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GENETIC ALGORITHMS IN INTEGRATED PROCESS PLANNING AND SCHEDULING – A STATE OF THE ART REVIEW

Mijodrag MILOŠEVIĆ[1], Dejan LUKIĆ[1,*], Mića ĐURĐEV[2], Jovan VUKMAN[2], Aco ANTIĆ[3]

[1)] Assistant Prof., University of Novi Sad, Faculty of Technical Sciences, Department of Production Engineering, Novi Sad, Serbia
[2)] PhD student, University of Novi Sad, Faculty of Technical Sciences, Department of Production Engineering, Novi Sad, Serbia
[3)] Associate Prof., University of Novi Sad, Faculty of Technical Sciences, Department of Production Engineering, Novi Sad, Serbia

Abstract: *This paper presents a review of genetic algorithms in integrated process planning and scheduling problems. According to the literature information, process planning and scheduling are two functions that were sequentially carried out in a manufacturing system, where scheduling was performed after process plans had been generated. Their integration highly improves the performance and efficiency of manufacturing systems. The integrated process planning and scheduling problem belongs to the class of most difficult combinatorial problems and it requires high efficient methods for finding optimal solutions. Genetic algorithms are one of the most famous metaheuristic algorithms based on the principles of artificial intelligence that found its use in various branches of science. Modern genetic algorithms proved to be very reliable in finding optimal process plans and schedules. Here, state of the art review of genetic algorithms for optimization of process planning, scheduling and their integration is shown. Many different modifications and hybrid approaches are briefly discussed. Mostly used genetic components and strategies are shortly presented with some sample parts that are often considered when testing genetic algorithm performances.*

Key words: *genetic algorithms, optimization, integration, process planning, scheduling.*

1. INTRODUCTION

Modern manufacturing environment is characterized by dynamic customer demands, increased product variety, demand for reduced production cycles, intense global competitions, and increased use of automation, which highlights the importance of adopting new technologies and systems to deal with this environment. According to [1], computer-integrated manufacturing (CIM) represents the most effective tool to deal with these challenges. Its main function is to integrate activities within the manufacturing system. Process planning and scheduling are two of the most important functions in modern manufacturing systems that have a major influence on transforming product design to a final part with the consideration of technological and timing aspects [2, 3]. The goal of process planning, on one side, is to determine appropriate manufacturing resources and operations sequences for each job in the system. The output result should give information about manufacturing processes and their parameters, optimal operation sequence, machines, fixtures and tool required to manufacture the part [2, 4, 5]. Production scheduling, on the other side, is focused on the allocation of available resources and the determination of appropriate starting and completion times of each job operation with the inclusion of some criteria, such as makespan, job tardiness, job lateness, flow time, etc. [1].

By tradition, process planning and scheduling are performed sequentially and separately, where scheduling was performed after process plans had been generated. In that case, decisions made in the process planning stage constrain the alternatives that can leave a positive influence in the scheduling stage [6]. However, this approach has become an obstacle to enhance the productivity and responsiveness of manufacturing systems and as an adequate solution, the integration of process planning and scheduling functions is proposed. According to authors [6, 7], the integration of these two functions overcomes several problems such as:

- Process planning function works in static where unlimited resources on shop floor are taken into consideration. This means that only favourable and most recommended machines, tools and other resources are selected for generating process plans which can lead to unrealistic and infeasible process plans for later stages.
- Sequential approach can lead to unbalanced resource load and create superfluous bottlenecks.

The constraints considered in the process planning phase may have already changed greatly because of the time delay between planning phase and execution phase which may lead to modifications of total production plans due to infeasibility of process plans.

- Different and conflicting objectives can cause problems in this integration assuming that process planning considers technological requirements of a job,

[*] Corresponding author: rg D. Obradovića 6, 21000 Novi Sad, Serbia;
Tel.: + 381 (0)21 48 52 331;
Fax: + 381 (0)21 45 44 95;
E-mail addresses: *lukicd@uns.ac.rs* (D. Lukić).

while scheduling is focused on timing aspects and allocation of jobs.

Considering the complexity of the integrated process planning and scheduling (IPPS) problem, it belongs to the class of NP-hard combinatorial problems among traveling salesman, vehicle routing, nurse rostering, and others with the similar complexity. Due to its huge space of possible solutions, more efficient algorithms have to be developed in order to search this space in a polynomial time [5]. In this paper, genetic algorithms (GAs) are emphasised as an appropriate and efficient metaheuristic algorithm which belong to the group of artificial intelligence methods. Many improved versions of GA can be found in the literature. Here, some of the most interesting approaches are briefly introduced and discussed.

