A VECTOR PERTURBATION APPROACH TO THE GENERALIZED AIRCRAFT SPARE PARTS GROUPING PROBLEM *

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ABSTRACT: The *Vector Perturbation Approach* is introduced for addressing the generalized parts grouping problem, identifying part families for a general set of suppliers, not just a single supplier. This method is driven by the need for flexible and lean supply chain systems. A *vector space model* is used to represent a set of operation sequences as opposed to the traditional matrix and integer programming models in Group Technology. Using this approach we find that we are able to generate part groups from 90% of the available parts, in which all the operation sequences are preserved. This contrasts with only 66% of the available parts grouped using the traditional methods. Furthermore, a vector representation of operation sequences provides an intuitive means for discovering the natural structure of the part data. From these results we conclude that this technique can dramatically improve the effectiveness of the entire supply chain.

I. INTRODUCTION

A key challenge to military readiness is the ability to maintain and quickly repair damaged aircraft. This challenge requires manufacturers and distributors of spare parts to be able to supply the military with the right part, in a short amount of time, for a reasonable price. Historically, this challenge has been addressed by developing and maintaining a very large spare parts inventory.

A solution to these types of problems is for part manufacturers to deliver a needed part in a matter of hours. This approach completely bypasses the need for an inventory of spare parts and thus greatly reduces inventory costs, as advocated by a number of *just-in-time* methods. These methods advocate the building of efficient manufacturing cells by grouping parts based on how they are made, often referred to as Group Technology (GT).[1,2]

The conventional application of GT is to create manufacturing cells for parts to be produced on a single manufacturing floor. A cell consists of a set of functionally dissimilar machines dedicated to the production of one or more families of similar parts. Grouping similar parts is considered as a part of the cell formation problem.[3] Most of the methods of addressing this problem are rooted in

* Research sponsored by the Defense Logistics Agency and the Lockheed Martin Energy Research Corporation under Contract No. SP0410-98-D-005
** Oak Ridge National Laboratory is managed by Lockheed Martin Energy Research Corporation for the United States Department of Energy under Contract No. DE-AC05-96OR22464

mathematical approaches[4] whose objectives are to optimize a single manufacturing environment under a number of constraints specific to this environment.

A new application of GT, driven by the need for flexible and "lean" supply chain management (SCM), has recently been introduced in the literature.[5] In that paper, a framework for approaching the *generalized parts grouping problem* was proposed based on the use of the Autonomous Intelligent Agent Technology (AIA) in combination with the extensions to traditional Group Technology. In the generalized parts grouping, rather than grouping parts based on a known set of manufacturing capabilities, these groups are developed for a general set of part manufacturers.

This paper presents the *vector perturbation approach* to the generalized parts grouping problem while further extending traditional GT approaches. The need for this method is dictated by major distinctions in the traditional, manufacturing oriented, and generalized, supply chain oriented, grouping problems. The fundamental distinction between these two problems is based on the differences in the objectives/constraints they seek to satisfy.

Traditional Approach

In traditional GT, the existing approaches can be distinguished as *structural* and *operational*. By structural we mean methods that group parts while building the manufacturing cells based on routing information alone. Some of these methods use this information in a limited sense by utilizing only a machine-part incidence matrix.[6-8] McAuley's[8] approach is a classical example in this category. Methods in the second category, which we referred to as operational, build cells while incorporating operational information such as part production volume, cost, a processing time, etc.[9,10] Since operational information is always manufacturer specific, methods in this category can not be directly applied to solve the generalized parts grouping problem found within most production supply chains.

The structure and operational approaches described above have a common objective, i.e., they strive to increase production effectiveness of a single manufacturing environment. This is achieved by identifying part groups and building manufacturing cells in such a way that each part group can be fully processed in a cell. Examples of mathematical formulations of this objective previously used are to minimize the inter and intra cell moves,[8] to maximize cell independence,[6,7] and to minimize the accumulative material handling costs.[11] Some production constraints used are the desirable number of cells, the maximum number of machines in each cell, or the maximum processing time.

