1-1-1990

Neural Networks in Manufacturing: Possible Impacts on Cutting Stock Problems

Cihan H. Dagli
Missouri University of Science and Technology, dagli@mst.edu

Recommended Citation

C. H. Dagli, "Neural Networks in Manufacturing: Possible Impacts on Cutting Stock Problems," *Proceedings of Rensselaer's Second International Conference on Computer Integrated Manufacturing, 1990*, Institute of Electrical and Electronics Engineers (IEEE), Jan 1990.
The definitive version is available at https://doi.org/10.1109/CIM.1990.128157

NEURAL NETWORKS IN MANUFACTURING: POSSIBLE IMPACTS ON CUTTING STOCK PROBLEMS

Cihan H. Dagli

Department of Engineering Management
University of Missouri-Rolla
Rolla, MO 65401

ABSTRACT

Neural networks, also known as parallel distributed processing is considered a revolutionary new approch for solving certain types of problems that have posed difficulty to engineers in the past. This paper examines the potential of neural networks and assesses the impact of parallel processing in the solution of stock cutting problem. Conceptual model proposed integrates a feature recognition network and simulated annealing approach. The model developed uses a neocognitron neural network paradigm to generate data for assessing the degree of match between two irregular patterns. The information generated through the feature recognition network is then passed to an energy function and the optimal configuration of patterns are computed using a simulated annealing algorithm. Basics of the approach are demonstrated with an example.

INTRODUCTION

Decision complexity is and will be an issue in manufacturing systems. This is due to the fact that excessive design and scheduling alternatives exist in the products to be produced and to choose an appropriate combination is not easy. The need to have flexible systems for achieving a competetive edge also increases the dimension of decision complexity. Due to excessive information to be generated by integration, there is a need for faster and smarter decision making systems that can provide better coordination among all manufacturing functions. Effective manufacturing system management necessitates the solution of combinatorially complex problems such as; scheduling, process control, feature based design, cutting and packing, mathematical programming model formulation with fuzzy or missing data, and flexible manufacturing cell and robot control, that exhibit ill-structured characteristics. There are successful neural network applications in pattern recognition and speech that exhibit the same ill-structured characteristics mentioned above. It is a matter of time to see a lot of neural network applications in the manufacturing area as well.

Intelligent systems in manufacturing are emerging to meet the new manufacturing competetive trust of the 90s; flexibility. Full automation will require integration of these systems on-line to various parts of computer integrated manufacturing systems as components of decision making. Under these conditions it will be possible to collect large quantities of data within a short period of time which necessitate temporary reasoning and adaptive control. Hence it will not be unusual to see a lot of integration of neural network technology with intelligent systems that integrate artificial intelligence and operations research for the solution of complex, time dependent, ill structured problems of manufacturing. Artificial neural networks will be an integral part of model based decision support systems for manufacturing. The impact of this new technology on process control, feature based design, stock cutting, and robot control is discussed below.

Process control is an important issue in the design of intelligent manufacturing systems that can respond to various signal generated either from shop floor or through other intelligent systems miles away. Pattern recognition is an essential input to effective process control. It could be possible to integrate neural networks to these intelligent systems for pattern identification. Back-propagation networks are proposed for event driven temporal sequence processing [30] . They can contribute to process control greatly along with other temporal or non-temporal pattern recognition techniques [29], [31], [32], [33], [34], [35], [36].

Featured based design is a recent approach to the problem of providing a link between CAD and CAM system. The features approach restricts the product designer and/or process planner to work with a set of features which have significance for design, analysis or manufacturing. Instead of using a model consists of lines, circles and points, the designer or process planner works with holes, pockets, slots for deriving manufacturing operations and sequences. The practical significance of this area of study is depicted in early examples of automated process planning. These demonstrations were limited in scope. The problem has several aspects. Various topics can be listed as; design by features, feature representation, automatic feature recognition, classification and coding, process planning, dimensioning and tolerancing, design evaluation for manufacturability. Artificial intelligence techniques have a natural application in this area. Neural networks could contribute greatly in feature representation and identification. There is no explicit research reported in literature along these lines. Neural networks designed for pattern recognition could have an impact in this area.

Robot control system design involves basically two steps, namely; derivation of a set of kinematic equations to express the physical constraints of the robot, sequences that move the robot from its current position to a target position are genarated through computer programs employing these equations. This type of approach works well at the laboratory level. It is not suitable in realistic environments basically, wear and tear on mechanical parts changes the kinematics of manipulators and sensor characteristics. These systems need high degree of autonomous adaptive learning to be able to avoid unexpected obstacles and respond to wear and tear of parts effectively. Neural network architectures offer an alternative approach for robot control design. Various articles are published in this area. Back-propagation neural networks are proposed by various researchers[37-41].