The paper is organized as follows. In the second chapter some modern GAs for solving process planning problem are shown with the representation of sample parts frequently used as benchmark models. The third chapter is focused on scheduling problems using the GA. The fourth chapter gives the insight to IPPS problems. In the fifth chapter the GA components are shortly described. Chapter six is the conclusion.

2. GENETIC ALGORITHMS

Genetic algorithms (GAs) are based on the principles of natural selection and are originally developed by Holland few decades ago [8]. They were discovered as a useful tool for search and optimization problems. In this chapter genetic algorithm is more thoroughly discussed. The emphasis is put on genetic components which are frequently used while implementing the GA on IPPS problems in the literature.

2.1 Chromosome representation

There are a number of different strategies of representing a chromosome within a population. They are shown in more detail in [9, 10, 11]. Representation or encoding defines the relation between coding space and solution space [12]. In other words, it considers coding solution into feasible domain (genotypes) for algorithm to perform search procedure and decoding solution from that space into phenotype, or space in which chromosomes can be evaluated. One example of decoding process can be seen in Figure 1.

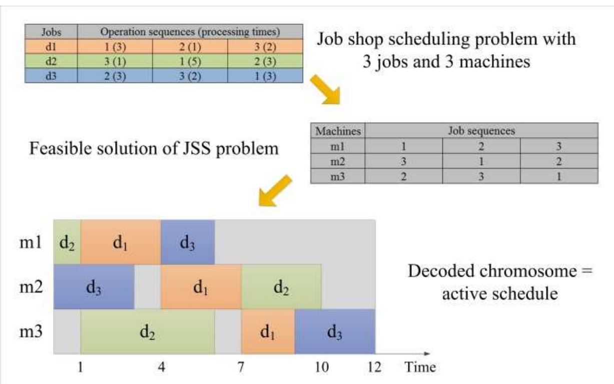

Fig. 1. Process of decoding a chromosome.

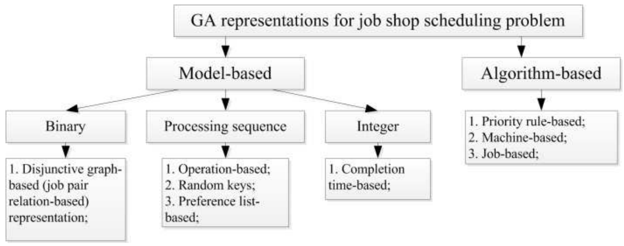

Fig. 2. GA representations for JSS problem [10].

According to [10], different types of representations are shown. Figure 2 illustrates this classification. For JSS and IPPS problems most frequently used representation is operation-based representation. This encoding type uses a single string of genes, where each job is represented by a number of genes equal to the number of operations it contains.

Based on the order of the generations given in this representation, each operation is assigned the earliest start time permitted by considering the machine availability constraints to generate feasible solution [10, 11].

2.2 Initialization of the population

Initialization of the population of chromosomes is one of the crucial tasks in GA due to the fact it affects the convergence speed and the quality of the final solutions. In general, population is generated by randomly representing string numbers of each chromosomes after which their decoding and evaluation can be performed. However, some authors have adopted other strategies for initializing population. In [13], authors developed two initialization strategies – global and local selection. Both of these strategies consider the assignment of operations to suitable machines by taking into account both the processing times and the workload of machines. For testing performance of the developed algorithm, both these strategies as well as random initialization are proportionally used when generating initial chromosomes.

2.3 Selection of individuals

Chromosomes are usually selected by applying an appropriate selection strategy. Roulette-wheel and tournament selection are two strategies that are mostly used for the problems considered in this paper. Roulette-wheel selection is based on selection of individuals with a probability proportional to the individual's fitness [14]. This strategy is moderately strong because other less fit individuals have too few chances to be selected. More efficient technique for selecting individuals is tournament selection. This selection runs so called "tournaments" among few individuals (usually between 2 and 7) that are randomly chosen from the population and one with the best fitness wins the tournament [3, 14]. The greatest advantage of this selection is that less fit individuals also have a great chance to be selected for reproduction.

2.4 Crossover and mutation

Crossover, on one hand, is the main operator applied in genetic algorithm which takes two parent chromosomes after selection process and produce children from them [14]. Considering that for process planning and scheduling problems permutations are used for representing possible solutions, specific crossover operators are required. One of the most frequent one is partially-mapped crossover (PMX). Beside that one, there are also order crossover, cycle crossover, linear order crossover, job-based crossover, position-based crossover, order-based crossover, etc. [11, 15].

