A neural network-based multi-objective genetic algorithm for designing cells incrementally in a dynamic environment

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Abstract: Cellular manufacturing consists of grouping similar machines in cells and dedicating each of them to process a family of similar part types. In this paper, a neural network-based multi-objective genetic algorithm for designing cells incrementally in a dynamic environment is presented. A new multi-objective nonlinear programming model is constructed. We use neural network to optimize two different objectives. In order to generate Pareto optimal fronts, Fast Non-Dominated Genetic Algorithm (NSGAII) is applied. Weighted similarity coefficients are computed and parts are clustered using a new self-organizing neural network .The neural network model was coded in Delphi to determine the efficient parameter combinations.
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1. Introduction

The cellular manufacturing problem has captured a great deal of attention of many manufacturers and researchers. The variety and the uncertainty of demand, variety of characteristics of the product and manufacturing process are the reasons that motivated the request for flexibility. Cellular manufacturing is a flexible manufacturing system (FMS) which can respond to the increasingly competitive environment facing manufacturers. Specially, manufacturers need to quickly improve their efficiency, response time and quality, but with a minimum of upfront investment of time and capital.

Cell formation is one of the important issues of cellular manufacturing systems. Many models and solution approaches have been developed to deal with the problem of cell formation but virtually all of them look at CM in terms of the total number of products to be made and the total number of machines or machine types available (or needed), and then try to plan a conversion of the entire shop into cells, possibly keeping a remainder cell. In other words, planning the conversion of a job shop to CM is performed comprehensively rather than incrementally (Shafer et al. 1999), as shown in Fig. 1

Wemmerlov (2000) in a survey done on 126 cells in 46 plants mentioned that academic (and some practitioner) writers on cell formation often seem to perceive the problem as one where multiple cells emerge from a single analysis of the factory, the reality is that most cells in industry are created and implemented sequentially over time. Incremental cell formation follows a sequential process of forming the cells proposed in the master plan. In this case cells were implemented one-by one rather than all-at-once, a sample of this kind of cell formation is illustrated in Fig. 2; a similar observation is made in Johnson (1998), Mahesh and Srinivasan (2002).

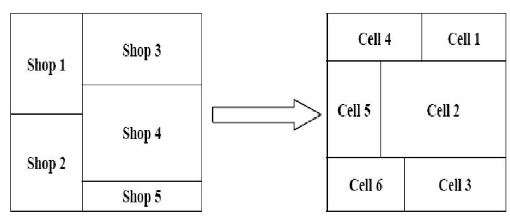

Figure 1: Non-incremental cellular manufacturing system

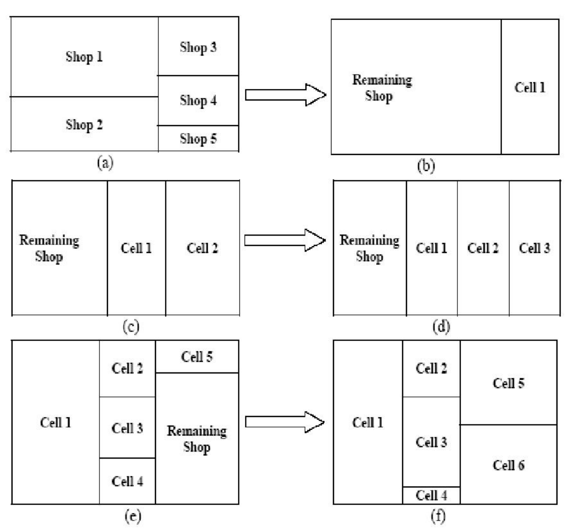

Figure 2: Incremental cellular manufacturing system

A survey by Adil and Ghosh (2005) mention several reasons for a company gradually implementing GT cells as follows:

1. To implement a pilot cell: A company may select a few strategically important parts/machines in a cell. This may provide fruitful learning experience for future cell implementation.
2. Economic reasons: Budget constraints may not permit a conversion of the whole plant into cells.
3. Master plan: Some companies follow a master plan where they gradually cellularize their plant.
4. Data not amenable to perfect grouping: There may be some bottleneck parts and bottleneck machines inherent that are not amenable to cellularization.
5. Service cell: Some machines serve multiple part families and hence may be dedicated to the shared service cell.