Stock cutting problem is another area that can benefit from this technology. Various pattern recognition neural networks exist. They could be modified and trained to meet the specific needs generated by cutting and packing problems. Temporal pattern recognition is also an issue in this application. As cutting patterns change in time creating a need to identify new pattern configurations. In this paper a conceptual model that can be used for the solution of stock cutting problems is proposed and basic concepts of the approach is demonstrated on a simple problem.

STOCK CUTTING PROBLEMS

The problem of allocating rectangular and/or irregular patterns arises frequently in applications where it has to be determined how a set of two-dimensional shapes will fit onto a large stock sheet of finite dimensions in such a way that the resulting scrap will be minimized. This problem is common to many industries such as aerospace, shipbuilding, steel construction, shoe manufacturing, clothing, flat glass and furniture.

Because of the diversity of the structures of real world stock cutting problems, there exists no general standard method for solving them. Over the years, two main approaches are emerged namely; heuristics and approaches based on linear programming relaxations.

Solution Approaches Proposed

Since 1950's, the cutting stock problem has received considerable attention as the computers have appeared as fast and economic information processors and the optimization techniques have developed. Solution of this problem is of considerable practical significance. A reduction of one percent in trim losses would mean a saving of approximately $120 million if half of the sheet metal production of USA in 1988 is used for cutting patterns for manufacturing.

Dimensionality, namely; one or two dimensions and shape of patterns, namely; irregular and regular and number of plates are the basic attributes generally used to classify these problems. Even the two dimensional single plate rectangular pattern problem is NP-complete [16]. The problem becomes more complicated for other combination of attributes. Thus, instead of trying to reach an optimal layout pattern most researchers has turn to heuristic solutions that generated the above classification.

The one-dimensional problem has the assumption that there is at least one side of equal length between all the patterns and the plates. In the two-dimensional problem a set of two-dimensional patterns are allocated on a single or multiple plates or for plates of variable length.

Optimization approaches proposed

Optimization is used extensively for the solution of these problems. The approaches proposed are summarized as survey articles [25], [20].

One dimensional cutting stock problems wherein the other two dimensions of the items being cut are assumed constant are studied initially. Various algorithms are proposed for the solution of these problems [15],[21-24],[26-27].

Dynamic programming is used extensively for this problem setting. Each type of pattern is considered as a stage. Decision variables are used to represent number of different pattern types allocated. Total allocated length up to a given stage is defined as state variable. Experience gained from the solution of one-dimensional single plate cutting stock problems is used for solving multi-plate problems. Gilmore and Gomory[17,18] express the one-dimensional, multi-plate, and rectangular cutting stock problem as an integer programming problem.

In their algorithm, all possible allocation alternatives for each stock sheet are formulated first and then an integer programming model is used to satisfy the desired demand with minimum scrap. However, obtaining all possible combination alternatives is a time consuming process. In order to reduce the computation time, they proposed a dynamic programming model. Hence, first the dynamic programming model is used for the generation of initial allocation alternatives, then an integer programming model is solved successively to obtain the optimum two-dimensional allocation.

Before the linear programming model is developed [14], a tree-search algorithm is developed for the solution of two-dimensional, single-plate, and rectangular cutting stock problems in which guillotine cuts are considered [9].

Adamowicz and Albano [1] also deal with this sub-class of cutting stock problems. In their algorithm, rectangular strips are generated by the patterns having one common dimension at least; then a subset of these strips is selected to lay out on the part of the stock sheet currently under examination. In another study, Albano[3] offers an interactive algorithm to improve the two-dimensional layout in which decision maker interventions are included. Albano and Orsini[4] allocate grouping of patterns onto rectangular strips in order to obtain guillotine type of cutting plans. Bengtsson[8] roughly distributes the patterns into a sufficient number of identical sheets, then improves this initial allocation by repetitive backtracking.

Gilmore and Gomory[19] handle the cutting stock problem of two-dimension, single-plate, and rectangular patterns through linear programming. The corresponding difficulty of the number of columns cannot in general be overcome for there is no efficient method for solving the generalized knapsack problem of this higher dimensional problem. However, a wide class of cutting stock problems of industry have restrictions that permit their generalized knapsack problem to be efficiently solved. All of the cutting stock problems that yield to this treatment are the ones in which the cutting is done in stages. Beasley [6-7] handles the two-dimensional, multi-plate and rectangular cutting stock problems in which guillotine type of cutting is considered. He presents a heuristic algorithm based upon a sophisticated cutting pattern generation procedure, a linear program and an interchange procedure. The objective of the approach is to find good sheet sizes for stock.

