# Investigation of Applications of SA in the Design of Dynamic Cellular Manufacturing Systems

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**Abstract-Manufacturing industries are under intense pressure from the increasingly competitive global marketplace. Shorter product lifecycle, time to market and diverse customer needs have challenged manufacturers to improve the efficiency and productivity of their production activities. Manufacturing systems should be able to adjust or respond quickly to adopt necessary changes in product design and product demand without major investment. Traditional manufacturing systems are not capable of satisfying such requirements. Although a cellular manufacturing system (CMS) provides great benefits, the design of CMS is complex for real life problems. The design of such a kind of manufacturing system under dynamic production environment, with variety and demand varying between each planning horizon, requires pervasive use of a Meta-heuristics such as Genetic Algorithm (GA), Simulated Annealing algorithm (SA), and Tabu Search (TS). The dynamic cell formation (CF) problem (involving the formation of a mathematical model depicting the variable product mix and demand across the planning horizons) is known to be one of the NP-hard combinational problems. Although some optimization algorithms can find the optimal solution for small- and medium-sized problems, they have a disadvantage in that the memory and computational time requirements are extremely high, and increase exponentially, as the problem size increases. In such situations, meta-heuristics are used for exploring and exploiting the search space to obtain good solutions. In contrast to other stochastic searches, SAs in particular have the following unique features: it does not get trapped in local minimum. Allow uphill moves controlled by parameter called temperature. Final result not dependent on initial state.These features often makes them a preferable choice over traditional heuristics. The objective of this paper is to review how the SA has been applied so far for the Design of Cellular Manufacturing System application. In this paper we present a comprehensive review of the works that applied SA for CMS deign and suggest some directions for future research.**

***Keywords: Cellular manufacturing systems; Metaheuristics; Simulated Annealing.***

## 1. INTRODUCTION

### *1.1 About CMS*

CMS involves the formation of part families based upon their similar processing requirements and the grouping of machines into manufacturing cells to produce the formed part families. A part family is a collection of parts which are similar either because of geometric shape and size or similar processing steps required in their manufacture. A manufacturing cell consists of several functionally dissimilar machines which are placed in close proximity to one another and dedicated to the manufacture of a part family. The tenet of CM is to break up a complex manufacturing facility into several groups of machines (cells), each being dedicated to the processing of a part family. Therefore, each part type is ideally produced in a single cell. Thus, material flow is simplified and the scheduling task is made much easier.

As reported in the survey by Wemmerlov and Johnson (1997), production planning and control procedures have been simplified with the use of CM. Obvious benefits gained from the conversion of the shop are less travel distance for parts, less space required, and fewer machines needed. Since similar part types are grouped, this could lead to a reduction in setup time and allow a quicker response to changing conditions. CM is a hybrid system linking the advantages of both job shops (flexibility in producing a wide variety of products) and flow lines (efficient flow and high production rate). In CM, machines are located in close proximity to one another and dedicated to a part family. This provides the efficient flow and high production rate similar to a flow line. The use of general-purpose machines and equipment in CM allows machines to be changed in order to handle new product designs and product demand with little efforts in terms of cost and time. So it provides great flexibility in producing a variety of products.

### *1.2 About dynamic CMS*

The concept of the dynamic cellular manufacturing system (DCMS) was first introduced by Rheault et al. (1995). In the traditional CMS any changes in the product demand over time is ignored from product redesign and other factors. It assumes that the product mix and part demand is constant for the entire planning horizon. The product mix refers to a set of part types to be produced at each period. In the dynamic environment, a planning horizon can be divided into smaller periods where each period has different product mix and demand requirements. Consequently, the formed cells in the current period may not be optimal and efficient for the next period. To overcome disadvantages of the traditional CMS, the concept of the DCMS is introduced. In DCMS, The length of the planning horizon directly depends on the natural of the product.