On the other hand, the crucial role of mutation operator is to introduce a diversification in the search process. Mutation prevents the algorithm to be trapped in a local optimum [14]. Shift, swap and inversion mutations are some of the mostly used mutation operators for IPPS problems [11]. They work with small probability in order to avoid the random search of the algorithm.

3. REVIEW OF PROCESS PLANNING

Computer aided process planning (CAPP) is considered as the key technology for computer aided design and manufacturing (CAD/CAM) integration and consists of the determination of processes and parameters required to convert a block (raw material) into a finished product [16, 17].

Process planning, as the crucial component in this system, is a complex decision-making process that involves some major tasks, such as the selection of machining operations for every feature, sequencing all operations considering precedence constraints, choosing available manufacturing resources, determining setup plans and machining parameters and so on. These activities must be performed simultaneously in order to achieve an optimal process plan against a predetermined criterion such as minimum processing time or minimum machining cost [18].

Each part that is going to be manufactured is defined by the set of manufacturing features which requires adequate operations for their machining. Within the process planning optimization task, many benchmark part models are given in the literature in order to test the performances of a method used for finding optimal process plans. Figure 3 illustrates several prismatic parts represented as solid models that are usually covered in this field of optimization.

According to represented part models, to clarify the process planning, parts are represented by manufacturing features. Figure 4 shows a part composed of *m* features, in which each feature can be machined by one or more machining operations (total *n* operations). Apart from that, each operation can be realized by several alternative process plans if different machines, cutting tool or setup plans are included [19]. Within the field of process planning optimization, TAD represents a direction from which a cutting tool can access when machining a feature. This direction helps in defining setup, or group of operations that own the same TAD while executed on the same machine continuously [20].

When defining process planning problem, apart from mentioned elements, some constraints have to be included. The geometric and manufacturing interactions between features as well as the technological requirements in a part are considered to generate so called, precedence relationships, or precedence constraints between operations [17]. In order to represent these constraints in an adequate way, matrices or graphs represent

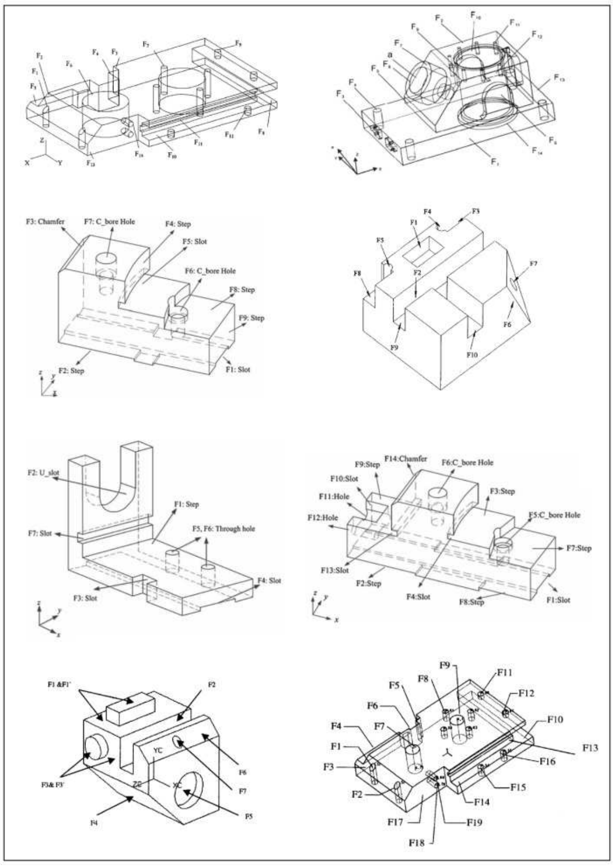

Fig. 3. Models of prismatic parts used in the literature

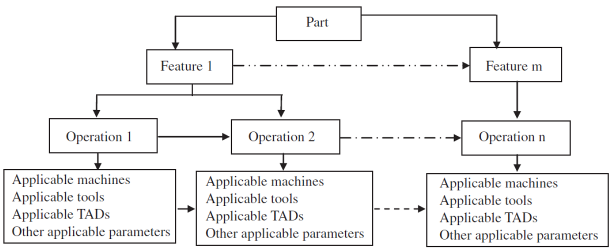

Fig. 4. Representation of a process plan [19].

the best choice. In [17], precedence constraints are divided into hard and soft ones. Hard constraints are the ones that should not be violated at any cost due to its effect on the feasibility of a process plan. On the other side, soft constraints affect the quality, cost or efficiency of a process plan and some of them can be violated during optimization.