Heuristic approaches proposed

Optimization approaches proposed have restrictions in application due to NP-complete nature of the problem. To overcome this difficulty various heuristic approaches are proposed.

Adamowicz and Albano [21] propose two-stage algorithms which are also applicable for rectangular patterns. In both algorithms, firstly a list of candidate rectangular modules are obtained from either rectangular patterns or rectangular enclosures of irregular and rectangular patterns. In the second stage, these rectangular modules are allocated onto the stock sheet.

For this sub-class of cutting stock problems, Albano and Sapuppo [5] Dagli and Nisanci [10] Dagli and Tatoglu [11-12] also propose heuristic algorithms which can process both rectangular and irregular patterns. The algorithm of Albano and Sapuppo[5] assumes only line segments for each side, whereas the latter two assume both line and arc segments for the sides of a pattern.

Dagli and Tatoglu[12] propose a two-stage hierarchical approach that deals with the two-dimensional allocation problems of irregular patterns in the multi-plate context. In the first stage of the procedure, initial allocation of patterns to the plates is made through mathematical programming; then based on this initial allocation detailed two-dimensional allocation is made through heuristic algorithms in the second stage.

Details of the second stage is reported in Dagli and Tatoglu [12]. Second stage becomes a single plate irregular pattern allocation problem. Detail allocation of patterns on the plate is made based on priority rules for patterns as maximum area first, minimum area first, minimum number of sides first maximum perimeter first etc. An analogy is drawn between the problem of detailed allocation and job-shop scheduling. The objective in job-shop scheduling is to increase the utilization of available time whereas the objective in two-dimensional detailed allocation is to increase the utilization of available plates' area. Details of the first stage is given in Dagli [13], namely; generation of the allocation alternatives of the rectangular approximations on the plates and determination of optimum allocation alternatives through the use of mathematical programming model.

Characteristics of Proposed Approaches

The following remarks can be made regarding to the approaches proposed for solving stock cutting problems.

- Heuristics play an important role, since they are flexible enough to take into account various additional restrictions and objectives appearing in practice. The quality of heuristics is generally problem specific, and they can identify a pattern which is "good" for the particular problem in question. They can be integrated into intelligent decision support systems easily.

- On the other hand, Linear Programming algorithms first solve the linear programming relaxation of the cutting pattern oriented model and search for an integer solution using complex methods or simply rounding up to the next integer. In almost all linear programming models proposed, a two stage approach is used. Initially various cutting patterns are generated based on given stock sheet dimensions and small pattern shapes, then a decision variable is assigned for each cutting pattern and a linear programming model is formulated.

- The Gilmore and Gomory approach is classical in delaying some of the pattern generation process and generating the required patterns during the solution process using shadow prices.

- Generally, linear programming approaches are not widely used in practice, and most of the time, heuristics are preferred for selecting patterns. This is basically due to the fact that the large number of possible patterns combinations (in the order of hundred millions) cannot be represented in linear programming formulations.

Due to the diffuculty in formulating constraints that prevent the overlaping of patterns in the solution approaches proposed, in literature cutting pattern generation is done prior to or within the solution phase. Most of the mathematical programming approaches used dealt with the rectangular cutting patterns. There is a limited research work done for determining optimal allocation of irregular shápes. Various approaches that integrate artificial intelligence and optimization methods with heuristic algorithms are also proposed Dagli[28]. These approaches provided acceptable results for specific problems in which pattern configurations and basic allocation heuristics are known as a result of excessive experience with patterns. Hence it is not easy to develop general models that can work under different pattern configurations using the basic ideas proposed. Emerging neural network technology could well contribute to the solution of these problems due to their parallelism and ability to recall different configurations. In the following sections a conceptual model that integrates neocognitron neural network architecture and simulated annealing algorithm is discussed. The concepts are demonstrated on a sample set of patterns.

FUNDAMENTALS OF NEURAL NETWORKS

Neural network models attempt to achieve good performance through dense interconnection of simple computational elements. They do not execute series of instructions; instead they respond in parallel to the inputs presented to them. The result is not stored in the memory location , but it consists of the overall state of the network after some equilibrium condition is reached.

Processing elements and interconnections are the two primary elements of a neural network. Processing elements, which are called neurons, are generally simple devices that receive input signals and based on these inputs they may or may not generate a signal output. The output signal of an individual processing element is send to other processing elements as input signals through interconnections between processing elements.

The structure of the neural network is defined by the interconnection architecture between the processing elements, the rules that determines possible responses to inputs and the rules governing changes in interconnections between processing units. Once a network is defined using the above attributes an appropriate inputs are applied to the network and its reaction is observed. If the network is designed properly , the overall state of the network after its reaction to the input should yield the desired pattern.

