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EVOLUTIONARY APPROACH TO THE DESIGN AND MANAGEMENT OF THE PRODUCTION IN SUPPLY NET

Abstract: This paper presents a survey of literature on genetic algorithms in solving optimization problems. The focus is brought on problems related to the design, organization, and management of the supply net. From the recent published literature, the author has identified the following types of problems as the most addressed: cellular organization, facility layout, and optimization of the workshop configuration, choice of locations for distributions centres, production planning and scheduling, assembly planning, and configuration of the supply net.

1. Introduction

Production in supply nets is a contemporary trend for manufacturing. Ideally, a good management supply net design can help companies to have better value-addition, reduce costs, and increase customer service level.

From the mathematical point of view, the supply net is a digraph, which has loops. Therefore, the traditional methods based on the network theory cannot be easily adopted in supply net management. Recently, many genetic algorithms (GAs) have been developed for the multi-objective problem. This paper describes how the genetic algorithm has been applied to optimization design of a manufacturing systems and supply net management.

Genetic algorithms were developed by John Holland [Holland 1975]. Its heuristic optimization algorithms mimic the mechanism of genetic evolution in biological nature. Genetic algorithms work with a population of potential solution to a problem. A population is composed of chromosomes, where each chromosome represents one potential solution. The population is evolved, over generations, to produce better solution to the problem. The process of reproduction, evaluation, and selection is repeated until a termination criterion is reached. A typical genetic algorithm uses two operators, crossover and mutation, to direct the population towards convergence at the global optimum [Ozmehmet Tasan, Tunali 2008].

2. Application of genetic algorithms in optimization of manufacturing systems

Genetic algorithms are one of the modern heuristic optimization techniques which have been widely adopted by many researchers in solving various problems. Table 1 presents the application of genetic algorithms in optimization of manufacturing systems.

Table 1. Application of genetic algorithms in optimization of manufacturing systems

Problem	References	Objective function
Grouping of parts and machines	Pierreval et al. (2003)	Inter-cell moves
Facility layout problem	Azadivar, Wang (2000)	Timing of material movements
	El-Baz (2004)	Total material handling cost
Dynamic facility layout problem	Balakrishnan et al. (2003)	Sum of the material flow and layout rearrangement costs
Lot sizing problem	Berretta, Rodrigues (2004)	Sum of production, inventory and setup costs
Scheduling problem	Chan et al. (2005)	Production cost
Planning and scheduling in multi-plants	Moon et al. (2002)	Total tardiness
Control problem in supply net	Ławrynowicz (2008)	Makespan
Control problem in multi-stage assembly systems	Perkoz et al. (2007)	Total operating costs

The manufacturing system is a part of a network structure of the supply chains in industrial process. Among widely encountered problems in the design of manufacturing systems, cellular manufacturing classically involves processing a collection of similar parts (parts families) on a dedicated cluster of machines or manufacturing processes (cells) [Singh 1993]. For example, by grouping similar parts (same set-up, or processing, or routing, etc.), one can take advantage of their similarities in design and manufacture. Similarly, by grouping machines together, inter-cellular movements can be reduced, thereby minimizing material handling costs. Furthermore, reductions in set-up time, manufacturing lead-time, design variety and work-in-process inventory can be achieved. As shown in Table 1, GAs have been applied to solve part-machine problems by Pierreval et al. (2003). This problem consists in grouping machines into cells and in determining part families such that parts of a family are entirely processed in one cell. A typical possible way to encode (in other words representation) solutions is to use a two-fold integer string. The first *m* positions of the string represent the assignment of the *m* machines, and the last *p* positions represent the assignment of the routes to the *p* parts. This coding is illustrated in Figure 1.

GAs find an application in optimisation of facilities layout [Kazerooni et al. 1997; Ponnambalam et al. 2001; Muruganandaram et al. 2005].

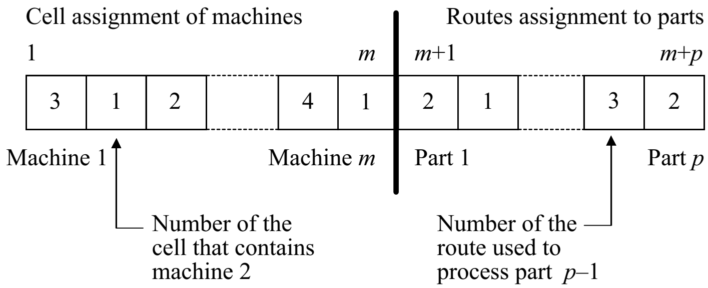

Figure 1. Coding of a solution

Source: [Pierreval et al. 2003].

The problem in machine layout design is to assign machines to locations within a given layout arrangement such that a given performance measure is optimized.

