APPLICATION OF ADVANCED PRODUCTION TECHNIQUES IN A 'REAL-WORLD' MANUFACTURING ENVIRONMENT

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ABSTRACT
In the present study, a medium sized Greek, fast moving consumer goods manufacturing company from the cosmetics industry was selected to implement advanced techniques in its production processes and then to evaluate the efficiency of potential changes on its operation. For this purpose Group Technology was adopted as the (re)organization tool of its production. Indices concerning the performance of the system were identified using 'real world' production results and statistical data collected by the company, in the past. The operational characteristics of twelve alternative production scenarios considered, were evaluated using the Cellular Manufacturing approach. In a subsequent step, the behavior of the manufacturing system as a whole, for each one of the different scenarios, was investigated using Discrete Events Simulation technique for a period of two years. Finally, Data Envelopment Analysis was employed to evaluate the efficiency of each scenario. Results indicated that more than one of these scenarios could be effective. In addition, significant improvements can be achieved in the system's performance, without actually changing its basic production parameters.

Keywords: Manufacturing cells, efficiency assessment, cosmetics products industry.

1. INTRODUCTION

The markets today, are characterized by the consumers' demand for an ever-greater variety of products in smaller quantities. Under these conditions maintaining high efficiency in batch operations of traditional, process oriented, manufacturing facilities is very difficult. Group Technology (GT) [1] is a manufacturing philosophy that organizes and uses information for grouping various parts and products with similar machining requirements (and/or design characteristics) into families of parts and corresponding machines into machine cells. The main objective of cellular manufacturing is to construct machine cells, to identify part families and ultimately to allocate part families to machine cells so to minimize interaction among different cells [2], [3]. This way, a number of manufacturing cells are constructed. With the implementation of cellular manufacturing, GT is capable of improving productivity and reducing costs in batch production so that it becomes comparable to those of mass production.

Fully independent machine cells, however, are rare in practice. Some parts need to be processed by more than one machine cells, inevitably leading to a number of intercellular moves. The designer of such systems tries to allocate machines to cells in such a way so to keep the interaction among cells to the lowest possible level, i.e. to cut down the presence of exceptional parts. The majority of research [3], [4], [5], focuses in the cell formation process using as main criterion the interaction among cells. Given a cell formation procedure, alternative cellular manufacturing configurations can be formed, using the above criterion, by varying the number of machines (some machine types can be easily replaced by others), the number of cells to be formed or the number of machines per cell.

When cellular manufacturing is introduced, managers must evaluate the system's performance under various conditions in order to identify and later to improve the most appropriate operating practices. The evaluation of alternative cellular manufacturing configurations (scenarios) requires comparison of several parameters concerning the implementation and operation of each scenario on the shop floor. Appropriate indices, which describe the performance level of each production scenario, (e.g. number of machines, work-in-process inventory, etc) were judiciously defined, utilizing production results and statistical data from previous periods. Collecting data for these indices in real-time conditions would be

either impossible or very cumbersome and costly. Thus, Discrete Event Simulation (DES) technique was employed to test each production scenario and collect the necessary data characterizing each one of the different cellular manufacturing configurations.

Among different evaluation techniques, Data Envelopment Analysis (DEA) is a methodology that assesses the performance of each production configuration considered in a non-arbitrary manner [6]. It is flexible enough to accommodate any parameters that are significant to the system under assessment and can provide the decision maker with guidelines and suggestions on how an inefficient production scenario can be improved in terms of the parameters involved in the evaluation.

The objective of this work is to illustrate how the adoption of advanced techniques can be employed to better organize the production of a specific manufacturing company. This paper in particular deals with the development of alternative cellular manufacturing scenarios and the investigation of the behavior of the associated production system for long periods. Factors that affect or describe the efficiency of the system are determined. GT, DES and DEA are briefly discussed. The present methodology follows the philosophy introduced in [7] and later extended in [8] and [9]. Nevertheless, the present work not only employs computational tools which are quite different from the above works, but it also focuses on the application of the methodology on a particular production system concerning of a medium sized Greek cosmetics products manufacturing company. The test case considered in this work is discussed in detail. Computational results included in the paper indicate that the proposed methodology can be a very useful tool in the hands of the management of the company.