Generalized Approach

In the generalized parts grouping problem, the objective is to group parts into families in order to optimize the efficiency of the entire supply chain rather than a single manufacturing floor. This process involves the following key stages:

(1) Grouping parts based on how they are made;
(2) Selecting a supplier for building each family of parts from a broad set of suppliers;
(3) Arranging the selected manufacturing environment to efficiently build these part families.

Any solution to this problem at a minimum is subject to the following constraints:

- The supply chain must respond to the immediate need for a spare part (time constraints);
- The cumulative inventories within the supply chain have to be minimized (waste constraints);
- Parts from the supply chain must be affordable (cost constraints).

Based on the above discussion, we conclude that 1) the traditional cell manufacturing problem and the generalized supply chain problem are quite different; 2) there is a need for the methods that provide a flexible solution to grouping parts from a broad set of suppliers rather than a single manufacturing floor and that consider the objectives/constraints specific to the supply chain operation in just-in-time environment.

This paper presents a generalized parts grouping method that meets these requirements. The remainder of the paper is organized as follows. The next section provides details of the vector perturbation method that we developed to group parts based on operation sequences and discusses its advantages and limitations. Different measures of parts dissimilarity are introduced for further evaluation. We then illustrate the method numerically. Finally, conclusions are given based on the results from this study.

II. METHOD DESCRIPTION

This Vector Perturbation Approach extends the current literature in GT by representing the operation sequences required to manufacture parts as a *vector space model*. From this model we can then identify independent part families. We define the *operation sequence* of a part as the ordering of the manufacturing operations required to construct the part. We chose the operation sequence representation over the routing card representation due to the fact that routing cards describe the specific machinery at a given manufacturer. In the generalized parts grouping problem, we need to consider operations over the entire supply chain, as opposed to a given supplier. Therefore, we believe that the operation sequence is an appropriate abstraction for the machinery used throughout a given supply chain.

In addition to this higher level of abstraction that operation sequences provide, we also need the capability to preserve the order of the operations. In the generalized grouping problem, part families must be as closely tailored to a supplier's capabilities as possible. This problem is not solved by merely providing a supplier with a family of parts that can potentially be built using a supplier's operations alone. The parts must flow through the supplier's manufacturing cell in a proper sequence. Therefore the sequence of operations is a key input to the generalized grouping problem.

This vector perturbation method contains the following essential steps:

(1) Representing the ordered operations of a part in the form of d-dimensional part vectors;
(2) Evaluating a relationship between each pair of part vectors using a dissimilarity function;
(3) Applying an appropriate similarity coefficient based clustering algorithm to determine part families based on the dissimilarity matrix computed in step 2);
(4) Finding a more optimal solution by changing the perturbation parameter δ.

II.1. Data Representation

Typically, to represent the operations required to build parts, a 2-dimensional matrix is used. There are a number of problems with this type of representation. Most notably, these are the loss of operation sequences information, the lack of support for visualizing the information, and the difficulty in discovering the natural structure of the data. To overcome these limitations we propose a new approach for representing part operation sequences. We begin with a set P of part operation sequences and a derived value *d of distinct operations* listed in all these sequences. We model each operation sequence as a vector $\boldsymbol{u}$ in the d-dimensional space R^d. This allows for one coordinate for each of the d operations. The j^{th} coordinate of a vector $\boldsymbol{u}$ is a number that relates the j^{th} operation with the given operation sequence. The value of the j^{th} coordinate can be expressed mathematically as follows

$$\text{õ}_j = \begin{cases} 0, & \text{if the operation sequence does not contain operation} \\ \grave{u}_j + \ddot{a} \cdot order(j), & \text{otherwise} \end{cases} \tag{2.1}$$

where

- ω_j is the weight assigned to each operation. This weight represents a non-operation based factor that may influence the grouping of the parts, for example, the cost of equipment, the unit operation time, its average workload, etc.;
- δ is the *perturbation parameter* used to represent the importance of the sequencing of operations;
- *order(j)* is the number that defines the order in which the operation *j* occurs in the operation sequence.

