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COORDINATION OF PRODUCT AND PROCESS VARIETY IN MASS CUSTOMIZATION WITH DATA MINING APPROACH

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Abstract: Mass customization results in proliferation of products and the corresponding routings. It thus necessitates a coordination issue regarding product and process variety. In addition to coping with product and process variety individually, the linchpin of variety coordination lies in the mapping relationships between the product and process domains. Due to the unstructured nature inherent in product and process variety mapping, it is difficult to coordinate product differentiation and process variation while leveraging product families upon consistent process platforms. Taking advantage of knowledge discovery from historical data, this paper proposes a systematic data mining approach to coordinating product and process variety. In the approach, product and process variety are handled in their individual domains by clustering products and routings into families. The mapping relationships in between are addressed through association rule mining. The potential of the proposed approach is illustrated through a case study of vibration motor mass customization. The performance of the data mining approach is evaluated based on sensitivity analysis.

1. INTRODUCTION

Manufacturers are faced with the design and production requirements from a high number of customer that introduces product variety. However, manufacturers can gain more competitive edges through offering a variety of customized products. On the other hand, overpursuit of individualized products often results in uncontrolled product proliferation, which not only confuses customers, but also increases product development cost and lead time. Product variety in the design domain originates from design specification changes to fulfill diverse customer needs. To produce product variety, an increased number of product changeovers in the production processes or routings (referred to as process variety), such as the changes of machines, tools, fixtures, setups, and production line layout, are observed on the shop floor. Unlike product variety, process variety in the process domain is always the source of prolonged production lead times, increased production cost, and deteriorated product quality due to the enormous variations in production. In manufacturing practice, production related to process variety are caused by design specification changes in product variety.

Affecting both the delivery of customized products and the achievement of low costs and short lead times, product and process variety are the major concerns in mass customization per se. Hence, the success of mass customization raises the importance in managing product and process variety and thus design and production. Taking into account the connections between product variety and process variety, the expected variety management can not only deal with two kinds of variety in their individual domains but it also addresses the correspondence in between these varieties. As a matter of fact, these correspondences are very important for manufacturers to make right planning decision so as to minimize production changeovers, and thus maintain a stable production.

In tackling product variety, a number of researchers have reported their approaches and methodologies, e.g., Ulrich (1995), Fisher et al., (1999), Meyer and Lehnerd (1997). Similarly, authors have addressed process variety management (Berry and Cooper, 1999; Buzacott, 1999; Lee and Tang, 1998). All the above work, handle product and process variety separately in their own domains (i.e., product variety in the design domain and process variety in the process domain) without considering the correlations and impacts in between. Although some work, e.g., (Jiao et al., 2005a; 2005b), proposed integrated framework to address product and process integration, the technical details in terms of how to achieve the integration were not provided.

Towards the end, this paper proposed a data mining approach to coordinating product and process variety for the success of mass customization. In the approach not only product and process variety are managed in their respective design and process domain, but also the mapping relationships in between are addressed.

2. OVERVIEW OF VARIETY COORDINATION APPROACH

Current design practice, e.g., variant design, enables a number of customized products to possess similar and/or same features, systems and components. These tailored products are designed to target customers in the same market segments and perform the same basic functionalities. Accordingly, different families, each of which is a collection of similar products can be distinguished in a manufacturer's databases. The basic functionalities imply a common product structure that is assumed by all variants in the family (Du et al., 2001). Thus, managing product variety involves the clustering of similar products into families and the construction of the common product structure that is same to all product variants in the family.

In spite of production variations in process variety, product similarity and commonality renders similar or exactly the same process elements in their routings. As a consequence, routings of products in a family are similar or same to one another. Similar to the generic product structure of a product family, a generic process structure exists and is assumed by all routings of products in the family. Process variety management encompasses the clustering of routings into families and the construction of generic process structures for each process family.

