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ORIGINAL ARTICLE

Product family formation based on complexity for assembly systems

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Abstract System complexity in development of products for the automated assembly systems causes significant issues, if left unaddressed. Products with similar level of complexity tend to cause similar issues in production. Development of product families based on complexity is an important tool to avoid such issues. This paper presents a novel approach to classify the products based on complexity level for assembly systems. Assembly aspects are then used, which define the complexity levels of individual parts. The individual part complexity level is further merged with the assembly sequence in the form of binary rooted trees. Hierarchical clustering is also employed to find the similarity coefficients of different products. These products are finally segregated based on the generated coefficients. Four products are used as a part of thorough case study to show the working principle of the proposed approach along with the results and associated discussion.

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1 Introduction

It has been an intuitively appealing belief that having a large product variety base will inspire sales for the competitive market and generate additional revenue [1]. Initially, as the products offered become more attractive, the sales are improved. But, with the continuous increase in variety, the law of diminishing returns suggests that the returns do not keep up with the expenses [2]. In such circumstances, the company is obligated to optimize its external variety with respect to the internal complexity based on product differentiation [3]. The design and development of product families is a recognized and effective method to control product variety for a diverse market forte [4, 5]. In addition to helping by reusing proven elements within firm's activities and outputs by balancing cost to the delivered variety ratio, product family formation can also provide an array of benefits including reduction in system complexity and development risks, improvement in the ability to upgrade the products, better responsiveness of the manufacturing processes, and upgraded flexibility [6]. The core intention of any company when investing in product family formation is to provide sufficient variety to its customers while keeping cost to the delivered variety ratio at an acceptable level within their manufacturing capabilities [7].

Owing to these increased variations in products, fluctuating market demands and massive production rates have changed the production paradigms considerably

[8]. Multiple new automated assembly lines have emerged to address these issues by providing rapid change in structure as well as hardware/software [9]. Moreover, customized system configurations for a product family can be generated for a group of products similar to various aspects [10]. This family formation can be based on several criteria such as similarity in shape of components, and assembly of components [11]. In general, all manufacturing systems consist of a diverse combination of resources such as workers, experts, managers, tools, machines, and computers. As time progresses, these systems become more and more complex due to the evolution of parts manufactured, their associated product features, shapes, etc. Modern manufacturing systems, hence, broadly set up their flow lines based on two distinct sequences: operation sequences for part manufacturing and assembly sequences for product formation. Furthermore, due to their highly automated nature, these systems have complex architectures. Many production stages such as material processing, handling, and transportation are integrated to produce complicated and intricate products. As the complexity of these systems increase, disruptive events like machine failures tend to increase as well. However, it is worthy to note that like many other things in life, complexity cannot increase indefinitely. There is always an "upper critical threshold" above which the complexity ceases to increase.

It is imperative to point out here that part/product complexity and system complexity are two separate entities. Complex products generally require a complex setup. It is sometimes possible to manufacture complex products using a relatively simpler system at the cost of system throughput (jobs per hour). Another alternative is to use a more dedicated system at the cost of system flexibility. Existing techniques when considering system complexity do not focus on the complexity of the products and therefore ignore the associated issues (e.g.,

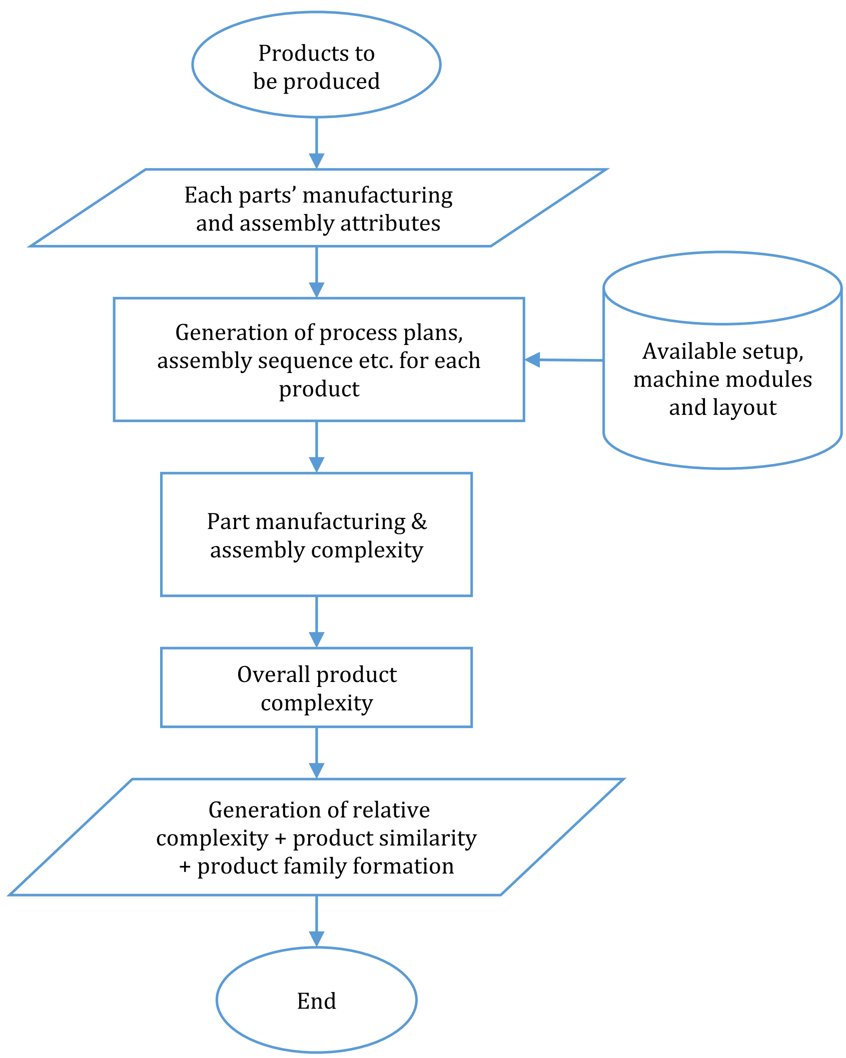


Fig. 1 Flow chart of the proposed methodology

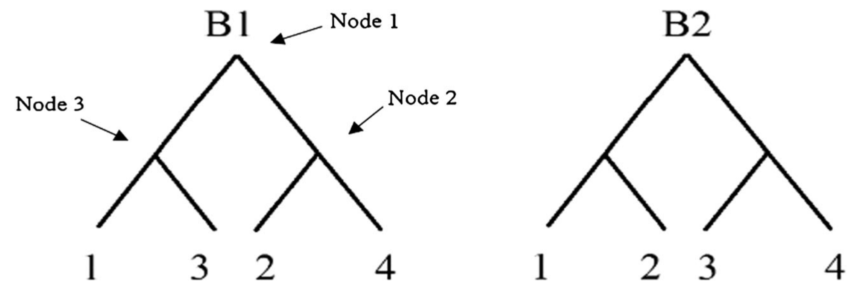


Fig. 2 Binary rooted trees for the example presented

unexpected errors and delays) especially when operations are considered along with assembly sequences as depicted in reconfigurable assembly systems (RAS) [12, 13]. A higher level of consideration towards complexity is recommended to the product family design stage especially when considering more decision variables/parameters spread across product, manufacturing process, and supply chain domains [14].

Therefore, a generic yet extendable methodology is proposed in this paper based on product family formation and examining the complexity of the individual parts as a head start. A complex industrial case study is also presented to test the generic methodology. The rest of the paper is divided as follows: Section 2 presents the literature review in the related area; Section 3 displays the proposed methodology in a detailed and elaborative manner; Section 4 tests the proposed methodology on an industrial case study; Section 5 displays the results along with their discussion; and, finally, Section 6 presents the conclusions drawn.

2 Literature review

The conceptual foundation of cellular manufacturing is based on group technology in which similar parts, based on various criteria, are grouped together [15]. As in many other aspects of reconfigurable manufacturing systems (RMS), the basis of part family formation lies in "cellular manufacturing." In literature, various researchers, based on various criteria, have grouped parts into part families. These include operational similarity, modularity, reusability, and demand.

