Applying Matrixed Pareto Analysis With Activity Based Costing For Operations And Cost Management

Eli Berniker
David E. McNabb

Pacific Lutheran University

Management decisions made in operations planning and control determine what goods will be produced, when, and in what quantities; these determinations, in turn, shape other functional areas, including marketing, purchasing, receiving, storing, pricing, record keeping, inventory control, accounting, and other financial activities. Production management systems have long been effective at ensuring optimal efficiency in the flow of raw materials and finished goods through the production cycle. However, the accelerated proliferation of product varieties and product mixes that include both high volume and low volume specialty products has made it difficult for management to establish effective cost management and pricing policies. This paper expands traditional Pareto Analysis, a proven tool used in production and inventory control systems, by incorporating opposed metrics to create an effective low-cost tool to disaggregate product mixes and more accurately identify and control production costs.

Operations planning and control is concerned with the efficient and effective allocation of resources. Total quality management, just-in-time delivery, activity based accounting, optimized production technology, and the theory of constraints are among the many management procedures and concepts developed in managements' efforts to optimize the distribution of scare resources (Berniker, 1997; Ronen & Spector 1992).

Pareto Analysis has been shown to be an effective measurement tool with applications in most of these procedures. Classification systems such as Pareto Analysis (ABC Analysis possibly the best known) have contributed significantly to the development of inventory controls and other production management systems (Bradford & Sugrue, 1997). Chu and Chu (1987) described an easy-to-follow six-step procedure for classifying products into their relevant Pareto categories.

The accelerated proliferation of product varieties and product mixes that include both high volume and low volume specialty products has made it difficult for management to establish effective cost management and pricing policies. Simple Pareto analysis does not provide the necessary information for production, pricing, and inventory decisions. Combining activity based accounting with Pareto analysis overcomes some of the key shortcomings of each process alone. According to Ronen and Spector (1992), in order to plan what will be a "good, reliable, and economic production line," the planner must consider the cost of the resource, its location in the production chain, and its internal (demand) fluctuations.

Since the 1980s, many U.S. manufacturing firms have been forced to consider manufacturing as a way to gain a competitive advantage. In this way, inventory management systems, just-in-time supply (JIT), lean production, continuous product improvement (CPI), and similar programs are typical of efforts manufacturers have had to implement to improve productivity, become more efficient, and cut costs and reduce wastes (Azari-Rad, 2004). In addition to these concerns, designing and supporting an optimal mix of products has become a particularly pressing problem for firms that support a great variety of product offerings; product mix decisions may be most difficult when long product lines also require a wide variety of complex manufacturing processes. While marketing in such firms traditionally supports a wide spectrum of offerings to satisfy all customer demands, production managers often find it difficult to recover the costs associated with small or unique production runs. In many cases, true costs of manufacturing these special goods are difficult, if not impossible, to ascertain. Traditional cost accounting techniques are particularly weak in these instances.

The cost accounting techniques which evolved at the beginning of the last century as part of the scientific management movement work well for firms with few products that are manufactured in relatively simple processes. These methods focus on direct labor hours as the primary object of control and the most direct measure of efficiency (Kaplan, 1990). However, as product offerings multiplied and manufacturing processes became more complex, mechanized, and automated, traditional methods of cost accounting were found to be inadequate and unreliable. In particular, as overhead costs increased in amounts and complexity, their allocation to specific products and processes on the basis of direct labor became problematic. This led to cross-subsidization between products and processes (Johnson & Kaplan, 1987). The major problem was that, in plants where a wide variety of products are produced, more complex products are undercosted, while simple products tend to be overcosted (Banker, et al., 1990). In what is clearly a misguided decision, many simple products were purchased from outside sources at what *appeared* to be lower costs; outsourcing in this way often led to even higher unit production costs and even lower profits.

The solution for operations managers was to identify an accurate cost accounting system that captures production costs in conditions of product complexity. To address the problem, the management accounting profession developed the Activity Based Accounting approach, the goal of which is to more reliably capture variations in overhead resources for individual products and processes (Kaplan, 1990).