Neural networks provide a greater degree of robustness or fault tolerance due their massive parallelism in their design. Damage to a few nodes or interconnections do not effect overall performance significantly. Most neural networks also adapt in time through changes to be made in interconnection weights to improve performance based on current results.

The ability to adopt and continue to learn are the essential attributes of neural networks in pattern recognition. Successful demonstrations of neural networks for speech and image recognition support the potential applications of this new technology in other areas.

PROPOSED APPROACH

The approach uses an energy function which considers area of the rectangle enclosing all the figures, level of similarity between pattern pairs and the degree of overlap of patterns in evaluating the configurations generated. Simulated annealing algorithm is selected as a solution technique.

Simulated annealing is a stochastic technique that has recently attracted significant attention as suitable for optimization problems of very large scale. It has effectively solved the famous TSP problem, finding the suitable itenarary for the traveling salesman to visit n cities. The method has also been successfully used for designing complex integrated circuits.

Metropolis et.al. [43] introduced a simple algorithm that can be used to provide an efficient simulation of a collection of atoms in equilibrium at a given temperature. This algorithm forms the basis of the simulated annealing method. In each step of the algorithm an atom is given a small random displacement and the resulting change in the energy of the system is computed. If energy change is less than zero the displacement is accepted, and the configuration with the displaced atom is used as the starting point for the next step. If the change in energy is greater than zero then the displacement is treated probalistically. The probability that the configuration is accepted for a given energy change is equal to $e^{-\Delta E/KT}$, where K is the Boltzman constant, T is the temperature.

There is an analogy between simulated annealing and thermodynamics, specifically with the way that liquids freeze and crystalize, or metals cool and anneal. At high temperatures, the molecules of the liquid move freely with respect to one another. If the liquid is cooled slowly, the thermal mobility is lost. The atoms are often able to line themselves up and form a pure crystal that is completely ordered over a distance up to billions of times the size of an individual atoms in all directions. This crystal is the state of minimum energy for this system. For slowly cooled systems nature is able to find this minimum energy state. On the otherhand if a liquid metal is cooled quickly it does not reach this state. So the essence of the process is slow cooling allowing ample time for redistribution of the atoms as they lose mobility.

The simulation of annealing applied to optimization problem involve the preperatory steps. First, one must identify the analogues of the physics concepts in the optimization problem itself: the energy function becomes the objective function, the configurations of particles become the configurations of parameter values, finding a low energy configuration becomes seeking a near optimal solution, and temperature becomes the control parameter for the process. Secondly, one must select an annealing schedule consisting of a decreasing set of temperatures together with the amount of time to spend at each temperature. Third, one must have a way of generating and selecting new configurations.

The annealing algorithm proposed by Kirkpatrick[44] consists of running the Metropolis algorithm at each temperature in the annealing schedule for the amount of time prescribed by the schedule, and selecting the final configuration generated as a near optimal solution. The Metropolis algorithm, which accepts configurations that increase cost as well as those that decrease cost, is the mechanism for avoiding entrapment at a local minimum. The annealing schedule consists of; initial temperature, temperature decrement, equilibrium and stopping criteria.

Energy Function :

The energy function for simulated annealing has three main components to map a given configuration of patterns into a positive real number. They are:

* Area of the rectangle that encloses all the patterns,
* Weighted sum of distances between patterns within the configurations,
* Area of overlapping patterns.

This can be represented in functional form as:

$$E = af_1 + bf_2 + cf_3$$

where f_1 denotes the area of the enveloping rectangle for all patterns, and f_2 represent the amount of overlap in a given placement and finally f_3 is a weighted sum distances of patterns within the configuration.

$$f_3 = {}_{i=1}\Sigma^{n}\ {}_{j=i+1}\Sigma^{n}\ (w_{ij}d_{ij})$$

Where d_{ij} is the distance between the patterns i and j in a given configuration and w_{ij} represents the tendency of the pattern i to attract pattern j. The values for this index for each pattern pair need to calculated prior to the simulated annealing approach. The contribution of each component to total energy is controlled through the parameters a, b, c that change based on the patterns allocated. Hence, it is possible to create different set of energy functions based on the irregularity of the shapes under consideration. Computation of w_{ij} values is an important issue as patterns change for different applications. The practicality of the approach increases as it becomes more general in considering various patterns. Hence, it is necessary to generate w_{ij}'s quickly and accurately. Since they represent the degree of fit between the patterns a method is needed to match and identify various pattern features. Pattern recognition neural network paradigms both self-organizing and feed-forward could be used for this purpose. In this study, neocognitron neural network architecture is selected as a possible generator for w_{ij} values. In the following section, a brief discussion of neocognitron architecture is provided.