For example, consider a hypothetical set of operation sequences for two parts as shown in Table 1. There are four (d = 4) distinct operations, resulting in a 4-dimentitional space. The operational sequence vectors are illustrated in Table 2.

TABLE 1.
Routing Sequences for Two Parts.

Part No.	Routing sequence
P_1	$O_2 - O_1 - O_4$
P_2	$O_3 - O_4 - O_1 - O_2$

TABLE 2.
Vectors Corresponding to Parts P_1 and P_2

Vector No.	Vector components
υ_1	$(1 + 2\cdot\delta,\ 1 + \delta,\ 0,\ 1 + 3\cdot\delta)$
υ_2	$(1 + 3\cdot\delta,\ 1 + 4\cdot\delta,\ 1 + \delta,\ 1 + 2\cdot\delta)$

II.2. Analysis of the Relations Using Dissimilarity Functions

Now that we have represented the data, we need to analyze the relations between parts, i.e., the similarity, or dissimilarity between them. To do this, five different dissimilarity coefficients are introduced and compared to each other.

(1) *Euclidean square distance* $D_e(\upsilon_i,\upsilon_j)$ showing the most natural relations for vectors in the Euclidean space. It is defined by

$$D_e(\vec{\upsilon}_i,\vec{\upsilon}_j)=\sum_{k=1}^{k=d}(\tilde{\upsilon}_{ik}-\tilde{\upsilon}_{jk})^2 \qquad (2.2)$$

Notice that clusters defined by Euclidean distance will be invariant to translations or rotations of the part vectors. However, they will not be invariant to linear transformations or other transformations that distort the distance relationship. Thus, introducing weighting terms for the operations can result in a different grouping of the parts into clusters.

(2) *Dissimilarity coefficient* $D_c(\upsilon_i,\upsilon_j)$ computed as the contraction of the Euclidean distance between two part vectors by a factor proportional to the number of common non-zero vector components, or the number of common operations in the part operation sequences

$$D_c(\vec{\upsilon}_i,\vec{\upsilon}_j)=\psi(n_c(\vec{\upsilon}_i,\vec{\upsilon}_j))\cdot D_e(\vec{\upsilon}_i,\vec{\upsilon}_j) \qquad (2.3)$$

where $\psi(n_c(\upsilon_i,\ \upsilon_j))$ is a function of the total number $n_c(\upsilon_i,\ \upsilon_j)$ of common non-zero vector components. For this analysis we set $\psi(n_c(\upsilon_i,\ \upsilon_j)) = 1\ /\ (1 + n_c(\upsilon_i,\ \upsilon_j))$, to avoid division by zero. The Euclidean distance measurement is strongly influenced by the dissimilarities of the vector coordinates. This dissimilarity measure distinguishes two pairs of part vectors at the same Euclidean distance as being different if the number of common operations between their part pairs is different. . The proposed dissimilarity coefficient weighs the Euclidean distance between vectors based on the similarities of the vectors.

(3) *City-block distance* $D_b(\upsilon_i,\upsilon_j)$ (i.e., Manhattan distance) defined by

$$D_b(\vec{o}_i, \vec{o}_j) = \sum_{k=1}^{k=d} \left| \tilde{o}_{ik} - \tilde{o}_{jk} \right| \tag{2.4}$$

(4) *McAuley's*[8] *dissimilarity coefficient* $D_M(\upsilon_i,\upsilon_j)$ defined by

$$D_M(\vec{o}_i, \vec{o}_j) = 1 - \frac{n_c(\vec{o}_i, \vec{o}_j)}{n_t(\vec{o}_i, \vec{o}_j)} \tag{2.5}$$

where $n_c(\upsilon_i, \upsilon_j)$ is the total number of *common* non-zero vector components as defined above and $n_t(\upsilon_i,\upsilon_j)$ is the total number of non-zero vector components of both vectors.

