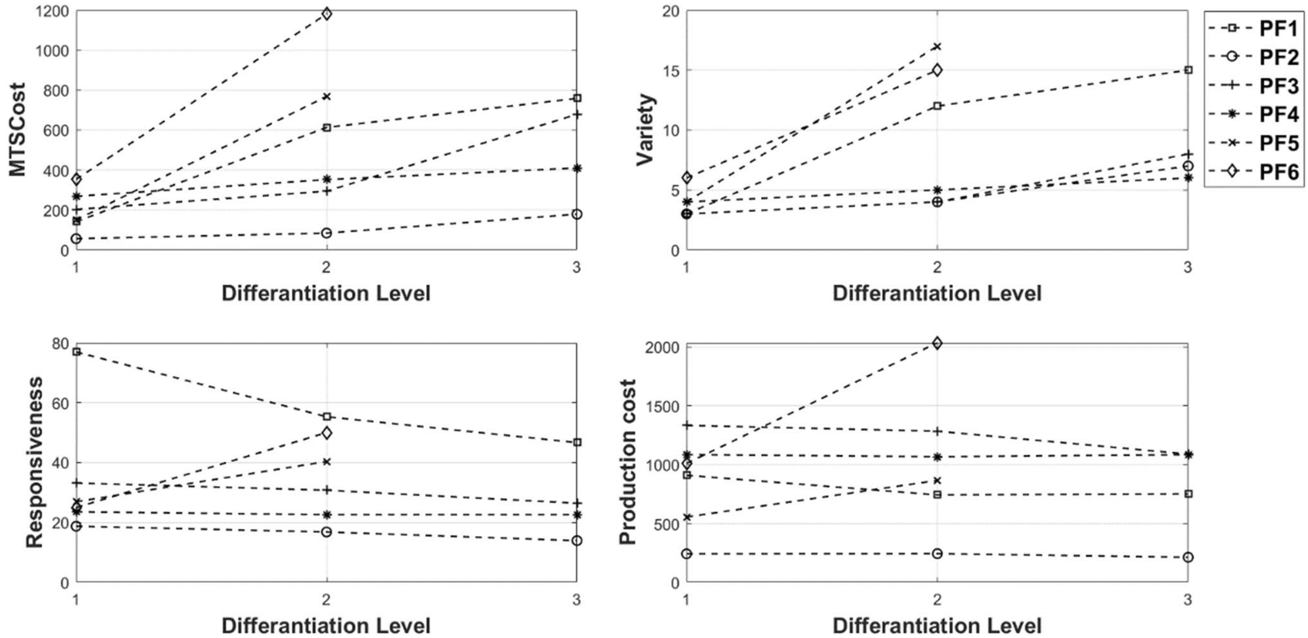


Fig. 10 Metrics' trend against the level of differentiation within each product family

5 Conclusions and future research

Changing customer requirements and regulations and dynamic market demands are leading to a huge increase of product variety. In this context, product platforms rise as an effective strategy implemented by several industrial companies to best cope with product variety. This paper contributes in proposing a two-step methodology for product platform design and assessing which allows to solve large-scale industrial problems thanks to the adoption of efficient algorithms. In particular, a novel algorithm for solving the LCS problem is developed, which, together with the k-medoids clustering algorithm, allows designing platforms that respect the precedence constraints of product variants' technological cycle, deciding whether a product variant should be managed with a DPD or MTO strategy, and assigning the DPD product variants to a product platform. In addition, a set of metrics to assess the impact of platform candidates on company and customer parameters is introduced in a second stage. The application of this methodology to a real case study involving the manufacturing of a family of plastic valves highlights the potential of product platforms to reduce the global impact of company and customer parameters. All potential product platform configurations are investigated and evaluated in terms of MTS cost, variety, responsiveness, and variant production cost. It emerged that all metrics are strictly correlated to both the number and width of product platforms. In particular, MTS costs and variety increase when the number and width of product platform increase. Conversely, responsiveness and variants production costs decrease when the number of product platforms increases until too wide platforms are selected. At this point, responsiveness and production costs start to increase because of the lower number of product variants that exploit the advantages of the DPD strategy. Furthermore, according to the proposed methodology, the product variants clustering led to the definition of a solution corresponding to the best trade-off among these four metrics. This solution, consisting of eight (8) product platforms from which twenty two (22) variants may be derived, allows reducing the sum of the metrics by 11.89% compared to the first solution ($k = 2$), consisting of one product platform from which four (4) variants can be derived. For $k < 9$, the product platform costs and the variety, occurring due to both product platforms and components managed with the MTS strategy, are lower than the total responsiveness and the total production cost. Conversely, for $k > 9$, the responsiveness and production costs are lower than the other two metrics because of the reduced assembly time and cost resulting from a reduced number of customization components. For $k = 9$, the best trade-off between the four metrics is obtained.