The DCMS is related to reconfiguration of manufacturing cells including part families and machine groups at each period. Reconfiguration involves swapping the existing machines between each pair of cells, called machine relocation, adding new machines to cells including machine replication, and removing the existing machines from cells. For example, if we encounter the season products, like clothing or heater/cooler equipments, the planning horizon may consist of two six- month periods or four three-month periods (Safaei et. al., 2009). A schema of the cell reconfiguration in the DCMS for two consecutive periods is schematically shown in Fig. 1. The system contains of two manufacturing cells for each period. Because of the processing requirements, machine 3 must be relocated from cell 1 to 2 and machine 7 from cell 2 to 1 at the beginning of period 2. Also, machine 8 must be added to cell 2 at the beginning of period 2 while machine 1 will not be used during period 2. In this case, either machine 1 keeps in the same cell or moves to another cell because of the cell size limitation. Considering the maximum cell size is equal to 4, machine 1 moves to the outside of cell 2 and machine 8 is replaced by that. Thus, the above reconfiguration requires three machine relocations.

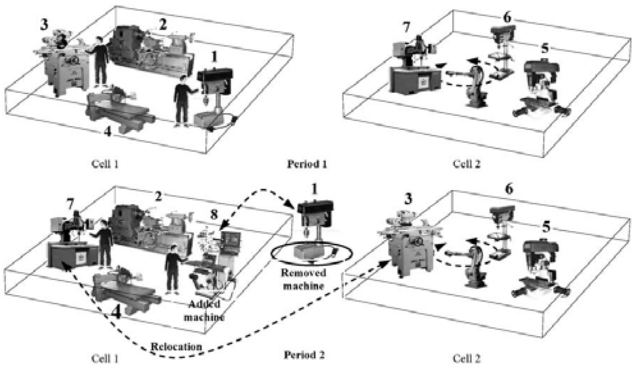

Fig.1. A schematic diagram of the cell re-configuration in a dynamic CMS

## 2. META-HEURISTICS

The most frequently found algorithms for GT found in the literature can be classified into the following categories: Part-Coding analysis, Array-based clustering, Graph partitioning, Similarity Coefficient, Mathematical programming, Meta-heuristic based, and Artificial intelligence (AI) based. The cell formation problem is a combinatorial optimization problem that is NP-hard. The optimization algorithms yield a globally optimal solution in a possibly prohibitive computation time. Most of the approaches listed above are heuristic-based tailored algorithms for solving specific part family and machine group problems. None of these approaches guarantee near optimal solutions. Meta-heuristics have emerged to solve combinatorial optimization problems with global or near-global optimal solution in a reasonable computation time. Meta-heuristics have been recently used to solve combinatorial optimization problems, of which the cell formation problem is typical. Since the cell formation problem is a difficult combinatorial optimization problem, recent search meta-heuristics, which are capable of solving practical problems have been developed such as simulated annealing (SA), genetic algorithm (GA), and tabu search (TS).

## 3. SIMULATED ANNNEALING

Simulated annealing is a probabilistic method proposed by Kirpatrick for funding the global minimum of a cost function that may possess several local minima. It works by emulating the physical process whereby a solid is slowly cooled so that when eventually its structure is “frozen”, this happens at a minimum energy configuration.

### *3.1. About Boltzmann distribution*

The Boltzmann distribution, one of the fundamental results in statistical thermodynamics, gives the probability that a system, which is a small part of a much larger system characterized by the temperature ‘T’, is in a microstate ‘r’. In other words, the distribution gives the probability that the system occupies the state ‘r’ when its surroundings is in a temperature ‘T’ and this distribution depends exponentially on the energy corresponding to the microstate or simply state ‘r’. The distribution is given by: Pr = exp(-Er/KT), where K is the Boltzmann constant. This result, which is widely used in most disciples of science and engineering, also finds its way into the realm of optimization methods as one of its analogs is used in the search technique: Simulated Annealing.

