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A HEURISTIC FOR DESIGNING MANUFACTURING FOCUS UNITS WITH RESOURCE CONSIDERATIONS

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Abstract

This paper presents a model of the plant-within-a-plant (PWP) design problem and demonstrates a heuristic for analyzing the problem. Although the benefits of a manufacturing focus have been articulated in the literature, methods for implementation with consideration for resource requirements have not been developed previously. In this study, we discuss the importance of including resource considerations and propose a methodology that can help managers arrive at a facility design with a high degree of focus and minimum resource needs. A heuristic is developed that incorporates the concept of order-winning criteria and volume into the focus design. The heuristic not only recognizes the effects of conflicting manufacturing tasks, but also considers resource costs and material flows between PWP units. Experimental results show that the proposed methodology offers managers the opportunity to generate and assess alternative PWP designs, which are otherwise unavailable. Overall, this research provides an analytical framework for further research in focused manufacturing.

1. Introduction

Achieving the status of a world-class manufacturer requires a direct linkage between the requirements of the marketplace and the manufacturing process needed to produce the products (Squire et al., 2006). Companies seek market advantage by emphasizing certain characteristics of their products or manufacturing systems such as low price, high quality, fast delivery, dependable delivery, product mix flexibility or volume flexibility. These characteristics are referred to as ***order winners***, criteria that firms choose to differentiate their products in the marketplace (Hill, 2000). However, many firms find their own advantage diluted because they produce items which require emphasis on different order winners on a common set of resources and infrastructure. Conflicts may arise when new products are introduced or when the firm enters new markets incrementally.

Many researchers have described the conflicting manufacturing tasks implied by an inconsistent set of order winners (Pesch and Schroeder, 1996; Bozarth and Edward, 1997; Mukherjee et al., 2000; Vokurka and Davis, 2000; Squire et al., 2006). For example, Venkatesan

(1990) describes how Cummins lost manufacturing focus due to incompatible market requirements. The firm's strength was originally to achieve low cost production through large, stable production runs on dedicated machining lines. Severe competition and shorter new product life cycles forced the company to be competitive on other dimensions such as fast delivery. As more new products were introduced, Cummins' markets became fragmented and required different operations capabilities in the plant. As a result, all products could no longer be efficiently manufactured with the same type of resources and infrastructure. In addition to the capability for low-cost production, Cummins needed another manufacturing capability that provided process flexibility, frequent setups and low-volume runs on general purpose machinery. The differences in managing such divergent capabilities generate significantly different infrastructure needs such as reward/incentive systems, manufacturing planning and control systems, vendor contracts, and quality management systems. For situations like Cummins', Skinner (1974) suggests focused manufacturing which limits the set of products, technologies, volumes and markets for which a plant is responsible. The resulting simplicity and consistency of the manufacturing system can enhance the firm's competitive position in the market. When an individual plant has to satisfy multiple competitive dimensions a "plant-within-a-plant" (PWP) system is proposed as a practical tool to resolve conflicting manufacturing tasks (Bozarth, and Edward, 1997; Hill, 2000; Hill 2008; Skinner, 1974).

The concept of PWP aims at achieving manufacturing focus by organizationally and physically separating a plant into several semi-autonomous manufacturing units. Each unit manufactures a limited set of products with the requirements of similar manufacturing tasks. The PWP design problem involves assigning products to PWPs (focus units) according to their consistency with respect to the order winners of the markets they serve, as well as assigning resources to PWPs to avoid unnecessary resource duplication and inter-PWP flows of material or products. Considering the large number of products manufactured and various types of resource required in a typical manufacturing plant, forming a PWP design to achieve manufacturing focus can be a very challenging task (Bozarth and Edward, 1997; Hallgren and Olhager, 2006; Kumar and Nottestad, 2009; Ye et al., 2009). As a result, despite the potential benefits of PWP (focus unit) design, the research on implementing such a design has been limited.

In general, past research has either conceptually narrated the benefits of focused manufacturing or empirically determined the benefits from small-scale case studies (Bozarth and Edward, 1997; Ketokivi et al., 2006; Hill, 2008). The primary objective of this study is to develop a heuristic to arrive at PWP design, incorporating both perspectives of strategic similarity and resource limitations. The following section reviews the extant literature to recognize the relevant PWP design issues and the existing design methodologies. Two mathematical models are subsequently developed to capture the dual perspectives of strategic similarity and resource limitation, followed by the discussion of the heuristic. The heuristic is tested and, finally, managerial implications and suggestions for future research are provided.

2. Literature Review

After Skinner's (1978)'s seminal article, there is a stream of research on PWP design methodology. Fine and Hax (1985) identify strategic product groups of a firm by making subjective judgments regarding the positioning of various product lines in the Hayes and Wheelwright product-process matrix (1984), but do not address how each strategic grouping would ensure a coherent set of manufacturing tasks and operations capabilities. Hill (2000) presents a methodology for segmenting markets in manufacturing terms that designates percentage weights for the order-winning criteria of every product. Hill suggests that plants can be organized by grouping products on the basis of common order-winning criteria. The order-winning criteria provide a good way of linking marketing and manufacturing perspectives during the formulation of PWPs. For example, a low-price market strategy for a certain group of products may translate into a priority for low cost manufacturing and a manufacturing task involving high volume runs on dedicated equipment. Alternatively, a strategy for another group of products which stresses product customization implies an emphasis on process flexibility which, in turn, dictates a manufacturing process and infrastructure that is able to adapt to design changes economically. Assigning these two product groups to the same process will often result in a hodgepodge of compromises which leaves manufacturing unable to serve either product market effectively. Many researchers have supported using order winners as focus criteria in situations where conflicting manufacturing tasks exist in a plant (Ketokivi and Jokinen, 2006; Mukherjee et al., 2000; Sheu and Krajewski, 1996).

In addition to order winners, the use of product similarity in volumes as a focus criterion can be found in practice (Hyer and Wemmerlov, 2006; Vokurka and Davis, 2000). Berk (1982) observed a manufacturing plant where "small jobs" (with low volume) were responsible for disrupting the manufacturing system. The small jobs accounted for only ten percent of direct hours but were responsible for almost half of the "troubles" such as machine setup conflicts, material movements, paperwork, coordination, work-in-process and feedback transactions. This effect of volume was also recognized by Cummins (Venkatesan, 1990). By separating the production of small jobs from large jobs, Cummins achieved immediate productivity and administrative improvements, work-in-process and paper work reductions, and simplified production control.

