Abstract
Classical approach to the formation of manufacturing cells is based on the application of similarity principles to a binary machine-part matrix. This approach ignores volume effect as well as dynamic demand pattern. This paper first identifies and characterises the volume effect based on two measures of manufacturing cell efficiency, i.e., average job flow time and total intercell travelling time. The effect of similarity coefficient threshold value on cell configuration based on binary and volume data was evaluated and tested statistically. Finally, the implication of cell configuration on systems performance under dynamic demand pattern is discussed with an example based on 80 machines and 820 parts.

Key Words
Group Technology, Cellular, Reconfigurable Manufacturing

1 INTRODUCTION
Since the introduction of the group technology (GT) concept by Mitrofanov in 1958 to provide a new approach of cellular manufacturing for efficient batch production, extensive research has been undertaken in recognition of its fundamental importance [1]. Classification systems, production flow analysis, CAPP, flexible manufacturing systems, all of them address specific issues of manufacturing based on group technology. Recent ideas and advances in batch manufacturing such as agile manufacturing, mass customisation, holonic manufacturing could also find the roots of group technology because of its simplicity and elegance. The idea of applying geometrical and/or technology similarity to form a manufacturing cell is well established. In its basic form, a machine-part incidence matrix consisting of simple binary 0-1 data is all that is required for subsequent calculations for cell formation. A large number of techniques including mathematical, statistical, heuristic, artificial intelligence and empirical modelling have been attempted with varying degree of success [2-7]. However, they remain in the stage of academic research with hardly any adoption by industry. This is the result of a combination of reasons. Firstly, the lack of a simple and robust computerized method capable of dealing with industrial scale problem. Secondly, the solution of the classical machine-part incidence matrix, if found, only offers a static solution which does not take into account the actual dynamic nature of manufacturing. With increasing market pressure for shorter product life cycle and more innovative products, the need to respond to environmental and sustainability issues, the trend towards mass customisation, the dynamic aspects of manufacturing play a key role in the design and optimisation considerations for a manufacturing system. The purpose of this paper is to examine whether the classical GT problem formulation could deal with such requirements and what changes are necessary to adapt the GT approach for reconfiguration of manufacturing cells for mixed low/mid volume production in an uncertain and rapidly changing market environment.

2 CLASSICAL MACHINE-PART MATRIX
The classical machine-part matrix is a pxm matrix consisting of p parts and m machines. All machines visited by ith part, p,, will be assigned a value of 1, otherwise 0. Arranging machines into cells and parts into families using 0-1 incidence matrix has been used extensively to accomplish cell formation mainly because the amount of information required is minimum. In this simplistic binary representation, it implies that the production quantity of each part is the same, i.e., unity. Consequently, a vital piece of information is lost. Other relevant information such as operation sequences, alternative sequences, processing times on each machine is not captured in this schema. This suggests that the classical machine-part matrix has a number of intrinsic weaknesses. Firstly, the design of a manufacturing system is directly related to production volume, operation sequences as high volume production will justify a customized flow line system. Therefore, the incorporation of production volume data in cell formation will provide a more representative manufacturing model but it is conveniently ignored. Secondly, the surge or decline of product demand will require manufacturing cell reconfiguration for optimizing performance measures. Yet this could not be achieved with the classical model. This research is therefore designed to investigate the volume effect on cell formation and its performance.

3 TEST MODELS AND ASSUMPTIONS
3.1 Test Incidence Matrix
The need for a better representation of manufacturing complexity for grouping machines into cells and parts into families has led to the incorporation of more variables such as volume, operation times, and operation sequences among others. It is therefore a valid question to ask whether the consideration of more variables could help to produce a better manufacturing cell arrangement as the inclusion of more variables demand more data to be collected and processed [7, 8]. In this paper, 0-1 incidence matrix is used for benchmarking purposes against production related data.
One of the biggest problems presented in literature is a case of 40 machines and 100 parts 0-1 matrix which is also used by other researchers in comparative studies [9]. In the present case, an incidence matrix of 80 machines and 820 parts is used to evaluate the impact of two methods for machine cell and part family formation.

A file containing the 820 part types with their corresponding production volumes, operation sequences and operating times was generated using an electronic spreadsheet observing the following considerations, i.e., each part volume was randomly generated from 1 to 1000 assuming a uniform distribution. The number of operations was generated randomly from a uniform distribution with a minimum value of 1 and a maximum value of 6 operations per part. Machines were assigned randomly to each operation assuming the same likelihood to be selected for performing an operation. Operating times were assigned randomly from a normal distribution with an average of 10 and standard deviation of 2 units of time per operation.

In order to obtain a global view of the 80 x 820 part-machine incidence matrix, an operation dispersion chart was produced setting the machines in the vertical axis and parts in the horizontal axis. The points represent whether the part requires the machine or not. Figure 1 shows the dispersion chart for the test matrix before any machine-part arrangement.

