# Manufacturing cell formation using back propagation networks

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**ABSTRACT**

Cellular Manufacturing System (CMS) is an application of Group Technology (GT) in which functionally dissimilar machines are grouped together to form a family of parts. This work gives an overview of the Back Propagation Network (BPN) based approaches to form the machine cells and component grouping for minimizing the exceptional elements and bottleneck machines. This method is applied to the known benchmark problems found in literature, and it is found to be equal or best when compared to in terms of minimizing number of exceptional elements.

## 1. Introduction

In today's manufacturing companies relentlessly places pressure on manufacturing systems to be enhanced in both efficiency and effectiveness. This is manifested by the fact of consumer markets in the rising tendency of greater variety of products and decrease in product life cycle. Traditional manufacturing systems such as product and process layout do not have met the dynamic manufacturing environment.

A number of newer manufacturing systems have been proposed such as agile, flexible, intelligent etc., among these newer manufacturing systems Group Technology (GT) and Cellular Manufacturing Systems (CMS) have drawn considerable attention in manufacturing organizations. The original concept of GT was first proposed by Mitrofanov (1966) and Burbidge (1971, 1977) CMS is application of the GT is identify part families and their associated machine groups so that each part family is processed within a machine group. The advantages of using CMS include reduction of set up time, material handling time, work in process inventory, through put time, delivery time and space. Cell formation is considered to be most difficult step in CMS design.

The objective of this paper is to minimize the number of exceptional elements and bottleneck machines using Back Propagation Network (BPN). This paper is organized as follows: In the next section review of the literature containing cell formation concept. Section 3 describes artificial neural network for cell formation. The experimental verification of proposed methodology in section 4. The section 5 deals with the results and discussions and finally conclusion in section 6.

## 2. Literature View

The machine-part incidence matrix based cell information has attracted most of the researchers, resulting there have been several methods to solve the cell formation problem without going into the details, some of the familiar approaches are:
❖Coding and classification: Hyer and Wemmerlov (1985) Karpathi and Suresh (1991) Opitz (1970) Hyde (1981)

❖Production flow analysis: Chu and Tsai (1990) Mc Cormick et al (1972) King and Nakornchai (1982)
❖Similarity coefficient approach: Mc Auley (1972) Seifoddini and Wolfe (1986) Kusiak (1988) Khan, Islam and Sarkar (2000) Chandrasekaran and Rajagopalan (1989) Srinivasan and Narendran (1991)
❖Mathematical programming: Choobinech (1988) Srinivasan, Narendran and Mahadevan (1990) Chen and Heragu (1999)
❖Graph theoretic approach: Rajagopalan and Batra (1975) Kumar et al (1986) Vanneli and Kumar (1986) Srinivasan (1994) Mukhopadhyay et al (2000) and Manimaran et.al.(2010)
❖Search methods: Boctor (1991) Sofianopoulou (1997) Adil Baykasoglu et al (2000) Onwubolu and Mutingi (2001)
❖Artificial Intelligence: Chu and Hayya (1991) Chu and Tsai (1993) Venugopal and Narendran (1994) Lee et al (1992) Kusiak and Chung (1991) Daggli and Huggahalli (1995)

These methods are found to produce good solution for well structured matrices, where part families and machine cells exist naturally. However, they fail to produce so, for ill structured matrices with many exceptional elements.

## 3. Artificial neural network for manufacturing cell formation

Artificial Neural Networks (Lippmann 1989, Yegnanarayana 2002) can be viewed as parallel and distributed processing systems which consists of a huge number of simple and massively connected processors. These networks can be trained offline for complicated mapping, such as of forming of manufacturing cells and determining the various faults can then be used in an efficient way. The Multi Layer Perceptron architecture is the most popular paradigm of artificial neural networks in use today. Figure 1 shows a standard multilayer feed forward network with three layers. The neural network architecture in this class shares a common feature that all neurons in a layer are connected to all neurons in adjacent layers through unidirectional branches. That is, the branches and links can only broadcast information in one direction, that is, the "forward direction". The branches have associated weights that can be adjusted according to a defined learning rule.