While the literature recognized the criteria of forming focus units, Sheu and Krajewski (1996) first proposed an analytical approach in formulating PWPs. They defined the PWP design as the problem of segmenting markets and organizing operations to support the diverse competitive requirements of these markets. A clustering analysis was developed to form focused product groups. Each product group is processed in a separate PWP. The methodology was tested using data collected from three companies. The clustering analysis successfully divided operations into manufacturing units that were far more focused than the manufacturing organization structured by management judgment alone. Their study was the first to demonstrate that an analytical approach can be more effective than management intuition in arriving at PWPs.

In general, these studies recognized the complexities of the PWP formulation and agreed on the need for a solution methodology. However, none of the previous studies adequately considered resource requirements in determining the appropriate focus. In other words, the underlying assumption was that the PWP design problem is an uncapacitated problem and therefore resource duplication problems between various focused product groups were not considered. In practice, dividing a factory into PWPs necessitates assignment of each product to a PWP while assuring that necessary resources are available to sustain the operations. Previous research has argued that product assignments should be based on considerations such as volume and order winner criteria. The underlying assumption is that if products within a group are consistent with respect to volume and order-winning criteria, the manufacturing tasks are also consistent. However, making product assignments without considering resource requirements (e.g. machine types and quantities, worker skills, etc.) will result in duplication of resources and a higher level of capital investment, as evidenced in actual industry practice (Hallgren and Olhager, 2006; Hyer and Wemmerlov, 2006; Sheu and Krajewski, 1996; Vokurka and Davis, 2000). The design of PWPs must involve assigning products to groups to achieve a high level of similarity in their manufacturing tasks while also assuring that the resources required to implement the PWP design are minimized. Consequently, this paper formulates the PWP design problem as a capacitated allocation problem and uses the similarity between products with respect to manufacturing ***order winners*** and ***volume*** as surrogates for the similarity of manufacturing tasks.

3. PWP – Mathematical Model

We decompose the PWP design problem into two inter-related mathematical models. Each model presents an extreme perspective of the problem. The first model determines the optimal number of PWPs, and their product assignments, such that the average manufacturing task similarity of the products assigned across all PWPs is maximized. We refer to this model as the "product assignment" model. The second mathematical model finalizes the number of PWPs and product assignments such that total annualized machine investment and inter-PWP transfers of products are minimized. We refer to the second model as the "investment efficiency" model. Note that each model identifies a key concern of management regarding the design of PWPs, yet no research to date has identified the decision variables, constraints, objectives and complexity of the PWP design problem. Due to the nonlinear nature of the problem, a two-stage heuristic is developed, using the mathematical models as a framework, to solve for a feasible PWP design that meets both the requirements of strategic focus and resource investment.

3.1 Product model

The objective of the product assignment model is to find the optimal number and composition of PWPs so as to maximize the total average degree of focus across all PWPs. To measure the degree of focus, or the consistency of manufacturing tasks across PWPs, we make use of the "manufacturing-task similarity" index between two products *i* and j defined as:

$$S_{ij}^{M} = \alpha \left\{ 1 - \left[\sum_{p \in p_i \cup p_j} \frac{\left| W_{ip} - W_{jp} \right|}{2} \right] \right\} + (1-\alpha) \left\{ 1 - \frac{1}{n[K(i,j)]} \left[\sum_{k \in K(i,j)} \frac{\left| B_{ik} - B_{jk} \right|}{Max(B_{ik}, B_{jk})} \right] \right\} \quad (1)$$

Where: P_i = set of order winners for product *i*;

W_{ip} = weight of order winner *p* assigned to product *i* such that $\sum_{p \in p_i \cup p_j} W_{ip} = 1$;

B_{ik} = average weekly volume of product *i* on resource type *k*, expressed in hours;

α = managerial parameter which sets the weight to assign to the degree of similarity of order winning criteria, $0 \leq \alpha \leq 1$;

$K(i, j)$ = set of resource types required by both products *i* and *j*;

$n\,[K(i, j)]$ = number of resource types required by both products *i* and *j*; and

$0 \leq S_{ij}^{M} \leq 1$.

The S^M index is composed of two parts. The first part incorporates the degree of similarity between two products' order winners by computing the average absolute value of the difference in their order winner weights. Summing this difference over all the order winners in the sets P_i and P_j and dividing by two gives the normalized average disparity in order winners between products *i* and *j*. For two products identically matched the summation term is zero, whereas for two products having no common order winners the summation term equals 1. Subtracting the summation term from 1 provides a measure of the order winner similarity between products *i* and *j*.

The second part of the index measures the degree of volume similarity between two products by computing the absolute value of the difference in volumes divided by the maximum volume of the two products, and summing over all resource types required in common by both products. To normalize the coefficient, the total is divided by the number of common resources required. In the case of $n[K(i,j)] = 0$, the similarity of volumes between products i and j is defined as zero since they do not share any resources.

Ideally, the decision of which order winners to emphasize must be integrated with the determination of how best to manufacture the product, including consideration for volumes. The manufacturing-task similarity index utilizes the parameter α to adjust the relative importance of volume in the design of PWPs. If both volumes and order winners are equally important in defining the manufacturing tasks, then $\alpha = 0.5$. Order winners are not a key consideration when $\alpha = 0$.

The objective of the product model is to maximize the degree of focus, calculated as the total average manufacturing-task similarity of all PWPs. The degree of focus is given by

$$f_1 = \sum_c \sum_i \sum_{j>i} \frac{S_{ij}^M X_{ic} X_{jc}}{N_c \left(N_c - 1\right) / 2} \tag{2}$$

Where: c = index of PWP;

N_c = number of products assigned to PWP_C;

$$X_{ic} = \begin{cases} 1, \text{if product } i \text{ is assigned to } PWP_c; \\ 0, \text{otherwise; and} \end{cases}$$

$0 \leq f_1 \leq 1$.

