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Nadežda ČUBOŇOVÁ[1], Tomáš DODOK[2], Zuzana SÁGOVÁ[3]

OPTIMISATION OF THE MACHINING PROCESS USING GENETIC ALGORITHM

Summary. This paper deals with genetic algorithms as an optimisation method and its use for optimisation of the machining process in the CAM system. Tool path verification and optimisation are two best ways of dramatically improving manufacturing operations while saving money with relatively little work. Genetic algorithms can be used for improvement of these operations and considerably reduce length of tool paths leading to the reduction of machine times and optimisation of cutting parameters. Provides the software application created to optimise processes of boring and local milling (Incomplete sentence; what or who provides).

Keywords: optimisation, genetic algorithms, CAM system

1. INTRODUCTION

Preparatory activities of the pre-production stage and their importance in terms of affecting the quality and price of produced parts constitute a huge space for the application of the *philosophy of optimisation*. The problems associated with optimisation of technological

[1] Faculty of Mechanical Engineering, University of Žilina, Univerzitná 8215/1, 010 26 Žilina, Slovak Republic. Email: nadezda.cubonova@fstroj.uniza.sk
[2] Faculty of Mechanical Engineering, University of Žilina, Univerzitná 8215/1, 010 26 Žilina, Slovak Republic. E mail: tomas.dodok@fstroj.uniza.sk
[3] Faculty of Mechanical Engineering, University of Žilina, Univerzitná 8215/1, 010 26 Žilina, Slovak Republic. Email: zuzana.sagova@fstroj.uniza.sk

processes are increasingly relevant given the opportunities of accessible solutions and use of computer technology [4,11]. Automated plants with deployed CNC technology utilise PC at the design stage, with subsequent transition to technology, using the CAD/CAM software. When solving optimisation tasks related to technological processes, it is necessary to optimise not only operations but also the used technological devices defined within the technological process operation segments to ensure maximum labour productivity and minimum costs or maximum profit. The modern concept of CAD/CAM systems enables optimising the process by a number of criteria. Optimisation can be based, for example, on *a semi-finished product.* The semi-finished product in a CAD/CAM system is gradually updated (modified) during the design and simulation of the machining process [10]. Each following operation includes machining of the remaining material only. This means elimination of unnecessary and inefficient movements and actions [12]. Computer-aided optimisation of machining processes (CAM – computer-aided manufacturing) utilises software applications where the method of performance is usually carried out using additional modules (optimisation programs). Optimisation programs enable maximisation, in the machining process, especially tool paths, cutting parameters, NC programs, etc., [13]. However, the tool path generated from CAD/CAM systems is not guaranteed as the optimal tool path and there are possibilities that the tool path distance is longer in order to complete each drilling process. Therefore, optimisation of the CNC machine tool path should be done before starting a machining process to ensure the tool path taken will produce the shortest path of cutting tool travel [1].

Optimisation of machining processes plays a key role in meeting the demands for high precision and productivity. The primary challenge for machining process optimisation often stems from the fact that the procedure is typically highly constrained and highly non-linear, involving mixed-integer-discrete-continuous design variables. Additionally, machining process models are likely discontinuous, non-explicit, or not analytically differentiable with the design variables. Traditional non-linear optimisation techniques are mostly gradient-based, which poses many limitations on their application to today's complex machining models. Mathematic analysis disposes of a large variety of mathematic models for solving a large variety of optimising problems. Nevertheless, many real-world tasks cannot be solved by these techniques, or their solutions, which are not as good as those of some other special nonlinear optimisation techniques. Therefore, some special optimisation techniques were designed as solutions close to the optimal one but search only in a very little fragment of the solution space. One of such optimisation technique is the Evolution Programming (EP). EP is the name of a large variety of optimisation techniques based on evolution principles. Genetic algorithms (GA) is one of these evolution techniques, which mostly imitate principles of a natural evolution process. GA presents itself as a very strong optimisation technique capable of solving very complicated task with large search space in a very short time with very good results. There is a lot of application, wherein any optimisation technique was used or another whose results can be improved. The field of application of genetic algorithms towards solving optimisation problems in engineering is almost unlimited. [2]. Prediction solutions optimisation problem depends on the correctness of the proposed action solution to a specific optimisation task. This involves determining the optimisation criteria and restrictive conditions, relating to the case and knowledge of the issue of genetic algorithms, which outwardly look like a universal solution, but requires an individual approach to each case.In conjunction with the Genetic Algorithm (GA) method, Kumar and Pacahauri [5] and Nabeel et al. [9] also used the Travelling Salesman Problems (TSP) to reduce the total time and distance of tool travel for drilling sequence. Finally, genetic algorithm is presented in this paper as an optimisation method with its use for the maximisation of the machining process in

the CAD/CAM system. It is a software application with the possibilities of crossing methods especially with TSP, created to optimise the processes of boring and local milling.