2. TECHNIQUES

2.1. CELLULAR MANUFACTURING APPROACH

The main concept in cellular manufacturing is the decentralisation of production into manufacturing cells, which are in essence flow shop ‘islets’ in a job shop environment. This is achieved by grouping the machines into clusters and the various parts into part families, in such a way that the processing of each part family is allocated to a single machine cluster.

The manufacturing systems Cell Formation Problem is formulated as a 0-1 integer programming problem as presented in [10]. The problem of partitioning parts and machines into cells is tackled using a heuristic algorithm based on a version of simulated annealing [4]. A trivial solution to the parts and machines partitioning problem would be to cluster the entire set of parts and machines into a single cell. This of course would eliminate any intercell movements among parts. However, this is far beyond what it is desired. Reasonable upper bounds on the size of the cells are usually assumed, in terms of machines. This limit on the number of machines per cell is often imposed in practice based on previous experience. In a cellular manufacturing system, in order to describe the real intercell traffic among parts, the parts operation sequences are considered. When the part routeing sheets are taken into account, one can easily calculate the total number of consecutive operations, i.e. total intermachine flow, based on all parts, between any two machines for all machines. Thus the total intermachine flow, which forms in our model the objective to be minimized, describes the exact total number of intermachine movements of all parts. This objective is minimized under the constraints of operation sequences, taking also into account the possibility for a part of performing two or more non consecutive operations on the same machine, regardless of the direction of move.

The following 0-1 integer programming formulation for the manufacturing systems Cell Formation Problem is given [4,10]:

$$min\ z = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} c_{ij}\left(1 - x_{ij}\right) \tag{1}$$

subject to

$$\sum_{i=1}^{k-1} x_{ik} + \sum_{j=k+1}^{n} x_{kj} \leq M - 1 \quad (k = 1,...,n) \tag{2}$$

$$\begin{aligned} x_{ij} + x_{ik} + x_{jk} &\leq 1 \\ x_{ij} - x_{ik} + x_{jk} &\leq 1 \\ -x_{ij} + x_{ik} + x_{jk} &\leq 1 \end{aligned} \qquad (i = 1,..., n-2, \quad j = i+1,..., n-1, \quad k = j+1,..., n) \tag{3}$$

$$x_{ij} = \begin{cases} 1, \text{ if machine } i,j \text{ are in the same cell,} \\ 0, \text{ otherwise} \end{cases} \tag{4}$$

$$i = 1,\ldots, n\text{-}1,\ j = i\text{+}1,\ldots,n$$

In the above formulation, n machines are allocated to cells of maximum size M. Two machines are connected if they belong to the same cell. Constraint (2) ensures that machine k is connected with at most M-1 other machines, and constraints (3), the 'triangle' constraints, ensure that within each cell all machines are connected to each other. The cost elements c_{ij} are calculated from data on the traffic of P parts between the n machines.

2.2. DISCRETE EVENT SIMULATION

Experimenting with the real, actual, manufacturing system under consideration would be ideal; however, this is seldom feasible. The cost associated with changing a system, for instance the number of manufacturing cells or the number of workers in each cell, etc, may be quite high, both in terms of capital required to implement the change and the lost output resulting from the disruption. Trying multiple changes with an existing system is usually impractical. DES seems to be the most appropriate among decision tools to investigate the performance of the system under quite different system configurations, scenarios.

A systematic procedure was followed for the development of the simulation model. A quite simple model was initially constructed, which was gradually enriched so to simulate the 'real world' environment with sufficient accuracy. Trial runs and comparisons to production outputs of the 'real world' system were used to appropriately modify the structure and tune certain critical parameters of the model. The simulation model, which was finally adopted in this work, was validated by comparing results of preliminary simulation runs to the behavior of the actual system.

The simulation model was able to take into account factors and parameters, which are indicative of the system's performance and make possible the comparative evaluation of the different scenarios. The characteristics of the model included information about the production resources utilized, i.e. number of machines and number of workers/machine operators hired, and performance output indices, namely: average machine and workforce utilization, machinery set-up time, average work in-process inventory and average product makespan. For each one of the different scenarios resulting from the application of cellular manufacturing, a discrete simulation model was run using the commercial simulation software package SIMFACTORY by CACI Inc [11].