Generation of attraction weights:

The Neocognitron has a hierarchical structure which simulates human vision system. The basic structure of the neocognitron paradigm is shown in Figure 1.,[42].

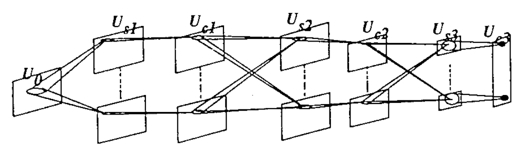


Figure 1. Structure of the Neocognitron

This multistage network consists of many stages. Each stage contains a layer of S-cells followed by a layer of C-cells. S-cells are feature extracting cells. They are activated only when a particular feature is presented at a certain position in the input layer. The feature which the S-cells extract is determined during the learning process. In lower stages, local features such as a line at a particular orientation are extracted. In higher stages, more global features, such as a part of a training pattern are extracted.

C-cells are employed in the network for positional shift and feature deformations. Connections from S-cells to C-cells are fixed and do not change during the learning process. The neocognitron is capable of training with both unsupervised learning and supervised learning.

In the proposed approach neocognitron can be used as a feature selector for various patterns. Features identified by this network can then be passed to a second neural network to determine the value of weights that measures the degree of match between them. Pattern feature recognition part of the approach is still under development. The weights used in the simulated annealing algorithm are calculated using conventional methods. However, preliminary tests done with restricted pattern data for feature recognition looks promising

BASIC STRUCTURE OF THE APPROACH

In this section structure of the proposed approach is described using a set of ten irregular patterns. In Figure 2 the patterns selected are depicted.

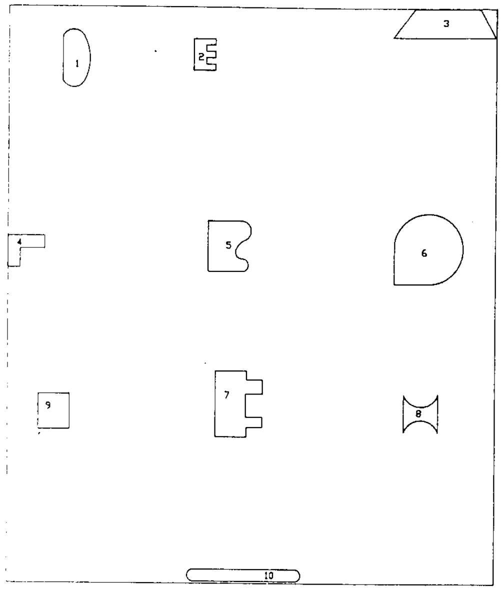


Figure 2 : Sample patterns used.

Simulated annealing algorithm selected requires calculation of attractiveness weights for pattern pairs. In the sample problem patterns are restricted to rotate in multiples of 90 degrees. Attractiveness weights of each pattern pair is calculated based on this restriction by evaluating all possible combinations. Rectangular enclosure is selected for each combination generated for pattern pairs. The one that gives the minimum packing density is selected as a weight to be used in the simulated annealing algorithm. In Figure 3 this procudure is depicted. In the final version of the system these computations could be automated using a feature recognition neural network such as neocognitron or other selforganizing neural network paradigms. Current reseach effort are concentrated on the simulated annealing algorithm.

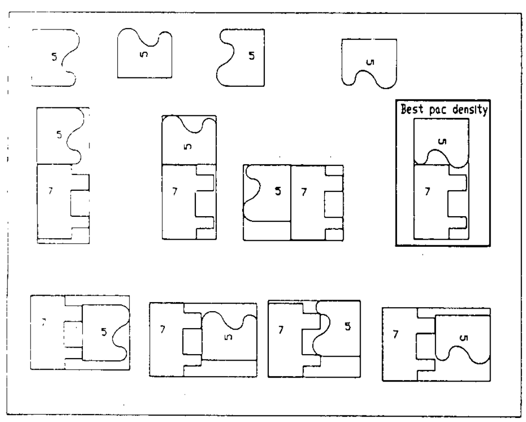
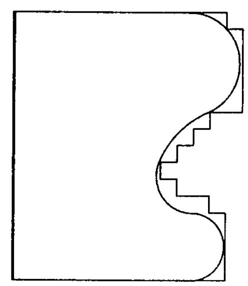


Figure 3 : Generation of weight matrix.