Future research will integrate the product platform design and assessment in a unique step that uses results obtained for one solution to generate a better solution. In addition, a similarity index considering other factors, e.g. the variants' demand, will be investigated. Finally, more comprehensive metrics will be included to assess the partition of the productive mix.

Appendix 1

Table 10 Technological cycles of product variants

Product variant	Technological cycle	Demand $Y_i(\frac{Unit}{year})$
P_1	$c_1, c_2, c_3, c_4, c_5, c_6, c_7, c_8, c_9, c_{10}$	1,267
P_2	$c_2, c_6, c_7, c_{10}, c_{16}, c_{17}, c_{18}, c_{19}, c_{20}, c_{21}$	1,316
P_3	$c_2, c_6, c_7, c_{25}, c_{26}, c_{27}, c_{28}, c_{29}, c_{30}$	1,238
P_4	$c_1, c_2, c_4, c_5, c_6, c_7, c_8, c_9, c_{10}, c_{54}$	1,184
P_5	$c_2, c_6, c_7, c_{10}, c_{16}, c_{18}, c_{19}, c_{20}, c_{21}, c_{55}$	1,170
P_6	$c_2, c_6, c_7, c_{10}, c_{25}, c_{27}, c_{28}, c_{29}, c_{30}, c_{56}$	1,049
P_7	$c_1, c_2, c_4, c_7, c_8, c_9, c_{10}, c_{11}, c_{12}, c_{13}, c_{14}, c_{15}$	1,300
P_8	$c_2, c_7, c_{10}, c_{13}, c_{15}, c_{16}, c_{18}, c_{20}, c_{21}, c_{22}, c_{23}, c_{24}$	1,168
P_9	$c_2, c_7, c_{10}, c_{13}, c_{15}, c_{25}, c_{27}, c_{29}, c_{30}, c_{31}, c_{32}, c_{33}$	1,093
P_{10}	$c_1, c_2, c_4, c_7, c_8, c_9, c_{10}, c_{12}, c_{13}, c_{14}, c_{15}, c_{57}$	1,296
P_{11}	$c_2, c_7, c_{10}, c_{13}, c_{15}, c_{16}, c_{18}, c_{20}, c_{21}, c_{22}, c_{23}, c_{24}, c_{58}$	782
P_{12}	$c_2, c_7, c_{10}, c_{13}, c_{15}, c_{25}, c_{27}, c_{29}, c_{30}, c_{32}, c_{33}, c_{59}$	952
P_{13}	$c_{13}, c_{34}, c_{35}, c_{36}, c_{37}, c_{38}, c_{39}, c_{40}, c_{41}$	781
P_{14}	$c_{13}, c_{40}, c_{41}, c_{42}, c_{43}, c_{44}, c_{45}, c_{46}, c_{47}$	910
P_{15}	$c_{13}, c_{40}, c_{41}, c_{48}, c_{49}, c_{50}, c_{51}, c_{52}, c_{53}$	619
P_{16}	$c_{13}, c_{34}, c_{35}, c_{36}, c_{37}, c_{38}, c_{39}, c_{40}, c_{41}, c_{60}$	754