This paper presents an analytical model for disaggregating product mixes and production processes as a foundation for more effective production and inventory control management policies and decisions. The model sets inventory carrying costs against stockout costs. Because of the multiple factor design, we call this model Matrixed Pareto Analysis (MPA). The description of the method is followed by a report describing an application of MPA in a wood-products manufacturing company.

Pareto Analysis Theory

Simple Pareto Analysis (SPA) has long been used in operations, inventory control, and cost management as a means of organizing data for decisions purposes (Azari-Rad, 2001; Bonney Bradford & Sugrue, 1997; Chu & Chu, 1987; Rai & Allada, 2003; Wendell, 1987; Wharburton, 2003). The method is used in so many different ways that it seems appropriate to briefly review the process as used for inventory control. Historically, the method derives from the work of the Italian economist and sociologist Vilfredo Pareto who introduced the concept in his Cours d'Economie Politique, published in 1896-7. Pareto proposed his 80-20 rule as an explanation of the consistent pattern of the distribution of incomes and wealth in society; 80 percent of the wealth of a society is controlled by 20 percent of the people.

Pareto's method is simple and easy to understand when applied to inventory management. The distribution of inventory is aggregated into three large blocks according to their rank order of turnover; the groups of products are labeled A, B, and C. The A block usually includes from 10 to 15 percent of the number of items in inventory; together, these represent from 60 to 80 percent of the total inventory value.

The B block includes about 25 percent of the total number of items, and from 15 to 20 percent of the total value. The C items include the largest percentage of the total inventory (usually around 50 to 55 percent); these items represent only 15 percent of the total inventory value. While the break points between these blocks vary considerably in practice, the general relationship (that is, the shape of the curve) remains relatively constant in the overwhelming majority of applications.

Different inventory control approaches are applied to each block of items. One example has been proposed by a Fortune 500 firm (Wendell, 1987): A-items should be monitored daily and orders adjusted to reduce inventory holding costs. B-items should be controlled using a standard economic order quantity model. C-items, maintained as a minimum safety stock, might not be monitored at all, but simply reordered when the safety stock was opened. Thus, from 50 to 60 percent of the total inventory commanded little or no attention, while A-items received intensive attention. This practice illustrates the managerial value of Pareto analysis. If inventory costs and levels are to be effectively controlled, efforts must be focused on those items that constitute the greatest value of the total inventory (Wendell, 1987). The greatest strength of the method lies in substituting objective counts for subjective "hunches" for performance measurement and control. There are, however, limitations to simple Pareto analysis.

Limitations of Simple Pareto Analysis

From a production planning viewpoint, the greatest limitation of Pareto Analysis is that it is unidimensional; categorization is typically based upon the aggregate value of product sales (stock turnover) alone. Thus, single high-value product category includes low-volume, high-cost items in the same group as low-cost, high-volume items. An argument can be advanced that these should be two different categories, each of which is managed differently. Control practices for high-volume, high-unit cost items should be different from control practices for high-volume, low-unit cost items. Equally, low-volume, high-cost items should be managed differently than low-volume, low-cost items.

A second limitation is that the analysis is unidirectional as well as one dimensional. A single parameter, turnover, is used to reflect all inventory costs, often neglecting those costs that are reduced by increasing inventory. The most important costs that counter inventory-carrying costs are stock-out costs-the costs associated with an inventory shortage or out-of-stock position. For example, if a product line includes high value-added items and commodity items, we would expect the losses from not selling the former to be high, while the stock-out costs of commodity items to be relatively low. Thus, different inventory management practices should be applied. However, once again, one-dimensional, simple Pareto analysis does not allow selectivity among such items.

To overcome the limitations of simple Pareto analysis with a more focused and selective approach to cost control strategies, we suggest using a matrixed Pareto analysis consisting of more than one parameter for defining categories.

Essential Criteria for a Production Decision Model

Kaplan (1990) identified the inability of traditional cost accounting systems to deal with the effects of changes that occur as a result of variation in production volume and product mix. Distortions in overhead cost allocations are introduced by shifts in product mix; simple summaries of per-unit costs become meaningless. Moreover, these distortions can become critical when a manufacturer fails to recognize the increasingly diverse nature of its output. Kaplan proposed a two-alternative solution to this problem: either develop product complexity indices, or entirely eliminate unit cost summaries. Neither of these suggestions has been found to be completely satisfactory.