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Feed forward neural network training is usually carried out using the back propagation algorithm. Training the network with back propagation algorithm results in a non-linear mapping between the input and output variables. Thus, given the input/output pairs, the network can have its weights adjusted by the back propagation algorithm to capture the non-linear relationship. After training, the networks with fixed weights can provide the output for the given input.
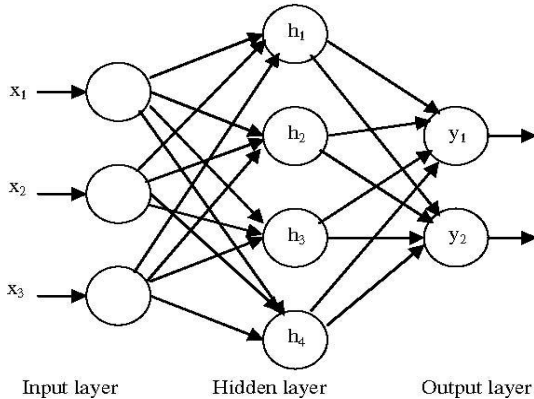


**Fig.1: Two layer feed forward network**

The standard back propagation algorithm for training the network is based on the minimization of an energy function representing the instantaneous error. In other words, we desire to minimize a function defined as

$$E(m) = \frac{1}{2}\sum_{q=1}^{n}[d_q - y_q]^2 \qquad (1)$$

where $d_q$ represents the desired network output for the $q^{th}$ input pattern and $y_q$ is the actual output of the neural network. Each weight is changed according to the rule:

$$\Delta w_{ij} = -k\frac{dE}{dw_{ij}} \qquad (2)$$

where k is a constant of proportionality, E is the error function and $w_{ij}$ represents the weights of the connection between neuron j and neuron i. The weight adjustment process is repeated until the difference between the node output and actual output are within some acceptable tolerance.

## 4. Development of neural network model for manufacturing cell formation

The models are developed for the manufacturing cell formation to group parts and machines into clusters by sequencing the rows and columns of a machine part incidence matrix, so as to minimize the exceptional elements of the block diagonal matrix. The proposed methodology for cell formation is based on using Artificial Neural Network (ANN) for minimizing the exceptional elements and bottleneck machines. The main purpose of selecting ANN as a tool is good generalization ability, fast real time operation and to perform the complicated mapping without functional relationship. Feed forward neural networks trained by back propagation algorithm are used for this purpose. The information required for the development of the neural network model is collected from Chandrasekaran and Rajagoplan (1989), for cell formation and also through off-line simulation.

In this paper, the input is a machine component incidence matrix [A=$a_{ij}$] made up of zero and ones such as rows indicate machines, columns represent components or parts and while $a_{ij}$=1 indicates that component j processing on machine i other wise $a_{ij}$=0. Hence machine component incidence matrix [A=$a_{ij}$] is taken as the input of the developed ANN model as shown in figure 2. The sections having the same size of matrices are

considered while developing the neural network model. Based on this consideration, the following four cases neural network models were developed for the cell formation problem.

Case 1: Data set 1
Case 2: Data set 2
Case 3: Data set 3
Case 4: Data set 4

The neural network approach for this purpose has two phases; training and testing. During the training phase, neural network is trained to capture the underlying relationship between the chosen inputs and outputs. After training, the networks are evaluated with a test data set, which was not used for training. Once the networks are trained and tested, they are ready to solve the cell formation problem. The following issues are to be addressed while developing a neural network model for cell formation problem.

a) Selection of input and output variables
b) Training data generation
c) Data normalization
d) Selection of network structure
e) Network training

### 4.1. Selection of input and output variables

For the application machine learning approaches, it is important to properly select the input variables, as ANNs are supposed to learn the relationships between input and output variables on the basis of input-output pairs provided during training. In ANN based cell formation problem, the input variables represent the machine component incidence matrix, and the output is the block diagonal matrix.

