HYBRID TABU SEARCH / GENETIC ALGORITHM IN MATLAB

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1 INTRODUCTION

Batch processes are often found in various fields of industry (e.g. chemical, computer, machine-industries etc). The advantages of batch processes include high flexibility that allows to quickly react to changes in demands, to change technology based on current situation, and to quickly introduce new or modified products. Batch processes also allow easier sharing of some of the resources (e.g. production units, storage capacities, manpower). Because a new product is often likely to be manufactured on existing equipment, the emphasis is on process planning and control rather than on sizing the equipment. Current trends in abovementioned industries are towards products with shorter life cycles and higher functionality that are tailored to specific market niches, and consequently process development problems are encountered very frequently. The development of new or modified products "from scratch" would be too costly and time-consuming, and so would be a purchase of new equipment, and for these reasons new products utilize existing equipment. This means that the problem of production scheduling in these plants is one of high importance.

Two categories of batch plants are widely recognized: multi-product plants and multi-purpose plants. In a basic serial multi-product plant, called flowshop, the production line consists of a single set of *m* processing stages, each machine is able to process one job at a time, the plant has only one path for all products, and this path consists of a chain of stages where no branches or loops exist. Hybrid flowshops can be derived from the classical multistage flowshop, with at least one stage being composed of two or more identical parallel machines (see Fig. 1). This work addresses the problem of finding optimum schedule for a set of *n* jobs on such a configuration, with the makespan of a schedule as the objective function, and describes an application of combination genetic/tabu search algorithm to solve the problem. The algorithm was created as a Matlab source code, and the work analyses the suitability of such approach.

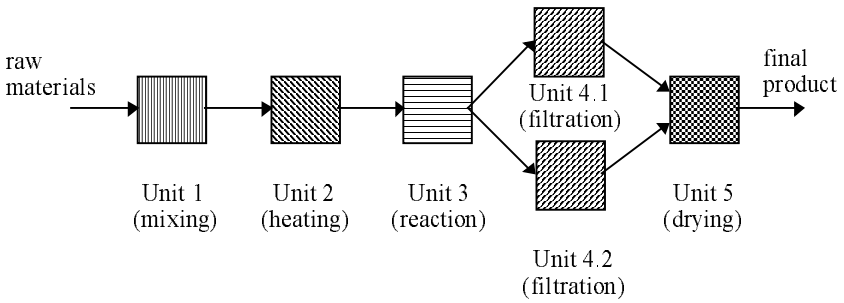

Fig. 1. *Example of a Hybrid Flowshop topology*

2 PROBLEM DESCRIPTION

The flexibility of batch plants puts increased demands on production planning and control. A series of campaigns, during which only one or few of the whole range of products are manufactured, is usually a result of mid-term planning. The individual campaigns are the input for the discussed problem of production planning and scheduling (PPS). Efficient plant operation can be reached using different optimization criteria, and one of the most used ones is minimization of makespan; this requires that batches (other terms such as "jobs" are used in some industries) enter the flowshop in such an order that operations thorough chain of units are as close to „lock step„ as possible. Finding optimum product sequence is an NP-hard problem even for simple flowshops - see Garey [4].

Most of the heuristic algorithms for the *m*-stage flowshop scheduling problem can be divided into four categories: applications of Johnson's two-machine algorithm, the use of a slope index for the batch processing times, the minimization of idle time on machines, and stochastic techniques such as tabu search, genetic algorithms and simulated annealing algorithms.

Palmer [9] first proposed a heuristic for minimizing makespan in a flow shop scheduling problem. The heuristic generates a slope index for jobs and sequences them in descending order of the index. Campbell et al. [3] developed a heuristic that is a generalization of Johnson's algorithm. Gupta [6] presented the minimum idle time (MINIT) algorithm based on the minimization of idle time at the last machine. Nawaz et al. [7] proposed that a job with larger total processing time should have higher priority in the sequence. More recently, Ogbu and Smith [8] used simulated annealing and Taillard [16] applied tabu search algorithm for makespan criteria.

The hybrid flowshop scheduling has attracted considerable attention in recent years. Both optimizing and heuristic techniques have been used as a solution methodology. The optimizing techniques used so far are mostly branch and bound and mixed integer programming. However, because of the NP-completeness of the problem, heuristics have been, in our view, more popular.

Salvador [11] proposed the branch and bound approach to solve a special case of permutation hybrid flowshop. Brah [2] formulated a mixed integer programming hybrid flowshop model. Brah [1] also discussed the complexity of the problem and establishes that the hybrid flowshop scheduling is indeed an NP-complete problem. Sridhar and Rajendran [14] used simulated annealing approach to minimize the total flow time. Santos et al. [12] developed a global lower bound for the FSMP makespan problem, and the same group of authors published an overview of various heuristics [13].

Most recent developments usually use variants of branch and bound approach, and try to combine them with other methods (e.g. Portmann et al. [10]), but other approaches (e.g. neural networks) are also used.

The difficulty of the problem leads to the fact that most works that try to solve such problems operate under some simplifying assumptions. The assumption we make is limiting the search space to permutation schedules, an approach also used by most other works on this problem.