2. GENETIC ALGORITHM (GA) IN BRIEF

Concisely stated, a genetic algorithm (GA) is a programming technique that mimics biological evolution as a problem-solving strategy. The *evolutionary program* is a probabilistic algorithm which manages the population of "n" individuals (chromosome) for "t" iterations. Each individual represents a potential solution to the problem and within the evolutionary program, it is presented as a data structure. Each solution is evaluated, and the result of the evaluation is a degree of suitability (fitness). The new population is then created selecting the most suitable individuals. Some of the individuals undergo the transformation using genetic operators and generate new solutions. There are single-transformations of *mutation type* (Fig. 1a) which will create a new individual through a small change in the structure itself and transformations of higher-order of *crossover type* (Fig. 1b), which will create a new individual combining parts of two or more individuals. After a certain number of generations, the program converges supposing that the best individual represents a nearly optimal solution [7].

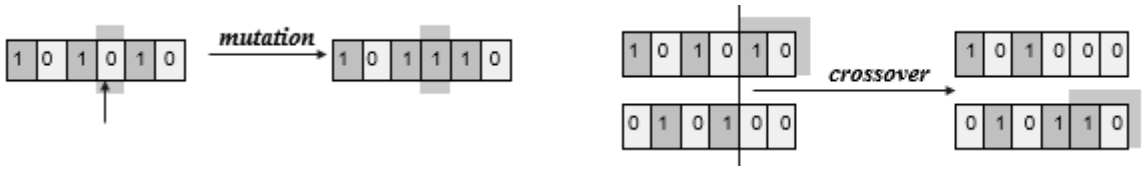


Fig. 1. Scheme of mutation (a), and single point crossover (b) [6]

For a specific task, several evolutionary programs can be proposed. These can differ in many ways. Different ways of the *individual´s inscriptions* can be used, genetic operators of individuals´ transformation can also differ similarly as methods of creating the initial population or management methods of restrictive conditions and parameters (population size, the probability of using genetic operators, etc.). However, all of them share basic principles, for example, the population of individuals undergoing some transformations (changes) and the individual struggle for survival during the process of evolution.

The best-known techniques among evolutionary algorithms are the *climbing technique* also known as local or neighbouring search, the *simulated annealing technique* and *genetic algorithms* that truly mimic evolutionary principles in nature. Before a genetic algorithm can be put to work on any problem, a method is needed to encode potential solutions to that problem in a form that a computer can process. These are the most common methods for solution encoding: *binary string* (0's and 1's), *string of values* (integer, real, letter...), *string encoded as permutation* (every value can appear in the string only once), *branching data structures* (trees), and *matrix encoding*. It must be taken into consideration that solution strings of evolutionary algorithms need not have a fixed length. Then, a selective mechanism would be applied to decide which individuals will be fit for selection for reproduction and which, on the other hand, will be discarded as unfit. There are many different techniques which can be used when creating a genetic algorithm for selecting the individuals to be transferred to the next generation; *Elitist selection, Fitness-proportionate selection, Roulette-wheel selection, Scaling selection, Tournament selection, Rank selection, Generational*

selection, Steady-state selection, and Hierarchical selection. Some of these methods are used individually, while others can be and are often used in combination.

Population size is a very important factor that influences the function of genetic algorithms. If the population is too small, the genetic algorithm can converge very quickly. However, if is too large, the genetic algorithm may require too much computational time, which makes it inefficient. In addition, the population diversity and selection pressure are influenced by the population size. An algorithm with varying population size does not use any of the earlier mentioned or similar selective mechanisms, rather it evaluates individuals by age.