### *3.2 SA approach*

According to the above discussion the probability that the system is in the state ‘r’ decreases with the Energy corresponding to the state i.e. the concentration of particles is higher at regions of low energy. A method for improving some mechanical properties of solids is Annealing where the material is heated to a very high temperature and subsequently cooled so that the large movements of atoms in the lattice completely obliterates any defects and thus leaving a hardened, more ductile material once room temperature is reached. This idea is analogously used as a solution-search technique for non-linear problems. Here the state ‘r’ is considered to be a solution and the Energy is considered the objective function. As the probability of transition in a continuous varying partition function is independent of the particle’s history it follows that this search technique has the Markov property. The goal is to reduce the energy. First an initial or trial population is generated either randomly or using any heuristic. The Energy or objective function is brought to a ground state or a global minimum from a state of high Temperature. At each temperature, the neighborhood of the current microstate is explored and the corresponding energy is determined. After that the temperature of the system is lowered according to a cooling schedule and iteration begins. This goes on until a terminating condition (usually a low temperature) is satisfied. Thus the main components for implementing the SA are:

i. Initial solution
ii. Assigning the Temperature
iii. Motion around a point’s neighborhood
iv. Cooling schedule
v. Terminating condition

### *3.3 Initial population and temperature*

The initial stage of the Simulated Annealing search is to generate the initial population or the set of trial solution. These initial solutions can be generated randomly. Each microstate corresponds to a solution of the system and the objective function of that solution is the energy of that microstate. A parameter called the temperature can be assigned in such a way that the probability distribution of each state obeys the Boltzmann Distribution.

### *3.4 Exploring neighborhood point*

A neighboring point in the vicinity of a point or microstate in question is generated randomly. The Energy function is determined and if it is much lower, it moves to that point and another point is randomly generated in the new neighbor hood. This procedure is repeated and then the temperature is lowered and then a new iteration begins.

### *3.5 Energy function*

The Energy, which is a function of state ‘r’, is the objective function which has to be minimized. If it is a maximization problem then the negative of the objective function is the Energy function. When moving around a neighbor of a microstate or a possible solution the energy function is explored in each case. The neighboring point is accepted if its energy were to be found lower than the previous point.

In SA implementation, a fitness function is used to evaluate and reproduce new chromosomes, called offspring for the generations to come. The purpose of the fitness function is to measure the goodness of the candidate solutions in the population with respect to the objective and constraint functions of the model.

### *3.6 Acceptance probabilities*

If a neighboring point is found to have a higher temperature, it doesn’t get immediately get rejected. It is sometimes accepted when a random number belonging to (0, 1) is above a predefined value. This number is generated either completely random or it is done by the Metropolis–Hastings ratio. If the random number belonging to (0, 1) is within the Boltzmann probability the new value is accepted.

r < Pr, the value is accepted
r > Pr, the value is not accepted

### *3.7 Cooling schedule and terminating criteria*

In the annealing process the temperature is reduced so that the material reaches thermal equilibrium. For Simulated Annealing, the temperature is lowered according a given cooling schedule as there is a high concentration of states with low energy in regions having low temperatures. A terminating condition stops the search algorithm and this could be the equivalent of room temperature.

## 4. REVIEW OF SA APPLICATIONS IN CMS DESIGN

A number of publications related to the design of CMSs have been published over the last three decades. Reviews of existing CM literature can be found in (Rajamani, 1996; Askin, 1997; Selim, 1998). According to those reviews, the existing CM design methods in the CMSs can be classified into the following categories: part coding analysis, cluster techniques, similarity coefficient, graph partitioning, mathematical programming, heuristic search, and AI-based approaches. However, there are not many publications presenting the review of CMS designs using SA. Some of the significant papers which used SA for the CMS design are reviewed below.

Sridhar and Rajendran (1993) considered the problem of scheduling in a cellular manufacturing system with the objective of minimizing the sum of completion times or total flow time of jobs. The proposed heuristic makes use of the Simulated Annealing technique and is developed in two stages. A good initial heuristic seed sequence obtained in the first stage is improved upon by a proposed new variant of the simulated annealing technique wherein three different perturbation schemes have been experimented.

Sofianopoulou (1997) presented the cell formation problem as a linear integer programming with the objective of minimizing the number of intercellular moves taking into account the machine operation sequence of each part without specifying in prior the number of cells to be used. The number of cells is automatically adjusted within the solution procedure. The problem is then solved using Simulated Annealing.

Su and Hsu (1998) considered three objectives in their model. The objectives are: minimizing the total cost of inter-cell transportation, intra-cell transportation and machine investment; minimizing intra-cell machine (in cell) load unbalance; and minimizing inter-cell machine (in plant) load unbalance. The authors then unify these objectives through weighting, and solve the model by means of parallel simulated annealing.