Because products are built from terms, may they be parts or assemblies, the tackling of mapping relationships in between product and process variety is carried out on the basis of item families. To discover the hidden yet potential associations behind enormous product and process data, association rule mining technique is adopted. Each time, the mining technique is applied to an item family and the discovered association rules are applicable to this family only. Figure 1 gives an overview of the proposed approach for coordinating product and process variety.

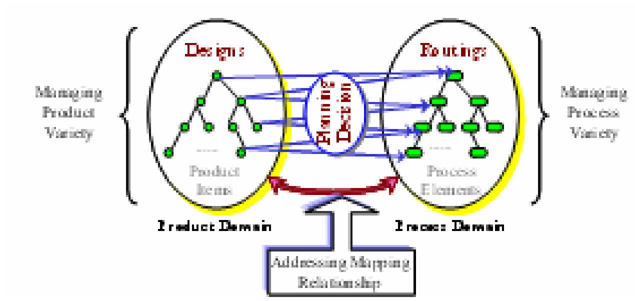

Figure 1. Variety Coordination in the Proposed Approach

3. COORDINATING PRODUCT AND PROCESS VARIETY

3.1 Managing Product Variety

In product variety management, three steps are involved to cluster given products into families and establish the corresponding generic product structures as well.

Step 1: Product similarity measure. Product similarity indicates the proximity of products: how similar the products are. Allocating products into their families should be based on the similarity of products. In order to measure product similarity, each product is decomposed into a number of assemblies and parts. Product similarity is thus measured based on the similarity of their child components. Since parts are located at the lowest levels of the product structure and cannot be decomposed further, measuring child component similarity begins with parts. The text mining procedure in Jiao et al. (2005b) is adopted to measure part similarity. The results are a number of part similarity matrices, each of which documents the pairwise similarity of parts of same types. The part similarity matrices are used for further computing assembly (including product) similarity. Assembly similarity is calculated based on the similarity of their child components at the immediate lower level. Thus, to reduce calculation complexity, assembly similarity measure is performed from the lower level of a product tree structure. In other words, the calculation starts from such assemblies that are parents of parts whose similarity measure has been obtained. Then assembly similarity measure is calculated in the higher levels progressively till the final product at the top level. The weighted bipartite matching method introduced by Romanowski and Nagi (2004) can be used to calculate assembly similarity. The final calculation results are a product similarity matrix, a number of assembly families and the corresponding assembly similarity matrices.

Step 2: Product family clustering. Based on the obtained product similarity matrix, similar products, i.e., products have higher similarity values, are clustered into same families, dissimilar products into different families. The fuzzy clustering approach discussed in (Jiao et al., 2005b) can be used to cluster products into families. The clustering results are a number of product families along with their members.

Step 3: Generic product structure construction. Using the concept of generic representation and the indirect identification of items (Hegge, 1992), all specific product data, including end products, assemblies, parts, design parameters, and value instances that belong to the same family, are incorporated into a single structure, i.e., the generic product structure. The tree unification algorithm in (Romanowski and Nagi, 2004) can be used to generate generic product structures for identified product families. Besides the generic structure, the unification result also includes a constraint set, which holds the alternate parent-child pairs together with their occurrence frequencies.

3.2 Managing Process Variety

Managing process variety can be achieved by clustering routings into families and constructing the underlying generic process structures.

Step 1: Process family grouping. Rather than measure routing similarity and then clustering routings based on the similarity result, routings can be distributed directly into families by referring to corresponding product families, that is, routings of products in a family are grouped together to form the process family.

Step 2: Generic process structure construction. Similar to a generic product structure, a generic process structure underlies all routings for producing a product family. Each node in it denotes a generic operation and is described by other generic process elements, such as a generic machine and generic fixtures. The instantiation of these generic process elements together with some necessary modifications leads to a particular routing, such that changeovers to existing processes on the shop floor are as fewer as possible line. To establish generic process structures, the approach in (Jiao et al., 2005b) can be used.