Age of the individual is equivalent to the number of generations during which the individual will be in the population managed by the algorithm. The individual´s age is proportional to its fitness and replaces thereby selective mechanisms. However, it also directly influences the population size in every step of the evolutionary process. This method describes the real natural selection in the most convincing manner. Lifetime (or age) is assigned to each individual at its origin and remains constant during the evolutionary process until its extinction. This means that the individual´s age is no longer recalculated. There are many ways of assigning age to individuals. It is obvious that the assignment of a constant value (greater than 1) would result in the population exponential increase. Equally, as there is no selection pressure on individuals, the assigning of constant age would result in a low-efficiency algorithm. Several strategies for the calculation of the age of individuals have been proposed and tested experimentally, for example [8]:

Proportional allocation:

$$LT = MinLT + \eta \frac{fitness(i)}{AvgFit} \tag{1}$$

Linear allocation:

$$LT = MinLT + 2\eta \frac{fitness(i) - AbsFitMin}{AbsFitMax - AbsFitMin} \tag{2}$$

Bi-linear allocation:

$$LT = MinLT + \eta \frac{fitness(i) - MinFit}{AvgFit - MinFit} \qquad AvgFit \geq fitness(i) \tag{3}$$

$$LT = \frac{1}{2}(MinLT + MaxLT) + \eta \frac{fitness(i) - AvgFit}{MaxFit - AvgFit} \qquad AvgFit \geq fitness(i) \tag{4}$$

Fitness (i) - fitness of the individual
AvgFit - average fitness in the current population
MinFit - minimal fitness in the current population
MaxFit - maximal fitness in the current population
MinLT - minimal lifetime value
MaxLT - maximal lifetime value
LT - lifetime value

$$\eta = \frac{1}{2}(MaxLT - MinLT) \tag{5}$$

Proportional evaluation - This originated from the idea of roulette selection; the age of the individual is proportional to its fitness. However, this evaluation has one great shortcoming; individuals, whose fitness greatly exceeds the average fitness, can be evaluated by very old age. *Linear evaluation* - the life of individuals is recalculated to the best suitability in the population. If, however, many individuals have the same rate of fitness, or near the maximum, this leads to a high evaluation and rapid expansion of the population. *Bi-linear evaluation* is a compromise between the previous two. It highlights the differences between the life expectancy of the best individualswhile taking into account the maximum and minimum length of life [8].

When selecting suitable individuals, they must be randomly modified in the hope that the fitness of the next generation will increase. Two methods are used for searching the problem space, namely: exploitation - when creating a new generation, it makes use of the "experiences" of previous generations to determine areas promising success in searching optimal solutions; but it carries the risk of being trapped in a local extreme; exploration - when creating a new generation it ignores the "experiences" of previous generations. The browsing process is conducted in unexplored areas thus avoiding deadlocks in a local extreme, which eventually slows down the process. During the browsing itself, the main function of the algorithm is to find the global extreme of hypersurface and not get stuck in any of the local extremes during the searching process. Local extremes usually work in parallel with several individuals making up the population. This is a discrete time process – individual generations gradually take turns. The process is repeated until the terminating condition is fulfilled. It may be the maximum number of generations or other acceptable limit. The fundamental principle of the genetic algorithm activity is shown in the flowchart (Fig. 2):