2.3. DATA ENVELOPMENT ANALYSIS

In recent years DEA has been utilized in a great variety of applications for evaluating the performance of different systems. Through DEA it has also been possible to gain new insight into systems that until then were extremely complicated to study because of the number and nature of parameters involved. DEA employs mathematical programming techniques to evaluate the efficiency of homogeneous decision making units (DMU), where DMUs can be, for instance, hospital units, retail stores, bank branches, etc. The efficiency is translated as the ratio of the weighted sum of outputs to the weighted sum of inputs.

In the present test case, the heart of the analysis lies in finding the best virtual cellular manufacturing layout for each given layout. If the virtual layout is better than the given one in terms of making more output with the same input or using less input for the same output then the given layout is considered inefficient. The procedure of determining the best virtual DMU can be formulated as a linear program. Assessing the performance of *n* different DMUs involves the solution of *n* different linear programming problems.

Charnes, Cooper and Rhodes [6] in 1978 proposed one of the most basic DEA models, appropriately termed as the CCR model. Given that there are n DMUs and associated numerical data for each of the *m* inputs and *s* outputs for all DMUs, the fractional mathematical programming problem that is solved in order to obtain values for the input weights ($\boldsymbol{v}_i$) (i=1,…,m) and the output weights ($\boldsymbol{u}_r$) (r=1,…,s) variables is the following [12]:

$$max \;\; z \;=\; \frac{\sum_{r=1}^{s} u_r y_{rj_0}}{\sum_{i=1}^{m} v_i x_{ij_0}} \tag{5}$$

subject to

$$\frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \;\leq\; 1 \quad (j = 1,\ldots,n) \tag{6}$$

$$u_r = 0\,, \quad (r = 1,\ldots, s) \tag{7}$$

$$v_i = 0\,, \quad (i = 1,\ldots, m) \tag{8}$$

Index j_0 refers to the DMU being evaluated. Objective function (5) maximizes the ratio of virtual output to virtual input of the DMU under evaluation by calculating the appropriate weights v_i and u_r. Constraints (6) ensure that this ratio does not exceed 1 for every DMU. This implies that the objective function value lies between 0.0 and 1.0; the latter value denoting that the DMU under examination is efficient. The above non-linear program is linearized and the solution of its linear equivalent produces the efficiency scores for all DMUs. In this work a particular extension of the CCR model, namely the output oriented variable returns to scale BCC model [12], [13], has been applied.

3. CASE STUDY

The test case under consideration in this work concerns the production system of a fast moving cosmetics products manufacturing company. Particular characteristics of this market are short product life cycles, fluctuations in demand and frequent changes in products packaging. In order for the system to be able to meet the above requirements it should be organized in flexible production lines that produce small batches of products over short periods of time.

The efficiency of 12 alternative cellular manufacturing configurations was evaluated. The DEA model validated a former project undertaken for adopting cellular manufacturing configuration in the production process of the company under consideration. The data collected consists of 891 products using up to 19 machine types, where each machine type could have several identical replicates. Machine sequence operations were taken into account in the formation of machine cells. A simulated

annealing algorithm proposed by the present author [4] was employed to define the 12 alternative cellular manufacturing configurations using the integer programming formulation (1-4). The 12 scenarios were created by varying: a) the number of machine types utilized b) the maximum number of machines allowed in a cell and c) the volume of production. The different scenarios considered are shown in Table 1.

Scenario name	Number of machine types utilized	Maximum number of machines allowed in a cell	Volume of production taken into account
DMU1	19	5	NO
DMU2	19	5	YES
DMU3	18	5	YES
DMU4	18	5	NO
DMU5	17	5	NO
DMU6	19	4	NO
DMU7	19	4	YES
DMU8	18	4	YES
DMU9	18	4	NO
DMU10	17	4	NO
DMU11	17	5	YES
DMU12	17	4	YES

Table 1. Scenarios considered

As the number of machine types utilized is decreasing the complexity of the production system is also decreasing, a fact that may favorably affect the efficiency of the system. Obviously, the maximum number of machines allowed in a cell, directly affects the number of individual cells formed, while it implicitly affects their efficiency. Cells with a relatively smaller number of machines are less complex, more flexible and promote workforce specialization and implementation of automation practices, which lead to productivity improvement.