3.3 Mining Associations between Product and Process Variety

While product and process variety management focuses on handling changes, variations and modifications in the product and process domains individually, correspondences in between have not been addressed. Association rule mining techniques can be used to tackle the correspondences through mining the implicit yet potential associations between product and process variety. Unlike a transaction database (*TDB*) in the traditional association rule mining contains items belonging to the same domain, items in a *TDB* in the proposed approach are from two different domains (i.e., the product and process domains), in that the intention of this research is to discover the associations between the two domains rather than interrelations in any single one domain. A transaction (*T*) in the *TDB* of an item family corresponds to a particular item variant, may it be a part or an assembly. Because parts and assemblies are described differently, i.e., design parameter value pairs for parts and child items for assemblies, the association rule mining for parts and assemblies is approached differently with the same procedure discussed below.

Step 1: Data preprocessing. This step attempts to preprocess raw data into the proper format so that association rule mining techniques can work on. The raw data should be processed based on the identified product and process families and each *TDB* is prepared for each item family. In a *TDB* for a family of a type P part, a *T* relates to a part variant, $p_i^* | \forall i = 1,\cdots,N$. The total number of *Ts* in the *TDB* is thus the same as that of part variants in the family. The product related items in a T_i are a list of design parameter values pairs of the associated p_i^*, i.e., $T_i \,|\forall i = 1,\cdots,N \sim \{P_s V_t\}_{m\times n}$, where $P_s V_t$ represents the t-th value instance of the s-th design parameter assumed by p_i^*, *m* is the total number of parameters in the family P, *n* is the total number of possible value instances of the s-th parameter with $n \le N$. The process data of a part include the set of operations (Os), machines (Ms), tools (Ts), and fixtures (Fs). Therefore, the process related items in a T_i are formulated as: $T_i \,|\forall i = 1,\cdots,N \sim \{O_s\}_p \times \{M_s\}_p \times \{T_s\}_p \times \{F_s\}_p$, where p is the total number of operations for producing p_i^*.

An assembly is formed by joining several child items, either of parts, assemblies, or the combination of two. An assembly variant, $a_i^* | \forall i = 1,\cdots,M$, of type A differs from one another in their unique configuration of child items. Thus, product related items in a T_i in the *TDB* of the family A relates to child items of the corresponding assembly variant $a_i^*|\forall i = 1,\cdots,M$, i.e., $T_i\ |\forall i = 1,\cdots,M \sim \{CI_xV_y\}_{E\times F}$, where CI_xV_y represents the y-th variant of the x-th type child item, *E* is the total number of child item types in the family A, and *F* is the total number of item variants of the x-th type. The process related item of T_i are formulated as $T_i\ |\forall i = 1,\cdots,M \sim \{O_t\}_q \times \{M_t\}_q \times \{T_t\}_q \times \{F_t\}_q$, where q is the total number of assembly operations for producing $a_i^*|\forall i = 1,\cdots,M$. Table 1 gives an illustration of *TDBs* for a part family and an assembly family, respectively.