For RMS, an algorithm was proposed by Abdi and Labib [16] for grouping of part families based on operational similarities using the Jaccard similarity coefficient [17]. Instead of using a single criterion, Galan et al. [18] proposed a systematic approach by incorporating multiple criteria such as modularity, reusability, compatibility, demand, and commonality. A weighting method called analytic hierarchy process (AHP) [19] was also used to agglomerate the five coefficients into a single coefficient after which a clustering technique called average linkage hierarchal clustering [20] was used to form a binary linkage rooted tree known as a dendrogram [21]. Many other clustering techniques [22] also exist for the formation of dendrogram. Using the concept of Jaccard similarity coefficient, a modified clustering algorithm was proposed by Rakesh et al. [23]. Considering two characteristics of RMS: capacity and functionality, a bi-criterion-based evolutionary genetic algorithm for the formation of production families, was developed by Pattanaik and Kumar [24]. Grouping products based on operations sequence is a common grouping criterion in manufacturing/machining applications [25]. Galan et al. proposed that it is important to consider the operation sequence in grouping parts to accommodate many products on the same line and reduce the required reconfigurations [18]. Variety management of products is hence not infrequent in literature [26].

Here, a question may arise. Why product families should be formed at the outset of complexity? It has been

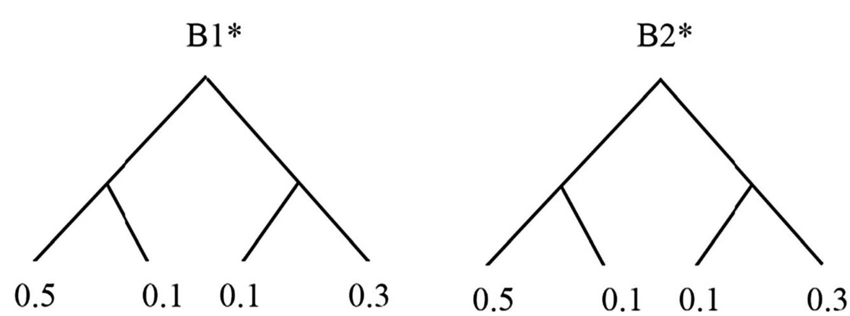
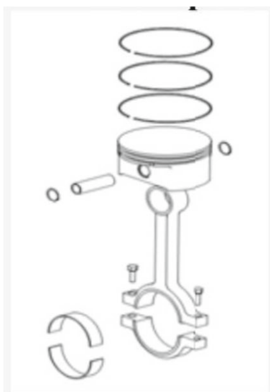
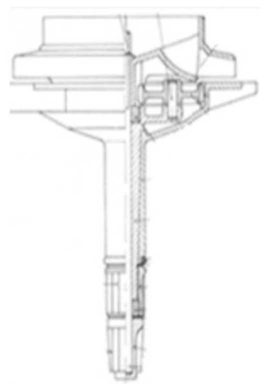
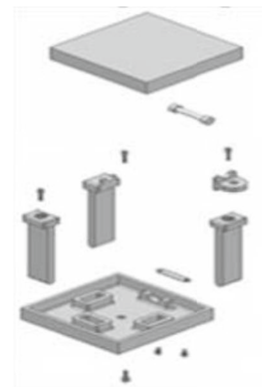


Fig. 3 Modified binary rooted trees for the example presented

Table 1 Comparison of existing complexity values from reference [24] and complexity values using the proposed complexity values

Engine Piston Assembly	Car Fan Motor	Domestic Appliance Drive	3-pin Electric Power Plug
			

Product	Complexity Value (From reference)	No. of Parts	**Normalized complexity** $(\mathbf{x_i})\mathbf{C_{part}}$	System Type	V_i , V_x	**Product complexity** $\boldsymbol{C_{pdt}}$
Engine Piston Assembly	6.38	8	0.7975	Mechanical	0.5, 0.5	0.8988
Car Fan Motor	5.76	9	0.6400	Electrical	0, 0.5	0.3200
Domestic Appliance Drive	5.85	9	0.6500	Electrical	0, 0.5	0.3250
3-pin Electric Power Plug	5.59	7	0.7986	Electrical	0, 0.5	0.3993

proved by researchers in the past that ignoring complexity leads to significant issues in productivity [27]. Hubbert [28] showed that severe problems with the electric systems of Mercedes E-series resulted from the complexity of those systems. Due to similar issues in products in a relatively short span of time, complexity has now become an essential criterion of product development [29]. Therefore, to reduce complexity, one must be able to assess it. One of the more common techniques is the complexity assessment of modular product families [30]. In reconfigurable systems [31], multiple factors contribute towards the overall complexity of the system

Table 2 Similarity matrix for the four products

M	Engine piston assembly	Car fan motor	Domestic appliance drive	3-pin electric power plug
Engine piston assembly	1	0	0.0086	0.1370
Car fan motor	–	1	0.9914	0.8630
Domestic appliance drive	–	–	1	0.8716
3-pin electric power plug	–	–	–	1

[32]. These include operation sequences, part features, and inter-part connectivity. Some of these factors contribute towards the part manufacturing complexity [33], while other factors affect part assembly complexity [34]. Using these factors, the overall complexity of the product can be computed [35] which subsequently helps in the formation of product families.

Consequently, the literature reviewed showed that although several criteria have been used for the formation of product families [18], complexity in conjunction with binary rooted trees has not yet been explored. Using the complexity of the individual parts and the complexity of the overall product, based on the increasing levels of complexity, product families can be formulated. It should be noted that complexity is one of the factors to be considered for product family formation. Moreover, there exists a sufficient gap for working towards product family formation based on complexity while considering other factors such as assembly joints. This will not only help alleviate certain complexity related issues, but will also group together the products with similar levels of complexity while avoiding disturbance in assembly setup, thus untying the complex products from simple ones. The subject paper, therefore, presents an approach to form product families based on complexity as explained above. The methodology for the approach is presented in detail in the following section.

3 Proposed product family formation method for RAS

This section describes the proposed method for product family formation for manufacturing and assembly systems based on complexity. Figure 1 shows the flow chart for the proposed approach. Major part attributes that play a significant role in the assembly of the overall product formation are considered in this approach.

Initially, from the available part data, all the relevant attributes to the designer are considered. These attributes can vary depending upon the industry and the associated products. Some of the possible attributes considered for this work are listed in the Appendix. After that, keeping in view the available setup, machine modules, etc. for the given setup, process plans and possible assembly joints are generated for each product. Next, the individual part and product complexities are tabulated using the existing techniques [34]. Finally, using the proposed methodology, part similarity coefficient, product similarity coefficient, and overall product similarity coefficient are formulated. Details of these are discussed in the subsequent sections.

3.1 Proposed similarity coefficient based on complexity of individual parts

Multiple techniques exist in literature for the computation of complexity of individual parts [36] as well as products [37]. The part complexity is primarily based on attributes such as feature types, number of features, surface finish, size, thickness, and weight. These attributes can be segregated into two main groups in which one contributes towards the part manufacturing complexity while the other caters mainly towards the product assembly complexity. As this research is based on product family formation for assembly systems, the attributes contributing towards product assembly complexity are considered. One of the techniques used for complexity index computation is hence applied using weighted factors on features as shown in Eqs. 1 and 2 [34]:

$$C_h = \frac{\sum_1^j C_{h,f}}{j} \tag{1}$$

where $C_{h,f}$ is the relative handling complexity factor, C_h is the average handling complexity, and j is the number of handling attributes considered.

$$C_i = \frac{\sum_1^k C_{i,f}}{k} \tag{2}$$

where $C_{i,f}$ is the relative insertion complexity factor, C_i is the average insertion complexity, and k is the number of insertion attributes considered. Now, the part complexity (C_{part}) based on these factors is computed as shown in Eq. 3 [34]:

$$C_{part} = \frac{C_h \sum_1^j C_{h,f} + C_i \sum_1^k C_{i,f}}{\sum_1^j C_{h,f} + \sum_1^k C_{i,f}} \tag{3}$$

To find similarity between parts, an upper and lower threshold is required. As complexity cannot increase indefinitely, there is an upper critical threshold above which complexity ceases to increase. Now, there are several options available at this junction. Three of these are as follows:

i. Set an unusually high complexity as the upper critical threshold to avoid possibility of any complexity value coming out greater than the upper threshold. A possible drawback of this approach is that the complexity of the real parts may turn out to be extremely small and incomparable with this number.
ii. Set a complexity value close to real parts' complexity values. This will make the complexity of real parts comparable to the maximum value, but the risk

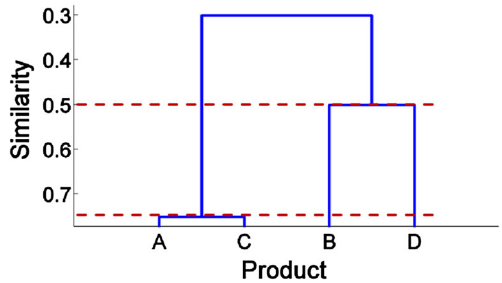


Fig. 4 A sample dendrogram for four products

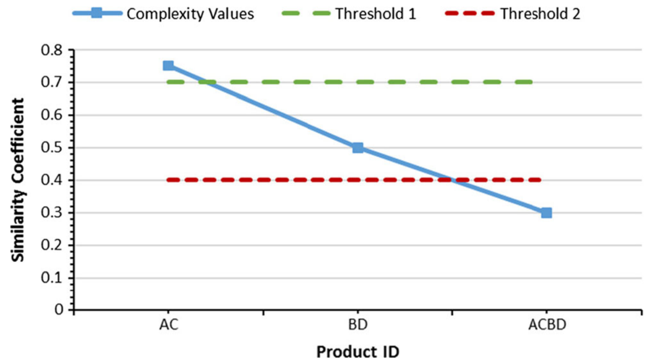


Fig. 6 Proposed similarity graph of dendrogram in Fig. 4

of model failure is much higher since it is possible for parts to have greater complexity than the upper threshold.

iii. Choose upper and lower threshold amongst the complexities of existing parts. This will not only remove the possibility of model failure, but also make a realistic comparison amongst parts.