As mentioned earlier, the cell formation problem (CFP) which groups machines into cells and parts into families has received considerable attention in literature. Mahesh and Srinivasan [16] clustered a number of techniques and provided an overview of various algorithms that forms cells comprehensively (i.e., non-incrementally) in total. However, empirical findings on cell formation ((Marsh et al. 1999, Wemmerlov and Johnson (2000), Johnson (1998), Mahesh and Srinivasan (2002)) suggest that cells are implemented incrementally. More recently, a few studies have developed methods for solving incremental cell formation problems. Shambu and Suresh (2000) simulated a shop floor under several degrees of cellularization for a wide variety of shop conditions. They measured the performance of hybrid cellular manufacturing, cellular manufacturing, and job shop in a dynamic environment. Balakrishnan and Cheng (2007) proposed a model which considers cell formation over a multi-period planning horizon with demand and resource uncertainties. In this study, cell formation has been done non-incrementally where at each period the cell configuration can be changed; however, planning, implementation or capital investment issues have not been addressed. Despite many previous researches, Nsakanda et al. (2000) stated that in some cases the implementation of a CMS is unhelpful. They showed that in this situations hybrid cellular configuration would be beneficial. Adil and Ghosh (2005) develop a mathematical model and a heuristic approach based on greedy random adaptive search procedures (GRASP) to address incremental cell formation problem. Rajakarunakaran (2006) solved the fractional cell formation problem (similar to incremental cell formation) using modified adaptive resonance theory1 network.

It is known that the CFP is one of the NP-hard combinational problems (Yasuda et al. 2005). On the other hand, most researches consider a single criterion while designers in the real world consider optimizing more than one criterion such as minimizing inter-cell movements and balance machine utilization. Hence, mathematically the problem is very hard. Approximation algorithms, or the heuristic method, have been developed to obtain an optimum or close to optimum non-dominated solutions. Multi-objective evolutionary algorithms (EA) are efficient methods to evaluate the pareto-optimal set in difficult multi-objective optimization problems, such as Vector Evaluated Genetic Algorithm (VEGA) (Schaffer, 1984).This paper presents new mathematical model and a hybrid approach based on neural network and GA in order to obtain the non-dominated solutions of a cellular manufacturing system where cells are formed incrementally. The solutions are produced and arranged based on NSGA-II and ANN is implemented to approximate the acceptable solutions because of complexity of these problems.

2. Material and Methods

2.1. Problem description

We focus on cell formation decisions incrementally. In the traditional cell formation approaches, designers tried to convert a job shop system to a cellular manufacturing system comprehensively while in reality it will be done incrementally. Hence, here a functional layout is considered in the beginning of the planning horizon with the planning horizon being composed of multi periods. N parts are considered with each part visiting shops based on its requirements. Generally M machines are available in shops. Our objective is to decide the number of cells formed in a period, and the assignment of machines to cells such that the total cost and the total number of exceptional elements are minimized. The total cost consists of intra-cell and inter-cell material handling, intra-shop material handling, inter-shop material handling and material handling between cell and shop costs and an element is exceptional element if the element visits more than one cell in a period.

Assumptions

1. The demand for each part type in each period is known.
2. The number of cells formed in each period is limited.
3. Each cell consists of a minimum and maximum number of machines.

4. The unit cost of inter-cell movements, intra-cell movements, intra-shop movements and movements between cell and shop are known and constant over time.
5. The number of machines available is known and constant over time.

2.2. Notations

The following notations are used throughout the paper:

c index for cells
u , t indices for periods
m index for machines
p index for parts
s index for shops
α intra-cell material handling cost
β inter-cell material handling cost
δ intra-shop material handling cost
γ cost of material handling between cell and shop
ω inter-shop material handling cost
D_{pt} demand for product p in period t
LB minimum number of machines to be assigned to a cell
UB maximum number of machines to be assigned to a cell
Cmax maximum number of cells can be formed in a period
M Number of machines
S Number of shops in the beginning of planning horizon
P Number of parts
T Number of periods
$|k_j|$ Number of members of set kj