Table 1. *TDBs* of Item families

(a) TDB of a part family			***(b) TDB of an assembly family***		
ID	**Trans-action**	**Items (product; process)**	**ID**	**Trans-action**	**Items (product; process)**
T1	P_1	$\{P_1V_1, P_2V_3, P_3V_1, P_4V_6; OT_1, M_1, T_1, F_1, OT_2, M_2, T_2, F_2, OT_3, M_3, T_3, F_3\}$	T1	A_1	$\{CI_1V_2, CI_3V_1, CI_4V_2, CI_6V_1; OT_1, M_1, T_1, F_1, OT_2, M_2, T_2\}$
T2	P_2	$\{P_1V_2, P_2V_1, P_3V_1, P_4V_6; OT_1, M_1, T_1, F_1, OT_2, M_2, T_2, F_2, OT_4, M_4, T_4, F_4\}$	T2	A_2	$\{CI_1V_2, CI_2V_2, CI_3V_1, CI_4V_3; OT_1, M_1, T_1, F_1, OT_2, M_2, T_2, F_2, OT_3, M_3, T_3, F_3\}$
T3	P_3	$\{P_1V_1, P_2V_3, P_3V_2, P_4V_2; OT_1, M_1, T_1, F_1, OT_3, M_3, T_3, F_3\}$	T3	A_3	$\{CI_1V_1, CI_2V_2, CI_6V_1; OT_1, M_1, T_1, F_1, OT_3, M_3, T_3, F_3\}$
T4	P_4	$\{P_1V_4, P_2V_3, P_3V_4, P_4V_1; OT_2, M_2, T_2, F, OT_3, M_3, T_3, F_3\}$	T4	A_4	$\{CI_1V_4, CI_3V_1, CI_4V_4; OT_1, M_1, T_1, F_1, OT_2, M_2, T_2\}$

Step 2: Mining association rules. The association rule mining technique is applied to the *TDB*s prepared in the above step to uncover associations. The inclusion of data from two domains in a *TDB* leads to the below general form of association rules for an item family: $A \Rightarrow B\ [Support = s\%,\ Confidence = c\%]$, where in mining part *TDBs*, $A = \{P_iV_j\}_{x\times y}|\forall i = 1,\cdots,x \le m,\ j = 1,\cdots,y \le n$, in mining assembly *TDBs*, $A = \{CI_iV_j\}_{x\times y}|\forall i = 1,\cdots,x \le E,\ j = 1,\cdots,y \le F$, in both cases, $B = \{O_i\}_a \wedge \{M_j\}_b \wedge \{T_s\}_c \wedge \{F_t\}_d|\forall i = 1,\cdots,a,\ j = 1,\cdots,b, s = 1,\cdots,c, t = 1,\cdots,d$, the values of *a*, *b*, *c* and *d* may or may not be the same, and s% and c% refer to the support and confidence for the rule, respectively. Similar to the traditional association rule mining, s% and c% are calculated as $s\% = \frac{Count(A \wedge B)}{Count(TDB)} \times 100\%$ and $c\% = \frac{Count(A \wedge B)}{Count(A)} \times 100\%$, where $Count(A \wedge B)$ is the number of *Ts* in the *TDB* of the item family that contain all product related items in A and all process related items in B, $Count(TDB)$ is the total number of *Ts* in the *TDB*, $Count(A)$ is the number of *Ts* in the *TDB* that contain all product related items in A.. As mentioned earlier, each T_i in the *TDB* represents a specific item variant in the item family, $Count(TDB)$ equals to the number of item variants in the family. The rule indicates that the occurrence of product related data in A (i.e., design parameter value pairs for parts and child items for assemblies) will most likely (at an s% support and a c% confidence) relate to that of process elements in B. Among many association rule frameworks and algorithms, Apriori (Agrawal and Srikand, 1994) can be adopted owing to its simplicity and strength.

4. CASE STUDY

The proposed variety coordination approach has been tested in an electronics company that produces vibration motors for hand phones. Figure 2 shows a vibration motor, its major assemblies and the product structure.