The product-perspective model is:

$$\text{Maximize } f_1 = \sum_c \sum_i \sum_{j>i} \frac{S_{ij}^M X_{ic} X_{jc}}{N_c \left(N_c - 1\right) / 2} \tag{2a}$$

Subject to:

$$\sum_c X_{ic} = 1 \qquad i = 1, 2, \ldots, I \tag{3}$$

$$\sum_i X_{ic} = N_c \qquad c = 1, 2, \ldots, U_c \tag{4}$$

$$F_c \leq N_c \qquad c = 1, 2, \ldots, U_c \tag{5}$$

$$\sum_c F_c = C \tag{6}$$

$$L_c \le C \le U_c \tag{7}$$

$$X_{ic} = (0,1) \qquad i = 1, 2, \ldots, I;\ c = 1, 2, \ldots, U_c \tag{8}$$

$$F_c = (0,1) \qquad c = 1, 2, \ldots, U_c \tag{9}$$

The decision variables and parameters not already defined are given below:

C = number of PWP_s;

I = number of products;

$$F_c = \begin{cases} 1, \text{if at least one product is assigned to } \text{PWP}_\text{c}; \\ 0, \text{otherwise;} \end{cases}$$

L_c = lower bound on number of PWP_s management will consider; and

U_c = upper bound on number of PWP_s management will consider.

The product assignment model assumes that Uc < I; if that were not the case, the solution maximizing the degree of focus is straightforward: assign each product to its own PWP. The degree of focus in each PWP would be 1.0, the maximum possible. The problem only becomes interesting when $Uc < I$ because at least one PWP must have more than one product. The objective function of the product model seeks to maximize the degree of focus of only those PWPs with more than one product assigned because they are the ones that face the potential for conflicting manufacturing tasks. A large value of f_1 reflects a high degree of similarity of manufacturing tasks across all PWPs, including those with only one product assigned to them.

3.2 Investment/Efficiency model

At the other extreme of the continuum we can look at the problem of designing the PWPs with the intent of minimizing the amount of total resource investment and the cost of moving products between PWPs. Formulating the problem from this perspective will tend to create PWPs with products that share common equipment and other resources, thereby minimizing the amount of duplicated resources. The investment/ efficiency model is:

$$\text{Maximize } f_2 = -\left[\sum_c \sum_m C_m Y_{mc} + \sum_{c' \neq c} \sum_m \sum_{i \in V_m} \frac{h_i q_i}{g_{im}} Z_{immc'} X_{ic}\right] \quad (10)$$

Subject to:

$$\sum_c X_{ic} = 1 \qquad i = 1, 2, \ldots, I \quad (11)$$

$$\sum_i X_{ic} = IF_c \qquad c = 1, 2, \ldots, U_c \quad (12)$$

$$\sum_c F_c = C \quad (13)$$

$$L_c \leq C \leq U_c \quad (14)$$

$$\sum_n \sum_{i \in V_n} Q_{mn} Z_{imnc} X_{ic} + \sum_{c' \neq c} \sum_{i \in V_m} Z_{immc} X_{ic'} \leq R_m Y_{mc} \qquad m = 1, 2, \ldots, M;\ c = 1, 2, \ldots, U_c \quad (15)$$

$$\sum_n Q_{nm} Z_{inmc} X_{ic} + \sum_{c' \neq c} Z_{immc'} X_{ic} \geq D_{im} X_{ic} \qquad i \in V_m,\ m = 1, 2, \ldots, M;\ c = 1, 2, \ldots, U_c \quad (16)$$

$$Y_{mc} \geq 0, \text{and integer} \qquad m = 1, 2, \ldots, M;\ c = 1, 2, \ldots, U_c \quad (17)$$

$$Z_{imnc} \geq 0 \qquad i = 1, 2, \ldots, I;\ m, n = 1, 2, \ldots, M;\ c = 1, 2, \ldots, U_c \quad (18)$$

$$X_{ic} = (0,1) \qquad i = 1, 2, \ldots, I;\ c = 1, 2, \ldots, U_c \quad (19)$$

$$F_c = (0,1) \qquad c = 1, 2, \ldots, U_c \quad (20)$$

The indices, decision variables, and parameters not already defined are given below:

m, n = indices for resource types, m, n = 1, 2, … M;

Y_{mc} = number of resources of type m assigned to PWPc;

Z_{imnc} = total time requirements of product i on resource type n to be carried out by resource type m in PWPc;

D_{im} = total estimated capacity (in hours) of resource m required for product *i* per year;

R_m = annual productive time for one unit of type m resource;

Q_{mn} = substitutability index of resource type *m* for *n*; an index greater than 1 indicates then m is more efficient than *n*; an index of 1 indicates that *m* and *n* are equally efficient; and an index less than 1 indicates that *m* is less efficient than *n*;

C_m = annualized equivalent total costs for a given economic life of machine *m* or annual costs for workers with skill *m*;

V_m = set of products that require operations on resource type *m*;

h_i = cost of moving one pound of product *i* between two PWP_s;

q_i = average weight (pounds) per unit of product *i*; and

g_{im} = average processing time of one unit of product *i* on resource type *m*.

The model assumes that $L_C > 1$ because, if $L_C = 1$, the solution maximizing f_2 is to have one PWP with all products assigned to it. Resources would be utilized to their maximum, and there would be no inter-PWP movement of products. Constraint set (15) imposes the capacity limitations of resource type m and ensures that the resources do not exceed their availability. The amount of inter-PWP movement is measured by the variables. Products assigned to PWP_C can be processed in $PWP_{C'}$ with resource type *m* if capacity exists and resource type *m* can process the product. Constraint set (16) ensures that each product receives its required processing time either on resource type *m* (its primary resource) in its assigned PWP_C, resource type *n* in PWP_C, or resource type *m* in $PWP_{C'}$.

The objective of the investment/efficiency model is to minimize total annual costs including the annualized resource investment cost and the inter-PW transfer cost, the latter of which occurs whenever the resource requirements are partially satisfied outside a product's assigned PWP. The transfer cost can be regarded as a type of transaction cost defined by Miller and Vollmann (1985). The transfer cost includes the costs of coordination, paper work, added machine setups, communication, material handling, and any other costs that are generated whenever products have to leave one PWP for another. The investment/efficiency model assumes that the transfer cost is directly proportional to the total weight of product moved between PWPs.