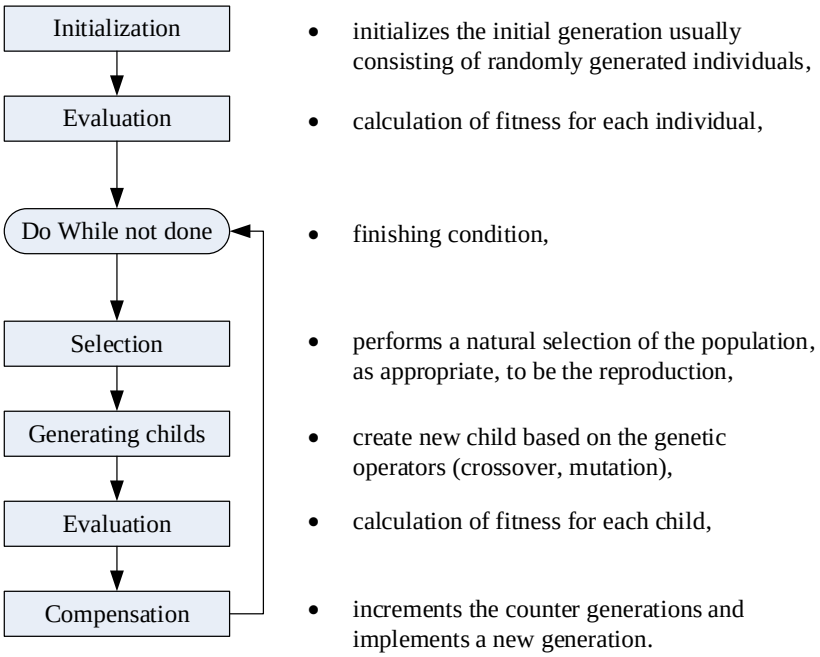


Fig. 2. Flowchart of genetic algorithm [7,14]

Genetic algorithms are highly effective means of optimisation and are applied mainly for the solution of problems with large or infinite number of solutions. Such a problem may be, for example, the determination of an optimal drilling path when the tool path passes through n points. Similar tasks can be found in many optimisation techniques called *Travelling Salesman Problems (TSP)* [7], a special type of problem, which evolutionary algorithms deal with. Definition of this task is very simple: the salesman has to visit each place within his trading area once and then return to the starting city. If he knows the cost of travelling among individual cities, how should he plan the tour for minimal costs? The search space is then the permutation of *n* cities; every permutation is then one possible solution and the optimal solution is the permutation with minimal travelling costs. Size of the search space is then *n*! TSP is a relatively old problem: Euler first described it in 1759 (under a different title). The name "Travelling salesman" was first used in 1932, in a German book: *Travelling salesman, how and what to do in order to obtain commission and be successful in his trade* [8]. The RAND Company presented TSP in 1948. The good reputation of this company helped the TSP become a famous and popular topic. In recent times, many algorithms have been designed for TSP solution using different methods and strategies.

TSP problem can be applied for optimisation of some technological processes such as drilling and local milling operations. Most of the common CAM and CAD/CAM systems use none or only some type of *linear mathematics* for the solution of similar tasks due to long computing time [3]. Due to its efficiency, GA can solve the mentioned problems within few minutes with brilliant results. Thanks to their fundamental functions and characteristics as *parallelism, schema theorem and crossing,* it is possible to create various optimisation applications.

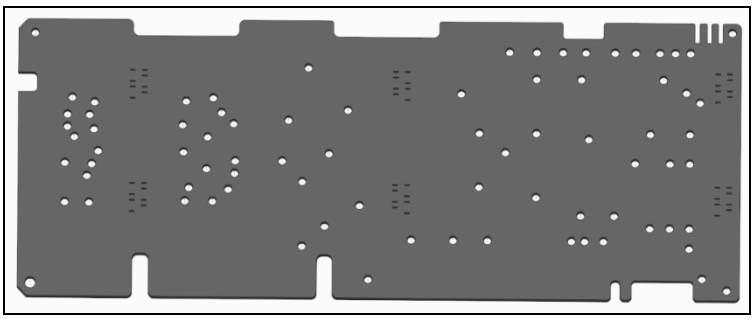
3. GA APPLICATION IN OPTIMISATION OF MILLING AND DRILLING PROCESS IN CAD/CAM

The Toolpath Optimiser application was designed for the best use of tool paths of drilling and local milling based on GA. During the design and creation of the genetic algorithm for the Toolpath Optimizer application, it was necessary to choose among many techniques and settings (for example, a problem inscription, method of crossover, selection and mutation, setting the probability of crossover and mutation, setting the size of population), by means of which the genetic algorithm could be assembled. Incorrect set up of a genetic algorithm could lead either to a too long optimisation process or to an unsatisfactory result of the optimisation process. The set-up genetic algorithm was implemented as an optimisation instrument for particular inputs and outputs (CL data from Creo Parametric 5.0) for created Toolpath Optimiser applications. The application was developed in the programming environment Borland Delphi, supplemented by the module for reading and writing of CL data, and finally experimentally validated on concrete examples of drilling and local milling. It also includes a function for the movement of the approaching point before drilling, which reduces inaccuracies of tool positioning caused by a backlash in the slides. Input and output data of the optimisation module are CL data of CAD/CAM system Creo Parametric 5.0. The experimental verification of the created optimisation software was applied to maximise the creation of the technological process of the parts shown in Fig. 3a, b.