The challenge of finding a useful means of disaggregating costs remains. Operations managers need a method of disaggregating costs that identifies intelligible cost drivers that are relevant to operational decisions. Several criteria for a useful method may be defined.

First, the method should be simple and intelligible. Second, it must deal effectively with the heterogeneity of products and the activities and processes required for their manufacture (Foster & Gupta, 1990). The method must be:

- Systematically accumulating,
- Control a large sum,
- Have diagnostic capability, and
- Be a vehicle for process cost management.

For cost management to improve the method must use multiple dimensions and include the ability to focus management attention as appropriate (Gronlund & Johnsson, 1990). In addition, the method should be possible to validate the cost categories and drivers used in the system. Finally, given that cost management is the goal, the method should be simple and economical in its application.

Goals for a New Production-Decisions Model

The primary goal of the Production-Decisions Model is to make it possible for management to quickly and effectively refine and interpret manufacturing and inventory data. Simple Pareto Analysis does this by creating useful subgroups based on Pareto distributions. But it does not go far enough. In principle, opposed costs associated with production and inventorying each "unique" product should be available for review in real time before every managerial decisions. In practice, however, when the firm's product mix reaches in the range of several hundred items such attention has been difficult if not impossible to achieve. Many firms in today's mature markets number their products in the thousands. Thus, a technique such as Matrixed Pareto Analysis (MPA) is needed to preserve the efficiency of simple Pareto classification into large subgroups while maintaining some capacity for refining these groups according to meaningful cost and contribution to margin measurement principles. If the groups that emerge are distinct, the difference-information should support better product and inventory decisions.

MPA appears remarkably robust with respect to the imprecision of data often found in manufacturing environments with an extensive variety of customer-selectable components and finishes, finished product designs and dimensions, and diverse product lines.

The MPA Model: Opposed Cost Parameters

MPA may be illustrated with a description in which a hypothetical simplified Pareto distribution is established for two measurement axes: inventory and gross margin. As suggested by Wendell (1987), inventory-carrying costs are proportional to the dollar value of annual usage and may be classified accordingly. Stock-out costs are more complex but can be simplified as the lost margin from missed sales. This enables the manager to consider two inventory costs concurrently: carrying costs and stock-out costs. The potential stock-out costs of an item may also be considered as being equal to, or at least proportional to, that item's annual contribution or gross margin[1] which, for simplicity, is labeled as Gross Margin in the following tables and figures.

[1] The firm in this case referred to the difference between direct labor and direct material costs and their discounted sales prices as "gross margin." This term suggests mark-ups and relates to marketing policies than the more accurate accounting concept of contribution. Whatever discrepancies these terms may signal are not relevant to the analysis.

Both measures should be considered over the same time frame. Simplification is achieved by breaking up the distribution into three groups labeled ABC and HML. The ABC categories refer to inventory carrying costs and the High-Medium-Low (HML)categories refer to the contribution margin, producing the nine-cell table shown in Table 1. The percentages are indicative of what might be expected from grouping a Pareto distribution. Sixty percent of the Gross Margin is contributed by the H group and 25 percent of the Sales Volume is from the B group. (Sales Volume serves as a surrogate representing the total amount of inventory that passed through the enterprise.) For clarity, we assign ABC to refer to undifferentiated sales groups and HML to undifferentiated Gross Margin groups. The cell, i.e. AH, refers to the Product Groups identified by distributing one group across the other.