Based on this, the similarity coefficient (Prt_{ij}) is then computed as shown in Eq. 4:

$$Prt_{ij} = 1 - \frac{\left|c_{part\,i} - c_{part\,j}\right|}{c_{\max} - c_{\min}}, 0 \leq Prt_{ij} \leq 1 \quad (4)$$

where $c_{\max}$ and $c_{\min}$ are the maximum and minimum part complexities. It should be noted that the obtained values are dependent upon the available part complexities. For instance, four parts: a, b, c, and d, have complexity values 0.5, 0.7, 1.3, and 1.4, respectively. As the highest and lowest values are 1.4 and 0.5, therefore, $c_{\max} = 1.4$ and $c_{\min} = 0.5$. Prt_{ab} will be computed as shown below:

$$Prt_{ab} = 1 - \frac{|0.5 - 0.7|}{1.4 - 0.5} = 0.778$$

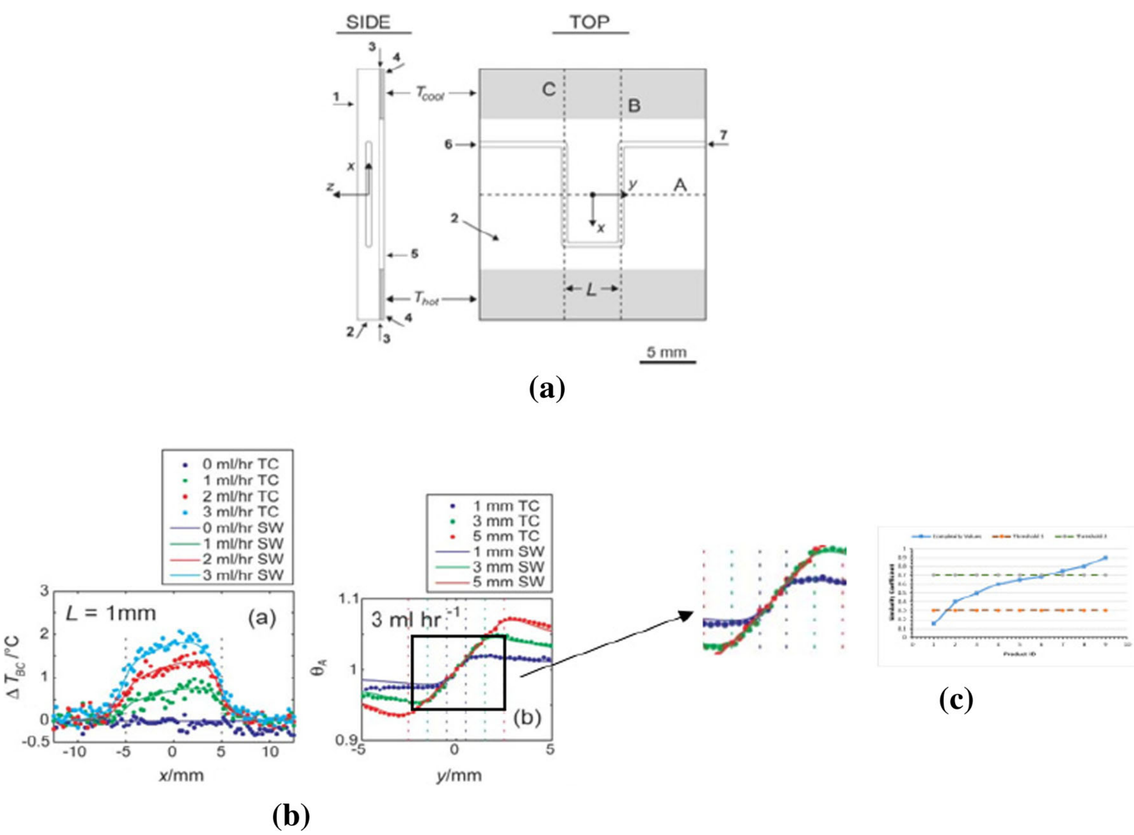


Fig. 5 Using a 2D plot of temperature effects [28] (b) of a U-type pipe bend (a) to form the similarity graph (c)

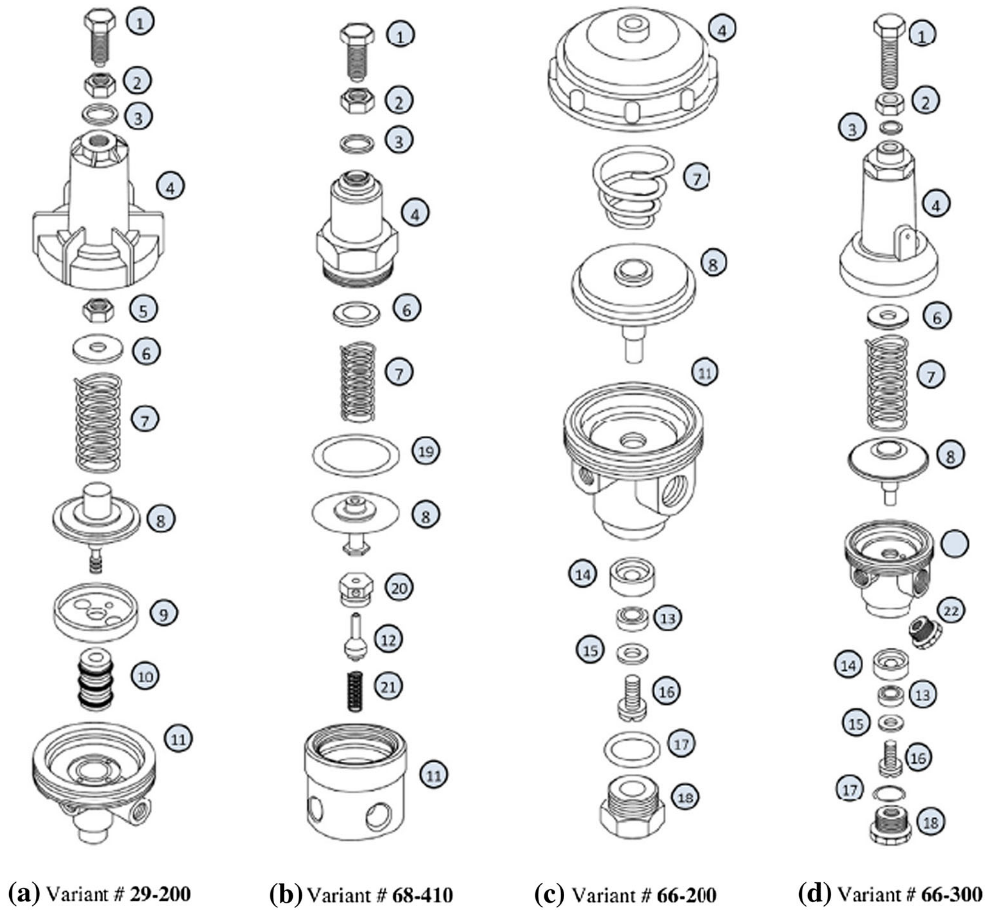


Fig. 7 **a**–**d** Four variants of compressors

3.2 Proposed similarity coefficient based on product assembly sequence

The assembly sequences can be represented as binary rooted trees showing parallel operation capabilities (see Fig. 2). The most commonly used metric for binary trees is the "Robinson-Foulds distance" [38]. This metric can be used to assess the similarity/dissimilarity between two or more assembly sequences. The part manufacturing sequence, however, is usually not represented as binary rooted trees due to the limited parallel operation capabilities.

