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OPTIMIZING OPERATIONS SEQUENCE USING MODERN PARTICLE SWARM OPTIMIZATION ALGORITHM

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Abstract: Operation sequencing as a part of the process planning problem has shown to be a complex optimization challenge in the literature belonging to the class of non-deterministic polynomial problems. Here, operation sequencing problem is represented on a simplified example from the literature and optimized using a metaheuristic approach. Precedence relationships among operations for appropriate features are defined and adjacency matrix is formed. The optimization methodology is based on the modern particle swarm optimization algorithm (mPSO) whose performances are enhanced by chaotic maps and genetic components, such as crossover and two mutation operators. The main focus of this work is on reducing the optimal cost of operation sequence with determination of an appropriate tool and TAD candidate for each operation in a sequence. One case study was conducted in order to test the performances of the proposed algorithm which proved to be very efficient for the simplified operation sequencing problem with excluded machines alternatives.
Keywords: operation sequence, particle swarm optimization, chaotic maps

1. INTRODUCTION

Computer aided process planning (CAPP) is a key technology between computer aided design (CAD) and computer aided manufacturing (CAM). Its main focus is on generating all the required information for converting a raw material block into a finished product. Generally, most important activities of process planning are the following [1, 2]:

- Acceptance and analysis of the input data, definition of machining faces or extraction of manufacturing features,
- Selection and definition of raw materials,
- Definition of a process plan,
- Selection and definition of machining processes, setups and setup sequences,
- Selection and definition of machining operations and their sequences,
- Selection and definition of machines, tools, fixtures, measuring instruments and other manufacturing resources,
- Selection and definition of cutting parameters and cutting strategies,
- Generating programs for NC manufacturing systems,
- Determination of machining time and cost, and
- Generating appropriate technological documentation (routing sheet, operation sheets, programs, etc.)

This paper is focused on a single activity of process planning which is the determination of optimal machining sequences. Operation selection joined with operation sequencing together form a famous process planning optimization problem that has been widely and thoroughly studied in the literature. Assuming the fact that we already have manufacturing features and machining operations selected and used as the input data for a part we want to optimize, the next necessary step of process planning is to find the best possible sequence of the given operations.

On one side, the operation selection is a task based on form-feature geometry, its technological requirements as well as mapping these specifications to appropriate operations or series of operations [3]. On the other side, operation sequencing may be formulated as an optimization problem, considering the fact that a number of possible sequences may grow with the increase of a number of operations and manufacturing resources required to perform those operations. These resources are considered to be appropriate machines and tools and are defined as the operation method as expressed in [4].

As an important segment of operation sequencing, precedence relationships among operations should be defined according to the geometrical and manufacturing interactions between features. These relationships form precedence constraints which make sure these interactions are not violated and machining process can be performed effectively.

Accordingly, numerous optimization techniques have been used and implemented so far in order to optimize operation sequences in process planning. Since the operation sequencing is very complex to formulate using classical techniques such as branch and bound, linear programming, dynamic programming and so on, metaheuristic algorithms have proved to be most effective for solving hard optimization problems which operation sequencing surely is. Literature is enriched with many different sources focusing on these intelligent implementations on process planning or operation sequencing problems. Authors have performed different case studies in the past in which some of the proposed prismatic parts are still used as benchmark models in the studies being conducted today. The following are some of the proposed methodologies for optimization of operation sequencing activity.

Authors in [5] developed simulated annealing technique for solving operation sequencing problem in which machining cost was used as an optimization criterion. Precedence cost matrix and reward-penalty matrix were used by the algorithm in order to ensure the feasibility of operation sequences. The authors tested this methodology on three case studies in which the SAT proved its efficiency.

Another example of metaheuristic implementation can be found in [6] which expressed the ant system algorithm for operation sequencing problem. The ASA methodology represents the advanced ant colony optimization algorithm emphasizing the improvement in precedence checks and ant cycles which largely influenced decrease in computational time of the algorithm. The authors demonstrated the efficiency of ASA on two interesting case studies.