Table 1: Two-Parameter Matrixed Pareto Analysis

	Gross Contribution to Margin		
Inventory Level	**60% H Items**	**25% M Items**	**15% L Items**
60% A Items	AH	AM	AL
25% B Items	BH	BM	BL
15% C Items	CH	CM	CL

Note: *The cell labeling convention used in this paper is identical to that used in spreadsheets, i.e. row/column. For example, the lower left cell is Row C, Column H.*

The descending diagonal (AH, BM, CL) is the expected outcome and yields no new information; those items that constitute 60 percent of inventory turnover should be expected to constitute a similar proportion of the contribution to gross margin contribution. If the other cells remained empty of items, the analysis will not yield useful results. However, three other cells are likely to contain important product groups. Cells AM and AL represent products with 'A' level inventory costs but only Medium- or Low-level contributions (gross margins). The AL group typically consists of commodity products with high demand but with low unit value; examples include milk in a supermarket or dimensional lumber at a lumberyard or building supply store. Given their lower contribution to gross margin, higher stock-out risks for AL items might be accepted. For example, a lumber wholesaler/retailer found that dimensional lumber (standard 2x4's etc.), represented a large part of sales to contractors yet delivered poor margins. The wholesaler considered a policy that allowed more stock-outs and authorized their outlets to make up shortages by buying from local competitors who also earned low margins.

Alternatively, the BH cell includes high value-added items; examples might include such items as decorative paneling or paint at the building supply store. Inventory management policies should be differentiated for these off-diagonal groups. Given their higher contribution to gross margin, management should consider higher safety stocks for BH items. Once these subgroups are established, other measures may be applied to further characterize each group. This will be demonstrated in the following case example.

An Application: Wood Products Company

Wood Products Company (WPC) is a locally owned West Coast manufacturing and assembling firm with a long history of operations in the specialty wood products industry. The firm produces more than 3,200 individual wood products and components. The firm's product lines vary from highly customized, albeit cataloged, parts and products to standardized high volume "commodity" items.

Following the logic of Rai and Allade (2003), the firm's product lines may be classified in two different ways: Single Product-type (with many variations) for all segments in the market, or Multiple Product-types (single product with a few variations) each of which is maintained for separate market segments. Product lines for stock-keeping records are predominantly finished products but also include parts and components that are fabricated or processed for internal and external applications.

For most of the firm's history it was generally assumed by management that the supply of special products gave the firm better access to dealers through whom the major part of their output is marketed. It was further believed that the highest profits were made on the higher value-added parts and products. However, when earnings failed to reach expectations several years ago, management became concerned about the impact on manufacturing costs, inventory costs, and market share that they suspected were the result of what appeared to be an accelerating and uncontrollable proliferation of product varieties. As product varieties increased, management found it difficult to establish consistent and effective cost management and pricing policies. A Matrixed Pareto Analysis was tested as a tool for improving product line depth and inventory decisions.

The next section describes these results (the data are systematically distorted to maintain proprietary confidentiality); the time period is indicated as annual but the actual data represent a different period). Furthermore, the data labels have been generalized somewhat to conceal their specific definitions. The adjustments made to Sales and Gross Margin reflect non-systematic price discounts granted by the firm during the time period. None of these changes undermine the conclusions.

Figure 1 is a simple Pareto Analysis distribution of WPC's annual sales volume. The classic Pareto pattern is exhibited for the 3,200 products. For this example, Pareto categories are labeled High, Medium, and Low rather than ABC. The vertical axis represents annual sales volume in units. H-category products constitute a higher proportion than found in a typical Pareto distribution, while the M and L products are also proportionately less.

Without further analysis, the simplest and most direct management interpretation of these distributions is that the H group clearly dominates in generating sales volumes and, therefore, similarly dominates in generating sales dollars and gross margins. Figure 1 should be replicated for Sales Dollars and Gross Margins, thus producing similar results.

Adjusted Sales vs. Adjusted Gross Margin

Greater assurance about the relative contribution for each category may emerge if the dimensions of sales dollars and contribution to gross margin are evaluated against