The two binary trees B_1 and B_2 having m_1 and m_2 number of leaves respectively can be taken as an example to illustrate the principle. The sets, D_1 and D_2, contain $m_1 - 1$ and $m_2 - 1$ number of subsets. Each subset contains the leaves under each node after which Robinson-Foulds distance can then be calculated by Eq. 5 [39]. This is further detailed by Eq. 6.

$$\mathrm{RF}(T1, T2) = \frac{1}{2}|D1 \Delta D2| \tag{5}$$

$$\mathrm{RF}(T1, T2) = \frac{1}{2}|D1 \backslash D2 + D2 \backslash D1| \tag{6}$$

Table 3 Individual part complexity for variant #29–200

Part no.	1	2	3	4	5	6	7	8	9	10	11	Product
C_h	*0.64*	0.64	0.68	0.69	0.64	0.68	0.69	0.75	0.64	0.72	0.72	
$\sum C_h$	*3.30*	3.30	3.70	3.85	3.30	3.70	3.85	4.46	3.30	4.19	4.19	
C_i	*0.68*	0.68	0.71	0.86	0.68	0.71	0.75	0.86	0.71	0.89	0.89	
$\sum C_i$	*2.31*	2.31	2.02	2.96	2.31	2.02	2.84	2.96	2.02	3.19	3.19	$\sum(x_i)C_{\mathrm{part}}$
C_{part}	*0.66*	0.66	0.69	0.76	0.66	0.69	0.72	0.79	0.67	0.79	0.79	0.714

Table 4 Individual part complexity for variant #68–410

Part no.	1	2	3	4	6	7	19	8	20	12	21	11	Product
C_h	0.64	0.64	0.68	0.69	0.68	0.69	0.68	0.75	0.64	0.72	0.69	0.72	
$\sum C_h$	3.30	3.30	3.70	3.85	3.70	3.85	3.70	4.46	3.30	4.19	3.85	4.19	
C_i	0.68	0.68	0.71	0.86	0.71	0.75	0.71	0.86	0.71	0.75	0.75	0.89	
$\sum C_i$	2.31	2.31	2.02	2.96	2.02	2.84	2.02	2.96	2.02	2.22	2.84	3.19	$\sum(x_i)C_{\text{part}}$
C_{part}	0.66	0.66	0.69	0.76	0.69	0.72	0.69	0.79	0.67	0.73	0.72	0.79	0.713

Here, the "Δ" symbol represents symmetric difference whereas the "\" symbol represents the dissimilarity between the subsets, i.e., $D1\backslash D2$ represents number of subsets present in D_1 but not in D_2, and vice versa. For example, the two trees shown in Fig. 2 each have four leaves and three nodes. For the tree B_1, node 3 forms the subset {1, 3}, node 2 has {2, 4}, and node 1 has {1, 3, 2, 4}. Therefore, B_1 has a subset D_1 = {{1, 3}, {2, 4}, {1, 3, 2, 4}}, and similarly, the tree B_2 has D_2 = {{1, 2}, {3, 4}, {1, 2, 3, 4}}. The order of the leaves within the subset is unimportant. Now, $D1\backslash D2$ turns out to be 2 as the subsets {1, 3} and {2, 4} are present in D_1 but not in D_2. Similarly, $D2\backslash D1$ turns out to be 2 as {1, 2} and {3, 4} are present in D_2 but not in D_1. Substituting these values in Eq. 6 results in: RF (B_1, B_2) = 0.5 (2 + 2) = 2.

Dissimilarity between the trees increases as the RF value increases. This RF value represents dissimilarity value between the trees. Now, instead of using numeric values of parts in the assembly sequences, taking the complexity values of the parts and accordingly generating RF value of the trees is proposed in this paper. The complexity values of each part can further be computed by any one of the many techniques already presented in literature [34, 40]. But, for this research, the complexity values are computed using the product assembly complexity [34]. For instance, the complexity values of parts 1, 2, 3, and 4 are 0.5, 0.1, 0.1, and 0.3, respectively. The modified rooted trees are shown in Fig. 3.

The modified D_1* = {{0.5, 0.1, 0.1, 0.3}, {0.5, 0.1}, {0.1, 0.3}} and D_2* = {{0.5, 0.1, 0.1, 0.3}, {0.5, 0.1}, {0.1, 0.3}}. Substituting these new values in Eq. 6, the new RF (B_1*, B_2*) = 0.5 (0 + 0) = 0. To compute the similarity value RF_s, Eqs. 7 and 8 are used.

$$\mathrm{RF}_s = \mathrm{RF}_{\max} - \mathrm{RF} \tag{7}$$

$$\mathrm{RF}_{\max} = \frac{m_1 + m_2}{2} \tag{8}$$

where RF_{max} is the maximum possible RF distance and m_1 and m_2 are the number of leaves of trees 1 and 2, respectively. Normalization of RF distance can be carried out using Eq. 9:

$$\mathrm{RF}_{\mathrm{sn}} = \frac{\mathrm{RF}_{\max} - \mathrm{RF}}{\mathrm{RF}_{\max}} \tag{9}$$

where RF_{sn} is the normalized RF distance. It should be noted that the RF distance cannot be set as the only measure for the calculation of product similarity coefficient. Therefore, after the computation of RF distance, the maximum number of possible assembly joints (PAJ_{max}) are generated using the basic definition (see Eq. 10) along with the number of possible assembly joints (PAJ) for a setup. Number of PAJs for a set of parts for a given products can be computed using Eqs. 10 and 11:

$$\frac{n_i^2 - n_i}{2} \geq \mathrm{PAJ} \geq (n_i - 1) \tag{10}$$

where n_i represents the number of parts of product i, $n_i - 1$ represents the minimum number of joints (PAJ_{min}), and $n_i^2 - n_i$ represents the maximum number of joints (PAJ_{max}) required to form a product.

$$\mathrm{PAJ}_j = \frac{n_i^2 - n_i}{2} - \left(\sum_{m=1}^{F_i} B(m,i,j,k) + \sum_{n=1}^{F_i} C(n,i,j,k) + \sum_{o=1}^{F_i} D(o,i,j,k) \right) \tag{11}$$

Table 5 Individual part complexity for variant #66–200

Part no.	4	7	8	11	14	13	15	16	17	18	Product
C_h	0.69	0.69	0.75	0.72	0.72	0.72	0.68	0.64	0.64	0.72	
$\sum C_h$	3.85	3.85	4.46	4.19	4.19	4.19	3.70	3.30	3.30	4.19	
C_i	0.86	0.75	0.86	0.89	0.83	0.83	0.71	0.68	0.71	0.80	
$\sum C_i$	2.96	2.84	2.96	3.19	2.72	2.72	2.02	2.31	2.02	3.18	$\sum(x_i)C_{\text{part}}$
C_{part}	0.76	0.72	0.79	0.79	0.76	0.76	0.69	0.66	0.67	0.75	0.734

Table 6 Individual part complexity for variant #66–300

Part no.	1	2	3	4	6	7	8	11	22	14	13	15	16	17	18	Product
C_h	0.64	0.64	0.68	0.69	0.68	0.69	0.75	0.72	0.72	0.72	0.72	0.68	0.64	0.64	0.72	
$\sum C_h$	3.30	3.30	3.70	3.85	3.70	3.85	4.46	4.19	4.19	4.19	4.19	3.70	3.30	3.30	4.19	
C_i	0.68	0.68	0.71	0.86	0.71	0.75	0.86	0.89	0.80	0.83	0.83	0.71	0.68	0.71	0.80	
$\sum C_i$	2.31	2.31	2.02	2.96	2.02	2.84	2.96	3.19	3.18	2.72	2.72	2.02	2.31	2.02	3.18	$\sum(x_i)C_{\text{part}}$
C_{part}	0.66	0.66	0.69	0.76	0.69	0.72	0.79	0.79	0.75	0.76	0.76	0.69	0.66	0.67	0.75	0.719

where B represents the number of assembly joint(s) omitted based on logical assembly constraints. C represents the joint(s) omitted based on datum constraints, and D represents joint(s) omitted based on other constraints. It has been observed in the past that only considering RF distance to compute similarity between assembly or part manufacturing sequences has led to significant issues. Products with completely different features ended up with the same RF distance. Therefore, the similarity coefficient (Eqs. 12 and 13) for the whole product is computed by considering RF distance as well as PAJ:

$$Pdt_{ij} = w_a \mathrm{RF}_{\mathrm{sn}} + w_b \left(1 - \left| \frac{\mathrm{PAJ}_i - \mathrm{PAJ}_j}{\mathrm{PAJ}_{\max} - \mathrm{PAJ}_{\min}} \right| \right) \tag{12}$$

$$\forall 0 < w_a < 1, 0 < w_b < 1$$

$$w_a + w_b = 1 \tag{13}$$

where Pdt_{ij} represents the product similarity coefficient and w_a and w_b represent the weightage factors for the product.