### 4.2. Training Data Generation

The generation of training data is an important step in the development of neural network models. To achieve a good performance of the neural network, the training data should represent complete information about the machine part incidence matrix. The training data is required for this purpose is generated through off line simulation. The machine part incidence matrix of four cases are collected from Chandrasekaran and Rajagopalan (1987)
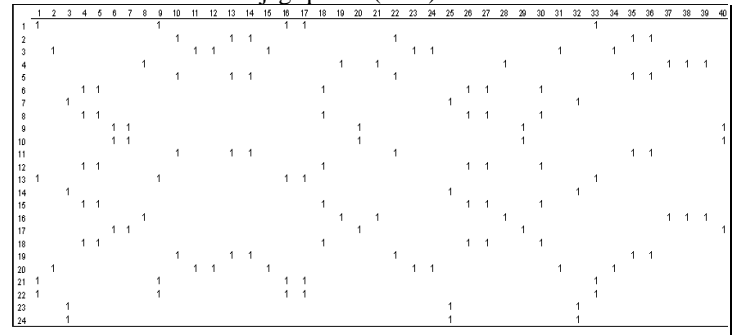


**Fig. 2: 24x40 Machine part incidence matrix (Data set 1)**

### 4.3. Data Normalization

During training of the neural network, higher valued input variables may tend to suppress the influence of smaller ones. Also, if the raw data is directly applied to the network, there is a risk of the simulated neurons reaching the saturated conditions. If the neurons get saturated, then the changes in the input value will produce a very small change or no change in the output value. This affects the network training to a great extent. To avoid this, the raw data is normalized before the actual application to the neural network. One way to normalize the data x is by using the expression:

$$x_n = \frac{(x - x_{min}) \times range}{(x_{max} - x_{min})} + starting\,value \qquad (3)$$

where, $x_n$ is the normalized value and $x_{min}$ and $x_{max}$ are the minimum and maximum values of the variable x .

### 4.4. Selection of Network Structure

To make a neural network to perform some specific task, one must choose how the units are connected to one another. This includes the selection of the number of hidden nodes and type of the transfer function used. The number of hidden nodes is directly related to the capabilities of the network. For the best network performance, an optimal number of hidden nodes must be properly determined using the trial and error procedure. The input layers of neurons equal to the number of parts and machines, and output layers have neurons equal to the number of cells.

### 5. Results and discussion

This section presents the details of the simulation study carried out on cell formation problem using the proposed method. The details of the ANN models developed to cell formation are presented here. The generated training data are normalized and applied to the neural network with corresponding output, to learn the input-output relationship. The ANN model used here has one hidden layer of tansigmoidal neurons, which receives the inputs, then broadcast their outputs to an output layer of linear neurons, which compute the corresponding values. The back propagation-training algorithm propagates the error from the output layer to the hidden layer to update the weight matrix. The algorithm used for the training of artificial neural network model is given below:

Step 1: -Load the data in a file.
Step 2: -Separate the input and output data.
Step 3: -Separate the training and test data.
Step 4: -Normalize all the input and output values.
Step 5: -Define the network structure.
Step 6:-Initialize the weight matrix and biases.
Step 7: -Specify the number of epochs.
Step 8: -Train the network with the train data.
Step 9: -Test the network with the test data.
Step 10: -Re-normalize the results.

The neural network model was trained using the back propagation algorithm with the help of MATLAB neural network toolbox. At the end of the training process, the model obtained consists of the optimal weight and the bias vector. After training, the generalization performance of the network is evaluated with the help of the test data of four models obtained as shown in Table 1 shows the various parameters of the neural network model. From this table it is found that the network has correctly classified all the data during the testing stage. This shows that the trained ANN is able to produce the correct output even for the new input. The BPN results with exceptional elements are shown in table 2. The diagrammatic results of the four data set problems are shown in appendix.

### 6. Conclusion

This paper has presented a neural network based approach for cell formation problem. Four separate models were developed for the four cases. The data required for the development of neural network model have been obtained through the off line simulation and machine part incidence matrix are considered. For the ANN Model the testing data are fed to the designed model to check the accuracy. The testing samples are different from the training samples and they are new to the trained network. Simulation results show that this neural network approach is very much effective for structured matrix cell formation problem. To further improve the performance of the model the input features of the network can be selected through dimensionality reduction techniques