P_{17}	$c_{13}, c_{40}, c_{41}, c_{42}, c_{43}, c_{44}, c_{45}, c_{46}, c_{47}, c_{61}$	677
P_{18}	$c_{13}, c_{40}, c_{41}, c_{48}, c_{49}, c_{50}, c_{51}, c_{52}, c_{53}, c_{62}$	549
P_{19}	$c_{10}, c_{15}, c_{50}, c_{51}, c_{52}, c_{63}, c_{64}, c_{65}, c_{66}$	519
P_{20}	$c_{10}, c_{50}, c_{52}, c_{64}, c_{66}, c_{67}, c_{68}, c_{69}$	947
P_{21}	$c_{10}, c_{50}, c_{51}, c_{52}, c_{63}, c_{64}, c_{65}, c_{70}, c_{71}$	210
P_{22}	$c_1, c_3, c_8, c_9, c_{10}, c_{15}, c_{72}, c_{73}, c_{74}, c_{75}$	386
P_{23}	$c_{10}, c_{15}, c_{16}, c_{17}, c_{19}, c_{20}, c_{21}, c_{72}, c_{74}, c_{75}, c_{76}$	280
P_{24}	$c_{10}, c_{15}, c_{25}, c_{26}, c_{28}, c_{29}, c_{30}, c_{72}, c_{74}, c_{75}, c_{77}$	331
P_{25}	$c_{10}, c_{15}, c_{78}, c_{79}, c_{80}, c_{81}, c_{82}, c_{83}, c_{84}$	493
P_{26}	$c_{10}, c_{15}, c_{78}, c_{79}, c_{80}, c_{81}, c_{82}, c_{83}, c_{84}, c_{85}$	364
P_{27}	$c_{78}, c_{79}, c_{83}, c_{84}, c_{86}, c_{87}, c_{88}$	500
P_{28}	$c_{78}, c_{79}, c_{84}, c_{85}, c_{86}, c_{87}, c_{88}$	329
P_{29}	$c_{10}, c_{15}, c_{78}, c_{79}, c_{80}, c_{81}, c_{82}, c_{84}, c_{89}$	473
P_{30}	$c_{10}, c_{15}, c_{78}, c_{79}, c_{80}, c_{81}, c_{82}, c_{84}, c_{90}$	297
P_{31}	$c_{78}, c_{79}, c_{84}, c_{86}, c_{87}, c_{87}, c_{89}$	215
P_{32}	$c_{78}, c_{79}, c_{84}, c_{86}, c_{87}, c_{88}, c_{90}$	343
P_{33}	$c_1, c_3, c_4, c_5, c_8, c_9, c_{10}, c_{15}, c_{91}, c_{92}, c_{93}$	389
P_{34}	$c_{10}, c_{15}, c_{16}, c_{17}, c_{18}, c_{19}, c_{20}, c_{21}, c_{91}, c_{92}, c_{93}$	237
P_{35}	$c_{10}, c_{15}, c_{25}, c_{26}, c_{27}, c_{28}, c_{29}, c_{30}, c_{91}, c_{92}, c_{93}$	344
P_{36}	$c_1, c_4, c_5, c_8, c_9, c_{10}, c_{15}, c_{54}, c_{91}, c_{92}, c_{93}$	264
P_{37}	$c_{10}, c_{15}, c_{16}, c_{18}, c_{19}, c_{20}, c_{21}, c_{55}, c_{91}, c_{92}, c_{93}$	239
P_{38}	$c_{10}, c_{15}, c_{25}, c_{27}, c_{28}, c_{29}, c_{30}, c_{56}, c_{91}, c_{92}, c_{93}$	314