3.2 Assumptions

A number of assumptions are made in this simulation model. In the first instance, all parts were assumed to be ready for processing at the beginning of the simulation, i.e., time zero. If more than one job was waiting for processing at the same machine, the job with the shortest total processing time, i.e., volume x operating time, was processed. Parts were moved from one machine to the next only after the last part in the batch was completed. The batch size was considered to be the same as the volume assigned to the part.

In the first simulation experiment, transportation time between machines was assumed instantaneous. However, in the second experiment, inter-cell travelling time was estimated randomly from a normal distribution with a mean of 200 and a standard deviation of 40 units of time. Intracell travelling time was generated randomly from a normal distribution with a mean of 20 and a standard deviation of 4 units of time. Each machine was assumed to have an infinite buffer to hold all the jobs waiting for processing.

3.3 Computation and Evaluation Criteria

The choice for cell formation algorithm is based on three considerations: robustness, computational efficiency and implementability. After due considerations, a form of Jaccard similarity coefficient was used. Single linkage cluster analysis was first used by McAuley [10] but there are many other forms of similarity coefficient [11]. The similarity coefficient hierarchical algorithm used in this research is a modified form based on Daita, et al [12]. The algorithm has been validated using data from examples in literature. In operation, machines were arranged into cells based on the similarity coefficient and then parts were assigned to the cells where the maximum number of operations were performed.

The algorithm for cell formation based on 0-1 data, volume data and the simulation of dynamic manufacturing as well as the overall system performance evaluation was implemented in Visual C++ running on a PC with a 663-MHz CPU. As an example, the 40 x 100 binary incidence matrix used by Chandrasekharan, et al was solved in less than 3 seconds with identical result [13]. For each reconfiguration of the present 80 x 820 binary incidence matrix, computation required was less than 20 seconds including calculation of systems performance parameters as discussed in this section.

Evaluation of grouping efficiency has been studied extensively. Sarker and Mondal reported 13 such efficiency measures with each one of them covering a specific aspect such as the degree of diagonalization [14]. In the present context, two parameters were chosen for evaluation purposes, i.e., average flow time $T_f$ and intercell travelling time $T_{inter}$. This is because both parameters are readily understood physically and conceptually and significant in terms of overall performance.

The equation of the average job flow time which includes waiting time is given in (1) whereas the equation for the total inter-cell travel time is given in (2):

$$T_f = \frac{1}{mG} \sum_{G_{ji}} \frac{1}{G_{si}} \sum_{j=1}^{G_{ji}} \sum_{k=1}^{N_{ji}} (t_{f,k} - t_{(j,k)})$$

$$T_{inter} = \sum_{i=1}^{P} \sum_{j=1}^{N_{O_{i}}} b(i,j)$$

3.4 SIMULATION EXPERIMENTS

The machine-part incidence matrix was arranged into cells considering only binary data. The similarity threshold value was manipulated to produce a number of cellular arrangements. Each arrangement consisting of a specific number of cells was evaluated using the information in the input file. The information for this period was saved in a file. Volume was reassigned to the parts as described and evaluation of the volume-based cellular arrangement was
made which provided comparative data for 0-1 and volume based configurations.

The next stage of the simulation experiment was to assign volume at the beginning of each period for examining the behaviour of each cellular arrangement under dynamic manufacturing conditions. In this study, results from 30 periods were obtained for average job flow time and total intercell travelling time. The same procedure was applied to the 0-1 and volume-based cellular configurations respectively over the entire 30 periods. The simulation experiment was repeated for 3, 5, 8, 9, 11, 13, 14 and 17 machine cells.

In order to evaluate the effects of the two different approaches to cellular configuration, a statistical test for a null hypothesis was undertaken. A t-test for the difference between the means of two independent groups with unknown variances was conducted to test the null hypothesis that both arrangements produce the same response average job flow time, first experiment, and inter-cell travelling time, second experiment. The alternative hypothesis was that there is a difference in the response as a consequence of the machine-part arrangement used. A significance level of 5% was used to test each null hypothesis.

4 RESULTS AND DISCUSSIONS

The number of cells in a given configuration is dependent on the threshold value of the similarity coefficient $S_i$. A lower threshold value produces a smaller number of cells in the configuration while a higher value results in a larger number of cells. In this research, a variation of $S_i$ from 0.16 to 0.54 produces configurations from 2 to 17 cells. A composite table showing the number of cells and their corresponding $S_i$ values based on 0-1 and volume data, their average job flow time and the result of the null hypothesis is given in Table 1. The results show that $S_i$ is sensitive to data type used in the incidence matrix and the pattern of significant differences between $T_f$ varies with the number of cells in a given configuration.