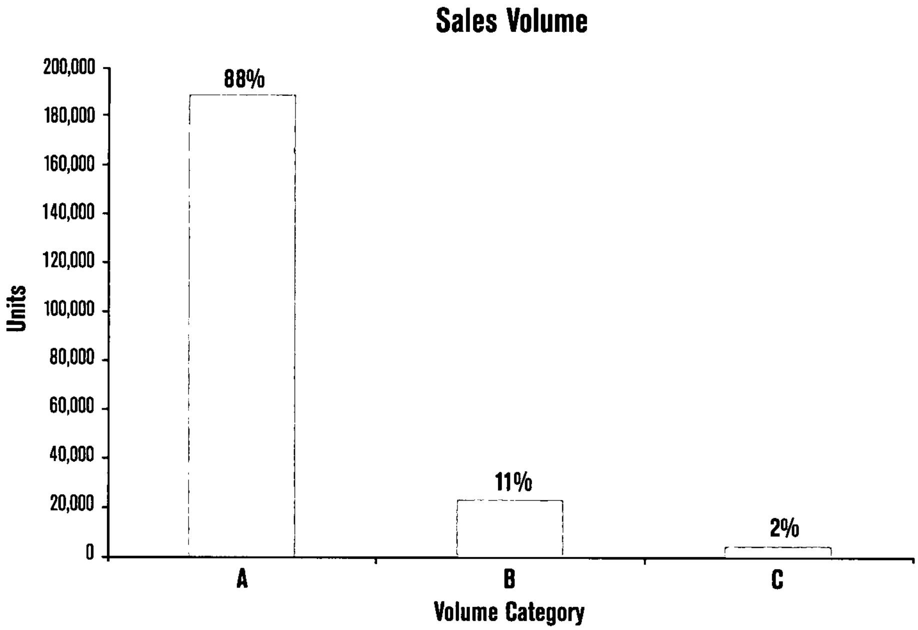

Figure 1: Pareto Distribution of Sales Volume for Wood Products Company

one another in a Matrixed Pareto Analysis. This analysis provides greater discriminatory precision by disaggregating the three traditional Pareto groups into nine separate cells, each representing a product group. For even greater precision, a fourth category of contribution to Gross Margin is included in the analysis, this raising the number of cells to 12. This additional category, N, applies to products that have negative gross margins.

Data for the 12 product subgroups are presented in Table 2. Cell entries represent sales and gross margin (all amounts are in thousands). Each sales group's data (A, B, and C) are distributed across four different levels of gross margin (H, M, L, and N).

Summing sales figures on the AH, BM, and CL diagonal produces a total of a little more than \$14.8 million, or only 55 percent of the company's annual sales of \$26.4 million. Thus, fully 45 percent of product sales do not conform to the expected relationship between sales and gross margins. This is the crux of the MPA approach: For accurate cost planning, management must disaggregate product populations into product groups with significantly different economic characteristics.

The value of disaggregation becomes immediately clear when the A-sales product group levels are examined. Product group AN (high volume, but with negative contribution to margin) corresponds to about 38 percent of all A-level sales. Moreover, it contributes a *loss* of \$651,000 to gross margin. Conversely, product group BH, while not a part of the A-Level sales group, contributes \$266,000 to gross margin. This is 12 percent of the gross margin for the entire operation. Each of the off-diagonal cells calls for different cost control and pricing strategies. Classification this way allows management to further explore the economic characteristics of its complete product line.

Table 2: Matrix Pareto Analysis: Adjusted Sales vs. Adjusted Gross Margin
Cell Entries = Sales Dollars; Gross Margin (both in $000)
Gross Margin ($000)

Sales $	H	M	L	N	Totals
A	12,824	1,052	177	8,530	22,583
	2,152	19	1	-651	1,521
B	933	1,412	296	531	3,172
	266	272	11	-48	501
C		258	316	40	614
		102	81	-7	176
Totals	13,757	2,722	789	9,101	26,369
	2,418	393	93	-706	2,198

Contribution to Margin

It is now possible to examine the average contribution to gross margin for products in each product group. Table 3 contains the percentage of gross margin to sales for each group. The average contribution of 8 percent across all products conceals significant differences: Product groups vary from negative 18 percent to positive 40 percent contribution. Each of the product groups may be further analyzed to reveal anomalies in the cost and price management policies of WPC.

Table 3: Percent Gross Margin and Group Averages
Gross Margin Group

Sales Group	H	M	L	N
A	17%	2%	1%	-8%
B	29%	19%	4%	-9%
C		40%	26%	-18%

WPC Average Gross Margin = 8%

Given the analysis and the available data, it is now possible to identify the cost characteristics of each product group including interesting ratios. For example, Table 4 displays the "M" level Contribution to Gross Margin Group distributed across three (A, B, and C) levels of Sales and other relevant data.