**Table 1: Parameters of the neural network model**

| Number of Hidden Layer | 1 (for all four data set) | | | |
|---|---|---|---|---|
| Number of Hidden nodes | 4 (for all four data set) | | | |
| Transfer Function used | Tansigmoidal (for all four data set) | | | |
| Maximum Number of Epochs | 1500 (for all four data set) | | | |
| Percentage of Classification | 100% (for all four data set) | | | |
| Training time (seconds) | Data set 1 | Data set 2 | Data set 3 | Data set 4 |
| Problem No 1 | 0.079 | 0.078 | 0.11 | 0.078 |
| Problem No 2 | 0.063 | 0.062 | 0.079 | 0.062 |
| Problem No 3 | 0.062 | 0.062 | 0.078 | 0.063 |
| Problem No 4 | 0.079 | 0.063 | 0.062 | 0.062 |

**Table 2: (Exceptional elements)**

| | Data set 1 | | Data set 2 | | Data set 3 | | Data set 4 | | Existing method | |
|---|---|---|---|---|---|---|---|---|---|---|
| | G | EE | G | EE | G | EE | G | EE | G | EE |
| Problem No 1 | 7 | 0 | 7 | 0 | 7 | 15 | 7 | 28 | 7 | 0 |
| Problem No 2 | 7 | 23 | 7 | 10 | 7 | 10 | 7 | 38 | 7 | 10 |
| Problem No 3 | 7 | 20 | 7 | 41 | 7 | 20 | 7 | 20 | 7 | 20 |
| Problem No 4 | 7 | 20 | 7 | 20 | 7 | 20 | 7 | 20 | 7 | 20 |

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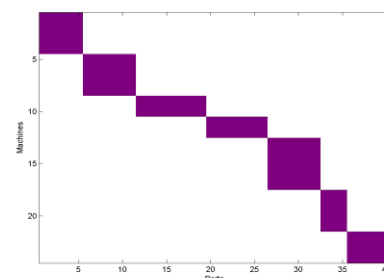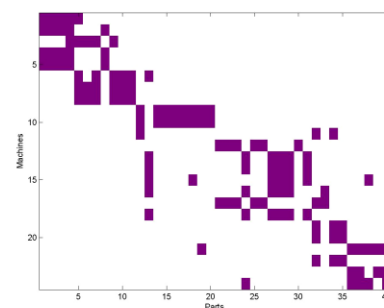
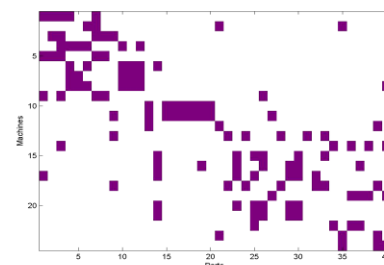**Appendix**