(5) *Dissimilarity coefficient* $D_r(\upsilon_i,\upsilon_j)$ defined by the ratio

$$D_r(\vec{o}_i, \vec{o}_j) = \frac{1}{1 + \dfrac{n_c(\vec{o}_i, \vec{o}_j)}{D_e(\vec{o}_i, \vec{o}_j)}} \tag{2.6}$$

If two vectors are the same, i.e. $D_e(\upsilon_i,\upsilon_j) = 0$, then the dissimilarity coefficient $D_r(\upsilon_i,\upsilon_j)$ is defined to be equal to 0, to avoid division by zero. Of particular note here is the observation that $0 \le D_r(\upsilon_i,\upsilon_j) \le 1$ and it is equal to 1 when there are no common non-zero components. Thus, the two parts are less dissimilar when the number of commons, n_c, operations in their routing sequences is larger and the Euclidean square distance $D_e(\upsilon_i,\upsilon_j)$ is smaller. It is also interesting to note here that if the perturbation parameter is ignored (in Equation (2.1) δ=0), the dissimilarity coefficient $D_r(\upsilon_i,\upsilon_j)$ reduces to McAuley's dissimilarity coefficient. The results for a grouping problem therefore, can be verified using this special case and compared with McAuley's for various changes of the perturbation parameter.

II.3. Advantages and Limitations of the Vector Perturbation Approach

The proposed vector perturbation method for grouping the parts has several advantages over existing approaches, particularly, when it is evaluated in terms of the generalized grouping problem.

The proposed approach is the first known method in the GT literature that builds a *vector space model* for a set of operation sequences. This model allows the representation of part operation sequences information and the ability to visualize the information and analyze the natural structure of the data. Additionally, one can apply geometric and linear algebra methods in analyzing part information within this type of model.

Most of the existing clustering techniques are strongly dependent on the shape, size and density of the clusters. With our vector representation there is the potential to transform the n-dimensional space into forms well suited for the clustering techniques. A choice of a particular clustering algorithm may also depend on the similarity measure used to define the relations between parts. At the simplest level, the vector representation of operation sequences naturally suggests numerical similarity metrics for parts, based on the Euclidean distance. However, many other related metrics (Mahalanobis distance, city-block distance, etc.) or nonmetric similarity functions (cosine measure, etc.) to relate two vectors can be introduced based on the nature of the data.

The proposed method takes into account both the 1) commonality of operations and 2) the similarity in operation sequences. These are the two essential features by which the similarity of parts can be characterized in the generalized parts grouping problem. The variation of the vector perturbation parameter provides a desirable compromise between the ease of resource assignment and the increase in production throughput by taking advantage of interleaving various parts through a common set of sequenced operations. Moreover, in real world applications all the operations may be not equally important due to their difference in costs, unit processing time, etc. This new method allows model heterogeneity among operations by assigning various weights to different operations.

Parts that are processed by the same operation more than once cause a special problem when unidirectional material flows in the manufacturing cells are assumed. So far, the proposed method assumes that the operation sequences do not contain backtracking operations. Research is underway to extend the method by making it "sensitive" to backtracking operations.

III. CASE STUDY

In this section, the proposed method is applied to the problem used by Burbidge[1] and frequently cited in the Group Technology literature. A list of parts and their operation sequences are shown in Table 3. Each element in the operation sequence denotes an operation and not a machine as specified by Burbidge. Since the method does not currently address backtracking, we have adjusted the data as follows. If an operation appears more than once in a routing sequence, only one of these occurrences was left to avoid backtracking; the rest are eliminated (crossed out in Table 3). The objective is to group 43 parts into families based on the similarity of their operation sequences.