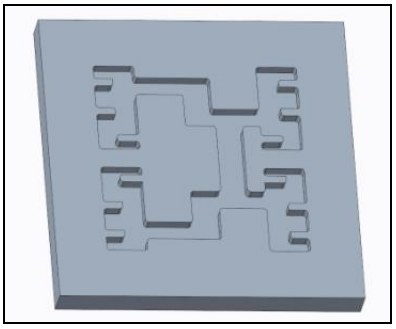
The problem of *drilling optimisation* can also be found in the electrotechnical industry in the production of circuit boards, and many other areas. The reason this problem is often solved in the production of circuit boards is that the drilling process itself is very short.

Movement of the tool out of contact with the machined surface presents an essential part of the production time. The second reason is the number of holes, that is, to find the optimal path for more than 20 points (Fig. 3a) becomes an almost unrealistic task under conditions of common practice [13].

Local milling is an operation that is performed after a previous operation of volume milling with a larger diameter tool (Fig. 3b). In places where a larger diameter tool could not remove the material, a smaller-diameter tool is used; this operation is called local milling. High requirements demand precision, and in drilling, the *moving towards the centre of holes* under the same vector is often applied. This helps eliminate inaccuracies caused by changes in the slides movement or movement of a machine table from positive to negative and vice versa. The application controls the tool path so that the tool approaches the positions of all holes under the same vector.



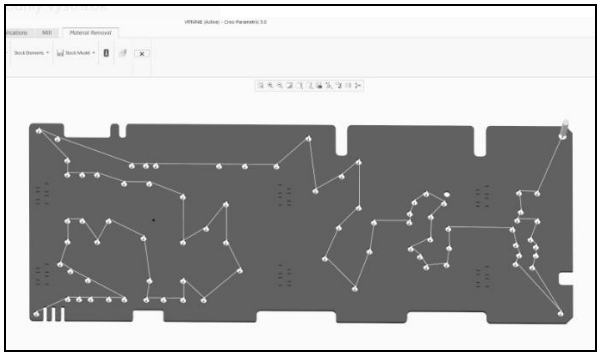
a)



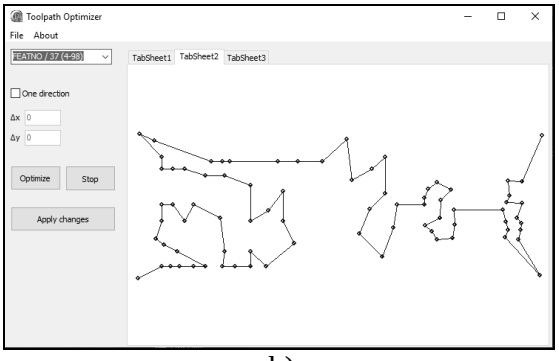
b)

Fig. 3. Illustrations a) of printed circuit boards for holes manufacturing by drilling operation, b) of local milling operation

A non-optimised tool path for the drilling process is generated with the system Creo then transformed into the CL data file and, subsequently, loaded into the Toolpath Optimiser application. Fig. 4a shows a tool path of the drilling process generated by the system Creo and Fig. 4b shows the non-optimised tool path loaded into the Toolpath Optimiser application.



a)



b)

Fig. 4. a) non-optimized tool path of the drilling operation generated by the system Creo b) non-optimized tool path loaded in the application Toolpath Optimizer

Optimisation process in the application starts with the confirmation of the selection sequence. Its graphical flow is shown in two tabs (Fig. 5). One shows the best path in each step of the evolutionary process (*Path length*) and the other gives graphical information about the evolutionary process (GA process). *GA process* shows the dependence of the found shortest path on the number of generations *(Length min).* It also shows the dependence of the average path length of all individuals from a particular generation on the number of generations (*Length av*g) and the dependence of the found longest path in the generation on the number of generations *(Length max). Path length* graphically displays the original length of a toolpath generated from the CL data file (*Length init*) and a new optimised path length (*Length new*) generated by GA. When the evolutionary process is completed, it is possible to compare the length of the new and original path, to compare the optimised path (Fig. 5), to decide whether the result meets the requirements or to repeat the evolutionary process.