El-Baz (2004) proposed an approach using genetic algorithm to solve facility layout problems. The approach considers different types of manufacturing layout environments. The proposed GA approach produces the optimal machine layout which minimizes the total material handling cost. The technique of GAs requires a string representation scheme (chromosomes). In this paper, the entire manufacturing plant/department is divided into *N* grids and each grid represents a machine location. In this study, a form of direct representation for strings is used. Figure 2 shows different examples of different types of production plant layout with their encoded chromosomes representation.

This chromosome string representation indicates one of the possible machine layout plans of each production type. Examples of flow shop layout containing 9 machines/departments, production flow line contains 5 workstations, multi-line production system contains 6 machine locations, and a closed loop layout type of 8 machines are presented in the figure. The location assigned with the letter 'e' represented an empty area where no machine is allowed to be located.

In recent years, GA has been proposed as an innovative approach to solve the dynamic plant layout problem. The dynamic problem involves selecting a static layout for each period and then deciding whether to change to a different layout in the next period. Balakrishnan et al. (2003) extend and improve the use of genetic algorithm by creating a hybrid GA for the dynamic plant layout problem. In this approach, the objective function is the sum of the material flow and the layout rearrangement costs for the planning horizon.

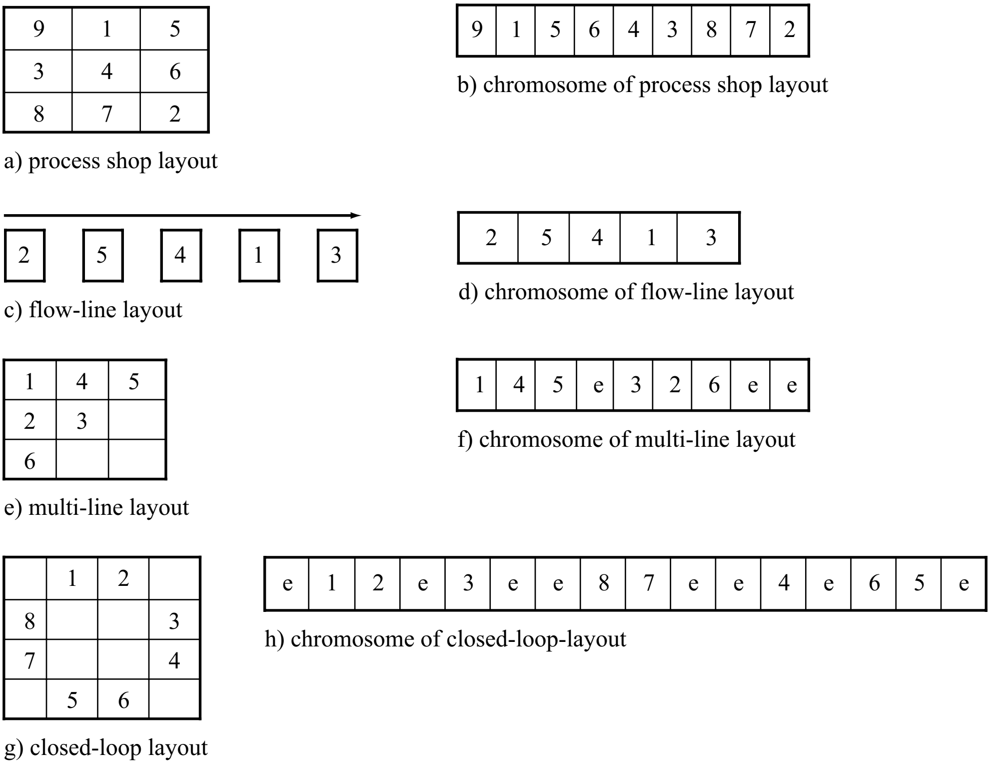

Figure 2. Types of layout and their chromosomes representation
Source: [El-Baz 2004].

Berretta and Rodrigues (2004) presented a memetic algorithm to solve the multistage capacitated lot-sizing problem, considering setup time and setup cost. In this study, the lot-sizing problem is described as follows. In a multistage production system there are N items to be produced in T periods in a planning horizon such that a demand forecast would be attained. The planning of each item depends on the production of other items, which are situated at lower hierarchical levels. The resources for production and setup are limited. The lead times are assumed to be zero. The objective function is to minimize the sum of production, inventory and setup costs in T periods.

Genetic algorithms have been widely applied in production planning and scheduling [Ławrynowicz 2006]. For example, Chen and Ji (2007) proposed a genetic algorithm for dynamic advanced planning and scheduling with frozen interval. Moon, Kim and Hur [Moon et al. 2002] presented integrated process planning and scheduling with minimizing total tardiness in multi-plants supply chain.