First, the input data has to be analyzed as to whether it has any sequencing problems. In the selected example, there are many part pairs that may cause problems when assigned to the same family, assuming that this family is processed in a unidirectional flow cell. For example, if the parts P_5=(7-4-14-3) and P_{21}=(3-14-7) are grouped together then any ordering of operations 3, 4, 7, and 14 within the production cell results in backtracking of material flow, and therefore, such pairs are considered as *prohibited pairs*.

Using the Burbidge input data, the values of a dissimilarity matrix have been computed for each of the dissimilarity coefficients described in Section II.2. To illustrate the method we set the operation weight $\omega_j = 1$ in Equation (2.1). For example, the dissimilarity between parts P_5 and P_{21} computed by McAuley's is $D_M(\upsilon_5,\upsilon_{21}) = 1 - (3/4) = 1/4$. The dissimilarity coefficient $D_r(\upsilon_5,\upsilon_{21})$ between the operation sequences of these parts is $D_r(\upsilon_5,\upsilon_{21}) = 1 / (1 + 3 / (1+2\cdot\delta+12\cdot\delta^2))$. If we set the value of δ=0.2, then $D_r(\upsilon_5,\upsilon_{21}) \cong 0.38$, which shows the effect of adding sequence information in determining part similarity.

The next step in parts clustering is to group parts according to the dissimilarity coefficients that were calculated. In this paper, the hierarchical agglomerative clustering algorithm that utilizes Ward's Minimum Variance criteria is used for parts grouping.[12] Figure 1 is a Phyllips tree, or dendogram, representing the breakdown of how the 43 parts, (Table 3), were actually grouped based on the McAuley's measure. The length of the branches shows how close one group of parts is to another. For all the dissimilarity matrices, there are five basic well-separated part groups. When the value of the perturbation parameter is small, the separation of the groups of parts is determined by their differences in requirements of operations. And only closer to the leaves, are the differences in the orders of operations more apparent, (see Table 5 and Table 6).

TABLE 3.
Operation Sequences for 43 parts and 16 operations Example Problem

				Operation Sequence				
P1	5	9	6	7	~~5~~			
P2	1	8	5	~~8~~	7	15	13	1
P3	7	12	10	7				
P4	8							
P5	3	14	4	~~3~~				
P6	5	13						
P7	2	5	15	~~2~~				
P8	7	4	5					
P9	3	10	4	7	~~3~~			
P10	8	1	15					
P11	7	11						
P12	7	5	9	~~7~~				
P13	6	5	9					
P14	3	5	4	~~5~~				
P15	4	7						
P16	4							
P17	2	13	5	~~2~~				
P18	8	15						
P19	3	~~5~~	7	4	5	14		
P20	7	10						
P21	~~3~~	7	4	14	3			
P22	4	11						
P23	3	5	4	7				
P24	7	10	12	11	8			
P25	6	9						
P26	9							
P27	10	11	7					
P28	1	8	7					
P29	3	4						
P30	10	11						
P31	7	9						
P32	1	~~8~~	5	15	8			
P33	4	14	5	~~4~~				
P34	2	5						
P35	13	2						
P36	2							
P37	0	1	~~8~~	7	5	15	8	
P38	1	8	7	15	~~8~~			
P39	5	9						
P40	~~8~~	1	5	8				
P41	4	8	14					
P42	0	~~1~~	8	5	1	15	~~0~~	
P43	4	~~5~~	7	14	5			