$$X_{cu} = \begin{cases} 1 & \text{If cell } c \text{ is formed in period } u \\ 0 & \text{Otherwise} \end{cases}$$

$$Y_{mcu} = \begin{cases} 1 & \text{If machine m is assigned to cell } c \text{ in period } u \\ 0 & \text{Otherwise} \end{cases}$$

$$Z_{pm} = \begin{cases} 1 & \text{If part p needs machine m} \\ 0 & \text{Otherwise} \end{cases}$$

$$B_{pcu} = \begin{cases} 1 & \text{If part } p \text{ visits cell } c \text{ in period } u \\ 0 & \text{Otherwise} \end{cases}$$

$$\delta_{pt} = \begin{cases} 1 & \text{If part p visits a cell in period } t \\ 0 & \text{Otherwise} \end{cases}$$

$$K_{mst} = \begin{cases} 1 & \text{If machine } m \text{ belongs to shop } s \text{ in period } t \\ 0 & \text{Otherwise} \end{cases}$$

$$\lambda_{pt} = \begin{cases} 1 & \text{If part } p \text{ visits a shop in period } t \\ 0 & \text{Otherwise} \end{cases}$$

$$\varsigma_{pst} = \begin{cases} 1 & \text{If part } p \text{ visits shop } s \text{ in period } t \\ 0 & \text{Otherwise} \end{cases}$$

2.2. The problem formulation

The objective functions and constraints can be formulated as follows:

Min z1 =

$$\sum_{t=1}^{T}\sum_{u=1}^{t}\sum_{c=1}^{c_{\max}} \alpha.X_{cu}.\sum_{p=1}^{P} D_{pt}.[\sum_{m=1}^{M}(Y_{mcu}.Z_{pm}) - B_{pcu}]$$
$$+ \sum_{t=1}^{T}\sum_{p=1}^{P} \beta.D_{pt}.\sum_{u=1}^{t}[\sum_{c=1}^{c_{\max}}(X_{cu}.B_{pcu}) - \delta_{pt}] +$$
$$\sum_{t=1}^{T}\sum_{s=1}^{S}\sum_{p=1}^{P} \delta.D_{pt}[\sum_{m=1}^{M}(K_{mst}.Z_{pm}) - \lambda_{pt}] +$$
$$\sum_{t=1}^{T}\sum_{p=1}^{P} \gamma.\lambda_{pt}.\delta_{pt}.D_{pt} +$$
$$\sum_{t=1}^{T}\sum_{p=1}^{P} \omega.D_{pt}[\sum_{s=1}^{S}\varsigma_{pst} - \lambda_{pt}] ,$$