Pattern representation is an important issue in solving stock cutting problems. Choice of efficient representation methods is important, especially for algorithms that require extensive computation time. In the proposed approach matrix representation is used. Each pattern is represented by a matrix of size K by L which is the minimum rectangular enclosure of the irregular shape. The value of K and L is determined based on the desired accuracy of computations. In Figure 4 repesentation for sample pattern number five is given. The attraction weight matrix calculated for ten sample patterns are given in Table 1.



$$\begin{bmatrix}
1&1&1&1&1&1&1&1&1&1&1&1&1&0\\
1&1&1&1&1&1&1&1&1&1&1&1&1&1\\
1&1&1&1&1&1&1&1&1&1&1&1&1&1\\
1&1&1&1&1&1&1&1&1&1&1&1&1&1\\
1&1&1&1&1&1&1&1&1&1&1&1&1&1\\
1&1&1&1&1&1&1&1&1&1&1&1&1&1\\
1&1&1&1&1&1&1&1&1&1&1&1&0&0\\
1&1&1&1&1&1&1&1&1&1&1&0&0&0\\
1&1&1&1&1&1&1&1&1&1&0&0&0&0\\
1&1&1&1&1&1&1&1&1&0&0&0&0&0\\
1&1&1&1&1&1&1&1&1&1&0&0&0&0\\
1&1&1&1&1&1&1&1&1&1&1&1&1&0\\
1&1&1&1&1&1&1&1&1&1&1&1&1&0\\
1&1&1&1&1&1&1&1&1&1&1&1&1&0\\
1&1&1&1&1&1&1&1&1&1&1&1&1&0\\
1&1&1&1&1&1&1&1&1&1&1&1&1&0
\end{bmatrix}$$

Figure 4: Pattern Representation

	1	2	3	4	5	6	7	8	9
1									
2	759.0								
3	900.5	640.8							
4	726.0	878.8	558.1						
5	865.5	770.3	637.2	601.0					
6	808.3	694.3	579.9	752.0	743.6				
7	539.8	507.9	491.0	561.1	623.7	652.0			
8	604.6	613.3	600.2	537.7	642.6	638.1	456.4		
9	825.2	872.3	774.0	769.2	839.1	725.6	562.7	694.2	
10	584.2	593.8	722.7	506.1	463.4	539.2	436.8	358.3	491.6

Table 1: Attraction Weight Matrix

To demonstrate the working of the simulated annealing algorithm three allocation configurations are generated. they are given in Figures 5,6,7. The value of enegy function is computed for each configuration.

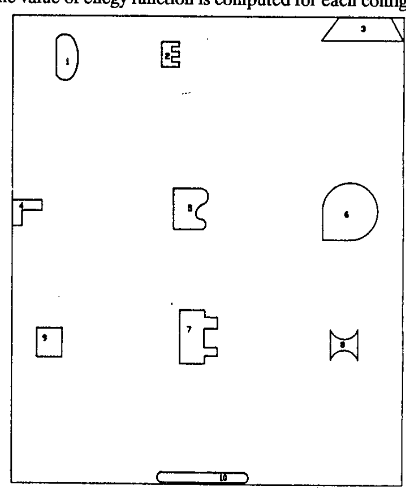


Figure 5: First allocation configuration

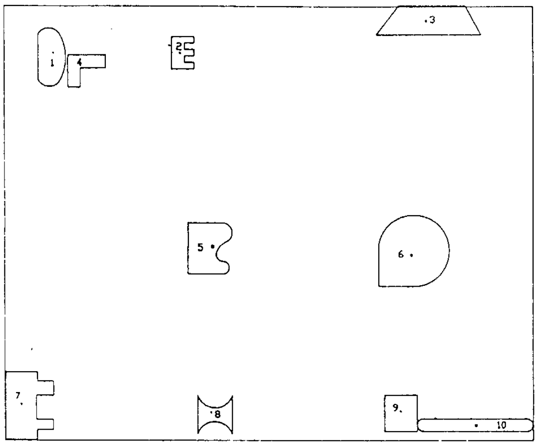


Figure 6 : Second allocation configuration

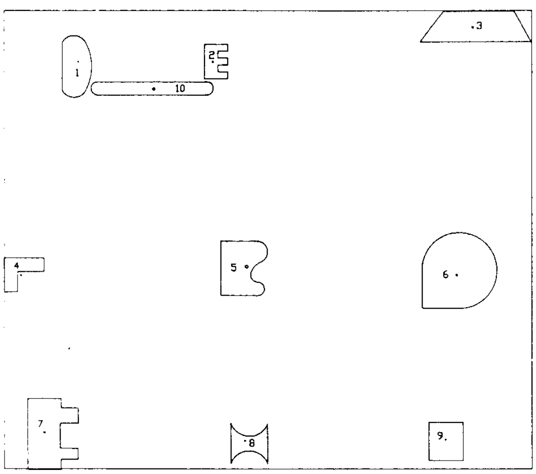


Figure 7 : Third allocation configuration

Configuration 1:

$$E = 40.12(a) + 0(b) + 110638.62(c)$$

Configuration 2:

$$E = 37.4(a) + 0(b) + 115707.33(c)$$

Configuration 3:

$$E = 34.02(a) + 0(b) + 110262.91(c)$$

Parameters a, b, c are selected based on set of patterns to be allocated. The value of these parameters will be the same for each configuration. The second configuration generated by the simulated annealing algorithm provides a higher energy value then the first configuration. At this stage of the algorithm probability of energy change is computed using Boltzman machine and compared with a probability value generated from a uniform distribution and this configuration is not accepted as the random number drawn was smaller than the computed probability, thus creating the third configuration. Computer code that will allocate fifty irregular patterns using simulated annealing algorithm is being developed.

CONCLUDING REMARKS

Neural network technology will definitely have an impact on manufacturing systems. Neural networks could contribute greatly to the solution of the problem due to their ability to identify various pattern configurations in the process of cutting pattern generation and their parallel architecture. The simulated annealing approach proposed in this study provided promising results. The idea of integrating feature recognition neural net with stochastic combinatorial optimization looks promising. However, more experimentation and theoritical developments are required in selection of paramaters a, b, c based on different pattern attributes and cooling schedule. Once the code that can process fifty irregular shapes is finished a lot of information will be collected that will shed light into the problems mentioned above. Neural networks will impact intelligent manufacturing systems of the 1990s and stock cutting problem that has been studied since 1960s will be treated in a different way based on the availability of this new parallel computation technology.

REFERENCES

[1] Adamowicz, M., and Albano A. (1976), "A solution of the rectangular cutting-stock problem", IEEE Transactions on Systems, Man and Cybernetics, 6, 302-310.

[2] Adamowicz, M., and Albano, A. (1976), "Nesting two-dimensional shapes in rectangular modules", Computer Aided Design, 18, 27-33.

[3] Albano, A. (1977), "A method to improve two-dimensional layout", Computer Aided Design, 9, 48-52.

[4] Albano, A., and Orsini, R. (1980), "A heuristic solution of the rectangular cutting stock problem", The Computer Journal, 23, 338-343.

[5] Albano, A., and Sapuppo, G. (1980), "Optimal allocation of two-dimensional irregular shapes using heuristic search methods" IEEE Transactions on Systems, Man and Cybernetics, 10, 242-248.

[6] Beasley, J.E. (1985a), "An algorithm for the two-dimensional assortment problem", European Journal of Operational Research, 19, 2, 253-261.

[7] Beasley, J. E. (1985b), "Algorithms for Unconstrained Two-Dimensional Guillotine Cutting", Journal of Operational Research Society, 36, 4, 297-306.

[8] Bengtsson, B.E. (1982), "Packing rectangular pieces - A heuristic Approach", The Computer Journal, 25, 353-357.

[9] Christofides, N., and Whitlock, C. (1977), "An algorithm for two-dimensional cutting problems", Operations Research, 25, 30-44.

[10] Dagli, C.H., and Nisanci, I.H. (1981), "A heuristic for cutting-stock problem", 6th International Conference on Production Research, 1, 9-16.

[11] Dagli, C.H., and Tatoglu, M.Y. (1983), "A computer package for solving cutting stock problems", 7th International Conference of Production Research, 1, 480-487.

[12] Dagli, C.H., and Tatoglu, M.Y. (1987), "An approach to two-dimensional cutting stock problems", International Journal of Production Research, 25, 175-190.

[13] Dagli, C. H. (1987), "Cutting Stock Problem: Combined Use of Heuristics and Optimization Methods", 9th International Conference on Production Research, 843-849.

[14] Dyckhoff, H. (1981), "A new linear programming approach to the cutting-stock problem", Operations Research, 29, 1092-1104.

[15] Eisemann, K. (1957), "The trim Problem", Management Science, 3, 3 279-284.

[16] Garey, M. R., and Johnson, D.S. (1979), "Computers and Intractability: A Guide to the Theory of NP-Completeness", San Francisco, Freeman.

[17] Gilmore, P.C., and Gomory, R.E. (1961), "A Linear Programming Approach to the Cutting-Stock Problem", Operations Research, 9, 849-859.

[18] Gilmore, P.C., and Gomory, R.E. (1963), "A Linear Programming Approach to the Cutting-Stock Problem -Part II", Operations Research, 11, 863-888.

[19] Gilmore, P.C., and Gomory, R.E. (1965), "Multistage cutting-stock problems of two and more dimensions", Operations Research, 13, 94-120.

[20] Golden, B. L. (1976), "Approaches to Cutting Stock Problem", AIIE Transactions, 8, 2, 256-274.