Authors in [7] implemented modified clustering algorithm on operation sequencing problem whose main characteristic is that the precedence constraints are firstly checked for selecting all possible next operations of the last operation in the sequence and their traveling costs are compared to choose the optimal feasible operation which has the minimum traveling cost in the sequence. Cost matrices are also used to determine precedences among operations and machining cost that is optimized.

Two important aspects of process planning, operation sequencing and setup planning were emphasized in case studies conducted in [8, 2]. Authors in [8] used genetic algorithm for optimizing integrated setup planning and operation sequencing including machining cost as an objective function and constraint matrix for generating feasible operation sequences. In [2], authors applied interesting approach which is not based on metaheuristics but on a simulation technique performed within SolidCAM system. Here, matrix of anteriorities was introduced and the machining time was optimized. The results of the simulation experiment showed to be very good in terms of setup plans and operation sequences for one case study.

The concept of our methodology is concerned with the implementation of particle swarm optimization algorithm for operation sequencing problem which is enhanced by adding chaotic behavior and genetic components such as crossover and mutation. The following section puts an emphasis on this methodology whose efficiency and robustness were proved on later described case study.

2. MODERN PARTICLE SWARM OPTIMIZATION ALGORITHM

Kennedy and Eberhart [9] are the founders of particle swarm optimization algorithm who was firstly introduced in 1995 and since then, numerous engineering problems have been solved using this method. The PSO is a population-based metaheuristic algorithm belonging to the field of swarm intelligence, one of the branches of artificial intelligence, Figure 1. It is an evolutionary algorithm that is inspired by social behavior of organisms in swarms, flocks or schools, such as flocks of birds or schools of fish. It imitates the natural process of foraging, of how for instance birds or fish behave during this intelligent process of search for food. Each individual's velocity and position are the crucial elements which affect personal and social experience of the swarm (i.e. flock or school). Their mutual collaboration towards achieving their goal as a group largely inspired the authors to create a computational method for solving different problems in the world.

The classical PSO starts with the initialization of a number of individuals called particles which are encoded in a predetermined way depending on the problem type. This population is then evaluated using appropriate fitness function which determines how good each particle is. Particles move in the search space of the problem with appropriate velocity which defines diversity of the search. Their positions are being updated across generations and they represent potential solutions to the problem. These solutions are evaluated in each generation of the particle swarm search where the local best position represents the best position achieved by a single particle so far while the global best position represents the best position achieved by a single particle in entire population. The global best is therefore the optimal solution found by the algorithm. Figure 2 illustrates the movement of particles and updating of their velocities.

Figure 1. Swarm intelligence in illustrated form

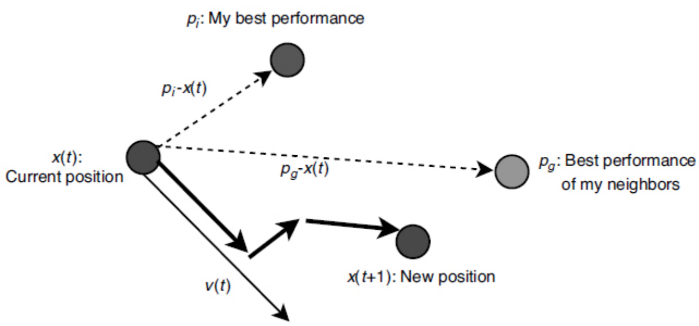


Figure 2. Movement of a particle in the search space and particle velocity update [10]

Taking into account the complexity of operation sequencing problem, even though the example in this paper is quite simplified, the classical PSO methodology showed to be very obsolete and inefficient for the given conditions. As many other instances in the literature, when approaching complex engineering problems classical metaheuristics require additional modifications in order to make them more robust and efficient for the search. This affects better algorithm convergence and much greater probability of finding the optimal solution.