A huge amount of literature on scheduling, including the approach with genetic algorithms, has been published within the last years, among others the work by Tavakkoli-Moghaddam (2007), Chan et al. (2005), Gao et al.(2007). But this approach often ignores the dividing of jobs and the relationship between the scheduling and planning in supply net. In most cases, the researchers study small-scale problems or only flow problems, where there are many constraints.

Various encoding techniques have been developed for scheduling problems. A tutorial survey of scheduling problems using genetic algorithms with different representations has been published by Cheng et al. (1996) and Ławrynowicz (2003).

In last years, control systems play an important role in implementing effective supply chain management methods. But its implementation would not be easy with the conventional information systems. Therefore, the main purpose in the recent years was to improve the efficiency of the traditional planning and control methods and explore a more effective and efficient approach to solving the same problem with the artificial intelligence. A survey of literature on evolutionary algorithms in control systems engineering can be found in the work of Fleming and Purshouse (2002).

Modern optimization technique for control problem in supply net has been published by Ławrynowicz (2008). The author proposes a new methodology that uses an expert system and a genetic algorithm to support production planning and scheduling in a supply net. In this approach, the production planning problem is first solved, and then the scheduling problem is considered within the constraints of the solution. It does not only offer short-term production planning and scheduling to meet changing market requirements that can better utilise the available capacity of manufacturing systems, but also provides support for control. In this research, the operation-based representation for job shop scheduling has been studied. This representation encodes a schedule as a sequence of operations and each gene stands for one operation. One natural way to name each operation is using a natural number. A schedule is decoded from a chromosome with the following decoding procedure: (a) firstly translate the chromosome to a list of ordered operations; (b) then generate the schedule by a one-pass heuristic based on the list. The first operation in the list is scheduled first, then the second operation, and so on. Each operation is allocated in the best available time for the corresponding machine the operation requires. The process is repeated until all operations are scheduled.

Experimental results indicated that the proposed GAs efficiently yields many alternative assembly plans to support the design and operation of an assembly system [Ozamehmet Tasan, Tunali 2008]. For example, Perkoz et al. (2007) developed a multi-objective model to optimally control the lead time of a multi-stage assembly system, using genetic algorithms. The multi-stage assembly system is modeled as an open queuing network. The objective functions are the total operating costs of the system per period (to be minimized), the average lead time (min), the variance of the lead time (min) and the probability that the manufacturing lead time does not exceed a certain threshold (max). They applied a representation with double strings.

3. Application of genetic algorithms in optimization of configuration of supply nets

Recent works have shown that the configuration of manufacturing systems through simulation optimization can be efficiently addressed using genetic algorithms (see Table 2). Hua and Hou (2008) proposed a genetic algorithm to solve the production allocation problem.

Table 2. Application of genetic algorithms in optimization of configuration of the supply net

Problem	References	Objective function
Production allocation problem	Hua, Hou (2008)	Penalty function
Distribution networks problems	Chan, Chung (2005)	Total cost
Configuration of the supply net – Minimum spanning tree problem (MST)	Zhou, (1999) Syarif et al. (2002) Zhou et al. (2002) Gen, Syarif (2005) Chen et al. (2007)	Total cost

Production allocation problems involve allocating plant output among many markets subject to capacity constraints and market demand in order to minimize the costs of the multinational company. This paper proposes an efficient encoding method with the corresponding crossover and mutation operators for GA, which integrates the decision path of a dynamic programming in the evolutionary process of genetic algorithms. A dynamic programming decision path is a valid candidate solution that satisfies all constraints for the solved problem. By this idea, our new encoding method encodes the constraints into chromosomes, so that a chromosome is a valid solution in the population of genetic algorithms.

Many researchers have studied optimization of distribution networks. Chan and Chung (2005) adopted GAs to minimize the total cost for a distribution network (i.e. the total lead time of demands, the total number of tardy demands, the total duration of tardiness time, and the mean absolute deviation of tardy demands). For enabling multi-criterion decision-making, the proposed algorithm combines analytic hierarchy process with genetic algorithms (GAs). The problem is divided into two parts – (I) demand allocation and transportation problem, and (II) production scheduling problem. In this approach, as mentioned above, one of the objective functions is to minimize the total system cost. Other objective functions are to minimize the total lead time of demands, the total number of tardy demands, the total duration of tardiness time, and the mean absolute deviation of tardy demands. In this approach, each chromosome represents a potential optima solution of a problem being optimized. According to the problem structure, two different types of chromosomes are designed. Chromosome type A is designer for Part I. This chromosome is represented by a 2-dimensional matrix, as shown in Figure 3a.