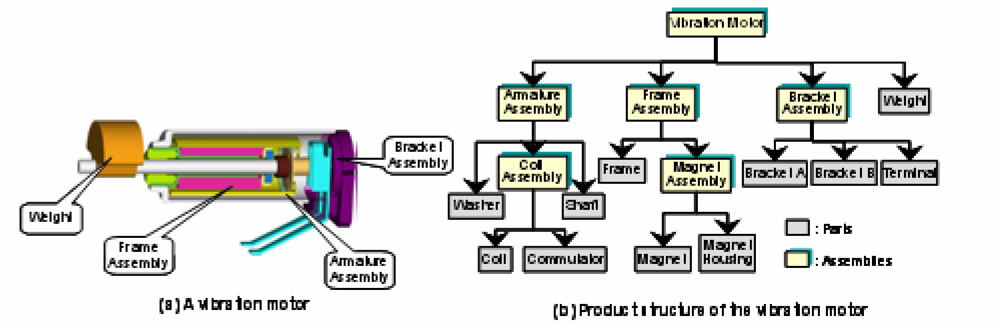

Figure 2. A Vibration Motor and its Product Structure

From the company's databases, 30 motors together with their routings are taken. For identifying the possible families that may exist in the 30 motors, product similarity is measured first according to the proposal. The measure results are given in Figure 3: a product similarity matrix of 30 motors. Then similar motors are clustered based on the similarity matrix and the results are given in Table 2.

The generic product structures are generated for each family in Table 2. For illustrative simplicity, only the generic product structure of family 1 in Table 2 is shown in Figure 4(a). The process families have been formed according to the product families, and the generic process structures have been constructed as well. Figure 4(b) shows the generic process structure of the family 1 in Table 2. The symbols in the generic process structure denote operations, e.g., "*MAO*" means *magnet assembly operation.*