The two mathematical models developed present two conflicting objectives associated with the PWP design. Using the product model will result in a solution with products assigned to PWPs having similar manufacturing task requirements, but may involve duplicating equipment and/or material transfers. The investment/efficiency model will suggest a solution with products assigned to PWPs on the basis of common resource requirements, but the manufacturing tasks in each PWP may vary widely. Neither perspective alone may yield a totally satisfactory PWP design. Therefore, a solution to the problem depends on the weight, or degree of emphasis, management wishes to place on product versus investment/efficiency considerations. We can restate the objective of the PWP design problem as

$$\text{Maximize } f_3 = \lambda(\tau_1 f_1) + (1-\lambda)(\tau_2 f_2) \tag{21}$$

subject to constraints (3) through (9) and (15) through (18). The parameters τ_1 and τ_2 are normalizing factors so that $0 < \tau_1 f_1, |\tau_2 f_2| \leq 1$, and $-1 \leq f_3 \leq 1$. The solution space can be defined by the value of λ. As the value of λ increases, holding the number of PWPs constant, the emphasis goes toward the product perspective and the assignments of products to PWPs increases the degree of manufacturing task similarity within each one. As the number of PWPs is increased for a given value of $\lambda > 0$ the product assignments are made to increase the degree of manufacturing task similarity while holding the increases to investment and inter-PWP transfers down as much as possible. Each value of λ may result in a different PWP design. Selection of the final design would be a function of the budget limitations, specific product assignments, and the implications of the suggested designs on the reorganization of the plant and its infrastructure.

4. PWP Heuristic

Due to the nonlinear nature of the problem, an optimal solution cannot be obtained from the mathematical model. Instead, a solution heuristic must be developed to generate a feasible PWP design. Heuristic approaches have been well utilized to solve complicated manufacturing problems, such as facility layout (Chiang, 2001), automated storage (Yu and Koster 2009), balancing multiple u-lines (Chiang, et al. 2007), manufacturing cell formation (Chu, 1993), automated guided vehicle systems (Kouvelis, et al. 1992), machine allocation (Urban et al. 2000), and many artificial intelligence issues (see Russell and Norvig, 1995).

Based on the mathematical models presented in the previous section, a two-stage PWP heuristic is developed and outlined in Figure 1. First, the product assignment module applies a clustering algorithm to derive the values for the $X_{ic'}$ variables. Once the $X_{ic'}$ values are determined, the combined mathematical model degenerates into a standard mixed-integer programming (MIP) model that is solved in the second stage of the heuristic. In the remaining section we present both the product assignment module and the resource-allocation module.

(insert Figure 1 about here)

4.1 Product assignment module

The product assignment module determines values for the X_{ic} variables while recognizing the implications of trade-offs between the product and the investment efficiency perspectives. The objective function in (21) is simplified by using two indices in place of the two nonlinear objectives f_1 and f_2. Representing the product market perspective is the manufacturing-task similarity index (S^M) defined in (1). The investment/efficiency perspective is represented by a resource similarity (S^R) index that gauges the number of required resource types that are common between two products. We choose Vakharia and Wemmerlov's (1990) index for the S^R index between products *i* and *j:*

$$S_{ij}^{R}=0.5\left\{\frac{\sum_{m\in M(i,j)}\gamma_{mi}}{\sum_{n\in N(i)}\gamma_{ni}}\right\}+0.5\left\{\frac{\sum_{m\in M(i,j)}\gamma_{mj}}{\sum_{n\in N(j)}\gamma_{nj}}\right\} \tag{22}$$

Where: $\gamma_{mi}=\begin{cases}1, \text{if resource type } m \text{ is needed for product } i;\\ 0, \text{otherwise};\end{cases}$

$M(i,j)$ = set of resource types required by both products *i* and *j*;

$N(i)$ = set of resource types required by product *i* (e.g. cutting tools, CNC drills, conventional lathes, skilled workers, etc.);

$0\leq S_{ij}^{R}\leq 1$.

The first part of the index is the number of resource types common to both products *i* and *j* divided by the number of resource types required to process product *i.* A similar ratio is computed for product *j*. A simple average is then taken of these two ratios. The index ranges between 0, the value when the two products share no common resources, and 1, the value when they require exactly the same resources. PWPs with high values of resource similarity will have less resource duplication across the plant and, consequently, will be less expensive than other designs.

As Figure 1 indicates, once the resource similarity and manufacturing task similarity indices have been computed, they are combined into a composite similarity matrix (S^C), $0\leq S_{ij}^{C}\leq 1$, for use in the cluster algorithm. The composite measure is the weighted average of the two similarity coefficients for each product pair:

$$S_{ij}^{C}=\lambda S_{ij}^{M}+(1-\lambda)S_{ij}^{R} \tag{23}$$

where λ = parameter reflecting the weight to be assigned to manufacturing-task similarity in the development of PWPs; and $0\leq\lambda\leq 1$.

With $\lambda = 0$, the S^C index will only reflect resource similarity and the clustering approach will produce PWPs with the least resource needs thereby placing a high level of consideration on total cost in the solution. The other extreme, $\lambda = 1$, produces PWPs with only order winners and volume considerations. These PWPs will usually require more duplication of resources but have a higher degree of manufacturing task focus. Thus, by adjusting λ we can derive PWPs with various emphases on cost versus manufacturing task considerations. This capability allows observation of the tradeoffs between degree of focus and resource requirements, an important practical consideration (Skinner, 1974; Sheu and Krajewski, 1996).

Figure 2 shows the cluster analysis procedure for the construction of PWPs. The clustering algorithm operates on the composite similarity index for each product-by-product pairing. The result is clusters of products that possess similar composite similarity.

(insert Figure 2 about here)

An average linkage clustering (ALC) algorithm is used in this research because the methodology has been reported to be superior to alternatives for similar applications (Anderbert, 1973; Cunningham and Ogilvie, 1971; and Sherman and Sheth, 1977). In general, ALC merges elements or groups of elements that are most similar until the stopping criterion is met. The similarity between a newly formed group and other elements/groups is defined as the average of the similarities between all pairs of elements in the two groups. In the case of PWPs, the S^C index is used as the criterion for combining products. For each iteration t, the updated S^C index between PWP_C and a newly constructed $PWP_{C'}$ is given by:

$$S_{cc'}^{C(t)} = \frac{\sum_{i \in J_c^{(t)}} \sum_{j \in J_{c'}^{(t)}} S_{ij}^{C(0)}}{N_c^{(t)} N_{c'}^{(t)}} \tag{24}$$

ALC requires a stopping criterion. The clustering algorithm will ignore any solutions where C is outside of the range of pre-specified lower and upper bounds, L_C and U_C, respectively. The search module will determine a specific value of C and λ, called C_0 and λ_0, which is the design currently being inspected. The clustering algorithm starts with the maximum possible clusters, (that is, the total number of products) and stops when it reaches C_0. Based on the ALC algorithm and the stopping rule, the clustering process for a given value of λ_0 is performed. The clustering algorithm produces alternative PWP designs specified by various values of C_0 and λ_0 selected by management. These solutions are then assessed by the resource allocation MIP model regarding their implementation costs.