The differences between product groups are best seen in the ratios. The percent-Gross Margin varies from 2 to 40 percent. The former represent commodity mark ups while the latter appear to be healthy margins. However, product group CM's 40 percent contribution to Gross Margin invites suspicion once it is revealed that the average sales per product in this group are 1.5 per year. These products may be enjoying a subsidy from higher volume products if set-up costs are pooled in manufacturing overhead rather than assigned to each product (a common practice).

Table 4: Cost Characteristics of Product Groups

Sales Level Category

Metric			
Sales Group	A	B	C
Gross Margin Group	M	M	M
Cell:	AM	BM	CM
Data			
Products	51	247	826
Sales $ (000)	$1,052	$1,412	$258
Gross Margin $ (000)	$19	$272	$102
Volume - Units Sold	10,338	10,201	1245
Ratios			
% Gross Margin	2%	19%	40%
Sales $/ Unit	$102	$138	$207
Gross Margin $/ Unit	$2	$27	$82
Sales $/ Product	$20,627	$5717	$312
Gross Margin $/ Product $372	$1101	$123	
Units Sold/year	203	41	1.5

Cell CM includes 826 products whose average annual contribution to Gross Margin is only $123. These are custom ordered products that generate set-up, control, and tracking costs. These costs may easily consume the entire projected margin on the sale. Indeed, further analysis at WPC revealed many such outcomes.

Other than for the Gross Margins, all of the data in the cell analysis is reasonably hard; sales dollars and counts of units and products. The Gross Margin is an estimate of the mark-up over costs and, given the cell analysis, should be interpreted with care and skepticism. While the costs of materials and direct labor may be readily associated with each product, pooled overhead costs such as set-up costs, management, handling, design, tracking, etc., are expected to be absorbed by the Gross Margin.

The Matrixed Pareto analysis raised many questions, a result entirely consistent with its purpose, which is to focus management attention on opportunities for improved cost management. However, it may also serve to identify useful ways to disaggregate complex cost information. That is the agenda of Activity Based Costing.

MPA and Activity Based Costing

A core problem for management accounting in manufacturing operations such as WPC is the complexity of product offerings and manufacturing processes. The challenge is to disaggregate products and processes into meaningful subsets with reasonably homogeneous cost characteristics. Simply put, the goal of Activity Based Costing is to disaggregate overhead pools into cost components so that more refined cost allocations can be made to particular products and manufacturing processes. Kaplan (1990) points out the inability of traditional systems to deal with the effects of changes in product volume and mix. "Distortions introduced by *mix* shifts occur when the organization fails to recognize the increasingly diverse nature of its output ... simple summaries of cost per unit are no longer meaningful." Kaplan's solution is to suggest either the development of "product complexity indices," or to eliminate unit cost summaries altogether.

Traditional cost management data is often problematic because it is not readily translated in ways relevant to operational decision challenges. Operations managers, often, must take the determinations of cost accountants on faith. The application of complexity indices can only exacerbate that situation. That may be one explanation for the systemic resistance to the substitution of these new cost drivers and performance measures for traditional measures. At least the old measures, if inaccurate and sometimes obscure, seemed more or less intelligible if only as a result of years of exposure. Thus, the challenge is to find useful means of disaggregating costs that identify intelligible cost drivers relevant to operational decisions.

Identifying Product Groups With MPA

As an example, suppose that WPC management wants to classify its products in terms of the kinds of overhead resources that they demand. Some of these resources are associated with the manufacture of parts and others with their assembly into final products. On average, WPC's final products are assembled from 10 to 30 components.

Much of the variety of the firm's 3,200 products is based on variations in one or more of these parts. Thus, this company may be dealing with 10,000 different part-combinations. Furthermore, a large variety of manufacturing operations are required to produce these basic components. Finished products use these components in different combinations. Required quantities vary greatly; they may involve production runs of several thousand or be limited to lot sizes of just one or two pieces. This is not an atypical level of complexity for many firms.