3.3 Proposed similarity coefficient based on merged complexity

The similarity coefficient for merged complexity measures the similarity between different products based on their overall complexity. In certain cases, it is possible that two products are similar both at part and product levels, resulting in a similar overall complexity coefficient. It is also possible that the products having completely different parts end up with a marginally different overall complexity coefficient.

On the one hand, products having low complexity within a certain product family result in oversimplification of the processes and in turn result in underutilization of assets. On the other hand, products having high complexity result in overcomplicated processes, thus causing unexpected accidents and delays. It should also be noted that the overall complexity coefficient is based on the complexities of individual parts and not on the part assembly sequence and joints as discussed previously in Section 3.2. Moreover, change in the basic system is yet another aspect to consider. For example, an electronic device with small, thin parts might oddly result similar to a mechanical transmission with heavy, tight-tolerance parts. To overcome this, the complexity computed using the handling, insertion attributes are combined with vector distances, V_i and V_x. The product complexity is then computed using Eq. 14:

Table 7 Part similarity matrix based on complexity for variant #29–200

Part	1	2	3	4	5	6	7	8	9	10	11
1	–	1	*0.75*	0.24	1	0.75	0.54	0	0.93	0	0
2		–	0.75	0.24	1	0.75	0.54	0	0.93	0	0
3			–	0.49	0.75	1	0.79	0.25	0.82	0.25	0.25
4				–	0.24	0.49	0.70	0.77	0.30	0.76	0.76
5					–	0.75	0.54	0	0.93	0	0
6						–	0.79	0.25	0.82	0.25	0.25
7							–	0.47	0.61	0.46	0.46
8								–	0.07	1	1
9									–	0.07	0.07
10										–	1
11											–

Table 8 Part similarity matrix based on complexity for variant #68–410

Part	1	2	3	4	6	7	19	8	20	12	21	11
1	–	1	0.75	0.24	0.75	0.54	0.75	0	0.93	0.44	0.54	0
2		–	0.75	0.24	0.75	0.54	0.75	0	0.93	0.44	0.54	0
3			–	0.49	1	0.79	1	0.25	0.82	0.69	0.79	0.3
4				–	0.49	0.7	0.49	0.77	0.3	0.8	0.7	0.8
6					–	0.79	1	0.25	0.82	0.69	0.79	0.3
7						–	0.79	0.47	0.61	0.9	1	0.5
19							–	0.25	0.82	0.69	0.79	0.3
8								–	0.07	0.56	0.47	1
20									–	0.51	0.61	0.1
12										–	0.9	0.6
21											–	0.5
11												–

Table 9 Part similarity matrix based on complexity for variant #66–200

Part	4	7	8	11	14	13	15	16	17	18
4	–	0.7	0.8	0.8	1	1	0.5	0.2	0.3	1
7		–	0.5	0.5	0.7	0.7	0.8	0.5	0.6	0.7
8			–	1	0.8	0.8	0.2	−0	0.1	0.7
11				–	0.8	0.8	0.2	−0	0.1	0.7
14					–	1	0.5	0.2	0.3	1
13						–	0.5	0.2	0.3	1
15							–	0.7	0.8	0.5
16								–	0.9	0.3
17									–	0.3
18										–

$$C_{pdt} = V_i + V_x \sum_{i=1}^{n} (x_i) C_{part} \tag{14}$$

where C_{pdt} represents the merged product complexity, x_i represents the weightage factor for individual part complexity (C_{part}), and V_i and V_x represent the vector distances for the product systems.

Three systems are considered: electrical, mechanical, and hybrid. For the electrical products, V_i and V_x are set to 0 and 0.5, respectively. Similarly, for the mechanical products, V_i and V_x are set to 0.5 and 0.5, respectively, and for the hybrid systems, V_i and V_x are set to 1 and 1, respectively. This aids in eliminating the possibility of products from different systems having the same complexity. For example, in ref. [36] on page 102 (Tab. 5.2), the complexity values of 6.38, 5.76, 5.85, and 5.59 respectively are chosen for four parts: engine piston assembly, car fan motor, domestic appliance drive, and 3-pin electric power plug. The complete computations for the four parts are shown in Table 1. It is evident that the normalized complexity (column 4) of all systems are significantly close. Now, after the application of Eq. 14, the value of product complexity (column 7) is significantly different for the electrical and mechanical systems. The overall similarity coefficient M_{ij} is calculated as shown in Eq. 15:

$$M_{ij} = 1 - \frac{|c_i - c_j|}{c_{\max} - c_{\min}}, 0 \le S_{ij} \le 1 \tag{15}$$

where c_i and c_j are the overall complexity coefficients of products i and j. Also, c_{max} and c_{min} represent maximum and minimum overall complexity coefficients amongst the given products. Using the modified complexity values (Table 1 column 7), the similarity coefficients based on the four products are shown in Table 2. The mechanical system (engine piston assembly) has significantly low similarity to the electrical system products (Table 2 row 2). The other products show a greater amount of similarity amongst one another.

3.4 Relative clustering

The more common methods used for product family formation include hierarchical clustering [21, 41] and precedence charts [42]. These trees are formed using various optimization techniques including but not limited to genetic algorithms (GAs). The results are then shown using a dendrogram (see Fig. 4) [19, 43].

Table 10 Part similarity matrix based on complexity for variant #66–300

Part	1	2	3	4	6	7	8	11	22	14	13	15	16	17	18
1	–	0.7	0.77	0.76	0.98	0.98	0.49	0.24	0.3	0.97	1	0.7	0.77	0.76	0.98
2		–	0.47	0.46	0.68	0.68	0.79	0.54	0.61	0.73	0.7	1	0.47	0.46	0.68
3			–	1	0.79	0.79	0.25	0	0.07	0.74	0.77	0.47	1	1	0.79
4				–	0.79	0.79	0.25	0	0.07	0.74	0.76	0.46	1	1	0.79
6					–	1	0.46	0.21	0.28	0.95	0.98	0.68	0.79	0.79	1
7						–	0.46	0.21	0.28	0.95	0.98	0.68	0.79	0.79	1
8							–	0.75	0.82	0.51	0.49	0.79	0.25	0.25	0.46
11								–	0.93	0.26	0.24	0.54	0	0	0.21
22									–	0.33	0.3	0.61	0.07	0.07	0.28
14										–	0.97	0.73	0.74	0.74	0.95
13											–	0.7	0.77	0.76	0.98
15												–	0.47	0.46	0.68
16													–	1	0.79
17														–	0.79
18															–