Min z2 = = $\sum_{t=1}^{T}[\sum_{u=1}^{t}\sum_{c=1}^{c_{\max}} B_{pcu} - 1]$

Where

$$X_{cu} \geq X_{(c+1)u}$$

$$(1 - B_{pcu}).\sum_{m-1}^{M} Y_{mcu}.Z_{pm} = 0$$

$$\sum_{m=1}^{M} Y_{mcu}.Z_{pm} \geq B_{pcu}$$

$$(1 - K_{msu}).K_{ms(u+1)} = 0$$

$$K_{msu} - K_{msu}.K_{ms(u+1)} - \sum_{c=1}^{C_{\max}} Y_{mc(u+1)} = 0$$

$$(1-\lambda_{pt}).\sum_{s=1}^{S}\sum_{m=1}^{M} K_{mst}.Z_{pm} = 0$$

$$\sum_{s=1}^{S}\sum_{m=1}^{M} K_{mst} Z_{pm} \geq \lambda_{pt}$$

$$(1-\delta_{pt}).\sum_{c=1}^{C_{\max}} B_{pcu} = 0$$

$$\sum_{c=1}^{C_{\max}} B_{pcu} \geq \delta_{pt}$$

$$\sum_{c=1}^{C_{\max}} Y_{mcu} \leq 1$$

$$(1-X_{cu}).\sum_{m=1}^{M} Y_{mcu} = 0$$

$$\sum_{m=1}^{M} Y_{mcu} \geq X_{cu}$$

$$(1-\zeta_{pst}).\sum_{m-1}^{M} K_{mst}.Z_{pm} = 0$$

$$\sum_{m-1}^{M} K_{mst}.Z_{pm} \geq \zeta_{pst} .$$

The objective functions (1) and (2) represent the total cost and the total number of exceptional elements respectively. The total cost consists the costs of intra-cell material handling (first term in objective function 1), inter-cell material handling (second term), intra-shop material handling (third term), material handling between cell and shop (fourth term) and inter-shop material handling (fifth term). The total number of exceptional elements includes between cells movements only. Eq. (3) ensures the order of cell formation in a period. Eqs. (4) and (5) show that part p visits cell c, when at least one of the required machines to process the part is allocated to the cell. Eq. (6) is to ensure that a machine could belong to a shop if it was in that shop in preceding period. Eq. (7) represents that a machine can be allocated only to a cell or a shop in each period. Eqs. (8) and (9) show that part p visits shop s when at least one of the required machines to process the part is allocated to this shop. Eqs. (10) and (11) ensure that a part moves inter-cell if the part visits more than one cell in a period. Eq. (12) ensures that each machine can be allocated to at most one cell in each period. Eqs. (13) and (14) ensure that a cell is formed in a period if at least one machine is allocated to the cell. Eqs. (15) and (16) show that part p visits shop s, when at least one of the required machines to process the part is allocated to the shop.

3. Results

Hybrid approach for incremental cell formation problem

As mentioned earlier, the evaluation of fitness functions for complex functions is time consuming and expensive. Hence, the combination of GA and ANN was performed in order to build a hybrid method capable of seeking near-optimal or even optimal neural networks for a given problem. The overall schema of the hybridized approach, reported in Fig. 3, consists of the following steps:

Initially, a number of random solutions are produced.

By using the proposed ANN, solutions are clustered into feasible and infeasible solutions.

New individuals are generated by implementing the GA operators (crossover, mutation).

NSGA II is performed to determine the Pareto fronts.

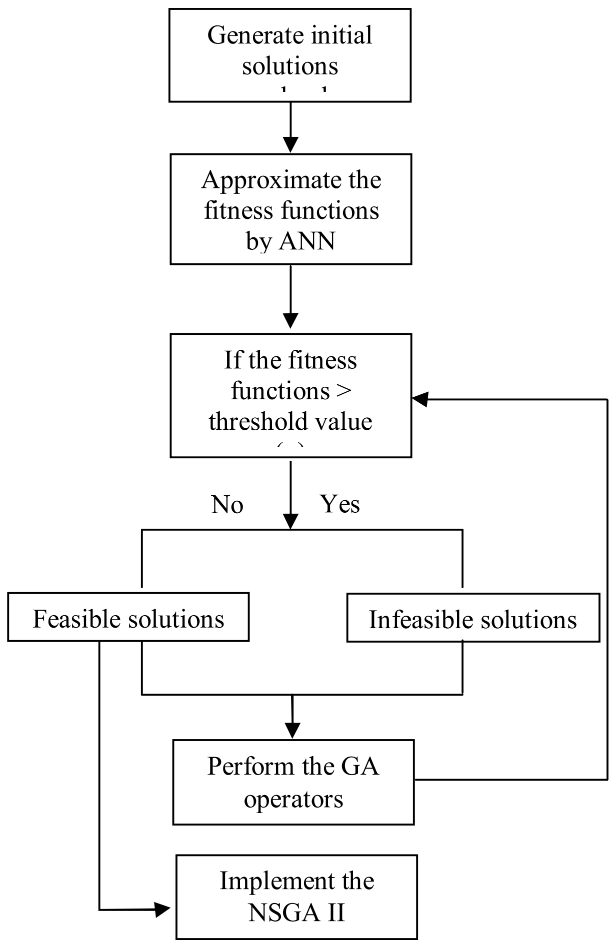

Figure 3: Diagram of the proposed method

3.1. The neural network for fitness function approximation

Artificial Neural Network (ANN) implemented by a Multilayer preceptron is a flexible scheme capable of approximating an arbitrary complex function. It consists of an input layer one or more hidden layers and an output layer. Backpropagation, which have been successfully used in modeling, classification, forecasting, design, control, and pattern recognition, is one of the most popular algorithms for training multilayer perceptrons.