Here, the classical PSO's performance is enhanced by adding chaos and genetic components. On one side, chaotic behavior has already been introduced in [11]. These authors developed the chaotic PSO for solving complex process planning problem whose capabilities were greatly improved by chaotic maps that were used to express stochasticity, ergodicity and certainty, properties which are crucial for the effective search. So, in that name, chaotic maps are included in this concept of the modern PSO and their representation is given in Figure 3. There are ten different chaotic maps which greatly influenced diversity of the mPSO. They are adopted from [12].

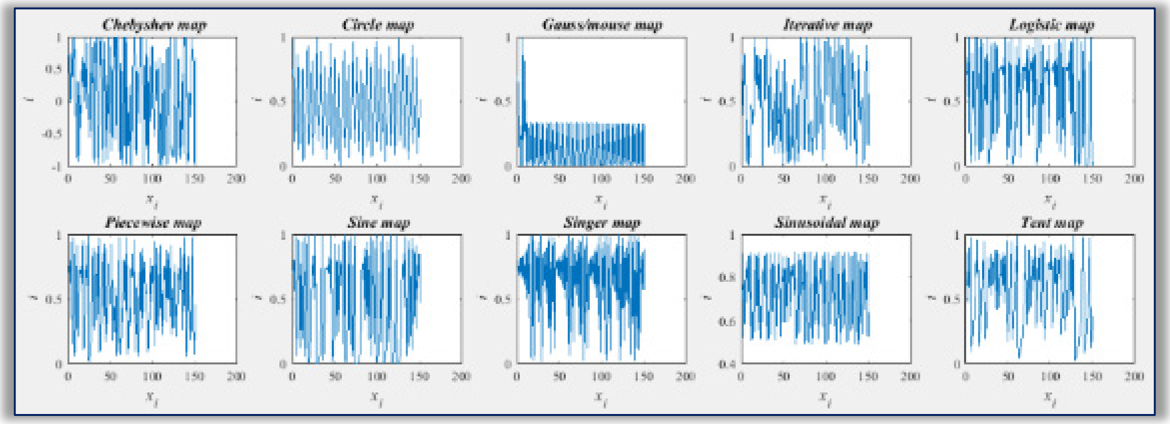


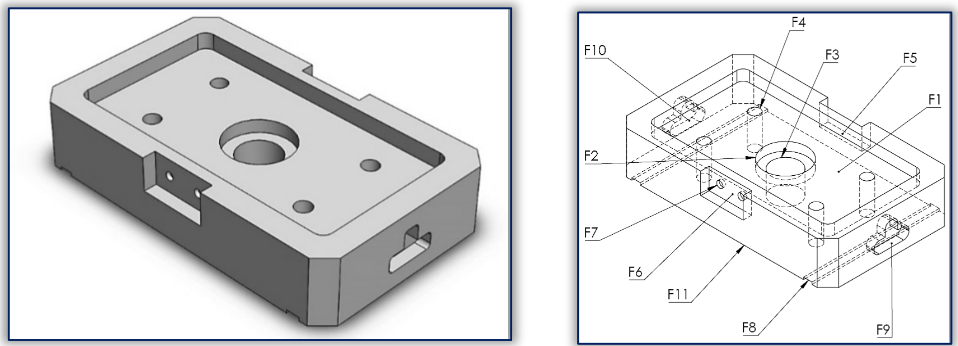
Figure 3. Chaotic maps generated in Matlab environment

The second modification that was done to the classical PSO was the introduction of the standard components of genetic algorithm, crossover and mutation. Genetic algorithm is one of the most famous evolutionary algorithm and metaheuristics whose components are still very adaptable to many novel algorithms. The purpose of crossover is to generate new individuals (offsprings) from the old ones (parents) and in that case provide new solutions and hopefully better ones. Mutation, on the other side, has the diversity properties, whose purpose is similar to the one of chaotic maps, to enable diversification, spreading the search and making sure as many neighborhoods of the search space are traversed. Two mutation operators are introduced in this study. One is shift mutation, based on the random selection of two operations in the sequence and exchanging their position in the sequence. The other mutation operator is concerned with changing tool and TAD candidate of a randomly selected operation from the sequence.

The next chapter will discuss the case study that was selected for testing the proposed mPSO algorithm.