The different cellular configurations computed, are collected in Table 2. Numbers in Table 2 refer to the corresponding manufacturing cell, i.e. machines characterized by the same number, say number 2, form the 2nd manufacturing cell for a particular scenario.

	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11	M12	M13	M14	M15	M16	M17	M18	M19
DMU1	1	1	2	2	2	3	3	4	1	1	4	1	2	3	3	3	2	4	4
DMU2	1	1	2	3	2	3	4	4	1	1	1	3	2	4	3	3	2	2	4
DMU3	1	1	2	4	2	3	4	4	1	1	1	-	2	4	3	3	2	2	4
DMU4	1	1	2	2	2	3	3	4	1	1	1	-	2	3	3	3	2	4	4
DMU5	1	1	2	-	2	3	3	4	1	1	1	-	2	3	3	3	2	2	4
DMU6	1	1	2	2	2	3	4	4	1	1	5	3	5	4	3	3	2	5	4
DMU7	1	5	2	1	2	3	4	4	1	5	5	5	2	4	3	3	2	3	4
DMU8	1	5	2	1	2	3	4	4	1	5	5	-	2	4	3	3	2	1	4
DMU9	1	1	2	2	2	3	4	4	1	1	5	-	5	4	3	3	2	3	4
DMU10	1	1	2	-	2	3	4	4	1	1	5	-	2	4	3	3	2	3	4
DMU11	1	5	2	-	2	3	4	4	1	5	5	-	2	4	3	3	2	1	4
DMU12	1	1	2	-	2	3	3	4	1	1	1	-	2	3	3	3	2	2	4

Table 2. Manufacturing cells formed

It is should be pointed out that for the sake of simplicity the manufacturing cells formation procedure (formulation 1-4), was applied to a production system with different machines only, i.e. replicate machine units of the same type were not considered. However, simulation results indicated that in

order to complete the required production volume (demand) for all parts, the number of machines utilized in each scenario had to be appropriately increased/adjusted by introducing replicate units.

For each one of the 12 manufacturing scenarios a DES model was run for a period of two years. The various parameters and indices that describe the behaviour/performance of the manufacturing system evaluated through the simulation runs are collected in Table 3. Columns TM and TW refer to the total number of machines used and workers/operators hired to operate the machines. The third column refers to the average work-in-process inventory (AWIP), which concerns products in various stages of production. Column AMKSP refers to the average makespan, which together with output index AWIP are of major importance for the assessment of the production system. Columns AMU and AWU contain the average machine and worker utilization respectively, while column AST refers to average machine setup times.

	TM	**TW**	**AWIP**	**AMKSP**	**AMU**	**AWU**	**AST**
DMU1	24	49	415741	19882	65.2	67.1	0.00
DMU2	26	54	341088	18678	61.6	59.9	4.40
DMU3	25	50	331942	17433	60.5	60.4	5.74
DMU4	24	50	334616	17507	63.4	62.1	4.14
DMU5	25	50	304091	17806	60.2	60.7	5.58
DMU6	26	58	336167	17491	62.7	60.1	1.57
DMU7	24	48	324165	20381	63.7	64.6	4.83
DMU8	24	51	349451	16909	63.7	60.4	4.23
DMU9	25	56	359541	18633	65.2	61.5	0.72
DMU10	23	50	361805	18678	67.8	64.9	2.85
DMU11	24	51	343587	16373	64.1	63.0	3.84
DMU12	25	50	304091	17806	60.2	60.7	5.58

Table 3. Simulation results for different scenarios

These results for the seven performance indices form the basic data to carry out the DEA evaluation. The first two columns form the inputs of the DEA procedure while columns 3-7 represent the outputs. For both inputs it is assumed that smaller values correspond to better cellular configurations. The DEA method assumes that all outputs considered should be as high as possible for a DMU. Since this is not valid for outputs AWIP and AMKSP, the data in those two columns must be transformed so that the usual assumption is also followed here. This transformation is achieved by subtracting the original value produced by the simulation runs for AWIP or AMKSP from the corresponding maximum value found among all DMUs. Thus, the actual data used by the DEA procedure are shown in Table 4.

