MANUFACTURING PLANT LAYOUT SUPPORTED WITH DATA MINING TECHNIQUES

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Abstract:

The question of plant layout is central in a manufacturing process. This question becomes even more important in a mass customization context, when large product diversity has to be managed. The manufacturing process, and specifically the plant layout, has to be designed taking into account this characteristic. When all products are similar, manufacturing plant layouts are relatively easy to design; difficulties come when most products are different and require specific manufacturing operations.
This paper proposes a methodology based on data mining techniques to define manufacturing plant layouts in a context of diversified products.
Different steps are proposed to achieve this goal. The methodology considers: 1/ identification of representative sets of products; 2/ identification of manufacturing processes and the relevant layout (for each set of products); 3/ categorization of new products (identification of the closest set of products).
The focus is on data transformations that enable to extract relevant information for the manufacturing plant layout.

Key words: product families, plant layout, data transformation, data mining.

1 Introduction

In nowadays markets, manufacturing companies have to be always more competitive. Manufactured products have to be customized, of the highest quality, delivered in the required place and time and at the lowest price. This is defined as mass customization [1].

Mass customization is often supported with a product platform that combines options and alternatives in order to satisfy individualized requirements. Customers select the options and alternatives they prefer to specify their own dedicated product [2]. Besides, this customization may imply a large product diversity to manage, every product may be different. For the suppliers it may induce small sets of variable quantities of different products to manufacture. That huge diversity has many impacts on the manufacturing process and can therefore endanger the product quality, the lead time, the cost, etc. [3].

The manufacturing process, and specifically the plant layout, has to be designed taking into account those characteristics. When all products are similar, manufacturing plant layouts are relatively easy to design; difficulties come when most products are different and require some specific manufacturing operations.

In a product family, all final products may be different, depending on the set on options and alternatives selected by diversified customers. On the manufacturing level, these differences may necessitate extra manufacturing or control operations. When a company manufactures many sets of variable quantities of different products, the manufacturing plant layout may be problematic to define.

According to Phillips, 30% of the cost of a manufactured part is due to handling [4]. Besides, handling is mostly impacted by the manufacturing plant layout. The layout of the manufacturing tools appears to be an essential condition for small production costs and for higher competitiveness.

In the context of the manufacturing of product families, this paper proposes to design manufacturing plant layouts with data mining techniques. Different steps are proposed to achieve this goal. The methodology considers: 1/ identification of representative sets of products (using association rules and/or clustering) – products from the same set will be considered to belong to the same product family (according to the manufacturing process); 2/ based on similarities on the manufacturing process, relevant manufacturing processes are identified and set in an adequate order for each product family (with association rules) – describing the plant layout; 3/ classification trees categorize new products to propose the closest product family and then the relevant layout.

Section 2 contains the problem specification. The context is outlined and a case study is provided that will be exploited all over the paper. Each step of the methodology is described in section 3. An emphasis is on data transformations necessary to complete each operation. Section 4 concludes the paper and proposes some extensions.

2 Problem specification

Consider a company that manufactures small quantities of many different products. That company disposes of a set of machines (M1, M2 … Mn) and gives a dedicated manufacturing process for each set of parts. Each manufacturing process is different and whatever the product family the quantities to manufacture are almost equivalent (there is not any "major" production).

The list of products and their manufacturing processes are presented in Table 1.

	Ref #	Qty/ week	Manufacturing process						
List of products	123	5	M1	M2	M4	M7			
	234	7	M4	M7	M2	M1			
	345	4	M5	M3	M6				
	567	8	M6	M5	M3	M7			
	…	…	…						

Table 1. List of products and their manufacturing processes.

This table represents for each product the quantity that is manufactured each week and the manufacturing process of each product. For example, there are 5 products #123 to be manufactured each week. The manufacturing process of each product #123 necessitates machines M1, then M2, then M4 and finally M7. And so on for each product.

From that data set, it is possible to extract much relevant information to define the manufacturing plant layout. Nevertheless, due to the large number of different sets of products to manufacture, Table 1 may be so large that it is impossible for a human being to have a global view on the data and to detect all relevant information for a plant layout.

In this case, data mining techniques may be advantageously employed. Data mining is defined as "the discovery of non-trivial, implicit, previously unknown, and potentially useful and understandable patterns from large data set" [5].