Appendix 2 Parameter values

Table 11 Component-independent parameters

c'	Cost of one order emission	2 €/order
c	Cost of one setup	50 €/setup
ξ_1	Percentage of the sum of inventory costs of components included in a platform	80%
ξ_2	Percentage of the sum of assembling costs of components included in a platform	80%

Table 12 Component-dependent parameters

Component j	$p_j(q_j < 5k)$ (€/unit)	$p_j(q_j = [5k;10k])$ (€/unit)	$p_j(q_j = [10k;15k])$ (€/unit)	$p_j(q_j > 15k)$ (€/unit)	h_j(€/unit*year)	γ_j (€)	τ_j(min)	δ_j(min)
c_1	12	9.6	7.2	4.8	2.4	9.00	1.80	480
c_2	8	6.4	4.8	3.2	1.6	18.00	0.90	480
c_3	9	7.2	5.4	3.6	1.8	9.00	0.90	1440
c_4	9	7.2	5.4	3.6	1.8	18.00	1.80	960
c_5	9	7.2	5.4	3.6	1.8	9.00	1.80	480
c_6	11	8.8	6.6	4.4	2.2	18.00	0.90	960
c_7	9	7.2	5.4	3.6	1.8	27.00	0.90	480
c_8	10	8.0	6.0	4.0	2.0	27.00	1.80	960
c_9	9	7.2	5.4	3.6	1.8	9.00	0.90	480
c_{10}	10	8.0	6.0	4.0	2.0	27.00	1.80	960
c_{11}	11	8.8	6,6	4.4	2.2	27.00	0.90	1440
c_{12}	12	9.6	7.2	4.8	2.4	9.00	0.90	960
c_{13}	9	7.2	5.4	3.6	1.8	9.00	0.90	1440
c_{14}	12	9.6	7.2	4.8	2.4	9.00	0.90	1440
c_{15}	8	6.4	4.8	3.2	1.6	9.00	1.80	960
c_{16}	8	6.4	4.8	3.2	1.6	27.00	1.80	960
c_{17}	9	7.2	5.4	3.6	1.8	18.00	1.80	1440
c_{18}	8	6.4	4.8	3.2	1.6	27.00	1.80	960
c_{19}	12	9.6	7.2	4.8	2.4	9.00	0.90	960
c_{20}	11	8.8	6.6	4.4	2.2	18.00	1.80	960
c_{21}	11	8.8	6.6	4.4	2.2	9.00	1.80	480
c_{22}	10	8.0	6.0	4.0	2.0	27.00	0.90	480
c_{23}	10	8.0	6.0	4.0	2.0	18.00	0.90	480
c_{24}	11	8.8	6.6	4.4	2.2	27.00	1.80	480
c_{25}	8	6.4	4.8	3.2	1.6	9.00	0.90	480
c_{26}	11	8.8	6.6	4.4	2.2	18.00	0.90	960
c_{27}	12	9.6	7.2	4.8	2.4	27.00	0.90	1440
c_{28}	12	9.6	7.2	4.8	2.4	27.00	1.80	480
c_{29}	9	7.2	5.4	3.6	1.8	18.00	1.80	480
c_{30}	12	9.6	7.2	4.8	2.4	18.00	1.80	960
c_{31}	9	7.2	5.4	3.6	1.8	27.00	0.90	1440
c_{32}	9	7.2	5,4	3.6	1.8	18.00	0.90	1440
c_{33}	12	9.6	7,2	4.8	2.4	18.00	0.90	1440
c_{34}	12	9.6	7,2	4.8	2.4	18.00	0.90	480
c_{35}	9	7.2	5,4	3.6	1.8	9.00	1.80	960
c_{36}	9	7.2	5,4	3.6	1.8	27.00	1.80	960
c_{37}	11	8.8	6,6	4.4	2.2	9.00	1.80	480
c_{38}	8	6.4	4,8	3.2	1.6	9.00	1.80	1440
c_{39}	12	9.6	7,2	4.8	2.4	9.00	0.90	960
c_{40}	9	7.2	5,4	3.6	1.8	9.00	0.90	1440
c_{41}	9	7.2	5,4	3.6	1.8	9.00	1.80	1440

Table 12 (continued)