4.2. Resource allocation module

Given C_0, the number of PWPs to design, and the corresponding $X_{ic'}$ values from the clustering algorithm, the resource allocation problem is to:

$$\text{Maximize } f_4 = -\left[\sum_{c=1}^{c_0} \sum_{m} C_m Y_{mc} + \sum_{c' \neq c}^{c_0} \sum_{m} \sum_{i \in V_m} \frac{h_i q_i}{g_{im}} Z_{immc'} X_{ic}^{'} \right] \tag{25}$$

Subject to constraint sets (15) through (18) where $X_{ic}^{'}$ is the value of X_{ic} determined in phase 1.

The resource allocation module is a mixed-integer linear program where $Y_{mc'}$ is the only integer variable. The number of integer variables will be much less than $M*C_o$, in general because typically every PWP will not require every resource type. Because product assignments are made in the first stage, the resource allocation model determines the amount of each resource type to house in each PWP, allowing for the possibility of product transfer between PWPs.

5. Application of the PWP Heuristic

This section applies two datasets to demonstrate the application of the proposed heuristic. The first dataset is selected from Berry et al., (1991) with the purpose of validating the technical accuracy of the product assignment module, while the second dataset is developed to demonstrate the application of the entire two-stage heuristic.

5.1 Validation of product assignment module

Berry et al.'s (1991) dataset was collected from a manufacturer of printed circuit board (Table 1). Management identified three order winners that characterized the demand for their products: price, delivery speed, and quality. We use the same dataset to validate the proposed product assignment module, the first stage of the heuristic. The procedure and details of this comparative test are included in the Appendix. The approach used by Berry et al. (here referred to as BBHK) differs from that used in the PWP product assignment module in several important ways. First, the BBHK approach is a statistical clustering method utilizing an average Euclidean distance metric and an average linkage clustering (ALC) algorithm. The PWP heuristic also uses an ALC algorithm, but it uses a different distance metric which allows us to adjust the emphasis placed on order winners, volume, and costs. Second, BBHK fine tunes the clusters generated from the ALC algorithm by reassigning products to other clusters using a K-means approach. We did not fine tune the clusters in this test, but the parameter α in the S^M index could be micro-adjusted to see if the composite similarity can be improved with increased emphasis on volumes or order winners. Finally, BBHK redefined the value of the volume variable to be 200 if the mean weekly production was at least 90 hours and zero otherwise. The PWP heuristic used the actual data to compare volumes between products as shown in (1).

Table 2 displays the results, including the product assignments from the manufacturer, Berry et al. (1991) and the proposed heuristic. Overall, both BBHK and the proposed heuristic dominate the current company grouping and the heuristic performs slightly better than BBHK approach with a higher degree of focus associated with the PWP design. Specifically, in most cases the proposed heuristic produces better product assignments regarding the variations of the volume and order-winner criteria within focus units.

(insert Table 1 & Table 2 about here)

Note the purpose of this test was not to determine which approach is better, but rather to demonstrate that the PWP heuristic assignment module yields logical results. Furthermore, the PWP heuristic can incorporate considerations for investment and transfer costs, something the BBHK approach is not equipped to do. The next section addresses the second stage of the PWP heuristic.

5.2 Two-stage heuristic

This section demonstrates the application of the complete PWP heuristic for a factory producing 20 products. Management desires to analyze the design implications of having four PWP units. Table 3 shows the machine types and processing times required by each product needed for V_m, Y_{mi}, $N(i)$, $M(i,j)$, B_{ik}, *and* g_{im}. Table 4 contains the order winner information for P_i and W_{ip}. A product can be processed at machines other than its "primary" machine but the penalty is a loss of efficiency. Table 5 provides the machine substitutability matrix. In addition, each product has (a) a transfer cost (h_i) of \$2 per pound, (b) a weight (g_i) of 3 pounds, and (c) an annual requirement (D_{im}) *on* each machine in $N(i)$ of 520 hours. Each machine is available 2000 hours per year (R_m) and has an annualized capital cost of \$6000. The value of α was set at 0.50.

(insert Tables 3, 4, and 5 about here)

Product assignments were determined for three different configurations using three values of λ: 0.00, 0.50, and 1.00. Each of the three PWP designs has its own distinct identity. Table 6 summarizes the product assignments for each design. The design for λ = 1.00 has the highest degree of focus and each of the four units has a distinctive manufacturing assignment. At the other extreme, with λ= 0.00, the product assignments are quite different because the emphasis has been placed on resource similarity. The units generally have a mixed manufacturing assignment requiring managers to cope with conflicting tasks. The degree of focus is the lowest. However, adjusting λ to a value of 0.50 produces still another PWP design. This design offers a degree of focus slightly less than the design for λ = 1.00 and has a very consistent assignment of products on a volume basis. Two of the units also have an order-winner emphasis. Other values of λ could generate even more alternatives to look at.

(insert Table 6 about here)

The decision as to which PWP design to implement must involve a consideration of the costs. In the PWP heuristic λ is a surrogate for the degree of importance placed on total cost. When λ = 0.00 products are assigned to PWP units because they share common machines but may bear little similarity of order winners. For λ = 1.00 each PWP unit has products with a high degree of commonality in order winners and volumes but may require a wide range of resource types. The implication is that some resources must be duplicated across PWP units to maintain focus.

Table 7 presents the number of different machine types required in each PWP unit. There is a 36 percent increase in the number of different machines required between the λ = 0.00 and λ = 1.00 designs. However, there is also a 51 percent increase in the degree of focus. The PWP heuristic can be used to analyze this tradeoff. While the design with λ = 1.00 gives the highest degree of focus, it is also the most expensive design. As λ is reduced to 0.50 the total cost is reduced 7.2 percent and the degree of focus drops by only 4.0 percent. While the actual impact of reducing the degree of focus by 4 percent needs debate, management can use the PWP heuristic to derive alternate PWP designs with less resource duplication if cost is a concern.