No data mining technique will be presented here; the emphasis is on data transformation and possible knowledge extraction for automatic design of plant layouts. For more information about data mining techniques and algorithms, the reader may refer to [6]. For applications of data mining techniques in marketing, sales and customer support see [7], for applications of data mining in manufacturing environments see [5], [8].

Previous researches focused on plant layout. It is possible to find methodologies [9], [10], [11] and algorithms [12], [13], [14], [15]. This paper will follow the Systematic Layout Planning method [9], in order to propose an alternative methodology based on data mining techniques. Data mining tools are proposed to generate most of the information that is needed.

3 Manufacturing plant layout

Several tasks of a manufacturing plant layout may be advantageously supported with data mining tools.

The proposed layout methodology with data mining techniques is represented on Figure 1. It combines three steps.

1/ identification of representative sets of products (using association rules and/or clustering) – products from the same set will be considered to belong to the same product family (according to the manufacturing process);

2/ based on similarities on the manufacturing process, relevant manufacturing processes are identified and set in an adequate order for each product family (with association rules) – describing the plant layout;

3/ classification trees categorize new products to propose the closest product family and then the relevant layout.

Figure 1. Layout methodology with data mining techniques.

Each step is described in the following subsections.

3.1 Identification of representative sets of products

A global layout may be defined from the manufacturing processes described in Table 1.

In order to identify representative sets of products, it is necessary to consider relevant sets of parameters. Group technology is often supported with matrix decomposition algorithms such as [16], [17], [18], [19]. Association rules may also be used [20]. For this application the focus is on clustering techniques. Clustering (called also segmentation) divides a population into smaller sub-populations with similar behaviour according to a predefined metric. Clustering maximizes homogeneity in each cluster and maximizes heterogeneity between clusters [21].

So as to apply clustering to data in Table 1 a first data transformation is necessary and leads to Table 2.

	Ref	Manufacturing process								
		M1	M2	M3	M4	M5	M6	M7	…	Mn
List of products	123	1	1		1			1		
	234	1	1		1			1		
	345			1		1	1			
	567			1		1	1	1		
	…	…	…							

Table 2. Modified data for clustering.

In Table 2, the lines represent the list of products and the columns represent the machines involved in the manufacturing processes. For example the first line means that for the manufacturing of products #123 machines M1, M2, M4 and M7 are necessary. Please note that information about order between the machines is lost, only constraints of existence appear.

Applied to Table 2 clustering methods lead to the following sets of products.

Cluster 1:	products {#123, #234, …}
Cluster 2:	products {#345, #567, …}
…	

Table 3. Clusters extracted from Table 2.

Each cluster is a potential manufacturing department. For example Cluster 1 proposes a department for the manufacturing of products {#123, #234, …} which requires machines M1, M2, M4 and M7. At this level an expert may validate the results and/or propose some changes in the allocation of the machines in each department such as duplication of machines. It follows groups of machines (departments). Consider the following departments are valid:

Dept 1:	machines {M1, M2, M4, M7}
Dept 2:	machines {M3, M5, M6}
…	

Table 4. Suggested departments.

In order to localise correctly all departments created previously next to each other, it is necessary to evaluate the circulation of products between them. Another data transformation will take advantage of former results.

For each product, movements between the departments must be identified and evaluated. Indeed one of the main objectives of a plant layout for manufacturing is to streamline the material flow. The focus must be on the minimisation of handlings: the distances material and operators have to cover (for production or maintenance) should therefore be evaluated.

Instead of movements of products from machine to machine such as in Table 1, movements from department to department are necessary.

By combination of Table 1 and Table 4, the following results are observed:

#123	#234	#345	#567
M1-Dept 1	M4-Dept 1	M5-Dept 2	M6-Dept 2
M2-Dept 1	M7-Dept 1	M3-Dept 2	M5-Dept 2
M4-Dept 1	M2-Dept 1	M6-Dept 2	M3-Dept 2
M7-Dept 1	M1-Dept 1		M7-Dept 1

Table 5. Manufacturing process of each part – department level.

The movements between departments may be identified. It occurs:

	Ref #	Qty/ week	Manufacturing process		
List of products	123	5	Dept 1		
	234	7	Dept 1		
	345	4	Dept 2		
	567	8	Dept 2	Dept 1	
	…	…	…		

Table 6. Manufacturing process – department to department.