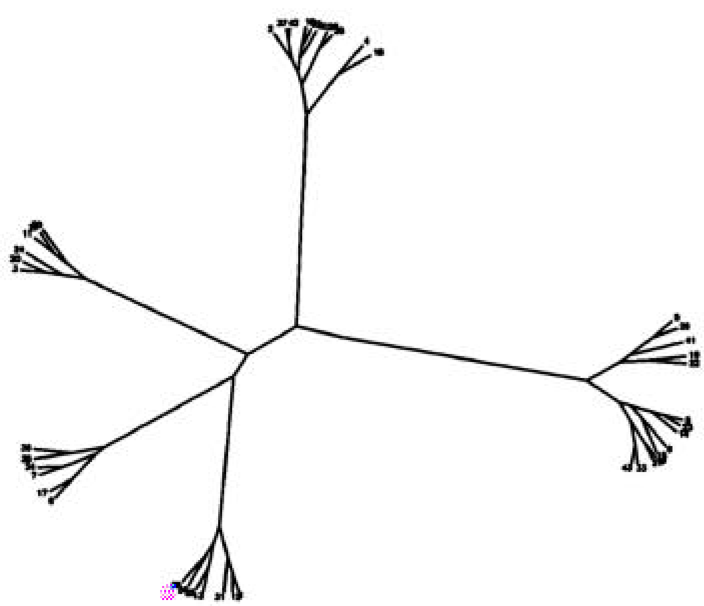

Figure 1. Dendogram for McAuley's dissimilarity matrix D_M

To evaluate the parts families generated for different dissimilarity measures we used the simple matching measure of comparison.[13] This measure is based on a 2 x 2 contingency table as shown in Table 4 in which all part pairs are classified for two partitions into four classes. Table 5 shows the comparison between the McAuley's partition and each of the considered dissimilarity coefficient based partitions for different number of part families. Each entry in Table 5 is in a form of a / (b + c). When the number of groups increases, the number of different assignments, or misses, is getting larger and the number of the same assignments, or hits, is getting smaller.

TABLE 4.
Contingency Table for Paired Comparisons between Partitions

Partition1/Partition2	**1**	**0**
1	a	b
0	c	d

- (1,1) class – two parts are assigned to the same family in the two partitions
- (0,0) class – two parts are assigned to different families in the two partitions
- (1,0) class – two parts are in the same family in the first partition and in different families in the second partition
- (0,1) class – same as (1,0) class but with the opposite assignment

TABLE 5.
Comparison of McAuley's Part Families with the Part Families for Different Dissimilarity Coefficient Measures

Dissimilarity Measure	**Number of Groups**					
	5	**6**	**7**	**8**	**9**	**10**
City Block Distance	135/82	119/44	107/28	97/34	66/65	58/67
Euclidean Distance	159/34	106/76	82/78	66/87	47/105	43/104
Euclidean Contracted	181/0	120/42	88/66	74/71	58/79	49/82
Dissimilarity Ratio	181/0	120/42	100/50	76/66	60/74	56/70

To compare the efficiency of the proposed method, the *sequence utilization measure*[14] has been used. This measurement is expressed as the ratio of the number of violated elements to the total number of prohibited elements. The results of this analysis for different dissimilarity measures and different number of groups are illustrated in Table 6. As one can see, the Euclidean distance based method performs the best and the McAuley's performs the worst out of all considered dissimilarity measures.

TABLE 6.
Analysis of Sequence Utilization for Different Dissimilarity Measures

	0.56	0.62	0.64	0.65	0.66	0.66
	0.59	0.73	0.85	0.87	0.88	0.90
	0.56	0.70	0.85	0.86	0.87	0.89
	0.60	0.59	0.68	0.68	0.80	0.86
	0.56	0.70	0.71	0.86	0.87	0.89

Grouping parts at various levels on the dendogram gives different part families. Table 7 shows a 7-group solution of the example problem using McAuley's and Euclidean distance dissimilarity measures. It can be noticed that the two solutions for the same problems are different – 82 hits vs. 78 misses from Table 5 in the assignments of parts to part families. The sequence utilization measure is also improved by 21% when the Euclidean distance combined with the vector perturbation approach is used compared to the McAuley's approach.