(insert Table 7 about here)

6. Conclusions and Discussions

In our discussions with managers who have introduced PWP designs in their plants the cost of duplicating resources was a major consideration. Sometimes this factor was the overriding concern. In this paper we have modeled the PWP design problem with a consideration for resource costs and demonstrated a heuristic for analyzing the problem. Of course, the final decision on such a major project can never be made solely on the basis of this heuristic or any other like it. Alternative PWP designs must be debated and all the qualitative aspects brought forward. Nonetheless, the PWP heuristic demonstrated in this paper could be used to generate the alternatives for that debate. It not only recognizes the effects of conflicting manufacturing tasks, but also recognizes capital costs and material flows between PWP units. It can be used to generate many different alternative designs by adjusting the weight of focus on product versus investment efficiency and/or the desired number of PWP units.

The approach presented in this paper addresses the PWP design problem as if the firm is designing a new plant and must acquire the resources for manufacturing. A straight-forward extension is to consider the situation where an existing plant needs to be divided into several PWP units. A more complex issue is to consider the PWP design problem over time. New products are introduced, and old products are discontinued, causing a dynamic change to the manufacturing tasks in each PWP unit (Sheu and Krajewski, 1996; Vokurka and Davis, 2000;

Hallgren and Olhager, 2006). To which PWP should new products be assigned so as to minimize the disruptive effects, given that each product addresses the specific needs of one of the market segments the firm serves? Issues such as these are worthy of future research.

In this paper, a PWP heuristic including a search module, the average linkage clustering algorithm, is utilized to best allocate resources. Indeed, other search algorithms might also fulfill the task. For example, simulated annealing is an approach to escape the local maximum and finally achieve the global optimum. It has been widely adopted in numerous manufacturing applications, such as facility layout (Chae and Peters, 2006), vehicle routing (Chiang and Russell, 1996), and others. Another well studied algorithm, Tabu search (Lin and Ying, 2009), can also serve similar purposes. It is certainly a future research venue to apply the aforementioned and other search algorithms into PWP problems.

The results of this study can also contribute to the practice of outsourcing and supply chain management. Fine and Whitney (1996) and Simchi-Levi et al. (2008) suggested that there are two major reasons for outsourcing: dependency on capacity and dependency on knowledge. Based on the concept of manufacturing focus, we argue that strategic congruence should be another parameter to consider in the outsourcing decision. Specifically, provided that not every single product is strategically congruent with other products in the same focus unit, a firm could explore the possibility of outsourcing incompatible products to improve the degree of focus. The proposed methodology in this study could help identify those incompatible products and assess the strategic and resource implications of their outsourcing.

Finally, another future research direction is to factor dynamic settings into the PWP design methodology. It has been well recognized that the manufacturing world is evolving over time. The life cycle of the products as well as the intense competition between firms might also pressure the firms to adapt to the changing manufacturing environment. As a result, forecasting (Adshead and Price, 1987) and learning (Mellat-Parast and Digman, 2008) could play significant roles in the PWP design and hence horn the firm's competition edge. Therefore, it will be important to observe the potential impact of improved forecasting and the effects of employee and organizational learning on PWP design in a dynamic competitive market.

Appendix. Validation of Product Assignment Module

The approach used by Berry et al. (here referred to as BBHK) differs from that used in the proposed PWP product assignment module in several important ways. First, the BBHK approach is a statistical clustering method utilizing an average Euclidean distance metric and an average linkage clustering (ALC) algorithm. The PWP heuristic also uses an ALC algorithm, but it uses a different distance metric which allows us to adjust the emphasis placed on order winners, volume, and costs. Second, BBHK fine tunes the clusters generated from the ALC algorithm by reassigning products to other clusters using a K-means approach. We did not fine tune the clusters in this test, but the parameter α in the S^M index could be micro-adjusted to see if the composite similarity can be improved with increased emphasis on volumes or order winners. Finally, BBHK redefined the value of the volume variable to be 200 if the mean weekly production was at least 90 hours and zero otherwise. The PWP heuristic used the actual data to compare volumes between products as shown in (1).

Table 2 shows the results of this comparative test. Since BBHK did not recognize investment or transfer costs, we set λ = 1.0. Also, α was set to 0.50 giving volume equal weighting relative to order winners. Two statistics are provided that helps determine the quality of the solutions. The vector μ_c contains the means of the four performance measures for products assigned to PWPc in the following order: $(\overline{B}_c, \overline{W}_{1c}, \overline{W}_{2c}, \overline{W}_{3c})$ where

$$\overline{B}_c = \frac{\sum_i \sum_{k \in N(i)} B_{ik}}{N_c};$$

$$\overline{W}_{jc} = \frac{\sum_{i \in I} X_{ic} W_{ij}}{N_c},$$ $j = 1$ represents price, $j = 2$ represents delivery speed, and $j = 3$ represents quality.

The mean of the volume variable determines whether the PWP is a low-volume or high-volume unit. To be consistent with BBHK, we use a cut off volume of 90 hours. Means for the other three variables indicate the relative emphasis placed on price, delivery speed, and/or quality. The standard deviations for these variables are measures of how closely related the products in that PWP are to each other.

Table 2 reveals that BBHK's three-unit assignment clearly dominates the company's current assignment with four units. The three-unit assignment with the PWP heuristic is very close to that of BBHK's. The first unit is identical. The PWP heuristic's second unit is slightly better than BBHK's in that the volume and quality criteria are more consistent and the delivery speed criterion is the same. The price criterion is slightly better in BBHK's solution. The third unit is slightly more consistent in BBHK's solution. Nonetheless, the two approaches resulted in very similar assignments, the difference primarily due to the placement of three products. More weight on the volume variable in (1) might have brought the two solutions even closer. We also did a four-unit assignment to show that improvements can be made in the consistency of the assignments relative to the four criteria by increasing the number of units. In this example, the fist unit of the three-unit solution was broken apart to form units 1 and 2 of the four-unit solution.