3 PROCESS MODEL

Batch processes can be modeled at many different levels of abstraction, and each of these levels is best suited for different purpose. The simplified models we use are based on time requirements of different operations occurring during manufacture. Based on the degree of simplification, different types of models of time requirements are recognized, but most of them are thanks to their nature flexible, applicable to description of most batch processes, because

the amount of process-specific elements is zero or minimal. Hybrid flowshop, as defined here, is described by following input data and assumptions:

- a set of n batches manufactured
- a set of m processing stages, arranged into a fixed sequence
- vector U, describing the topology of the plant; in hybrid flowshop at least one processing stage contains more than one processing unit
- processing times matrix T, its elements t_{ij} corresponding to processing time for operation j and batch i
- a unit may only process one batch at a time
- once started, a unit must complete the processing of a batch
- all processing units in a single stage are identical in performance
- storage policy - algorithm was tested under one of the commonly used interstage storage policies - unlimited intermediate storage (UIS)

A schedule for this problem is an assignment of units to batches that meets all the constraints described above. The makespan of a schedule is the time of completion of the last operation performed on a given set of batches minus the time the first operation began at.

4 COMBINED TABU SEARCH/GENETIC ALGORITHM

Our previous works on scheduling problems showed us that both the tabu search and genetic algorithm are suitable tools for solving such problems. Each algorithm, however, has some disadvantages. The algorithm we have developed is a combination of both approaches, and tries to combine the positives of the two methods.

4.1 TABU SEARCH PRINCIPLES

Rather than being a single algorithm, the tabu search (TS) would be better described as a set of concepts that the algorithms falling under this heading share [5]. For this reason, there is no single algorithm called tabu search, and the discussion here is limited to algorithms we have used in our work. The algorithm we use is descended from the local improvement techniques, and while deterministic (at least in its basic variant) it is often classified as stochastic because of its properties and behavior. Many of the variants of the algorithm incorporate some random elements and are truly stochastic. Unlike downhill search it descended from, the tabu search algorithm is able to leave local optimum and continue the search. Tabu search heuristics starts from an initial solution, and at each step such a move to a neighboring solution is chosen to hopefully improve objective criterion value. This is close to a local improvement technique except for the fact that a move to a solution worse than the current solution may be accepted. Algorithm tries to take steps to assure that the method does not re-enter a solution previously generated which serve as a way to avoid becoming trapped in local extreme. The variant of the algorithm we use accomplishes this by recency-based data structure called tabu list that contains the moves that are discouraged at the current iteration. A move remains a restricted one only for a limited number of iterations. Algorithm is not guaranteed to find optimum solution; however, experimental results show that even if not successful it does find good near-optimum solution.

4.2 GENETIC ALGORITHMS

Genetic algorithms (GAs) are a general methodology for searching a discrete solution space in a way that is similar to process of natural selection procedure in biological systems. The

algorithm is a remarkably general one, and it can be applied to different problems if following conditions are met:

a) solutions to the problem can be expressed in form of a string of characters

b) a „fitness“ criterion, which in some way quantifies the quality of a solutions, can be computed for any valid string

c) strings in which „part“ of a good solution is present are rewarded by allocation of a higher fitness than „average“ strings

Genetic algorithms, as the name implies, are a type of algorithms, not a single one. This means that many variants of the basic idea exist, and that individual applications may be highly different. However, every variant should include following operations: (1) a method for encoding solutions to the problem into a string of characters; (2) an evaluation function which takes a string as an input and returns a fitness value which measures the quality of the solution the strings describes; (3) an adaptive plan, whose purpose is to produce new, improved generation of solutions from the current one.

The strings encoding the solutions are often binary coded. This encoding, however, is not well suited for our purpose. Instead, the string is composed of a sequence of unique identifiers. Each identifier is represented by an integer number, and identifies a corresponding batch. The use of such an alphabet does not violate the principles of GAs. Encoding the solution in this way is enabled by the fact that the optimization is performed under the assumption of permutation schedules. The strings containing substrings with small makespan generally have smaller total makespan compared to average strings, as required in c), allowing the use of GAs.

4.3 COMBINATION TABU SEARCH/GENETIC ALGORITHM

The algorithm combines the principles of the two approaches. At initiation it creates a set of random valid solutions, and for several iterations it optimizes them using tabu search-based method. Then the algorithm applies genetic principles to the set of solutions, and this creates a new generation of solutions. The solutions retained from the previous generation keep the associated tabu lists; new solutions begin with clear tabu lists. The process of several tabu-principles iterations followed by a genetic-principles iteration continues until computation termination criteria are met.

This approach combines the advantages of the two algorithms and mitigates the disadvantages. Pure tabu search that uses only one solution can easily miss some promising areas of the search space, and a larger set of parallel solutions does not exchange information. Genetic algorithms, thanks to the nature of the problem solved, show lower solution quality with increasing problem size; the most prominent cause is the damage to solutions that occurs during solution crossover. The combined algorithm we propose combines the parallelism and information-exchange of genetic algorithms with a strong local optimization of the recency-based tabu search.