3. CASE STUDY – RESULTS AND DISCUSSION

In order to test performances of the proposed algorithm, a case study has been conducted. The prismatic housing part illustrated in Figure 4a is adopted from [8] and represents the model used in our study.



(a) (b)

Figure 4. Prismatic housing part, a) 3D solid model b) Extracted features of the model [2]

According to the rules for recognizing and extracting manufacturing features for the observed part, features for the given housing part are extracted and illustrated in Figure 4b [2]. Based on the extracted features, appropriate machining operations are recommended and listed in Table 1. Associated tools with their cost indices for performing these operations are also proposed and given in Table 2.

Following the defined machining operations and recommended tools, potential tool and TAD candidates are defined according to the study conducted in [2]. These alternatives are represented in Table 3. The notable difference from the study in [8] that we adopted is the omission of machine candidates which assumes the fact that all operations for machining the defined features are performed on a single machine. Therefore, the entire machining process consists of alternative sequences of operations, their selected tool candidates and alternative setups on one machine.

Table 1. Recommended machining operations for housing part [2]

Features	Rough machining	Semi finish	Finish
F1	Rough turning		
F2	Counter boring		
F3	Drilling	Core drilling	Reaming
F4	Drilling		
F5	Rough milling		
F6	Rough milling		
F7	Drilling		
F8	Rough milling		
F9	Rough milling		
F10	Rough milling		
F11	Rough milling	Finish milling	

Table 2. Recommended cutting tools with cost indices [2, 8]

Tool ID	Tool name	Cost index
T1	Drill 1	7
T2	Drill 2	5
T3	Drill 3	3
T4	Counterbore drill	8
T5	End mill cutter 1	7
T6	End mill cutter 2	10
T7	End mill cutter 3	15
T8	Core drill	30
T9	Reamer	20
T10	Slot cutter	15

Table 3. Available tool and TAD candidates for the defined operations [2]

Features	Operation ID	Tool candidates	TAD candidates
F1	Rough milling (op1)	T5, T6, T7	-z
F2	Counter boring (op2)	T4	-z
F3	Drilling (op3)	T2, T3	+z, -z
	Boring (op4)	T8	+z, -z
	Reaming (op5)	T9	+z, -z
F4	Drilling (op6)	T2	+z, -z
F5	Rough milling (op7)	T5, T6, T7	-y, -z
F6	Rough milling (op8)	T5, T6, T7	+y, -z
F7	Drilling (op9)	T1	+y
F8	Rough milling (op10)	T6, T7	+z
		T10	+y, -y
F9	Rough milling (op11)	T5, T6, T7	-x
F10	Rough milling (op12)	T5, T6, T7	+x
F11	Rough milling (op13)	T5, T6, T7	+z / +x, -x / +y, -y
	Rough milling (op14)	T5, T6, T7	+z / +x, -x / +y, -y

Considering the given input data for optimization of operations sequence, an appropriate precedence relationships may be primarily defined based on which an adequate adjacency matrix can be formed. The following Table 4 represents the precedence relationships for the housing part. Table 5 represents the adjacency matrix for the housing part with associated numbers referring to precedencies among operations in a sequence. The number of machining operations for the housing model matches the number of rows and columns in the represented adjacency matrix. Each number 1 represents the precedence relationship meaning that operation in the observed row has to be performed prior to the operation in the observed column. Number 2 in the matrix means that the observed operations has to be performed in the same setup.

Table 4. The precedence relationships between operations for the housing part

Operations	Precedence relationships
op1	op1 must be performed prior to op3 and op6
op3	op3 must be performed prior to op4
op4	op4 must be performed prior to op2 and op5
op8	op8 must be performed prior to op9
op13	op13 must be performed prior to op14
op14	op14 must be performed prior to op6 and op10