A first attempt at classification of parts and processes might utilize annual direct labor hours matched against part volume. Intuitively, it might be expected that those parts that accumulate the greatest portion of the total direct labor hours should also represent a similar portion of the total part volume. However, the Matrixed Pareto analysis suggests otherwise. These data are displayed in Table 5.

Table 5: Matrixed Pareto Analysis - Parts
(Direct Labor Hours vs. Part Volume)

	Direct Labor Hours		
Volume	**H Parts**	**M Parts**	**L Parts**
A Parts	AH	AM	AL
B Parts	BH	BM	BL
C Parts	CH	CM	CL

As noted above, the diagonal cells, [AH, BM, and CL] confirm intuitions and do not add information. Cells AM and AL represent high volumes with low direct labor hours. This is what we would expect from automated production processes and, accordingly, machine overhead costs might be more relevant for this subgroup. Alternatively, cells BH and CH represent labor intensive product groups. Each cell appears to represent a different resource consumption profile as a basis for cost allocations. The MPA enables accountants to remove part of one component of pooled overhead, machine overhead costs, and allocate it directly to off-diagonal subgroups defined by the analysis.

Identifying Machine Groups

A similar approach may be used to classify manufacturing processes and machines. Many different machines are used at WPC to manufacture the component parts. In many ways, the plant is organized like a job shop. How might the machines be classified from a cost management perspective? As displayed in Table 6, two potential metrics, among many, are the 1) volume and 2) variety of parts produced by a machine. Identical machines might be grouped and rank ordered in terms of the total number and variety of parts they produce. Assuming a full data set, the analysis should yield a useful classification.

Table 6: Matrixed Pareto Analysis –
Machines: Product Volume vs. Variety

Metric	**Volume A Machines**	**Volume B Machines**	**Volume C Machines**
Variety H Machines	HA	HB	HC
Variety M Machines	MA	MB	MC
Variety L Machines	LA	LB	LC

Consider the characteristics of machines in each of the corner cells. Cell LA represents highly specialized machines dedicated to producing a small variety of parts in high volumes. We would expect set up costs per part to be proportionately low in this cell. Cell HC represents general purpose machines that produce a large variety of parts in small lots. Set up time should be quite high as a proportion of total machine hours. Cell HA represents the ideal of flexible manufacturing systems and the production of high volumes of a large variety of parts. Capital costs may be particularly high. Cell LC represents machines with low utilization. They are machines infrequently used but for which there are no substitutes when needed. A primary cost may be their unused capacity and space utilization. Here, again, components of the pooled overhead may be more directly allocated to specific groups of machines.

Validity Testing

Both of the above analyses suggest useful subgroups for the allocation of overhead costs. However, the selection of metrics only exemplifies the many different ways to classify parts, products, processes, or machines. For example, reject rates, rework required, or other quality measures might have been used. Some processes might better be classified by scrap rates.

The purpose of classification is to identify groups of parts or machines for which the distribution of indirect costs differs across the population of parts or machines. Consider the proportion of set up hours to total machine utilization. It might be expected that each of the corner cells in the above matrix is significantly different. This hypothesis can be tested using a Multi-Way Analysis of Variance (MANOVA.) First, sample each of the cells; then establish the average set up proportions and their standard deviations for each cell and for the entire population. Finally, test for significant differences. This may also be a useful way to test for subgroup validity.

The ideal outcome would be well-differentiated groups with little overlap in terms of their overhead costs. A more likely outcome is that cell boundaries will need to be shifted to create valid subgroups. In some instances, more or fewer subgroups will emerge. Finally, if there is considerable overlap between subgroups, we should conclude that the selected metrics are incorrect.

Validity must be understood in the context of the present challenges of cost accounting. An accountant in a large manufacturing corporation described the allocation of pooled overhead costs to direct labor as "spreading peanut butter thickly." The utility and validity of MPA for Activity Based Costing will be defined by the reduction in pooled "peanut butter" and the increased direct allocation of specific costs to parts and processes. MPA will not yield high levels of precision. However, given the present state of allocation methods, it should yield a considerable improvement.