While it appears that, with the departments selected previously, product #123 just stays in Dept 1, products #567 moves from Dept 2 to Dept 1. Knowing the number of products #567 to be manufactured each week and the lot size for handling; it is easy to construct an activity relationship diagram such as Figure 2.

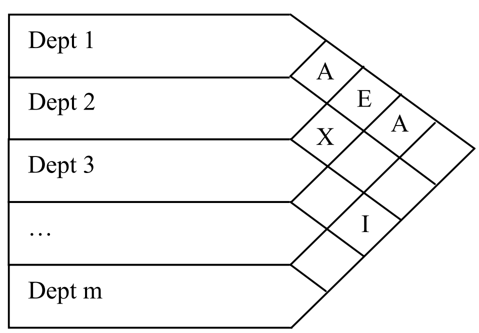

Figure 2. Activity relationship diagram [11].

It is then relatively easy to place all departments. Different tools exist for that task; for example [22] or [23] can be cited.

3.2 Identification of relevant manufacturing processes

For the second step of the methodology, all machines belong to specific departments and the departments are situated next to each others. The objective is now to identify a relevant manufacturing process into each department so as to place the machines in an adequate order.

For each department (group of machines of Table 4) the data (Table 1) are filtered (See Table 7).

Dept 1	Ref #	Qty/ week	Manufacturing process				
List of products	123	5	M1	M2	M4	M7	
	234	7	M4	M7	M2	M1	
	567	8	M7				
	…	…	…				

Table 7. Manufacturing process of each product.

It is necessary to extract identical sequences in the manufacturing processes. The sequence M4-M7 as to be identified in both products #123 and #234. The data transformation proposed in [24] makes it possible.

In the following table (Table 8), each column X_Y means Machine X is the precedent of Machine Y. B_X sets that Machine X begins the manufacturing process and X_F that Machine X finishes the manufacturing process. The number of lines for each product reference is proportional to the quantity per week (it could also be divided by a common denominator). Each line of the table describes the manufacturing process of a product.

For example the fist line of the table means that a product of reference 123, begins with Machine 1 (B_1), then goes to Machine 2 (1_2), it goes from Machine 2 to Machine 4 (2_4), from Machine 4 to Machine 7 (4_7) and Machine 7 is the final machine of this manufacturing process (7_F).

	Manufacturing process																		
Ref #	B_1	B_2	B_4	B_7	1_2	1_4	1_7	2_1	2_4	…	4_2	…	4_7	…	7_2	…	1_F	…	7_F
123	1				1				1				1						1
123	1				1				1				1						1
123	1				1				1				1						1
123	1				1				1				1						1
123	1				1				1				1						1
234			1					1					1		1		1		
234			1					1					1		1		1		
234			…					…					…		…		…		
234			1					1					1		1		1		
567				1															1
567				1															1
567				…															…
567				1															1
…																			

Table 8. Developed data for each product in each department.

Association rules may be extracted from Table 8.

Association rules stress the strong associations within the data [25]. Rules are given with two metrics (support and confidence) that make it possible to evaluate the strength of the rule. Support considers the number of occurrence of the left side of the rule in the data, while confidence represents the ratio between the right side of the rule appearance into the data and the support of the rule. Rules with high support and confidence are strong and may be considered.

Suppose that the rule " 4_7 = 1 " is the strongest rule of Table 8. It means that machine M4 is most often used just before machine M7. Then it may be advantageous to consider the placement of machine M4 next to machine M7 in the order of the flow. And so on from the strongest rules to the weakest until all machines are placed. Some contradictions may appear because all sets of products are different. Some sets of products may not follow the flow.

It results a layout for each department that is automatically generated from the data.

3.3 Classification of new products

The last step of the methodology takes advantage of the plant layout that was proposed previously. Any new product to be manufactured will be automatically classified in the adequate department(s) by classification trees [26] (Figure 3).