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Table 1. Weekly volume and order winning criteria weights for a sample of printed circuit assemblies*

Product Number	Projected weekly Production volume (hours)	Projected order winners (%)		
		Price	Delivery speed	Quality
1	913	80	20	0
2	56	40	0	60
3	8	30	50	0
4	123	50	25	25
5	178	100	0	0
6	196	60	40	0
7	200	20	0	0
8	15	0	25	0
9	584	100	0	20
10	34	50	50	40
11	56	50	50	40
12	279	100	0	30
13	6	0	20	30
14	522	80	0	20
15	77	60	0	0
16	134	60	0	0
17	13	30	0	0
18	33	40	0	0
19	29	40	0	0
20	449	80	20	0
21	94	50	0	0
22	3	0	0	0
23	16	0	0	0
24	50	0	0	0
25	4	0	0	0
26	17	0	0	0
27	1	0	0	0
28	8	0	0	0

*Data taken from Berry et al., 1991

Table 2. Test results for PWP*

Unit	Current Assignment	BBHK assignment (Berry et al., 1991)	PWP assignment 1	PWP assignment 2
1	Pilot line 1, 2, 3, 4, 5, 6, 7 μ_1 (239, 54, 19, 12) σ_1 (306, 28, 20, 23)	Low volume, price, delivery speed 3, 8, 10, 11, 13, 22, 23, 24, 25, 26, 27, 28 μ_1 (18, 11, 16, 0) σ_2 (18, 19, 21, 0)	Low volume, price, delivery speed 3, 8, 10, 11, 13, 22, 23, 24, 25, 26, 27, 28 μ_1 (18, 11, 16, 0) σ_1 (18, 19, 21, 0)	Low volume, price, delivery speed 3, 10, 11 μ_1 (33, 43, 50, 0) σ_1 (20, 9, 0, 0)
2	Other 8, 9, 10, 11, 12, 13, 14 μ_2 (214, 54, 21, 3) σ_2 (250, 42, 22, 8)	High volume, price 1, 4, 5, 6, 7, 9, 12, 14, 16, 20, 21 μ_2 (334, 71, 10, 8) σ_2 (244, 24, 14, 13)	High volume, price 1, 5, 6, 7, 9 ,12, 14, 20 μ_2 (415, 66, 10, 3) σ_2 (239, 25, 14, 7)	Low volume 8, 13, 22, 23, 24, 25, 26, 27, 28 μ_2 (13, 0, 5, 0) σ_2 (14, 0, 9, 0)
3	Vending machines 15, 16, 17, 18, 19, 20, 21 μ_3 (118, 51, 3, 23) σ_3 (52, 17, 8, 17)	Low volume, price, quality 2, 15, 17, 18, 19 μ_3 (42, 42, 0, 36) σ_3 (22, 10, 0, 14)	Low volume, price, quality 2, 4, 15, 16, 17, 18, 19, 21 μ_3 (70, 46, 3, 31) σ_3 (42, 10, 8, 16)	High volume, price, quality 1, 5, 6, 7, 9 ,12, 14, 20 μ_3 (415, 66, 10, 0) σ_3 (239, 32, 14, 0)
4	Spares 22, 23, 24, 25, 26, 27, 28 μ_4 (118, 51, 3, 23) σ_4 (52, 17, 8, 17)			Low volume, price, quality 2, 4, 15, 16, 17, 18, 19, 21 μ_4 (70, 46, 3, 31) σ_4 (42, 10, 8, 16)

Note * Each cell in the table shows (1) the unit title, (2) the products assigned to the unit, (3) a vector of means (μ_C) for volume and the order winning criteria weights for price, delivery speed, and quality, and (4) a vector of standard deviations (σ_C) for volume and the order winning criteria weights for price, delivery speed, and quality.

Table 3. Machine requirements, volumes, and standard process times per unit of the example

Machine type	Product																			
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1	10		20					10		20	20	40			40			40	10	
2		40				20	10				20					20	40		10	40
3			20	10		20		10				40	20		40		40	40		
4	10			10				10	10	20		40	20		40		40			40
5		40				20	10		10				20	10		20				
6		40	20						10	20				10		20				
7	10	40			10		10						20	10			40		10	
8	10	40			10		10	10	10				20			20		40	10	
9		40		10	10		10				20	40			40	20				
10	10						10				20		20	10					10	40
11						20	10		10		20					20			10	
12				10		20					20		20	10			40	40		
8_{im}	2.0	0.5	1.0	2.0	2.0	1.0	2.0	2.0	2.0	1.0	1.0	0.5	1.0	2.0	0.1	1.0	0.5	0.5	2.0	0.5

Note: The matrix includes information on machine requirements and volume. The entries reflect weekly volumes expressed in machine hours (B_{ik}) the set of products that require operations on machine *m* (V_m), and the set of machines required for products *I(N(i))*. The process times per unit of a product are the same for all machines in this example.

Table 4. Order-winning criteria weights of the example

Product	**Order-winning criteria weights**			
	Price	Quality	Delivery Speed	Product flexibility
1	0.50	0.30		0.20
2	0.27	0.73		
3	0.54		0.26	0.20
4	0.25			0.75
5		0.22	0.68	0.10
6	0.60		0.20	0.20
7			0.22	0.78
8	0.67			0.33
9		0.72		0.28
10	0.25	0.65	0.10	
11	0.30		0.58	0.12
12	0.11	0.11		0.78
13	0.30		0.60	0.10
14	0.10		0.25	0.65
15		0.80		0.20
16			0.75	0.25
17	0.15		0.10	0.75
18	0.70	0.30		
19	0.72	0.10	0.18	
20		0.64		0.36

Table 5. Machine substitutability matrix

Machine Type	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*11*	*12*
1	1.0									0.8		0.7
2		1.0	0.7				0.8					
3		0.7	1.0						0.8			
4				1.0		0.7		0.7				
5	0.8				1.0						0.8	
6				0.8		1.0				0.7		
7		0.7					1.0	0.8				0.8
8	0.7			0.7				1.0				
9			0.8						1.0			
10			0.8							1.0		0.8
11					0.8	0.8	0.8				1.0	
12					0.7				0.8			1.0

Note: A substitutability index of 1.0 indicates that resource *m* and *n* are equally efficient. A substitutability index of less than 1 indicates *m* is less efficient than *n*. For example, a value of 0.8 means that *m* is only 80% as efficient for substituting *n*, and therefore takes more time to perform the same risk.