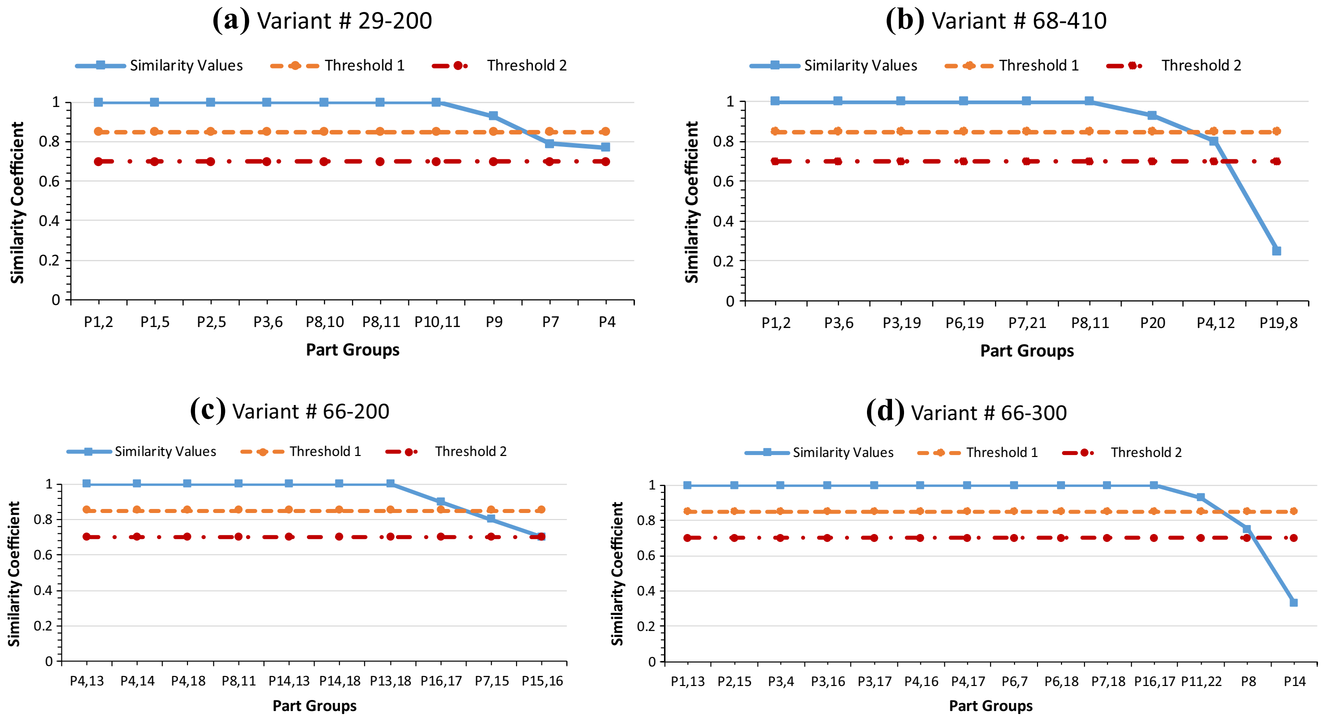
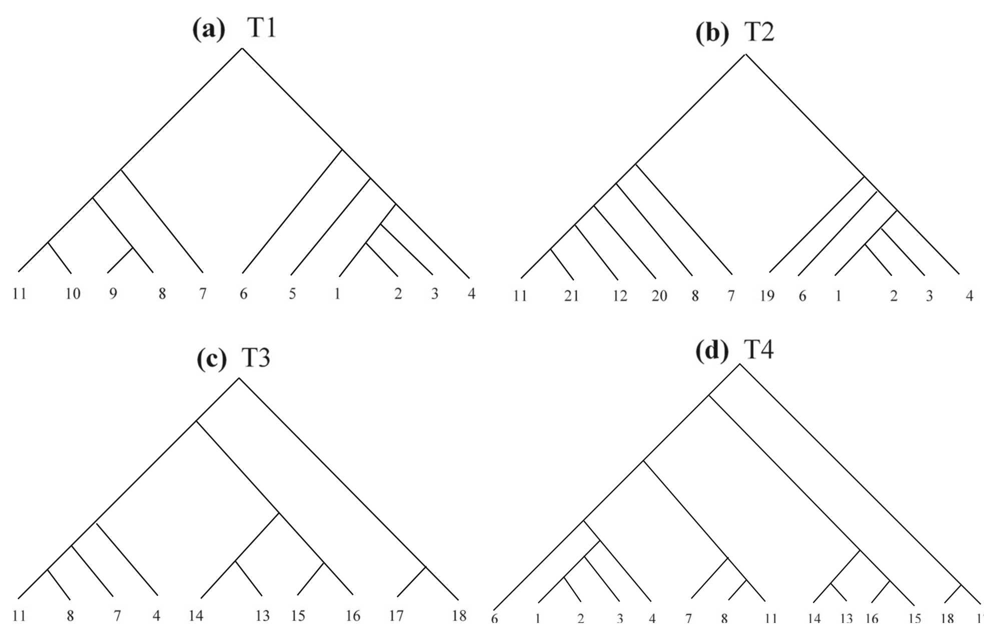


Fig. 8 Binary rooted trees for the four variants as presented in literature [45]. **a** T1: variant #29–200. **b** T2: variant #68–410. **c** T3: variant #66–200. **d** T4: variant #66–300

In the proposed relative clustering technique, when there are more than one similarity coefficients involved, a weighting method is applied to form similarity coefficient matrix (Eqs. 4, 12, and 15). The method is similar to the hierarchical clustering technique used in literature.

Now, instead of using conventional techniques involving dendrogram, similarity graph is developed by studying the 2D plots used to observe the temperature effects of turbulence in fluid mechanics (see Fig. 5) [44]. These curves are used to observe the turbulent behavior of fluids by observing temperature variations under different volumetric flow rates for various pipe configurations. The work presented shows a “U-type” pipe bend in Fig. 5a. Flow is passed through this pipe and turbulence behavior is then observed. The graphs formed for temperature difference between lines B and C (U-type bend) in Fig. 5a is shown in Fig. 5b. ΔT_{BC} represents the surface temperature difference and θ_A

Fig. 9 **a**–**d** Part similarity graphs for the four products



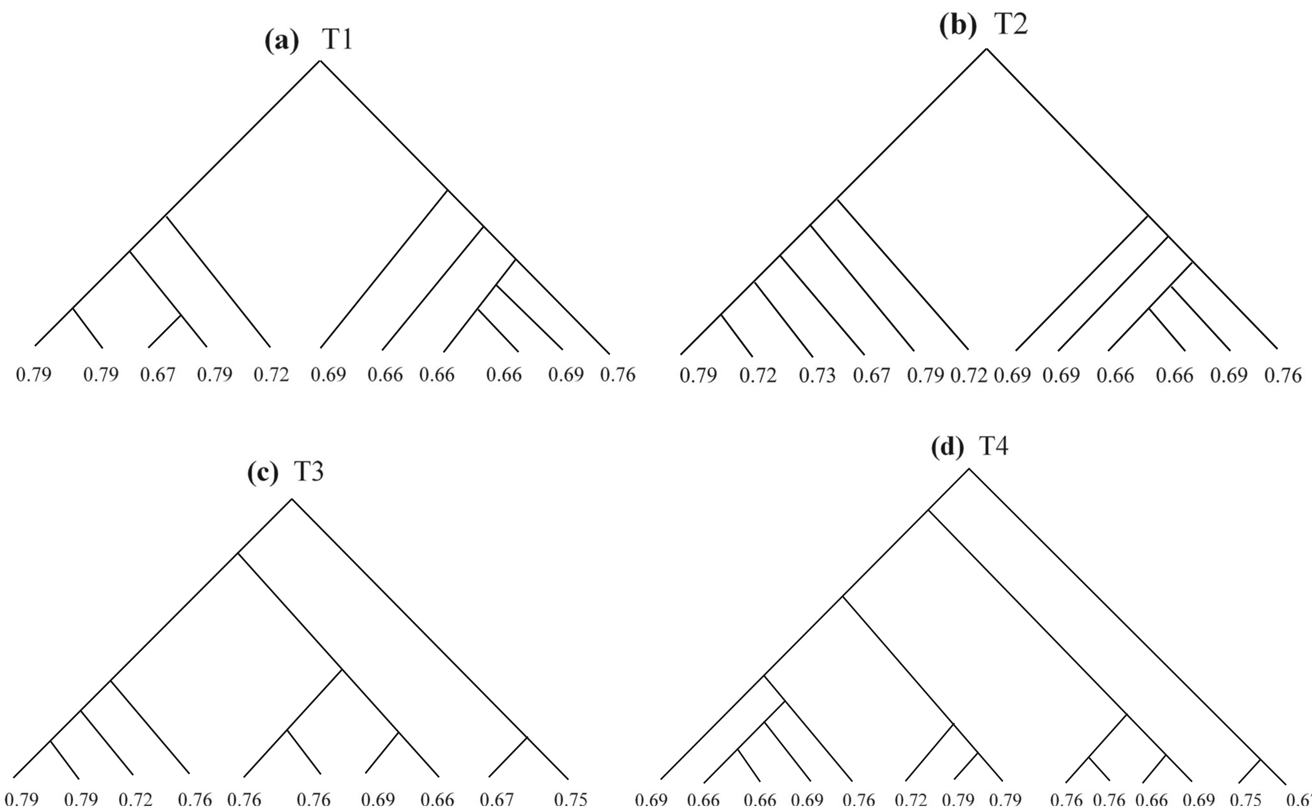


Fig. 10 Modified binary rooted tress for the four variants using part complexity. **a** TM1: variant #29–200. **b** TM2: variant #68–410. **c** TM3: variant #66–200. **d** TM4: variant #66–300

represents normalized temperature difference. If the resulting curves formed under different boundary conditions are closer to the mean, it can be concluded that pipe configuration under the given conditions has less turbulent behavior. Observing the curves for the normalized temperature difference closely, the same concepts can be applied for product family formation (Fig. 5c), i.e., designing a product family dendrogram alternative, a similarity graph based on the same principles. Product similarity values increase gradually towards the higher normalized threshold of 1. This is further elaborated by the example in Fig. 6.