	TM	**TW**	**AWIP**	**AMKSP**	**AMU**	**AWU**	**AST**
DMU1	24	49	0	499	65.2	67.1	0.00
DMU2	26	54	74653	1703	61.6	59.9	4.40
DMU3	25	50	83799	2948	60.5	60.4	5.74
DMU4	24	50	81125	2874	63.4	62.1	4.14
DMU5	25	50	111650	2575	60.2	60.7	5.58
DMU6	26	58	79574	2890	62.7	60.1	1.57
DMU7	24	48	91576	0	63.7	64.6	4.83
DMU8	24	51	66290	3472	63.7	60.4	4.23
DMU9	25	56	56200	1748	65.2	61.5	0.72
DMU10	23	50	53936	1703	67.8	64.9	2.85
DMU11	24	51	72154	4008	64.1	63.0	3.84
DMU12	25	50	111650	2575	60.2	60.7	5.58

Table 4. Input and output data used for the DEA evaluation

4. EVALUATION RESULTS AND DISCUSSION

The DEA methodology was applied in the data of Table 4 using the BCC model and the results produced are presented in Tables 5, 6 and 7. Table 5 depicts the efficiency scores of the twelve different scenarios considered. As it can be seen, nine of the twelve scenarios are efficient (efficiency scores are equal to 1.0). Looking more carefully at the inputs and outputs of the inefficient DMUs, one can observe that they require more production resources from the two inputs, compared to the other DMUs, without however producing more output. Namely, scenarios DMU2, DMU6 and DMU9 employ 26 machines and 54 operators, 26 machines and 58 operators, 25 machines and 56 operators respectively, without producing significantly better results.

DMU1	1.0000	**DMU7**	1.0000
DMU2	0.9669	**DMU8**	1.0000
DMU3	1.0000	**DMU9**	0.9696
DMU4	1.0000	**DMU10**	1.0000
DMU5	1.0000	**DMU11**	1.0000
DMU6	0.9839	**DMU12**	1.0000

Table 5. Efficiency scores of cellular manufacturing configurations

Table 6 presents the reference set for each inefficient DMU. In this table, each column corresponds to an efficient DMU. The reference set is formed by those efficient DMUs that can act as models (i.e. DMUs that correspond to columns with non-zero elements) for the inefficient ones. For each row, therefore, in Table 6 weights are assigned to efficient DMUs in order to form a virtual/model DMU to which the corresponding inefficient one should resemble. Thus, the reference set of inefficient DMU2 consists of DMU3, DMU7, DMU10 and DMU11 and in particular DMU2 should use as its model a virtual DMU resembling by 35.98 % to DMU3, by 30.55% to DMU7, by 27.80% to DMU10 and by 5.67% to DMU11.

	DMU1	**DMU3**	**DMU4**	**DMU5**	**DMU7**	**DMU8**	**DMU10**	**DMU11**	**DMU12**
DMU1	1.0000								
DMU2		0.3598			0.3055		0.2780	0.0567	
DMU3		1.0000							
DMU4			1.0000						
DMU5				1.0000					
DMU6				0.3381			0.2544	0.4075	
DMU7					1.0000				
DMU8						1.0000			
DMU9				0.0637			0.9171	0.0192	
DMU10							1.0000		
DMU11								1.0000	
DMU12									1.0000

Table 6. Reference sets

Table 7 illustrates how the inputs and outputs of the inefficient DMU's from the original data set of Table 4 can be adjusted so that they become efficient. Consider inefficient DMU2, for example. DMU2 could become efficient if the number of machines TM would decrease from 26 to 24.08 and the number of operators TW from 54 to 49.45. On the other hand, if one would consider adjustments to the outputs, DMU2 would become efficient if outputs were increased in the following way: output