$$\left[\begin{array}{cccccccccccccccccccccccccccccc}
1 & .61 & .94 & .63 & .61 & .65 & .62 & .60 & .66 & .87 & .67 & .24 & .84 & .88 & .19 & .72 & .87 & .73 & .30 & .80 & .29 & .77 & .40 & .30 & .74 & .37 & .36 & .40 & .32 & .36 \\
.61 & 1 & .62 & .78 & .80 & .77 & .71 & .73 & .82 & .57 & .83 & .38 & .44 & .44 & .38 & .81 & .57 & .85 & .46 & .51 & .38 & .47 & .14 & .42 & .46 & .18 & .23 & .19 & .17 & .13 \\
.94 & .62 & 1 & .60 & .62 & .66 & .61 & .61 & .67 & .88 & .67 & .23 & .83 & .83 & .21 & .71 & .88 & .78 & .31 & .79 & .28 & .78 & .41 & .31 & .74 & .35 & .35 & .35 & .33 & .35 \\
.63 & .78 & .60 & 1 & .92 & .92 & .83 & .90 & .88 & .55 & .83 & .50 & .49 & .53 & .55 & .82 & .55 & .83 & .44 & .48 & .36 & .49 & .20 & .41 & .46 & .25 & .16 & .24 & .11 & .24 \\
.61 & .80 & .62 & .92 & 1 & .91 & .89 & .88 & .83 & .57 & .86 & .52 & .51 & .51 & .53 & .81 & .61 & .85 & .47 & .50 & .41 & .48 & .14 & .43 & .49 & .18 & .22 & .22 & .18 & .22 \\
.65 & .77 & .66 & .92 & .91 & 1 & .89 & .94 & .85 & .59 & .82 & .56 & .55 & .55 & .49 & .88 & .59 & .88 & .45 & .51 & .42 & .53 & .16 & .45 & .45 & .17 & .26 & .23 & .24 & .17 \\
.62 & .71 & .61 & .83 & .89 & .89 & 1 & .88 & .79 & .53 & .82 & .50 & .59 & .59 & .45 & .87 & .57 & .83 & .41 & .50 & .38 & .49 & .14 & .46 & .45 & .17 & .18 & .18 & .16 & .25 \\
.60 & .73 & .61 & .90 & .88 & .94 & .88 & 1 & .86 & .60 & .80 & .54 & .52 & .55 & .52 & .80 & .57 & .85 & .44 & .48 & .39 & .49 & .19 & .38 & .49 & .22 & .16 & .27 & .24 & .18 \\
.66 & .82 & .67 & .88 & .83 & .85 & .79 & .86 & 1 & .62 & .89 & .44 & .57 & .57 & .47 & .89 & .62 & .94 & .53 & .59 & .45 & .56 & .20 & .48 & .53 & .17 & .16 & .20 & .14 & .11 \\
.87 & .57 & .88 & .55 & .57 & .59 & .53 & .60 & .62 & 1 & .59 & .33 & .75 & .79 & .28 & .59 & .92 & .63 & .39 & .87 & .32 & .83 & .42 & .32 & .87 & .39 & .41 & .40 & .42 & .37 \\
.67 & .83 & .67 & .83 & .86 & .82 & .82 & .80 & .89 & .59 & 1 & .45 & .57 & .57 & .46 & .83 & .64 & .85 & .54 & .55 & .50 & .56 & .16 & .45 & .57 & .21 & .17 & .14 & .16 & .11 \\
.24 & .38 & .23 & .50 & .52 & .56 & .50 & .54 & .44 & .33 & .45 & 1 & .14 & .14 & .95 & .43 & .30 & .44 & .86 & .21 & .87 & .22 & .58 & .85 & .22 & .52 & .46 & .50 & .48 & .43 \\
.84 & .44 & .83 & .49 & .51 & .55 & .59 & .52 & .57 & .75 & .57 & .14 & 1 & .95 & .19 & .66 & .75 & .62 & .20 & .87 & .17 & .86 & .28 & .18 & .83 & .38 & .36 & .38 & .41 & .45 \\
.88 & .44 & .83 & .53 & .51 & .55 & .59 & .55 & .57 & .79 & .57 & .14 & .95 & 1 & .17 & .66 & .75 & .62 & .20 & .87 & .23 & .82 & .29 & .17 & .77 & .36 & .42 & .36 & .37 & .37 \\
.19 & .38 & .21 & .55 & .53 & .49 & .45 & .52 & .47 & .28 & .46 & .95 & .19 & .17 & 1 & .37 & .32 & .42 & .86 & .18 & .80 & .22 & .52 & .87 & .17 & .48 & .44 & .51 & .53 & .49 \\
.72 & .81 & .71 & .82 & .81 & .88 & .87 & .80 & .89 & .59 & .83 & .43 & .66 & .66 & .37 & 1 & .61 & .93 & .48 & .57 & .45 & .56 & .24 & .52 & .51 & .17 & .16 & .23 & .21 & .21 \\
.87 & .57 & .88 & .55 & .61 & .59 & .57 & .57 & .62 & .92 & .64 & .30 & .75 & .75 & .32 & .61 & 1 & .68 & .43 & .86 & .29 & .89 & .45 & .35 & .87 & .38 & .44 & .43 & .41 & .37 \\
.73 & .85 & .78 & .83 & .85 & .88 & .83 & .85 & .94 & .63 & .85 & .44 & .62 & .62 & .42 & .93 & .68 & 1 & .45 & .56 & .45 & .58 & .16 & .44 & .60 & .21 & .28 & .17 & .15 & .13 \\
.30 & .46 & .31 & .44 & .47 & .45 & .41 & .44 & .53 & .39 & .54 & .86 & .20 & .20 & .86 & .48 & .43 & .45 & 1 & .24 & .93 & .28 & .70 & .98 & .32 & .58 & .54 & .57 & .59 & .60 \\
.80 & .51 & .79 & .48 & .50 & .51 & .50 & .48 & .59 & .87 & .55 & .21 & .87 & .87 & .18 & .57 & .86 & .56 & .24 & 1 & .25 & .95 & .40 & .26 & .96 & .47 & .43 & .46 & .48 & .48 \\
.29 & .38 & .28 & .36 & .41 & .42 & .38 & .39 & .45 & .32 & .50 & .87 & .17 & .23 & .80 & .45 & .29 & .45 & .93 & .25 & 1 & .30 & .65 & .64 & .33 & .62 & .57 & .59 & .58 & .59 \\
.77 & .47 & .78 & .49 & .48 & ..53 & .49 & .49 & .56 & .83 & .56 & .22 & .86 & .82 & .22 & .56 & .89 & .58 & .28 & .95 & .30 & 1 & .44 & .26 & .95 & .46 & .46 & .44 & .46 & .46 \\
.40 & .14 & .41 & .20 & .14 & .16 & .14 & .19 & .20 & .42 & .16 & .58 & .28 & .29 & .52 & .24 & .45 & .16 & .70 & .40 & .65 & .44 & 1 & .27 & .41 & .80 & .84 & .88 & .81 & .79 \\
.30 & .42 & .31 & .41 & .43 & .45 & .46 & .38 & .48 & .32 & .45 & .85 & .18 & .17 & .87 & .52 & .35 & .44 & .98 & .26 & .94 & .26 & .27 & 1 & .22 & .51 & .55 & .59 & .56 & .51 \\
.74 & .46 & .74 & .46 & .49 & .45 & .45 & .49 & .53 & .87 & .57 & .22 & .83 & .77 & .17 & .51 & .87 & .60 & .32 & .96 & .33 & .95 & .41 & .22 & 1 & .47 & .49 & .44 & .43 & .43 \\
.37 & .18 & .35 & .25 & .18 & .17 & .17 & .22 & .17 & .39 & .21 & .52 & .38 & .36 & .48 & .17 & .38 & .21 & .58 & .47 & .62 & .46 & .80 & .51 & .47 & 1 & .95 & .95 & .88 & .90 \\
.36 & .23 & .35 & .16 & .22 & .26 & .18 & .16 & .16 & .41 & .17 & .46 & .36 & .42 & .44 & .16 & .44 & .28 & .54 & .43 & .57 & .46 & .84 & .55 & .49 & .95 & 1 & .94 & .93 & .91 \\
.40 & .19 & .35 & .24 & .22 & .23 & .18 & .27 & .20 & .40 & .14 & .50 & .38 & .36 & .51 & .23 & .43 & .17 & .57 & .46 & .59 & .44 & .88 & .59 & .44 & .95 & .94 & 1 & .92 & .95 \\
.32 & .11 & .33 & .11 & .18 & .24 & .16 & .24 & .14 & .42 & .16 & .48 & .41 & .37 & .53 & .21 & .41 & .15 & .59 & .48 & .58 & .46 & .81 & .56 & .43 & .88 & .93 & .92 & 1 & .93 \\
.36 & .13 & .35 & .24 & .22 & .17 & .25 & .18 & .11 & .37 & .11 & .43 & .45 & .37 & .49 & .21 & .37 & .13 & .60 & .48 & .59 & .46 & .79 & .51 & .43 & .90 & .91 & .95 & .93 & 1
\end{array}\right]_{30x30}$$