The product identification numbers (IDs) (x-axis) are placed in decremental values of similarity coefficients (y-axis). The products having higher similarity coefficients show greater complexity-based similarity. The products are assigned to the product family based on the similarity coefficients generated. Two thresholds are chosen at similarity value of 0.7 and 0.4. The products having similarity coefficients above upper threshold are more similar than the products between thresholds 1 and 2, and so forth. Applying this concept on the dendrogram of Fig. 4, products *A* and *C* have high similarity coefficient than products *B* and *D*, and all products have overall similarity of 0.30. Comparing the dendrogram with the proposed similarity graph (Fig. 6) and setting threshold as 1 (S1 = 0.7) for the product family formation, the only product family formed is of products *A* and *B*. If threshold is set as 2, two families, *AB* and *CD* can be formed. If, however, the threshold is set even lower (say 0.2), all the products *ABCD* fall into a single product family. The dendrogram shows the similarity coefficient while assembling the parts to obtain the final product, and it does not show the similarity of all the parts. The proposed similarity graph, however, shows all the product combinations with high similarities, graphically. This can help to form product family of more than two parts

Table 11 Similarity index using conventional binary rooted trees (a) and proposed binary rooted trees (b).

Product	(a)				Product	(b)			
	T1	T2	T3	T4		TM1	TM2	TM3	TM4
T1	–	0.29	0.00	0.26	TM1	–	0.29	0.00	0.35
T2		–	0.00	0.33	TM2		–	0.10	0.42
T3			–	0.55	TM3			–	0.55
T4				–	TM4				–

Table 12 PAJs for the four products

Product	a	b	c	d
PAJ	11	11	9	13
PAJ_{max}	55	66	45	91

Table 13 Product similarity coefficients (Pdt) for the four products with $w_a = 0.5$ and $w_b = 0.5$

Product	T1	T2	T3	T4
T1	–	0.64	0.48	0.65
T2		–	0.53	0.69
T3			–	0.73
T4				–

as shown in the results. There are two possible methods of forming thresholds: defining an arithmetic value (e.g., 0.5, 0.7) or setting a given number of products (e.g., maximum product family of four products). Both alternatives are possible and are used in the industry. If on the one hand the number of variable products is a matter of concern, then latter method is applied. If on the other hand the similarity between these products is a matter of concern, then the former method is applied.

There are two main advantages of similarity graph.

1) The proposed similarity graph shows all product families having similarity above that threshold, like a dendrogram. But, in the dendrogram, it is difficult show the number of product groups having similarity above a threshold. This phenomenon is graphically shown in the similarity graph via number of dots above threshold.
2) As the similarity graph shows groups of products as dots instead of lines, the similarity graph is capable of handling more data in a confined space.

Further elaboration of the proposed clustering techniques is carried out in the following sections.

4 Industrial case study

An industrial case study involving four variants of compressors as shown in Fig. 7 is used to demonstrate the formation of product families using the proposed techniques for individual part and overall product complexity. Smaller parts like washers, nuts, and bolts have also been considered. Careful examination shows that most of the parts are designed to fit in only a particular manner. Also, most of them are symmetric. Other factors similarly play an important role in the computation of complexity of these parts, the complete details of which can be found in the Appendix.

Table 14 Product complexities (C_{pdt}) and product similarity coefficient (M) for overall product complexity

Product	T1	T2	T3	T4
C_{pdt}	0.857	0.856	0.867	0.860
M	T1	T2	T3	T4
T1	–	0.92	0.08	0.77
T2		–	0.00	0.69
T3			–	0.31
T4				–

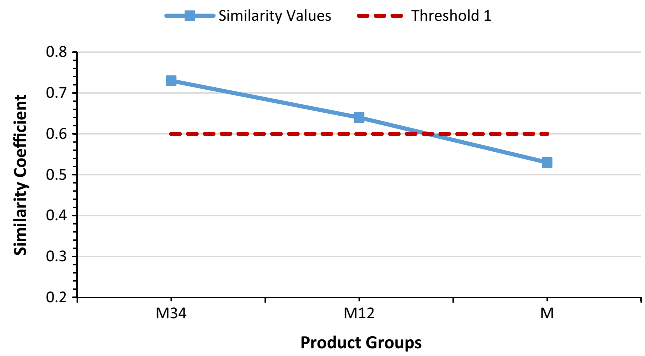


Fig. 11 Product similarity graph for the similarity coefficient Pdt

The proposed model is initially developed in Excel and then imported into MATLAB. $C_{h,f}$ and $C_{i,f}$ for each part of the four products are computed using tables provided in the Appendix [34]. To illustrate the basic computations in the Appendix, handling and insertion complexity values of part 1 of product variant #29–200 (Italicized in Table 3) are as follows:

- Handling: Symmetry = 1, Size = 0.74, Thickness = 0.27, Weight = 0.5, Grasping and manipulation = 0.91, Assistance = 0.34, Nesting and tangling = 0.58, Optical magnification = 0.8.
  Sum of these factors = 5.14.
  Number of factors = 8.
  $C_h = 5.14/8 = 0.64$.
  Sum $\times C_h = \sum C_h = 5.14 \times 0.64 = 3.30$
- Insertion: Holding down = 0.54, Alignment = 1, Insertion resistance = 0.87, Accessibility and vision = 0.57, Mechanical fastening = 0.42.

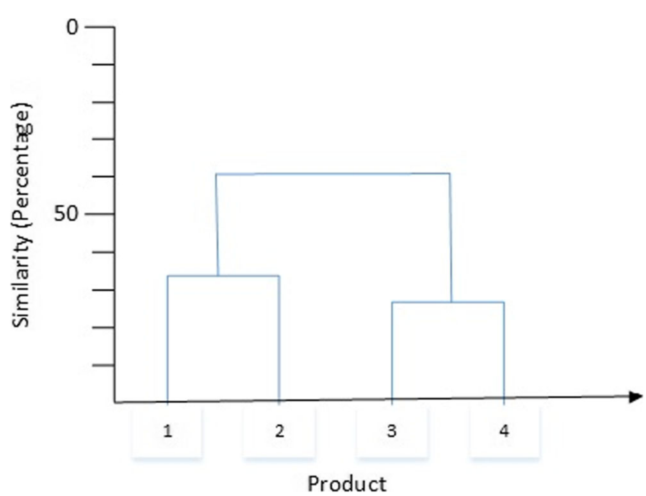


Fig. 12 Dendrogram for similarity coefficient Pdt

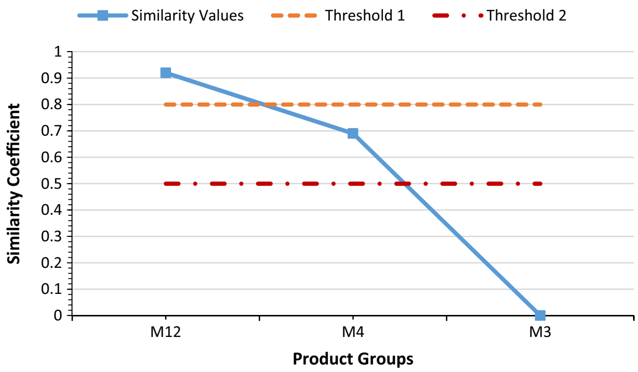


Fig. 13 Product similarity graph for the similarity coefficient M

Sum of these factors = 3.40.
Number of factors = 5.
$C_i = 3.40/5 = 0.68.$
$\text{Sum} \times C_i = \sum C_i = 3.40 \times 0.68 = 2.31$

$$C_{part}: \frac{C_h \sum_1^j C_{h,f} + C_i \sum_1^k C_{i,f}}{\sum_1^j C_{h,f} + \sum_1^k C_{i,f}} = \frac{0.64 \times 3.30 + 0.68 \times 2.31}{3.30 + 2.31} = 0.66$$

C_h and C_i are computed using Eqs. 1 and 2. C_{part} is then computed using Eq. 3. The results of the remaining parts for the variant #29–200, 68–410, 66–200, and 66–300 are then shown in Tables 3, 4, 5, and 6, respectively. After computing the individual C_{part}, similarity coefficients for the parts are calculated using Eq. 5. The values are shown in Tables 7, 8, 9, and 10. These values represent the similarity between individual parts within a single product. For example, similarity value of 0.75 (Italicized in Table 7) shows that parts 1 and 3 have a 75% similarity. Once the similarity matrices have been formed, binary rooted trees of the four variants (Fig. 8) were developed based on their part joining precedence to form the product. After that, the modified binary rooted trees were formed by replacing the part numbers with the complexity values (C_{part}). Further work using these graphs is detailed in results.