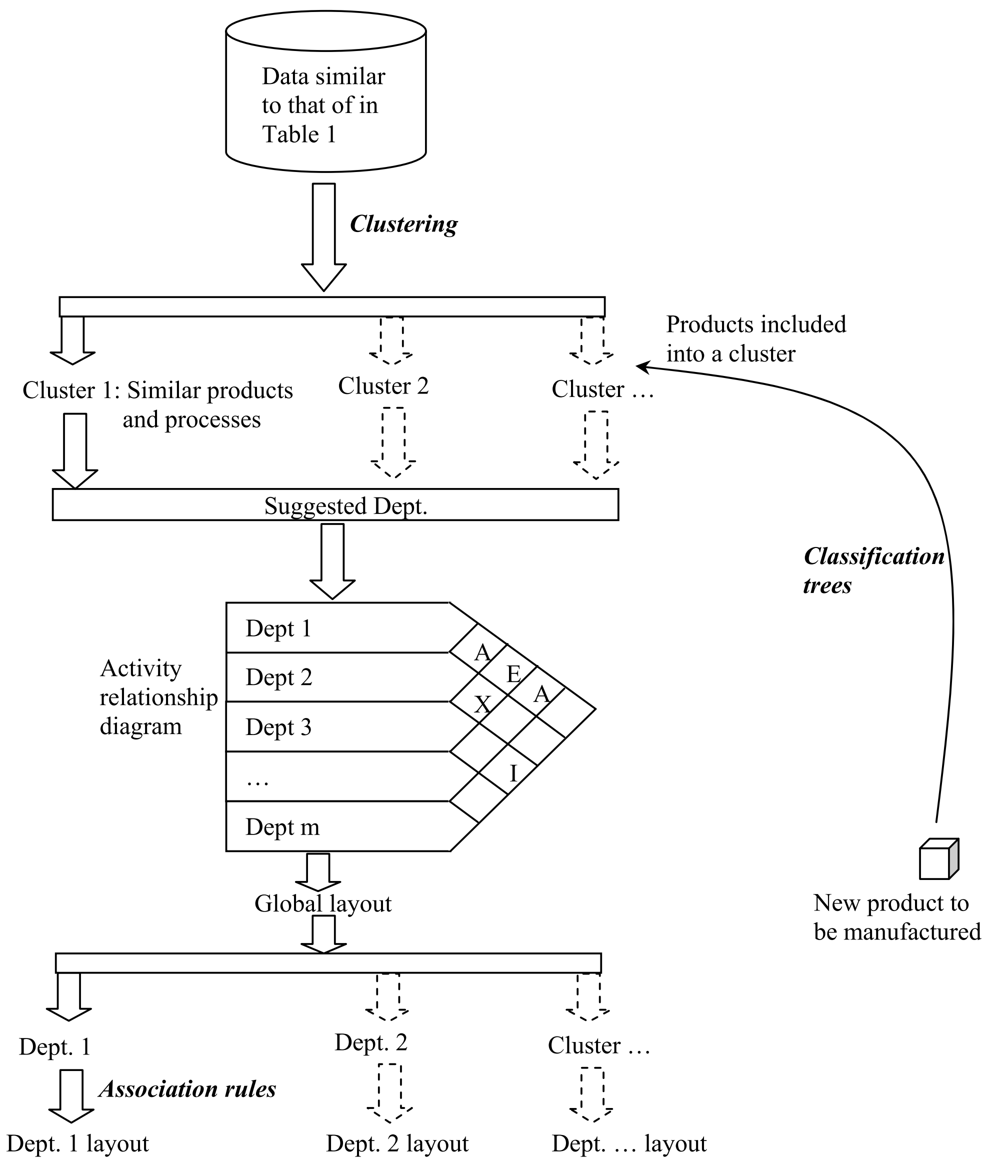

Figure 3. Classification of new products.

Classification trees may learn from Table 2 (Modified data for clustering) and Table 4 (Suggested departments) what the conditions that lead to define a department are. When a new product is to be manufactured, it is automatically associated to the closest cluster and then to the closest layout.

4 Conclusions and further work

This paper proposes a methodology to design a manufacturing plant layout automatically, with data mining techniques, from the production routing of each product.

This approach enables, when no "major" product can be identified, to define an alternative layout without over sizing the plant. The information needed to perform this definition is one that is always at disposal (the routings) and therefore doesn't require a consuming (in time and resources) information retrieval.

The method proposed here doesn't consider organisational criteria such as workers abilities or cross trading; this aspect of plant layout should be addressed in a second step. Data mining techniques could then be used on data representing the skills needed for each operation.

From time to time it is important to reconsider the whole process of layout planning. The new parts may overlap the olds one and a new plant layout may be generated.

Further researches may include the consideration of other products' attributes such as parts' fragility or volume; the aim of the plant layout will then be the minimization of the breakages or the handling volume.

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