TABLE 7.
Part Families for a 7-group Solution Using McAuley's and Euclidean's Dissimilarity Measures

	McAuley	Euclidean Distance
Family 1	{1, 12, 13, 25, 26, 31, 39}	{1, 12, 13, 25, 26, 31, 39}
Family 2	{2, 10, 28, 32, 37, 38, 40, 42}	{4, 10, 18, 28, 38, 40}
Family 3	{6, 7, 17, 34, 35, 36}	{6, 7, 17, 34, 35, 36}
Family 4	{4, 8, 9, 14, 15, 18, 19, 21, 23}	{8, 14, 15, 16, 23, 29}
Family 5	{33, 43}	{5, 19, 21, 33, 41, 43}
Family 6	{3, 11, 20, 24, 27, 30}	{3, 9, 11, 20, 22, 24, 27, 30}
Family 7	{5, 16, 22, 29, 41}	{2, 32, 37, 42}

The next question that comes up in the analysis of the vector perturbation approach is whether the proposed method is "sensitive" to the variations of the perturbation parameter and what are the suggested default values for this parameter.

Viewing the problem geometrically, when the perturbation parameter is set $\delta = 0$ and the operation weight is set $\omega_j = 1$ in Equation (2.1), each operation sequence is mapped in one of the vertices of the d-dimensional unit hypercube. We call these vertices the *resource centers*. In this case, the operation sequences (O_1-O_2-O_3) and (O_3-O_2-O_1) will be mapped to the same resource center. When sequencing is taken into account, the goal is to map each operation sequence into a point of R^d in the vicinity of its corresponding resource center. Thus, if L is the maximum routing length in the set of all operation sequences, then taking $\delta < (1 / L)$ will guarantee that the distance between any pair of points in the same neighborhood will be less than the distance between any pair of points from the different neighborhoods. In all the examples above, we set $\delta_{default} = (0.99 / L)$. Table 8 summarizes the results of 8-group clustering for different perturbations of the parameter δ. The results are the pair wise comparisons (in terms of hits and misses) of part families obtained using the McAuley's and D_r dissimilarity measures with different values of δ. The last row in the table specifies the values of sequence utilization measure[14] for each of the considered cases.

TABLE 8.
Sensitivity to the Variations of the Vector Perturbation Parameter

	McAuley	**D_r (d = 0.05)**	**D_r (d$_{default}$ = 0.14)**	**D_r (d = 0.25)**
McAuley	——			
D_r (d = 0.05)	**92/42**	——		
D_r (d$_{default}$ = 0.14)	**76/66**	**93/24**	——	
D_r (d = 0.25)	**85/51**	**102/9**	**92/21**	——
Sequence Utilization:	**0.65**	**0.73**	**0.86**	**0.78**

IV. SUMMARY AND CONCLUSIONS

This paper has presented a vector perturbation approach to the generalized parts grouping problem. The need for this method is dictated by major distinctions in the traditional, manufacturing oriented, and generalized, supply chain oriented, grouping problems. The major features of this method are:

(1) It builds a vector space model to represent part operation sequence information. This technique improves visualization and discovery of natural part groups as high-density sets of points in n-dimensional vector space. We believe that this is the first model of this type that has been proposed in the GT literature;
(2) It groups a collection of parts for a general set of suppliers, not just a single known supplier;

(3) It provides a desirable compromise between the ease of resource assignment and the increase in production throughput by taking advantage of interleaving various parts through a common set of sequenced operations. This feature is due to the variation of the vector perturbation parameter.

Results from the presented case example illustrate the capability of this approach to generate part groups with a 90% sequence utilization measure. This contrasts to the 66% value achieved with the traditional approaches. This demonstrates the ability to process more parts within a unidirectional flow line cell.

This method was also applied to three large sets of C-130 and F-16 aircraft part data. The results, though preliminary, are very promising. Our conclusion is that the Vector Perturbation Approach is well suited to address the generalized grouping problem, and can be used to enhance the efficiency and utilization of most supply chain systems.

ACKNOWLEDGEMENTS

This research was supported in part by an appointment to the Oak Ridge National Laboratory Postdoctoral Research Associates Program administered jointly by the Oak Ridge Institute for Science and Education and Oak Ridge National Laboratory. We would like to thank Michael Borgsmiller for providing with the software programs used throughout this project.

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