Table 5. Adjacency matrix of the housing model

	Op1	Op2	Op3	Op4	Op5	Op6	Op7	Op8	Op9	Op10	Op11	Op12	Op13	Op14
Op1	0	0	1	0	0	1	0	0	0	0	0	0	0	0
Op2	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Op3	0	2	0	1	0	0	0	0	0	0	0	0	0	0
Op4	0	1	0	0	1	0	0	0	0	0	0	0	0	0
Op5	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Op6	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Op7	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Op8	0	0	0	0	0	0	0	0	1	0	0	0	0	0
Op9	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Op10	0	0	2	0	0	0	0	0	0	0	0	0	0	0
Op11	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Op12	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Op13	0	0	2	0	0	0	0	0	0	0	0	0	0	1
Op14	0	0	2	0	0	1	0	0	0	1	0	0	0	0

The problem of optimizing operation sequence of the housing part contains 14 machining operations with the total of 10 tool candidates and 6 tool approach direction (TAD) candidates which vary for each feature (Table 3). According to the defined input data for the mPSO algorithm, the required parameters are set as follows: population size is 80 individuals, maximal number of generations is 200, the inertia coefficient is set to be 0,5 with linear decrease to 0,2 during generations, personal and social acceleration coefficients are set to 1, probability of crossover is 60% and probabilities for two mutation operators, shift mutation and candidate mutation, are both 40%.

The algorithm was coded in Matlab programming environment and tested on the laptop with Windows 7 OS, Intel Core i3 2,10 Ghz and 3 GB RAM. The mPSO was run 10 times for each chaotic map resulting in total of 100 runs. The best operation sequence with associated tool and TAD is the one with the least total machining cost and is represented in Table 6.

Table 6. Optimal operation sequence with tools and TADs

11	8	1	7	12	13	14	10	3	4	5	9	6	2
5	5	5	5	5	5	5	1	3	8	9	1	2	4
-x	-z	-z	-z	+x	+z	+z	+z	+z	+z	+z	+y	-z	-z
Total machining cost: 869 Fitness: 0,0012 Chaotic map: Iterative													

Taking into account chaotic character of the mPSO, the most suitable results were obtained by using Iterative and Circle map, with the slight emphasis on the latter which provided better average result in 10 runs.

Also, as included in [2, 8], setup planning may also be mentioned in this case study. The setup planning strategy for the observed housing part is represented in Table 7. Comparing to the study in [8], the number of setups for the housing is the same, six different fixture setups. On the other side, authors in [2] obtained better results focusing on setup planning and obtained five different setups by using the simulation technique developed in CATIA software. Worth mentioning is the thing that CATIA software only provides estimation of machining times which is not included in the optimization performed in this study.

The algorithm performed well assuming the fact the operation sequencing problem was simplified and machine candidates are excluded from the study meaning that the entire machining process for the housing is performed on a single machine but in different setups as shown in Table 7.

Table 7. Setup planning strategy for the housing part

Setup number	Tools	TADs	Executing operations
1	5	-x	Op11
2	5	-z	Op8, Op1, Op7
3	5	+x	Op12
4	5,5,1,3,8	+z	Op13, Op14, Op10, Op3, Op4
5	1	+y	Op9
6	3	-z	Op6, Op2

4. CONCLUSIONS

This paper introduced the modern particle swarm optimization algorithm for solving the operation sequencing problem which belong to the group of complex optimization problems in the literature. The task is to find the optimal operation sequence for performing machining operations in an appropriate order while generating manufacturing features on an observed part. Among sequences, algorithm is also employed in determining appropriate cutting tools and tool approach directions for each machining operation in a sequence. Chaotic maps as well as genetic components, crossover and mutation were adopted in order to improve the performance of the algorithm. The case study focusing on the housing, a prismatic part adopted from the literature, was conducted in order to test the performances of the proposed mPSO algorithm. Precedence relationships among features and were defined for the given problem and the appropriate precedence matrix was formed to ensure feasibility of the sequence. Machining cost was used as an objective of optimization and the results showed that the mPSO performed very well in the search process for finding optimal operation sequences using different chaotic maps. Machining process for the housing used a single machine with different number of setups which is also represented in this study. The future research will be focused on process planning optimization and the implementation of novel metaheuristic algorithms that have been recently introduced in the field of swarm intelligence.

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