**Fig. 7: (data set 1-1)**



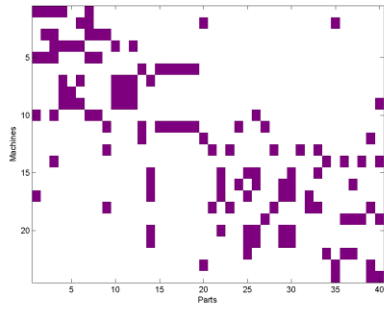**Fig. 8: (data set 1-2)**



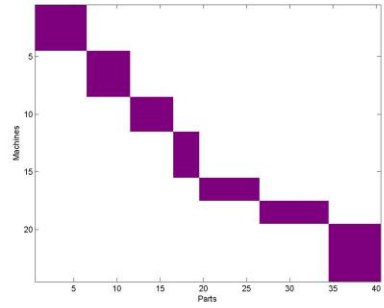**Fig. 9: (data set 1-3)**

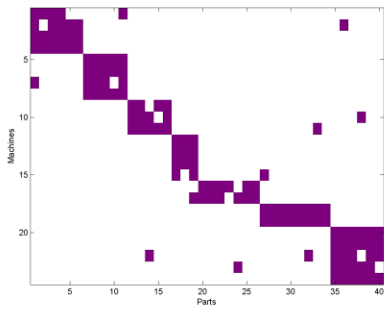**Fig. 10: (data set 1-4)**


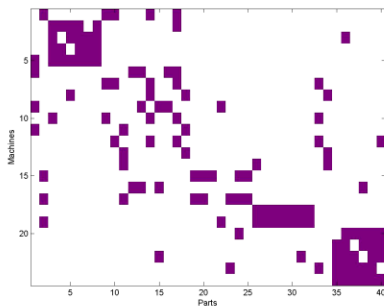**Fig. 15: (data set 3-1)**


**Fig. 11: (data set 2-1)**


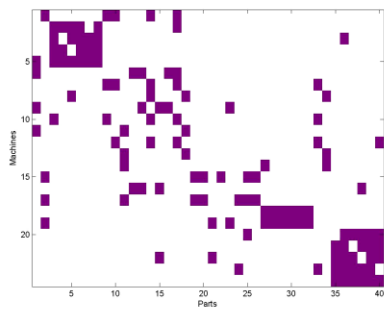**Fig. 16: (data set 3-2)**


**Fig. 12: (data set 2-2)**


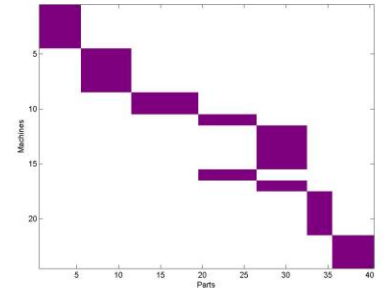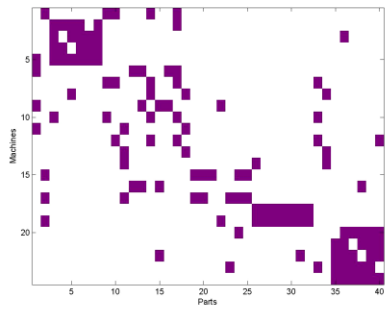**Fig. 17: (data set 3-3)**


**Fig. 13: (data set 2-3)**
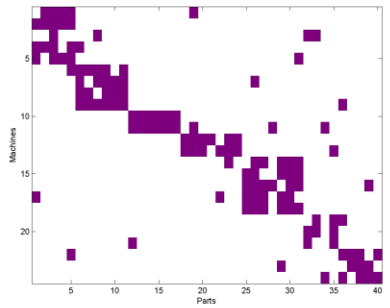

**Fig .18: (data set 3-4)**
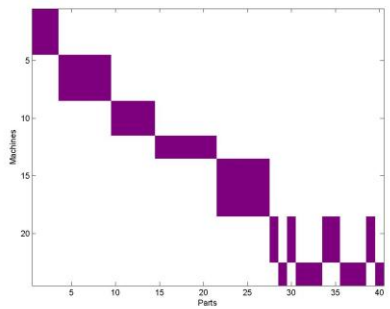

**Fig. 14: (data set 2-4)**
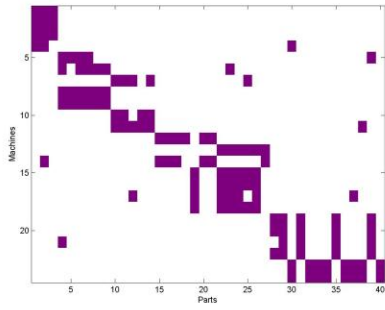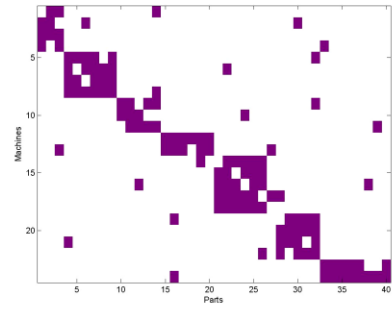

**Fig. 19: (data set 4-1)**

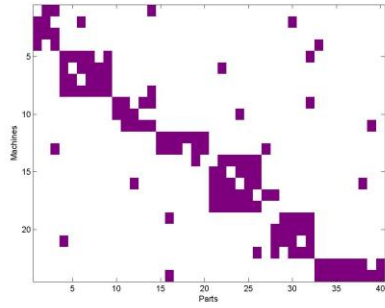**Fig. 20: (data set 4-2)**



**Fig. 22: (data set 4-4)**



**Fig. 21: (data set4-3)**