[21] Haessler, R. W. (1978), "A Procedure for Solving the 1.5 Dimensional Coil Slitting Problem", AIIE Transactions, 10, 1, 70-75.

[22] Haessler, R. W. (1980), "A Note on Computational Modifications to the Gilmore-Gomory Cutting Stock Algorithm", Operations Research, 28, 4, 1001-1005.

[23] Haessler, R. W. (1980), "Multi-machine Roll Trim -Problems and Solutions", TAPPI, 63, 1, 71-74.

[24] Hahn, S. G. (1968), "On the Optimum Cutting of Defective Sheets", Operations Research, 16, 6, 1100-1114.

[25] Hinxman AI (1980) "The trim loss and assortment problems: A survey"; European Journal of Operational Research 5, pp. 8-18.

[26] Rijeckaert, M. J. (1986), "Heuristics and the Role of Microcomputers for the One-Dimensional Cutting Stock Problems", Operations Research Varfahren, 56, 85-92.

[27] Roodman, G. M. (1986), "Near-Optimum Solution to One-Dimensional Cutting Stock Problem", Computers and Operations Research, 13, 6, 713-719.

[28] C. H. Dagli,(1990) "Knowledge -Based Systems for Cutting Stock Problems", European Journal of Operational Research, Vol. 44, pp 160-166.

[29] C. Sung and C. E. Priebe, (1988) "Temporal Pattern Recognition", IEEE International Conference on Neural Networks, pp. 689-696.

[30] K. Shimohara, T. Uchiyama and Y. Tokunaga,(1988) "Back-Propagation Networks for Event-Driven Temporal Sequence Processing", IEEE International Conference on Neural Networks, pp 665-672.

[31] R. P. Lippmann,(1987) "An Introduction to Computing with Neural Nets", IEEE ASSP Magazine, vol. 3, no. 4, pp. 4-22.

[32] P. Castelaz, J. Angus and J. Mahoney,(1987) "Application of Neural Networks to Expert Systems and Command of Control Systems", Proceedings of the Western Conference on Expert Systems, pp. 118-125.

[33] N. H. Farhat,(1987) "Optoelectronic Analogs of Self-Programming Neural Nets: Architecture and Methodologies for Implementing Fast Stochastic Learning by Simulated Annealing", Applied Optics, vol. 26, no. 23, pp. 5093-5103.

[34] J. Barhen, N. Toomarian and V. Protopopescu, "Optimization of the Computational Load of a Hypercube Supercomputer Onbaord a Mobile Robot", Applied Optics, vol. 26, no. 23, pp. 5007-5014, December 1987.

[35] T. Kohonen, G. Barna and R. Chrisley,(1988) "Statistical Pattern Recognition with Neural Networks: Benchmarking Studies", IEEE International Conference on Neural Networks, pp. 61-68.

[36] S. Y. Kung and J. N. Hwang,(1988) "Parallel Architectures for Artificial Neural Nets", IEEE International Conference on Neural Networks, pp. 165-172.

[37] R. Elsley,(1988) "A Learning Architecture for Control Based on Back-propagation Neural Networks", IEEE International Conference on Neural Networks, pp. 587-594.

[38] E. P. Gardner,(1988) "What the Robot's Hand Should Tell the Robot's Brain: Feature Detection in a Biological Neural Network", IEEE International Conference on Neural Networks, pp. 557-565.

[39] H. Liu, T. Iberall, G. A. Bekey, (1988) "Building a Generic Architecture for Robot Hand Control", IEEE International Conference on Neural Networks, pp. 567-574.

[40] A. J. Pellionisz, (1988) "Intelligent Decisions and Dynamic Coordination: Properties of Geometrical Representation by Generalized Frames Intrinsic to Neural and Robotic Systems", IEEE International Conference on Neural Networks, pp. 603-610.

[41] D. H. Graf and W. R. LaLonde, (1988) "Neural Controller for Collision-Free Movement of General Robot Manipulators", IEEE International Conference on Neural Networks, pp. 77-84.

[42] Dagli C.H., Ashouri R., Leininger G., and McMillan B.,(1990) "Composite Stock Cutting Pattern Classification Through Neocognitron", Proceedings of International Joint Conference on Neural Networks, pp. II-587, Washington DC.

[43] Metropolis N., Rosenbluth A.W., Rosenbluth M.N., Teller A.H., and Teller E.,(1953), "Equations of State Calculations by Fast Computing Machines", Journal of Chemistry and Physics 21, pp. 1087-1091.

[44] Kirkpatrick S., Gelatt Jr. C.D., Vecchi M.P., "Optimization by Simulated Annealing", Science 220, pp. 671-680.