AWIP from 74653 to 77211.61, output AMKSP from 1703 to 1761.37, output AMU from 61.6 to 63.71, output AWU from 59.9 to 63.08 and output AST from 4.40 to 4.55. Similarly, DMU6 and DMU9 can be transformed into efficient ones by adjusting the values of the corresponding inputs or outputs respectively. It is then a matter of judgment, which scenario will the decision maker eventually follow. Cost elements should also be taken into account since two efficient scenarios, as for example DMU3 and DMU10, can utilize different amount of machinery which implies different amount of investment. Thus, scenarios DMU4, DMU8 and DMU10 seem to be more attractive for the manufacturing company, since not only are efficient according to the DEA analysis, but also reflect the company's goals for smaller investment and increased customer satisfaction.

	Input TM		**Input TW**		**Output AWIP**		**Output AMKSP**		**Output AMU**		**Output AWU**		**Output AST**	
DMU1	24.00	*100.00%*	49.00	*100.00%*	0.00		499.00	*100.00%*	65.20	*100.00%*	67.10	*100.00%*	0.00	
DMU2	24.08	*92.62%*	49.45	*91.57%*	77211.62	*103.43%*	1761.37	*103.43%*	63.71	*103.43%*	63.08	*105.31%*	4.55	*103.43%*
DMU3	25.00	*100.00%*	50.00	*100.00%*	83799.00	*100.00%*	2948.00	*100.00%*	60.50	*100.00%*	60.40	*100.00%*	5.74	*100.00%*
DMU4	24.00	*100.00%*	50.00	*100.00%*	81125.00	*100.00%*	2874.00	*100.00%*	63.40	*100.00%*	62.10	*100.00%*	4.14	*100.00%*
DMU5	25.00	*100.00%*	50.00	*100.00%*	111650.00	*100.00%*	2575.00	*100.00%*	60.20	*100.00%*	60.70	*100.00%*	5.58	*100.00%*
DMU6	24.08	*92.63%*	50.41	*86.91%*	80872.03	*101.63%*	2937.14	*101.63%*	63.72	*101.63%*	62.71	*104.34%*	4.18	*266.01%*
DMU7	24.00	*100.00%*	48.00	*100.00%*	91576.00	*100.00%*	0.00		63.70	*100.00%*	64.60	*100.00%*	4.83	*100.00%*
DMU8	24.00	*100.00%*	51.00	*100.00%*	66290.00	*100.00%*	3472.00	*100.00%*	63.70	*100.00%*	60.40	*100.00%*	4.23	*100.00%*
DMU9	23.15	*92.59%*	50.02	*89.32%*	57962.53	*103.14%*	1802.82	*103.14%*	67.24	*103.14%*	64.60	*105.03%*	3.04	*422.63%*
DMU10	23.00	*100.00%*	50.00	*100.00%*	53936.00	*100.00%*	1703.00	*100.00%*	67.80	*100.00%*	64.90	*100.00%*	2.85	*100.00%*
DMU11	24.00	*100.00%*	51.00	*100.00%*	72154.00	*100.00%*	4008.00	*100.00%*	64.10	*100.00%*	63.00	*100.00%*	3.84	*100.00%*
DMU12	25.00	*100.00%*	50.00	*100.00%*	111650.00	*100.00%*	2575.00	*100.00%*	60.20	*100.00%*	60.70	*100.00%*	5.58	*100.00%*

Table 7. Virtual inputs and outputs

5. CONCLUSIONS

In this paper, the conversion of the production procedure of a Greek fast moving cosmetics products manufacturing company from a functional layout to a cellular one is investigated. A three-stage methodology was employed. First, an integer programming problem was solved through a heuristic algorithm to produce twelve different cellular manufacturing scenarios. Next, those production scenarios were tested via simulation and the necessary data concerning the operational characteristics of each one of the different cellular manufacturing configurations were collected. A commercial simulation software package was employed for this purpose, to produce, for each scenario, measures for the seven performance indices -2 inputs and 5 outputs- considered by DEA. DEA was finally applied to evaluate the efficiency of the alternative cellular manufacturing layouts/scenarios. DEA results demonstrate that several efficient layouts exist. On the other hand, as far as the inefficient scenarios are concerned, guidelines are provided on how to improve and transform them into efficient ones.

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