Table 1: Results of average job flow times and null hypothesis of experiment 1.

<table>
<thead>
<tr>
<th>No of Cells</th>
<th>Similarity threshold $S_i$</th>
<th>Average job flow time</th>
<th>Ho</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>0-1 Data</td>
<td>Volume</td>
</tr>
<tr>
<td>2</td>
<td>0.20</td>
<td>22033.40</td>
<td>21940.03</td>
</tr>
<tr>
<td>3</td>
<td>0.25</td>
<td>21837.67</td>
<td>21875.20</td>
</tr>
<tr>
<td>5</td>
<td>0.28</td>
<td>22171.97</td>
<td>21621.57</td>
</tr>
<tr>
<td>8</td>
<td>0.36</td>
<td>21704.57</td>
<td>21245.63</td>
</tr>
<tr>
<td>9</td>
<td>0.38</td>
<td>22213.70</td>
<td>21245.63</td>
</tr>
<tr>
<td>10</td>
<td>0.42</td>
<td>21841.60</td>
<td>21474.53</td>
</tr>
<tr>
<td>11</td>
<td>0.44</td>
<td>22026.83</td>
<td>21813.73</td>
</tr>
<tr>
<td>13</td>
<td>0.47</td>
<td>22025.83</td>
<td>21996.00</td>
</tr>
<tr>
<td>14</td>
<td>0.50</td>
<td>21833.37</td>
<td>21080.70</td>
</tr>
<tr>
<td>17</td>
<td>0.54</td>
<td>21429.37</td>
<td>21558.57</td>
</tr>
</tbody>
</table>

For a more detailed study on the actual systems performance including non-zero traveling time as per experiment 2, the configuration of 9 cells is used as an illustrative example. Firstly, plots of the average job flow time varies with the dispersion diagram for the same configuration but with different $S_i$ threshold values. When $S_i$ was increased from 0.37 to 0.38, the volume-based configuration changed to a 10 cells arrangement. In general, the $S_i$ value for volume-based method is always lower than 0-1 method for the same number of cells.

On the effect and sensitivity of similarity coefficient with 0-1 and volume based cellular configurations, the example of the 9 cells configuration is again used. Figures 4 and 5 show the dispersion diagram for the same configuration but with different $S_i$ threshold values. When $S_i$ was increased from 0.37 to 0.38, the volume-based configuration changed to a 10 cells arrangement. In general, the $S_i$ value for volume-based method is always lower than 0-1 method for the same number of cells.

Following the same 9 cell example, Figures 6 and 7 shows the 3D model of the cellular configurations where manufacturing volumes are represented by scaled triangles, i.e., the higher the volume, the bigger the triangle. In Figure 6, which is based on 0-1 data, some parts with high volume fall outside the diagonal blocks. On the other hand, the configuration shown in Figure 7 based on volume data tend to include high volume parts inside the diagonal blocks because machines that process parts with high volume are more likely to be placed in the same cell.

5 CONCLUSIONS

The use of classical machine-part incidence matrix based on 0-1 data for the configuration of manufacturing cells does not take into consideration important parameters such as production volume, processing sequences and time, intracell and intercell materials handling time.
This investigation has demonstrated that the inclusion of volume data has led to a significant difference in intercell travelling time while the impact on average job flow time is indifferent.

The number of cells for a given incidence matrix is directly dependent on the threshold value of similarity coefficient but the systems performance cannot be determined without subjecting the configuration for evaluation under dynamic manufacturing conditions. In the simulation experiments conducted in this research, it has revealed that volume-based cell configurations outperforms 0-1 based ones using $T_{ave}$ as the criterion.

Based on the simulation results, it is proposed that cell configuration for dynamic manufacturing conditions has to take into account volume data instead of merely forming diagonal blocks within the incidence matrix using binary data. Reconfiguration of manufacturing cells is a realistic possibility as the algorithm based on similarity coefficient is highly efficient in solving a large scale 80 machines by 820 parts incidence matrix. Finally, there are scopes to incorporate other relevant manufacturing data for further improvement of cell configuration.

![Figure 4: Cell configuration based on 0-1 data with a $S_0$ threshold value of 0.38.](image1)

![Figure 5: Cell configuration based on volume data with a $S_1$ threshold value of 0.38.](image2)

![Figure 6: A 3D view of the cell configuration based on 0-1 data for experiment 2.](image3)

![Figure 7: A 3D view of the cell configuration based on volume data for experiment 2.](image4)

6 ACKNOWLEDGEMENTS

The authors would like to thank 'Secretaria de Educacion Publica-Programa De Mejoramiento Del Profesorado' and 'Universidad Autonoma De Ciudad Juarez' in Mexico for sponsoring this investigation.

7 REFERENCES