Mapping Cross Subsidization

Matrixed Pareto analysis may also be used directly to test the usefulness of cost drivers by mapping cross subsidization between products. For example, management might test direct labor overhead allocations against set up frequency as representative of ordering costs (Table 7). The matrix may, or may not, produce meaningful cells. If few products appear in off-diagonal cells, it is possible to conclude that a cost driver based on set up costs will not meaningfully reallocate costs to products. If the off-diagonal cells are dense, there is evidence of cross-subsidization.

Table 7: Matrixed Pareto Analysis - Overhead Allocation (Direct Labor vs. Set- Up Frequency)

Metric	Direct Labor H Products	Direct Labor M Products	Direct Labor L Products
Set Up Freq. H Products	HH	HM	HL
Set Up Freq. M Products	MH	MM	ML
Set Up Freq. L Products	LH	LM	LL

As before, the diagonal cells do not add any information. However Cells **HM** and **HL** represent subgroups with low direct labor and frequent set ups. We saw such products in the WPC case. They were low volume small lot products. The table suggests that if overhead is allocated on the basis of direct labor only, these subgroups enjoy a subsidy for their share of set up costs. Alternatively, cells **MH** and **LH** represent high volume items with infrequent set ups, i.e. larger lot sizes. Given direct labor as the driver of overhead allocations, these product subgroups are subsidizing other groups at least in terms of set up costs. A large variety of cost drivers may be tested in this manner to identify candidates for further study.

Validation of MPA

The purpose of MPA is to raise questions with respect to cost, inventory, sales or other business policies. The test of MPA's utility, therefore, is whether or not a MPA segregation of products or processes results in subgroups that merit differential policies. For example, in Table 2, the sales and inventory policies for high margin products should be different than for low margin or negative margins products. In principle, sophisticated techniques may be applied to the matrix to quantify the optimum differences in these policies as a function of Gross Margin. In practice, the assumptions governing such policies are more complex than can be optimized in a two dimensional matrix. The validity of MPA derives from the ability to identify subsets that merit consideration of differential policies.

Conclusion

The Wood Products Company case exemplifies the successful application of a Matrixed Pareto Analysis to operations and cost management. The method succeeded in highlighting a set of cost and operational problems and enabled management to focus their attention on product subgroups that were particularly problematic.

The application of Matrixed Pareto analyses at WPC initiated a management review of their entire product line. Close to 25 percent of the products were evaluated for potential elimination. An effort was made to associate set up costs with low volume products and pricing was reviewed accordingly. Much discussion was generated between marketing, manufacturing, and accounting about the merits of various product offerings, product costs, and the sales volumes necessary to justify product manufacturing. Many issues remain to be resolved but it appears evident that the traditional business practices of the firm have been challenged.

Few products were dropped by WPC. It was argued by Sales that their larger customers would not purchase their high volume products unless they could also get the low volume special products. One of the authors noted that that hypothesis could be tested using MPA. On one axis, we rank order customers by volume, against the products they purchased by volume. We reasoned that if the Sales argument was true, we would find high volume customers buying across the range of products. That seemed doubtful. More likely, they rarely bought the very low volume products. We suspected that particular customers were "cherry picking" the low volume products.

The MPA would have revealed the purchasing practices of high, medium, and low volume customers. The management chose not to proceed with the second analysis given the discussions that emerged from the prior analysis.

Matrixed Pareto Analysis is a low cost methodology for disaggregating products and processes into groups defined by opposing economic metrics. These groups permit differential analyses in support of more effective decision making. Research is required to validate the potential and actual utility of MPA in support of managerial and cost allocation decisions. The methodology may be further developed by the addition of a third dimension allowing for greater refinement of product or process groups.

The key is to apply Pareto Analyses based on opposed metrics. The disadvantages of single dimensional Pareto Analyses are overcome by disaggregating various subgroups. Moreover, Matrixed Pareto Analysis should be a useful method to discover useful product and process subgroups for the allocation of indirect costs and, in a simplified form, to identify suitable cost drivers. It also appears to be a relatively low cost methodology. However, its effectiveness can only be ascertained through actual research and application. It is hoped that Matrixed Pareto Analysis will prove a useful and effective addition to both management accounting and operations management practice and research.

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