Figure 3. Product Similarity Matrix of 30 Vibration Motors

Table 2. Product Families in 30 Vibration Motors

Motor Families	Product Members
Family1	PP1, PP2, PP3, PP4, PP5, PP6, PP7, PP8, PP9, PP10, PP11, PP13, PP14, PP16, PP17, PP18, PP20, PP22, PP25
Family2	PP12, PP15, PP19, PP21, PP24
Family3	PP23, PP26, PP27, PP28, PP29, PP30

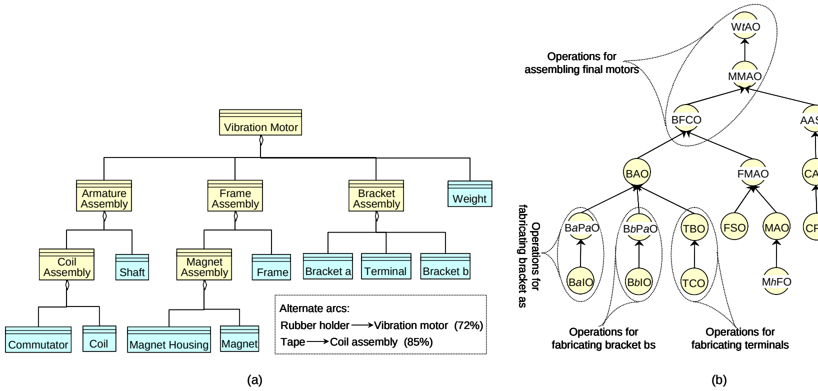

Figure 4. The Generic Product and Process Structures of the Motor Family 1 in Table 2