Chromosome type A

Customer order	1	2	3	4	5	1	2	3	4	5
Gene location	1	2	3	4	5	6	7	8	9	10
Supplier	W_1	W_3	W_2	W_3	W_1	M_1	M_2	M_2	M_2	M_1
Transportation mode	1	1	2	1	1	1	2	1	1	1
	Region 1					Region 2				

Figure 3a. Chromosome type A

Source: [Chan, Chung 2005].

	Basic segment										Extended segment		
Supplier	W_1	W_3	W_2	W_3	W_2	M_1	$>M_2$	M_2	M_2	M_3	F	E	$*R$
Transportation mode	1	1	2	1	1	1	2	1	1	1	2	1	1
Gene location	1	2	3	4	5	6	7	8	9	10	11	12	13
	1	2	3	4	5	1	2	3	4	5	1	2	3
	Customer number					Customer number					Manufacturing plant number		

Figure 3b. Chromosome type B

Source: [Chan, Chung 2005].

In the supplier row, region 1, the value of gene represents the warehouse number, and the location of the gene represents the customer number. This implies that the corresponding demand will be supplied through the corresponding warehouse assigned. In region 2, the value of gene represents the manufacturing plant number, and the location of the gene represents the customer number. This implies that the corresponding demand will be produced in the corresponding manufacturing plant allocated. With a similar interpretation, the transportation row shows the transportation mode to adopt. In region 1, it indicates the transportation mode between the warehouse and customer for a particular demand. In region 2, it indicates the transportation mode between manufacturing plant and warehouse for a particular demand. Chromosome type B is designed for Part II, as shown in Figure 3b. The production scheduling row indicates the ranking number of demand in the production scheduling in its manufacturing plant assigned.

In recent years, GA has been proposed as an innovative approach to solve the configuration of the supply net. In the supply net optimization, the minimum spanning tree (MST) problem is of great importance. This problem can be viewed as an optimization model that integrates facility location decision, distribution costs, and inventory management for multi-products and multi-periods [Gen, Syarif 2005]. The multi-criteria MST is a more realistic representation of the practical problem in the configuration of the supply net. The minimum spanning tree problem is to find a least-cost spanning tree in an edge-weighted graph. In many published works [Chen et al. 2007; Gen, Syarif 2005; Zhou et al. 2002], a genetic algorithm approach is developed to deal with this problem. The proposed methods adopt the Prüfer number as the tree encoding. Prüfer describes a one-to-one mapping between spanning trees on n nodes and strings of n-2 nodes labels. The Prüfer number encoding procedure has the following major steps:

Step 1: Let vertex j be the smallest labeled leaf vertex in a labeled tree T.

Step 2: Set k to the first digit in the permutation if vertex k is incident to vertex j.

Step 3: Remove vertex j and the edge from j to k, we have a tree with $n – 1$ vertices.

Step 4: Repeat above steps until one edge is left and produce the Prüfer number orpermutation with n – 2 digits in order.

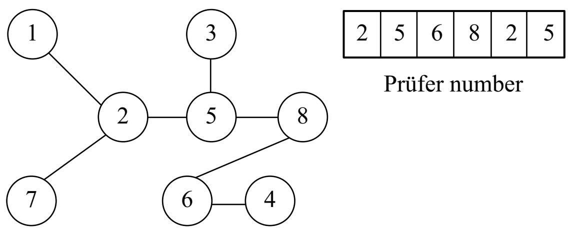

Figure 4. A tree and its Prüfer number

Source: [Zhou, Gen 1999].

An example is given to illustrate this encoding [Zhou, Gen 1999]. The Prüfer number [2 5 6 8 2 5] corresponds to a spanning tree on 8-vertex complete graph represented in Fig. 4. The construction of the Prüfer number is described as follows: locate the leaf vertex having the smallest label. In this case, it is vertex 1. Since vertex 2 (the only vertex) is incident to vertex 1 in the tree, assign 2 to the first digit in the permutation, then remove vertex 1 and edge (1,2). Now vertex 3 is the smallest labeled leaf vertex and vertex 5 is incident to it, assign 5 to the second digit in the permutation and then remove vertex 3 and edge (3,5). Repeat the process on the subtree until edge (5,8) is left and the Prüfer number of this tree with 6 digits is finally produced.

4. Summary

This paper demonstrates how genetic algorithm can be used to optimize the production management in supply nets for multiple objectives. The study shows that the proposed by researchers genetic algorithms are effective in solving optimization problems.

As for the GA perspective, it is noted that two important issues have been extensively studied. One is how to encode a solution of the problem into a chromosome and the other is reproduction of new individuals by using genetic operators. In this study, the focus is on the coding problem.

When the optimization problem scale is not too large, the proposed in literature traditional methods are able to obtain the optimal solution within a reasonable running time. The study shows that the proposed by researchers evolutionary algorithms are effective in solving the large scale problems.

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