Table 6. Comparison of three alternative PWP designs

(a) PWP design with no resource consideration (λ = 1.00) (Degree of focus = 0.724)

PWP	Product Number	μ_C (volume, price, quality, delivery speed, product flexibility) σ_C (volume, price, quality, delivery speed, product flexibility)
1. Cost, large volume	6, 12, 18, 19	μ_1 (28, 53, 13, 10, 25) σ_1 (13, 25, 11, 10, 32)
2. Quality, large volume	2, 10, 15, 20	μ_2 (35, 13, 71, 2, 14) σ_2 (9, 13, 7, 4, 15)
3. Flexibility, small volume	1, 4, 7, 8, 9, 14, 17	μ_3 (14, 22, 15, 8, 53) σ_3 (10, 24, 26, 10, 23)
4. Delivery, small volume	3, 5, 11, 13, 16	μ_4 (18, 23, 4, 57, 16) σ_4 (4, 21, 9, 17, 6)

(b) PWP design with resource/manufacturing tasks consideration (λ = 0.50) (Degree of focus = 0.69

PWP	Product Number	μ_C (volume, price, quality, delivery speed, product flexibility) σ_C (volume, price, quality, delivery speed, product flexibility)
1. Small volume I	1, 5, 7, 8, 9, 14, 19	μ_1 (10, 28, 19, 19, 34) σ_1 (0, 31, 24, 22, 26)
2. Small volume II	3, 6, 10, 11, 13, 16	μ_2 (20, 33, 11, 42, 15) σ_2 (0, 20, 24, 24, 8)
3. Large volume, quality	2, 20	μ_3 (40, 14, 69, 0, 17) σ_3 (0, 14, 4.5, 0, 18)
4. Large volume, flexibility	4, 12, 15, 17, 18	μ_4 (34, 24, 24, 2, 50) σ_4 (12, 24, 30, 4, 33)

(c) PWP design with complete resource consideration (λ = 0.00) (Degree of focus = 0.481)

PWP	Product Number	μ_C (volume, price, quality, delivery speed, product flexibility) σ_C (volume, price, quality, delivery speed, product flexibility)
1. High resource similarity I	3, 4, 8, 10, 12, 15, 18	μ_1 (24, 36, 27, 5, 32) σ_1 (12, 27, 31, 9, 30)
2. High resource similarity II	1, 7, 11, 19	μ_2 (13, 38, 10, 25, 27) σ_2 (4, 24, 12, 21, 30)
2. High resource similarity III	6, 9, 13, 14, 17, 20	μ_3 (20, 23, 14, 24, 39) σ_3 (12, 21, 32, 20, 23)
4. High resource similarity, delivery	2, 5, 16	μ_4 (23, 9, 32, 48, 11) σ_4 (12, 13, 31, 34, 10)

Table 7. Number of machine types required (C=4)

λ	Number of machine types PWP unit 1	PWP unit 2	PWP unit 3	PWP unit 4	Average number of machine types per PWP	Degree of focus	Total cost
0.00	7	7	10	9	8.25	0.481	$177,699
0.50	12	12	8	8	10.00	0.695	$184,595
1.00	11	10	12	12	11.25	0.724	$198,856

Figure 1. Two-stage PWP heuristic

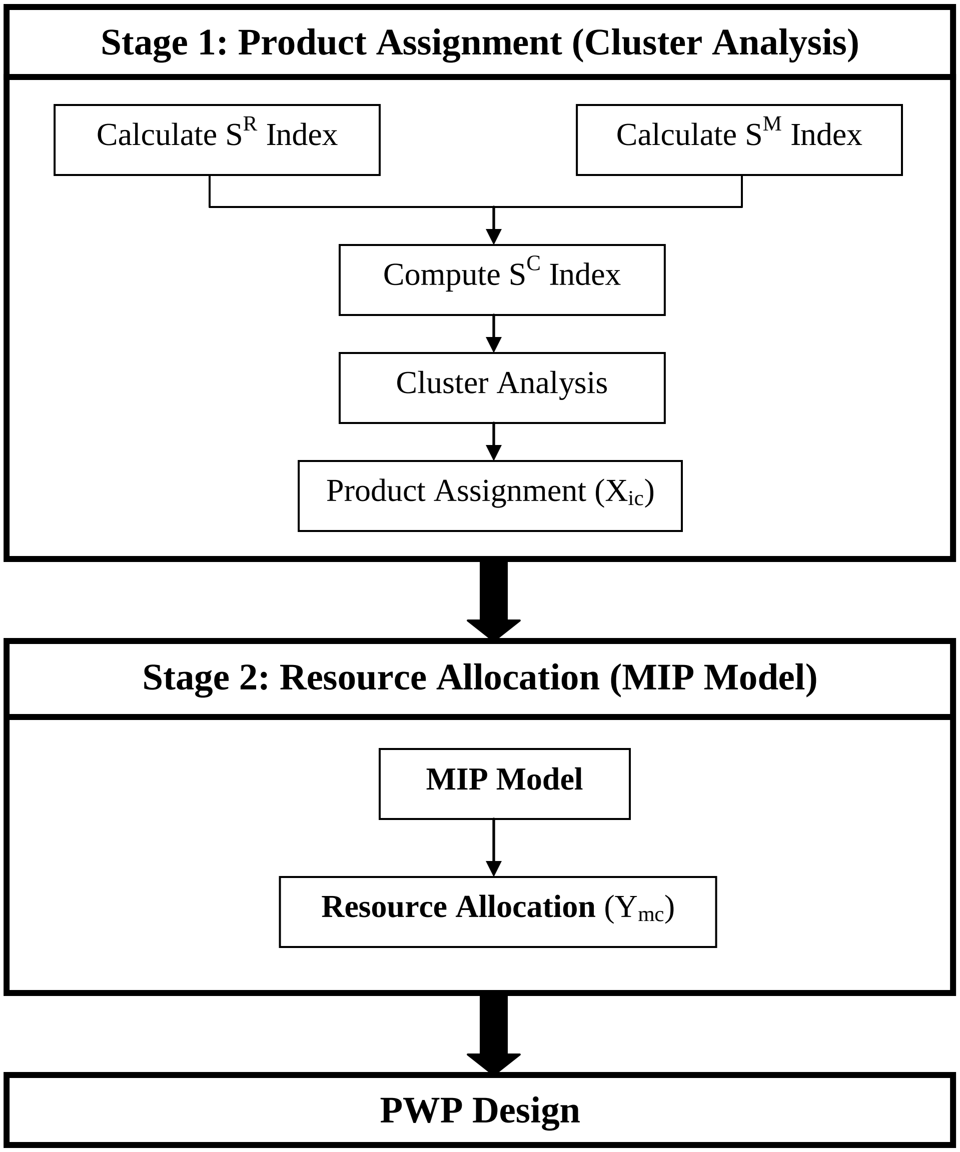

Figure 2. Flowchart of clustering algorithm