We design an ANN which consists of an input layer, two hidden layers and output layer shown in Fig. 4.

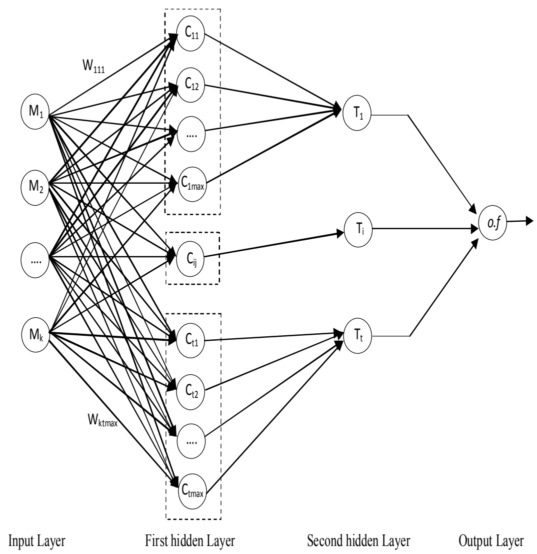

Figure 4: A multilayer perceptron

The input layer represents the available machines in shops and the output layer the approximation of objective functions that include M units and 1 unit respectively. All the nodes in the input layer are connected to every node in the first hidden layer. The first hidden layer is clustered into T sections where every section includes Cmax units. The jth node of ith section of first hidden layer represents the cell number j at period i. The weight Wijk associated with unit i of input layer and unit k of section j of hidden layer represents the dependency of machine i to cell k in period j.(Fig. 5).

Let the vector Wjk = [wijk , …, wmjk]denotes the input and W 'jkl represents the output of the unit k of section j of hidden layer. The output of hidden layer units is a function of activation function (φjk) where is defined by following relation:

$$W'_{jkl} = \varphi_{jk}(W_{jk}) = \begin{cases} W_{jk} & if \quad LB \le \sum w_{ijk} \le UB \\ \infty & otherwise \end{cases}$$

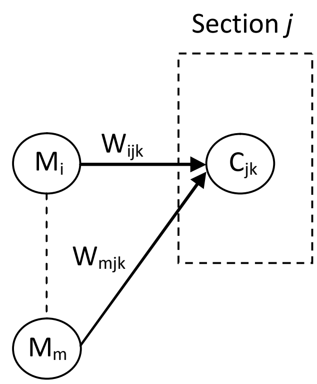

Figure 5: Inputs to a unit of hidden layer

The second hidden layer parallel to first hidden layer sections includes T units. All nodes of same section of first hidden layer are connected to a related node of second hidden layer. For example, the kth unit of section j of first hidden layer will be connected to jth unit of second hidden layer. The input vectors to second hidden layer W 'jkl form a new weight between first and second layer units connection is called W"j where W"j is a Cmax-by-M matrix.

4. Discussions

Here we use a Hopfield neural network to produce optimal Pareto points. The input and output layers consist of M×H and (Cmax+S) ×H neurons respectively, where M is the total number of machines, H is the number of periods, Cmax is the maximum number of cells can be constructed per period and S is the number of shops. Neuron i of input layer is connected to neuron j of output layer with weight Wij. Wij mention that machine i in period h belongs to cell c or shop s. Dph and Zpm are the inputs to input layer and Ymcu is the output and its value is binary.

$$y_{mcu} = \begin{cases} 1 & if \ \dfrac{\sum_{p=1}^{P} Z_{pm}.D_{ph}}{\sum_{p=1}^{P} D_{ph}} \ge \alpha \\ 0 & otherwise \end{cases}$$

Where α is a threshold value.

5. Conclusions

In this paper, we have proposed a new neural network-based multi-objective genetic algorithm for designing cells incrementally in a dynamic environment which can be used to solve combinatorial Optimization problems, in particular the part family formation problem which arises within cellular manufacturing environments. The proposed approach differs from previous work since we have not relied upon additional tuning. An attractive characteristic of the proposed approach is that it is open to extension to other neural features, which would further increase its efficiency. Another avenue for increasing its efficiency is the inherent parallelization capability of neural networks.

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