The following text attempts to briefly discus some implementations of GA for solving process planning problem. In paper [18], authors implemented genetic algorithm for process planning problem with hybrid graph method for representing precedence relationships between operations. They used knowledge-based representation to represent a process plan with all its components. Also, modern and effective crossover and mutation strategies are used. Besides that, two different heuristic algorithms are employed in order to repair infeasible chromosome after initial phase and mutation. Similar approach can be found in [17], in which authors combined GA with tabu search metaheuristic.

Process planning problem is divided into preliminary and detailed process planning in papers [19, 21]. In preliminary stage, compulsive constraints (order and clustering constraints) are analysed for the purpose of finding feasible operation sequences, and in the detailed stage, based on optimization constraints, appropriate machine, tool and TAD are selected for each operation in a sequence and optimal solutions are generated. In [19], authors implemented GA in both stages, while in [21] intelligent search is used instead of GA in the preliminary stage.

In [22], setup planning and operation sequencing are integrated in so called ISOS approach. With the consideration of precedence and tolerance relationships between features, the GA is used to optimize operation sequence, setup for machining the part and selection of the machine, cutting tool and TAD for each operation.

Each of these few examples from the literature used the minimization of machining (production) cost as an optimization criterion for evaluating process plans. These machining cost is defined by machine cost, machine change cost, tool cost, tool change cost and setup change cost.

4. REVIEW OF SCHEDULING

Production scheduling is a decision-making process that deals with the allocation of manufacturing resources to tasks over given time period and its goal is to optimize one or more criteria [23]. Within the field of scheduling optimization, a number of operations of each job are allocated to each machine in a system. Jobs are usually observed as parts, and a large number of parts can be considered when approaching this type of combinatorial problem.

In years, many scheduling systems have been considered, among which job shop and flow shop scheduling are the most frequently used. Within the IPPS problem, job shop is used as a primary system for solving required tasks. According to [23, 24], job shop scheduling problem can be defined as follows: "given n jobs which have to be processed without interruption for a given period of time on given machine. The sequence of machines for each job is predetermined (task of process planning), and each of them can process at most one job at a time".

Also, flexible job shop scheduling problems (FJSSP) are covered in the literature. FJSSP represents an extension of the classical job-shop problem in which each operation must be processed on a machine chosen among a set of available ones [25, 26]. These problems are divided into two types [27]: Total FJSSP, where each operation can be processed on any machine among *M* existing machines on the shop floor; and Partial FJSSP where each operation can be processed on one machine from a subset of *M* existing machines on the shop floor. Some examples of implementations of GA on job shop scheduling problems are shortly discussed below.

Effective genetic algorithm for solving FJSSP is implemented in [13]. The most interesting part in this approach is population initialization where represented chromosomes are generated by applying three different strategies. Local selection, global selection, and random selection are proportionally used as effective strategies for generating population of high-quality initial chromosomes.

The proposed modified GA approach given in [28] consists of: an effective selection method called "fuzzy roulette wheel selection", a new crossover operator that uses a hierarchical clustering concept to cluster the population in each generation, and a new mutation operator that helps in maintaining population diversity and overcoming premature convergence.

Authors from [26] used new, job permutation, strategy for chromosome representation for their so called, new GA. This algorithm was tested on real time data from a drug manufacturing company with three shops included in job shop scheduling system.

Cyclic FJSSP is introduced in [29]. Here, more real manufacturing situation is considered where jobs are manufactured in batches over infinite time horizon with some definite time intervals (cycles). Based on mixed integer linear programming model, GA and SA are used for solving this type of scheduling problem.

5. REVIEW OF IPPS

As mentioned before, process planning and scheduling are two very important functions in manufacturing system and there is a strong relationship between them which led to the problem of IPPS. Similar to the job shop scheduling problem defined in the previous chapter, the IPPS problem can be defined as follows [30]: "given a set of n jobs which are to be processed on machines including alternative process plans, manufacturing resources and other precedence constraints, select suitable process plan, resources and sequence the operations so as to determine a schedule in which the precedence constraints among operations can be satisfied and the corresponding objectives can be achieved".

The outcome of process planning is the information about manufacturing processes and the identification of machines, tools and fixtures. Considering a large number of alternative process plans for each job, schedules use them as their input and their task is to schedule the operations on the machines while respecting the precedence relations given in process plans [31].