Abdelmola et. al (1999) used simultaneously both machine groups and part families and solve using Simulated Annealing. In traditional manufacturing systems, parts that require different machines have to move through different manufacturing cells to complete the required operations. This intercell movement will increase the total material handling cost and decrease the system productivity. This paper describes that high variety of parts can be produced in small batch sizes.

Xambre and Vilarinho (2003) have introduced multiple functionally identical machines in the cellular manufacturing systems to introduce a new degree of freedom in the problem-the allocation of operation of specific machines. There are two stages involved in obtaining the initial solution. In the first stage, operations are allocated to machines by decreasing order of their usage rate. In the second stage machines are grouped into cells taking into account the operations they process and the flow between the operations.

Rahimi-Vahed (2005) proposed a non-linear mathematical programming model taking in to account two kinds of cells: (1) Common cells that are able to manufacture different kinds of products and (2) specific cells that can only manufacture a specific product. Considering a given time horizon, it is to find these cells and their families of their parts in a manner that part demand in each period are satisfied in a batch size form. To form cells in order to manufacture a part or products, three criteria were taken into account simultaneously: (1) Minimization of the sum of the costs of delay in delivering a product to consumers by the above two cells in each period, (2) minimization of sum of costs of common and specific cells to remain idle in each period and (3) maximization of the unused capitals. To achieve these goals, two kinds of capital constraints were observed: (1) capital constraints for construction and formation of cells and (2) capital availability constraints for the provision of equipments to manufacture products. An efficient hybrid meta-heuristic based on mean field annealing (MFA) and simulated annealing (SA) so-called MFA-SA is used to solve the proposed model. In this case, MFA technique is applied to generate a good initial solution for SA.

Safaei et. al (2008) considered a mixed integer programming model to design the cellular manufacturing systems (CMSs) under dynamic environment. In dynamic environment, the product mix and part demand change under a multi period planning horizon. An efficient hybrid meta-heuristic based on mean field annealing (MFA) and simulated annealing (SA) so called MFA-SA is used to solve the proposed model. In this case, MFA technique is applied to generate a good initial solution for SA.

Tai-Hsi Wu (2009) proposed a simple yet elective simulated annealing-based approach, SACF, to solve the cell formation problem. He also introduced strategies for searching better neighbor-hood solutions to improve the current solution and move towards the optimal solutions. The neighborhood of a given solution is defined as a set of all feasible solutions that can be reached by a single move/transition. In his study implemented a single-move interactively. The single-move is an operation that moves a part j from its current cell i (source cell) to a new cell j (destination cell). The new move made is denoted (i', j). For the single-move, a move that results in the most improvement in the objective function value from the current solution is selected.

In today's dynamic business environment, shorter time periods should be considered where the product mix and demand may vary from period to period. For this problem Defersha and Chen (2009) considered an integrated problem of production planning and dynamic system reconfiguration in cellular manufacturing systems where production quantities are also decision variables. To solve this NP hard problem they also developed a heuristic algorithm based on multiple Markov chain simulated annealing to allow multiple search directions to be traced simultaneously.

## 5. CONCLUSION

In this paper various papers from the literature which applied the SA for the design of CMS were investigated and reviewed. From the review, it is found that the grouping efficiency of the Simulated Annealing is based upon the way the operators (coding, temperature) are used. In general, the probability of achievement to optimal solution will be increased by improving and developing the SA operations. Therefore further research may be attempted to obtain the better solution with reduced time using SA, especially for the large size industrial problems. Also, available methods for designing CMSs do not consider in an integrated manner several important factors. These factors are the dynamic and stochastic nature of production requirements, and the availability of routing flexibility. By considering these factors, CM design solutions can be improved. Only meta-heuristics techniques such as SA have enough capabilities to handle this kind of complex NP-hard problems. Also the combined meta-heuristics such as SA-GA, SA-Tabu, Mean Field annealing-SA, parallel SA adaptive SA etc may be attempted to improve the solutions of the complex large-sized problems.

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