After motor families have been identified, association rule mining is enacted to discover the mapping relationships between product and the corresponding process families. Table 3 shows the prepared transaction database for *bracket a* family. The magnum Opus (http://www.rulequest.com/) is employed for mining associations in the *TDB* in Table 3. Figure 5 (a) gives the rule mining process in Magnum Opus. The mining results are shown in Figure 5 (b).

Table 3. Transaction Database for *Bracket A* family

Transaction IDs	Bracket a Variants	Design Parameter Value Pairs	Process Elements
001	Ba1	Material (ABS), Shape (Square), Thickness (1.67mm), Number of fusing holes (1), Length (3.05mm)	InjectorHS35, LocatorIII, AdjustorA, TrayTV, Pre-alignment JigTI
002	Ba2	Material (Polythene), Shape (Half-Oval-Rectangle), Thickness (1.67mm), Outer diameter (4.32mm), Number of fusing holes (3), Length (3.8mm)	InjectorLS507, LocatorIII, AdjustorDE, TrayU, Pre-alignment JigXS
003	Ba3	Material (Round), Shape (Round), Thickness (0.94mm), Number of fusing holes (5), Outer diameter (4.32mm)	InjectorN1044, LocatorIV, AdjustorA, TrayU, Pre-alignment JigRS
004	Ba4	Material (Nylon), Shape (Trapezoid), Thickness (1.67mm), Outer diameter (4.82mm), Number of fusing holes (5), Length (4.78mm)	InjectorNII11, LocatorIII, AdjustorDE, TraySS, Pre-alignment JigSSII
…	…	…	…
0015	Ba15	Material (ABS), Shape (Round), Thickness (1.30mm), Outer diameter (4.82mm), Number of fusing holes (3)	InjectorHS35, LocatorAP, AdjustorP, TraySS, Pre-alignment JigRS

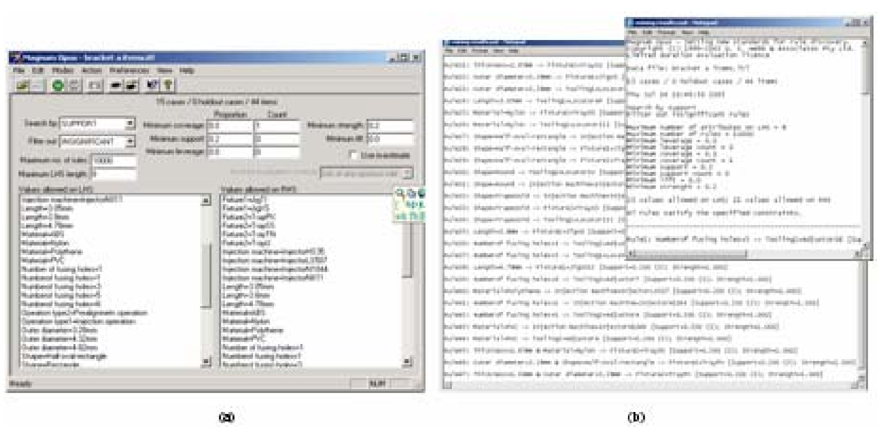

Figure 5. Association Rule Mining in Magnum and Mined Rules for the *TDB* in Table 3

5. CONCLUSIONS

In mass customization, the linchpin of effective variety management lies in the handling of correspondence between product and process variety due to the complexity and unstructured nature inherent in these interconnections. A variety coordination approach using data mining techniques is proposed in the paper to tackle these issues. In addition to identifying product and process families and thus manage product and process variety, the association rule mining technique is applied to address the mapping relationships in between.

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