Tabu search components of the algorithm are similar to the pure tabu search algorithm we have used in our previous works. We use fixed-length recency based tabu list. The neighborhood generation method we use is pairwise exchange: it exchanges positions of two batches in the schedule, and the move is selected using fastest descent technique.

Genetic components are similar to GA described in [15]. Makespan of solutions in a generation is transformed into fitness using either a linear interpolation or a slightly modified linear fitness scaling. Parents of a new generation are selected using deterministic reproduction with single-string elitism and stochastic remainder sampling; the process uses the best makespan found since the solution in question was evaluated in genetic iteration, not the current makespan of

the current solution. We use the crossover operator proposed in [15], with the addition of a safeguard that allows crossover should all the chosen parents be copies of one solution. In this case the algorithm selects a random other solution in the current generation as the second parrent. Mutation operator used is random pairwise exchange.

In this work the algorithm stops after a pre-set number of consecutive unsuccessful genetic iterations. This means that computation stops when maximum number of consecutive genetics-based steps that do not improve objective criterion value is reached; the best solutions that were found during this time are used as the results.

This works presents the results of preliminary tests of the algorithm; the algorithm presented is still being developed. This means that we present results for two variants of fitness computation. The evaluation function is based on the objective function, i.e. the computation of makespan. Considering that the ranges of processing times, as well as other values, can change for different applications, it is hardly possible to use the raw makespan value, and it must be somehow transformed to allow better algorithm function. In our case we first use the equation (1) to recompute makespans of a given generation to satisfy the condition c) required for genetic algorithms.

$$Fitness\_new = Makespan\_max * 1.2 - Makespan \quad (1)$$

This new fitness is then transformed, either to a value in range <5;100> using linear interpolation, with the minimum fitness in a generation equal to 5 and the maximum one to 100, or using linear fitness scaling with built-in safeguards to prevent certain error states (e.g. negative fitnesses).

One of the advantages of heuristic algorithms such as the one we propose is the way the constraints of the problem are treated. As long as neighborhood generation, crossover, and mutation operators guarantee that only valid solutions will be generated, the algorithm itself does not have to take any constraints into account, because all are incorporated into the objective function. This means that for similar problems with different constraints the algorithm, aside from minor changes of parameters, requires only rewriting of objective function calculation and associated code to become applicable.

The random elements in the genetic parts of the algorithm guarantee asymptotic convergence towards the global optimum, because the combination of stochastic remainder sampling and mutations ensures that in infinite number of iterations the algorithm visits all valid solutions (of which there is a finite number), including the optimal ones.

5 ALGORITHM EVALUATION

This paper present the results of preliminary tests of the algorithm; the algorithm presented is still being developed, and we expect to test it on a greater variety of problems (e.g. different intermediate storage policies, larger problems)

5.1 TEST PROBLEMS

As it was impossible to predict the exact nature of specific real problems should the algorithm be applied to solution of such, we used a method common in similar studies. The problems the program was tested on were sets of randomly (within defined parameters) generated input data matrices. The dimensions of solved problems varied, and the results presented in this paper are the ones for the problems with n/m={10/5, 12/8, 15/10}. The range of processing times was 1-50; each stage contained 1 or 2 processing units.

5.2 ALGORITH IMPLEMENTATION

All the algorithms were realised as source codes in Matlab. While the speed of such a solution is lower compared to some other possible methods, it offers all the functions and advantages of the Matlab environment. Furthermore, the speed of heurostic algorithms results into acceptable computation times, favourable to commercial MI(N)LP solvers, even for „human- readable" source codes not optimized for speed. Our work proves that Matlab can be used as a tool for AI applications such as genetic algorithms.

5.3 ALGORITHM PERFORMANCE

The algorithm was tested against pure TS and pure GA that use the same principles as the algorithm we propose. The results indicate that performance of the combined algorithm is better than that of either pure TS or pure GA.

TABLE 1

Statistics of algorithm performance for various problem dimensions, interpolated fitness

	Search success rate [%]			Average computation time [%]		
Problem dimension	TS/GA	TS	GA	TS/GA	TS	GA
10/5	99	94	77	100	100	94
12/8	87	91	57	100	120	77
15/10	77	64	17	100	115	51

Low performance of the GA is, we believe, caused by fitness calculation. Linear fitness scaling improved the search success rate of GA for 10/5 problems up to 97%, but the code occasionally failed because of problems caused by linear fitness scaling and associated code (one of the reasons for such errors are problems with floating point operations precision). As the algorithm is still being developed, and other variants (e.g. other neighborhood definitions) are being tested, no detailed analysis was available at the time of submission of this work.

6 CONCLUSIONS

The algorithm we have proposed is able to optimize schedules for a hybrid flowshop, minimizing the makespan, and the performance of this algorithm is better than of both pure tabu search and pure genetic algorithm. The algorithm is, thanks to its composite nature, more adaptable to changes, and retains the advantages commonly associated with heuristics. Solution quality is higher than for tabu search, and the random elements in the genetic parts of the algorithm guarantee asymptotic convergence towards the global optimum. Matlab source codes that implement these algorithms run at acceptable speeds on PC-class computers.

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