In recent years, in the area of IPPS, some integration models have been discussed and employed for this purpose. There are three basic integration models according to [2, 32, 33]: non-linear process planning (NLPP), closed-loop process planning (CLPP) and distributed process planning model (DPP).

The main advantage of NLPP model is the generation of all alternatives of process plans for each part and their ranking according to process planning optimisation criteria. However, this causes a combinatorial explosive problem which is considered as a drawback [2, 33]. Flowchart for this model is given in Figure 5.

CLPP model is based on a dynamic process planning system with a feedback mechanism. The real-time process plans can be generated by following a feedback from production scheduling system. The biggest disadvantage

Fig. 5. Non-linear process planning model [32].

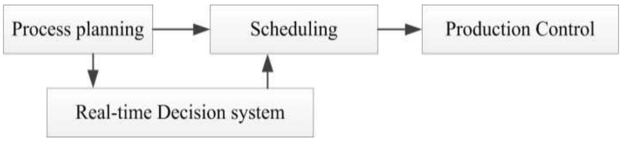

Fig. 6. Closed-loop process planning model [32].

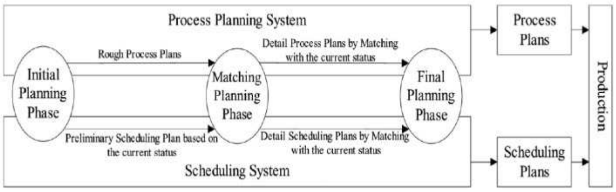

Fig. 7. Distributed process planning model [2].

of this model is that process plans has to be regenerated in every scheduling phase which cause the real-time data of the current shop floor status to be hardly acquired and updated [2, 33]. Fig. 6 illustrates the flowchart of CLPP integration model.

The methodology of DPP model is based on concurrent engineering approach which assumes the simultaneous performance of both process planning and scheduling functions. This ensures an interactive, collaborative and cooperative way of performing [2, 33]. The tasks are divided into two phases where preliminary process plans and schedules are generated in the first phase, while detailed plans are found in the second, matching phase according to the current status in shop floor. The DPP model is shown in Fig. 7.

Authors [3] implemented modified GA for IPPS problem. In this case, the IPPS model combines NLPP and DPP model's advantages. The process planning and scheduling are carried out simultaneously with the consideration of a large number of alternative process plans. In the phase of process planning optimization, the GA selects "s" process plans for each job which are, then used for generating an optimal schedule. Production time is used as an objective for process planning, while makespan and balanced level of machine utilization are objectives for scheduling.

In [4], an effective GA is implemented for multi-objective IPPS problem. Also, three types of flexibilities are considered: process, sequence and machine flexibility. Assuming that multi-objective problem is covered, authors included makespan, total machine workload and maximal machine workload as three objectives considered simultaneously. Also, during the algorithm search procedure, Pareto set is used to store and maintain the solutions obtained. Several Pareto optimal solutions could be obtained during this procedure.

Object-coding GA is introduced in [34]. This algorithm is coded in Java and his most interesting feature is object-coding chromosome representation where "object" refers to a machining operation on a dedicated machine for IPPS problem. In accordance with this, modern genetic operations are also used for appropriate evolution of the represented chromosomes. In addition, unusual selection and replacement strategies are integrated simultaneously in order to improve the overall quality of the population of chromosomes.

In [35], a mathematical model of IPPS problem is formulated and an evolutionary algorithm is used for solving the problem. The mathematical model is thoroughly defined with makespan, job tardiness and balanced level of machine utilization as scheduling criteria, and manufacturing cost as major criterion for process planning. The EA approach is almost identical to the GA given in [3, 36]. The experiment results are given for integration and non-integration model where the first one showed its complete superiority over the second one.

6. CONCLUSION

The research presented in this paper was a state-of-the art review of genetic algorithms in integration of process planning and scheduling. These two functions are generally regarded as two separate tasks in manufacturing system. Therefore, their integration was one of the challenges. Assuming that there are a large number of alternative process plans and schedules, efficient techniques have to be applied in order to find optimal solutions. One of the widely accepted methods is genetic algorithm, metaheuristic based on the biological process of natural selection. Here, the genetic algorithm was briefly presented with its most significant components, such as representation, selection, crossover and mutation. Also, some applications of the genetic algorithm in the field of process planning and scheduling are discussed in short. The last chapter of the paper was focused on the integration models that are studied in the literature.

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