Component j	$p_j(q_j < 5k)$ (€/unit)	$p_j(q_j = [5k;10k])$ (€/unit)	$p_j(q_j = [10k;15k])$ (€/unit)	$p_j(q_j > 15k)$ (€/unit)	h_j(€/unit*year)	γ_j (€)	τ_j(min)	δ_j(min)
c_{42}	8	6.4	4,8	3.2	1.6	27.00	0.90	960
c_{43}	8	6.4	4,8	3.2	1.6	18.00	0.90	1440
c_{44}	11	8.8	6,6	4.4	2.2	9.00	1.80	1440
c_{45}	8	6.4	4,8	3.2	1.6	18.00	0.90	960
c_{46}	12	9.6	7,2	4.8	2.4	18.00	0.90	960
c_{47}	10	8.0	6.0	4.0	2.0	9.00	1.80	960
c_{48}	10	8.0	6.0	4.0	2.0	27.00	0.90	960
c_{49}	8	6.4	4,8	3.2	1.6	27.00	1.80	1440
c_{50}	8	6.4	4,8	3.2	1.6	18.00	1.80	1440
c_{51}	12	9.6	7,2	4.8	2.4	9.00	0.90	480
c_{52}	10	8.0	6.0	4.0	2.0	27.00	1.80	960
c_{53}	8	6.4	4,8	3.2	1.6	9.00	1.80	480
c_{54}	10	8.0	6.0	4.0	2.0	9.00	0.90	960
c_{55}	12	9.6	7,2	4.8	2.4	9.00	0.90	1440
c_{56}	9	7.2	5,4	3.6	1.8	18.00	1.80	480
c_{57}	12	9.6	7,2	4.8	2.4	18.00	1.80	1440
c_{58}	9	7.2	5,4	3.6	1.8	9.00	1.80	960
c_{59}	12	9.6	7,2	4.8	2.4	18.00	0.90	960
c_{60}	10	8.0	6.0	4.0	2.0	18.00	1.80	1440
c_{61}	11	8.8	6,6	4.4	2.2	18.00	1.80	960
c_{62}	11	8.8	6,6	4.4	2.2	9.00	0.90	960
c_{63}	9	7.2	5,4	3.6	1.8	9.00	1.80	1440
c_{64}	11	8.8	6,6	4.4	2.2	18.00	0.90	480
c_{65}	10	8.0	6.0	4.0	2.0	18.00	1.80	960
c_{66}	11	8.8	6,6	4.4	2.2	27.00	0.90	1440
c_{67}	10	8.0	6.0	4.0	2.0	9.00	1.80	960
c_{68}	11	8.8	6,6	4.4	2.2	18.00	0.90	480
c_{69}	9	7.2	5,4	3.6	1.8	9.00	1.80	1440
c_{70}	9	7.2	5,4	3.6	1.8	18.00	0.90	480
c_{71}	11	8.8	6,6	4.4	2.2	9.00	0.90	480
c_{72}	11	8.8	6,6	4.4	2.2	9.00	1.80	480
c_{73}	11	8.8	6,6	4.4	2.2	27.00	1.80	960
c_{74}	8	6.4	4,8	3.2	1.6	27.00	0.90	960
c_{75}	11	8.8	6,6	4.4	2.2	9.00	1.80	960
c_{76}	8	6.4	4,8	3.2	1.6	9.00	1.80	960
c_{77}	12	9.6	7,2	4.8	2.4	27.00	1.80	960
c_{78}	8	6.4	4,8	3.2	1.6	18.00	0.90	480
c_{79}	12	9.6	7,2	4.8	2.4	9.00	1.80	960
c_{80}	8	6.4	4,8	3.2	1.6	27.00	1.80	480
c_{81}	9	7.2	5,4	3.6	1.8	18.00	0.90	960
c_{82}	9	7.2	5,4	3.6	1.8	18.00	0.90	1440
c_{83}	9	7.2	5,4	3.6	1.8	18.00	1.80	1440
c_{84}	10	8.0	6.0	4.0	2.0	9.00	0.90	960
c_{85}	10	8.0	6.0	4.0	2.0	18.00	1.80	960
c_{86}	12	9.6	7,2	4.8	2.4	18.00	0.90	480
c_{87}	12	9.6	7,2	4.8	2.4	27.00	1.80	480
c_{88}	10	8.0	6.0	4.0	2.0	27.00	0.90	1440
c_{89}	8	6.4	4,8	3.2	1.6	18.00	1.80	1440
c_{90}	11	8.8	6,6	4.4	2.2	27.00	1.80	1440
c_{91}	11	8.8	6,6	4.4	2.2	9.00	1.80	960
c_{92}	8	6.4	4,8	3.2	1.6	18.00	0.90	480
c_{93}	9	7.2	5,4	3.6	1.8	27.00	1.80	480