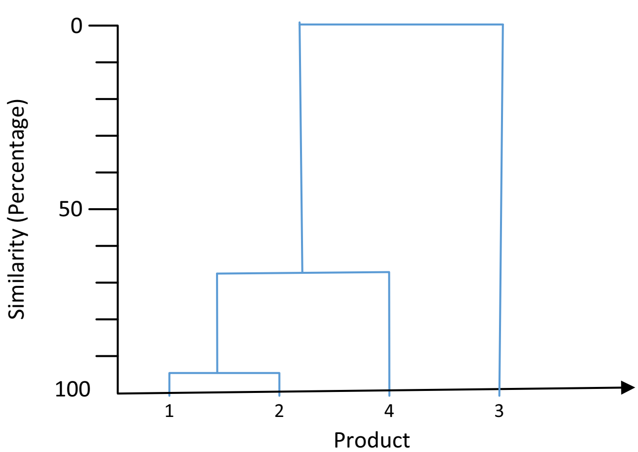


Fig. 14 Dendrogram for the similarity coefficient M

5 Results

The part similarity graphs are obtained by applying the proposed model on four products (Fig. 7) using the complexity coefficients as a measure from Tables 5, 6, 7, and 8 (see Fig. 8). Threshold 1 and threshold 2 are set to 0.85 and 0.70 respectively. These threshold values were decided based on the outputs from part similarity matrices and are subject to change based on the specific part family outputs. Based on these values, considering threshold 1, part families formed are (1,2), (1,5), (2,5), (3,6), (8,10), (8,11), and (10,11) as binary paired groups (because they all have a similarity value 1), or a complete family of parts 1, 2, 3, 5, 6, 8, 9, 10, and 11 for the variant #29–200. So, by the proposed model, more than two parts (nine in this case) can be grouped in to a single part family. If threshold 2 is considered, then 7 and 4 are also included in the part family. The part families for the remaining variants can be observed from Fig. 8b–d as well.

Moving on from part family towards product family, as discussed in the previous section, for the four products used as case study in this paper, the binary rooted trees were developed by multiple authors previously [45–47] as shown in Fig. 9 [48]. The modified binary trees were then developed using the binary rooted trees, and the complexity values are presented in Tables 3, 4, 5, and 6 (see Fig. 10). Utilizing Eqs. 5–9, the normalized RF distances for the four products were developed and are shown in Table 11.

A comparison is further shown in Table 11 between the binary rooted trees (conventional) and modified binary rooted trees (proposed). It should be noted that the results shown for the modified binary rooted trees are completed after applying the PAJs on the trees (see Table 12). As discussed in the previous sections, the normalized RF distance cannot be set as the only measure for the computation of similarity index. Therefore, using the simulated values of possible assembly joints (Table 12) and applying Eqs. 12 and 13, the product similarity coefficients (Pdt) are shown in Table 13. If the data of Table 13 is compared with that of Table 11 (a), significant differences can be observed. It should also be noted that the two weightages w_a and w_b (see Eq. 9) are set to 0.5. These are subject to change.

Finally, for the overall product similarity coefficient (M_{ij}), the overall part complexity coefficient is required. This was computed and is shown in the last columns of Tables 3, 4, 5, and 6. As all four are mechanical parts, therefore V_i and V_x are both set to 0.5. Applying these values to Eq. 14 reveals the values of C_{pdt} which are then applied to Eq. 15 to find M_{ij} (tabulated in Table 14).

The product similarity graph and the dendrogram for the product similarity coefficient "Pdt" are shown in Figs. 11 and 12 and for the product similarity coefficient "M" are shown in Figs. 13 and 14, respectively. It is evident that the families formed are completely different irrespective of the threshold set for the products. Two factors cause this phenomenon: one, the RF distance and PAJs are considered in the RF based complexity and, two, in the similarity coefficient M, the overall product complexity is catered based on system-based vectors. Hence, the formation of different product families is justified. It is indeed possible in certain cases to arrive at the same product families using *M* and *Pdt*. But, that is conditional to the fact that the assembly sequences, joints, and their variations do not play any role in the complexity of the products.

6 Conclusion

A model for the product family formation based on complexity was presented in this paper. The model is initially focused on part complexity but is specifically designed for assembly system complexity. The complexity attributes considered are assembly-focused. The hierarchical groups between different parts within the products were also considered. The model is novel in multiple ways. Firstly, RF distance has not been used to compute complexity previously. Also, the addition of possible assembly joints' coefficients (see Table 13) allows the model further depth. Moreover, there is a strong possibility that two products varying in all major aspects may end up with the same complexity-based RF distance. The PAJs allowed the model another basis for differentiation. Furthermore, the addition of system-based vectors allowed to further distinguish between products. With the help of these contributions, the odd chance of a mechanical- and electrical-based product ending up with very high similarity coefficients is diminished. Another novelty is the proposed similarity graph. This can be used as an alternate to the dendrogram allowing the user much more data in a confined space and allows the user to set quantity-based thresholds.

The developed model for the formation of product families is part focused, but as a future work, it can be modified to accommodate a wide range of products. For instance, if the parts are being assembled in parallel assembly lines (based on the parallel capability of the machine), Eq. 8 can be modified to accommodate this change. In addition, since the model starts off from the complexity of individual parts, it can be extended to manufacturing as well, if the part complexity is modified to accommodate the part manufacturing. However, multiple changes may still be required to fully incorporate manufacturing into the model. Weighted method was used to incorporate the assembly joints into the RF distance and complexity-based similarity coefficients. This is a very common method to incorporate multiple factors. Another possible method is multi-level integration.

The main technique to define and carry out the similarity calculations was integer programming. Some of the main reasons include its conventional ease of use, its ability to define and simulate the similarity matrices with ease, and its reputation in previous research.

Finally, the model was compared with the previous work on complexity. The complexity values of the previous authors for products from different systems were very close to one another. After the application of the proposed complexity coefficient, the results were significantly different. Similarity coefficient was then computed, and the results were displayed using both dendrogram and similarity graphs.

Nomenclature

$C_{h,f}$	Relative handling complexity factor
C_h	Average handling complexity factor
$C_{i,f}$	Relative insertion complexity factor
C_i	Average insertion complexity factor
C_{part}	Individual part complexity
Prt_{ij}	Similarity coefficient between parts *i* and *j*
RF	Robinson-Foulds distance
RF_{sn}	Normalized Robinson-Foulds distance
$RF_{\max}$	Maximum Robinson-Foulds distance
$m_1, m_2 \ldots m_n$	Number of leaves for the binary rooted trees
$D_1, D_2 \ldots D_N$	Sets containing part groups based on binary rooted trees
PAJ	Number of possible assembly joints
$w_a, w_b \ldots w_n$	Weightage factors
Pdt_{ij}	Similarity coefficient between products *i* and *j*
M_{ij}	Overall product similarity coefficient between products *i* and *j*

Appendix

Table 15 Some of the possible attributes considered for this work

Group	Attribute	Description	Average complexity factor, C_f
Handling attributes	Symmetry ($\alpha + \beta$)	$\alpha + \beta < 360$	0.70
		$360 \leq \alpha + \beta < 540$	0.84
		$540 \leq \alpha + \beta < 720$	0.94
		$\alpha + \beta = 720$	1.00
	Size	> 15 mm	0.74
		6 mm < size ≤ 15 mm	0.81
		< 6 mm	1
	Thickness	> 2 mm	0.27
		0.25 mm < size ≤ 2 mm	0.5
		≤ 0.25 mm	1
	Weight	< 10 lb (light)	0.5
		> 10 lb	1
	Grasping and manipulation	Easy to grasp and manipulate	0.91
		Not easy to grasp and manipulate	1
	Assistance	Using one hand	0.34
		Using one hand with grasping aids	1
		Using two hands	0.75
		Using two hands with assistance	0.57
	Nesting and tangling	Parts do not severely nest or tangle and are not flexible.	0.58
		Parts severely nest or tangle or are flexible.	1
	Optical magnification	Not necessary	0.8
		Necessary	1
Insertion attributes	Holding down	Not required	0.54
		Required	1
	Alignment	Easy to align or position	0.86
		Not easy to align or position	1
	Insertion resistance	No resistance	0.87
		Resistance to insertion	1
	Accessibility and vision	No restrictions	0.57
		Obstructed access or restricted vision	0.81
		Obstructed access and restricted vision	1
	Mechanical Fastening processes	Bending	0.34
		Riveting	0.58
		Screw tightening	0.42
		Bulk plastic deformation	1
	Non-Mech. fastening processes	No additional material required	0.58
		Soldering processes	0.67
		Chemical processes	1
	Non-fastening processes	Manipulation of parts or sub-assemblies (fitting or adjusting of parts…)	0.75
		Other processes (liquid insertion…)	1

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