Appendix 3

Table 13 Detailed metrics values at each iteration

k	MTS cost (€)		V (unit)		R (min)		P (€)	
	MTS_p	MTS_c	L	$\lvert C_{MTS} \rvert$	R_{DPD}	R_{MTO}	$Prod_{DPD}$	$Prod_{MTO}$
2	104,657	382,675	1	7	9.131	283.680	182,128	6,503,430
3	239,591	697,859	2	10	24.999	229.398	912,371	5,168,156
4	259,478	739,578	3	11	43.756	203.905	1,065,489	4,945,530
5	285,457	782,330	4	12	61.553	182.735	1,323,160	4,626,500
6	312,338	812,625	5	13	68.769	167.828	1,455,358	4,458,840
7	472,895	1,064,959	6	17	61.097	142.353	1,706,230	3,782,969
8	647,415	1,237,221	7	20	59.182	125.524	2,001,246	3,158,867
9	822,033	1,478,061	8	24	66.874	98.612	2,419,218	2,324,401
10	955,940	1,646,748	9	32	67.836	66.909	2,572,159	1,937,127
11	1,053,387	1,751,762	10	38	68.797	46.243	2,680,083	1,653,631
12	1,189,080	1,846,066	11	44	70.238	34.216	2,836,275	1,373,104
13	1,210,150	1,846,066	12	44	78.896	25.552	3,041,801	1,136,339
14	1,226,642	1,864,565	13	45	85.164	14.957	3,210,344	951,743
15	1,226,642	1,864,565	13	45	85.164	14.957	3,210,344	951,743
16	1,235,782	1,912,059	13	48	76.992	13.526	3,116,212	979,487
17	1,234,208	1,928,671	13	49	68.336	17.864	3,046,306	1,037,086
18	1,233,463	1,949,844	13	50	63.522	19.801	2,959,738	1,103,852
19	1,213,441	1,949,844	13	50	62.549	20.774	2,727,880	1,342,024
20	1,193,174	1,949,844	13	50	61.104	22.227	2,679,714	1,422,890
21	1,193,174	1,949,844	13	50	61.104	22.227	2,679,714	1,422,890
22	1,193,174	1,949,844	13	50	61.104	22.227	2,679,714	1,422,890
23	1,193,174	1,949,844	13	50	61.104	22.227	2,679,714	1,422,890
24	1,193,174	1,949,844	13	50	61.104	22.227	2,679,714	1,422,890
25	1,193,174	1,949,844	13	50	61.104	22.227	2,679,714	1,422,890

Table 14 Metrics values for each *k* and normalized total value

k	MTS cost		V		R		P		Normalized total value
	€	Normalized	Unit	Normalized	Min	Normalized	€	Normalized	
2	487,333	0.000	8	0.000	292.811	1.000	6,685,558	1.000	0.5000
3	937,451	0.167	12	0.073	254.397	0.817	6,080,527	0.769	0.4564
4	999,056	0.190	14	0.109	247.661	0.784	6,011,019	0.743	0.4565
5	1,067,787	0.215	16	0.145	244.287	0.768	5,949,660	0.719	0.4621
6	1,124,963	0.237	18	0.182	236.597	0.732	5,914,198	0.706	0.4639
7	1,537,854	0.390	23	0.273	203.450	0.573	5,489,199	0.544	0.4449
8	1,884,636	0.518	27	0.345	184.706	0.484	5,160,113	0.418	0.4415
9	**2,300,094**	**0.672**	**32**	**0.436**	**165.486**	**0.392**	**4,743,619**	**0.259**	**0.4401**
10	2,602,688	0.785	41	0.600	134.745	0.245	4,509,286	0.170	0.4500
11	2,805,149	0.860	48	0.727	115.040	0.151	4,333,714	0.103	0.4604
12	3,035,146	0.945	55	0.855	104.454	0.101	4,209,379	0.056	0.4890
13	3,056,216	0.953	56	0.873	104.447	0.101	4,178,140	0.044	0.4925
14	3,091,207	0.966	58	0.909	100.122	0.080	4,162,087	0.038	0.4982
15	3,091,207	0.966	58	0.909	100.122	0.080	4,162,087	0.038	0.4982
16	3,147,841	0.987	61	0964	90.518	0.034	4,095,699	0.012	0.4993
17	3,162,880	0.992	62	0.982	86.200	0.014	4,083,392	0.008	0.4989
18	3,183,307	1.000	63	1.000	83.323	0.000	4,063,590	0.000	0.5000
19	3,163,285	0.993	63	1.000	83.324	0.000	4,070,904	0.003	0.4988
20	3,143,018	0.985	63	1.000	83.331	0.000	4,102,604	0.015	0.5000
21	3,143,018	0.985	63	1.000	83.331	0.000	4,102,604	0.015	0.5000
22	3,143,018	0.985	63	1.000	83.331	0.000	4,102,604	0.015	0.5000
23	3,143,018	0.985	63	1.000	83.331	0.000	4,102,604	0.015	0.5000
24	3,143,018	0.985	63	1.000	83.331	0.000	4,102,604	0.015	0.5000
25	3,143,018	0.985	63	1.000	83.331	0.000	4,102,604	0.015	0.5000

Bold represent the main result of the paper

Author contribution All authors contributed to the study conception and design. Material preparation was performed by Alberto Regattieri. Data collection and analysis were performed by Marco Bortolini, Francesca Calabrese, and Francesco Gabriele Galizia. The first draft of the manuscript was written by Francesca Calabrese and Francesco Gabriele Galizia, and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

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Declarations

Competing interest The authors declare no competing interests.

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