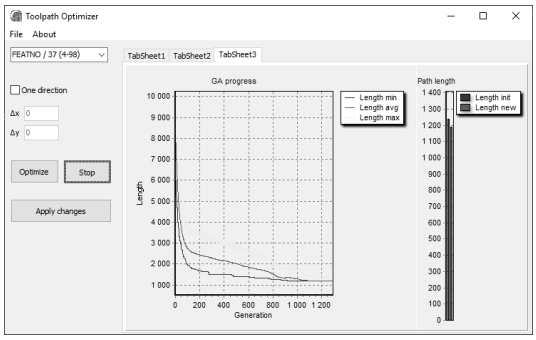
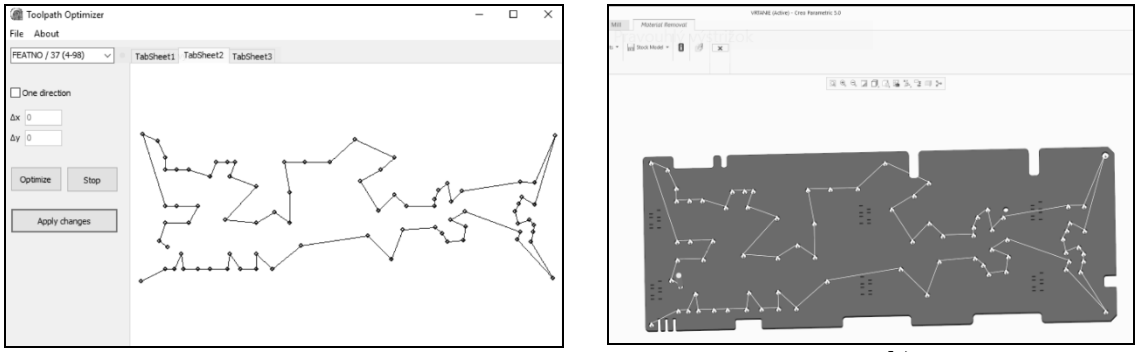


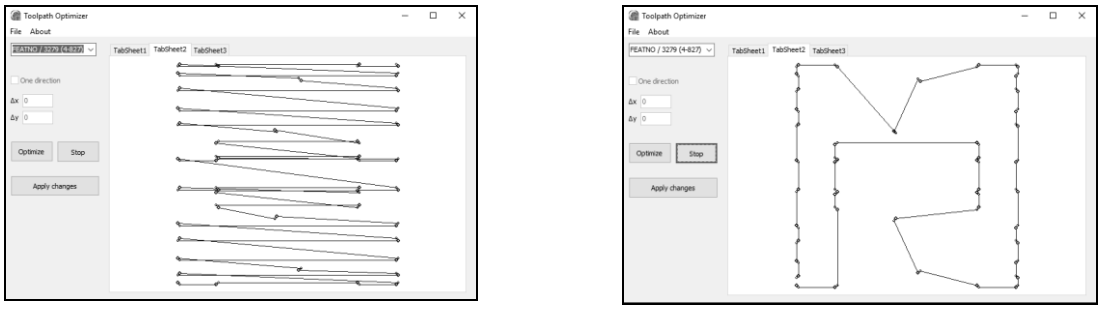
Fig. 5. Graphical flow of the optimisation process at the drilling operation

Having accepted the optimised path (Fig. 6a), the CL data file is edited. The optimised tool path can be loaded and displayed in Creo (Fig. 6b) and consequently processed by the post-processor to NC code for a particular CNC machine.



a) b)

Fig. 6. a) optimised tool path generated by the application Toolpath Optimiser, b) optimised tool path of the drilling operation loaded in the system Creo



a) b)

Fig. 7. Tool path of a local milling operation.
a) non-optimised tool path generated by system Creo,
b) optimised tool path loaded in the application Toolpath Optimiser

From the point of view of tool rapid traverses, the local milling process is similar to the process of drilling. Both processes use the same genetic algorithm, the only difference is in the work of CL data field. Fig. 7 shows a simple example of tool path optimisation process using the *Local Mill* sequence in CAD/CAM system Creo, at Fig.7a is an original non-optimised tool path generated by the system Creo; Fig.7b shows the same tool path optimised by the *Toolpath Optimiser*. The graphical flow of the optimisation process at the milling operation is depicted in Fig. 8. The genetic algorithm which forms the core of the Toolpath Optimiser proved to be a highly effective means of optimisation. The result may be considered highly satisfying. With smaller optimisation tasks - about twenty points - the optimisation process takes only a few seconds [6].

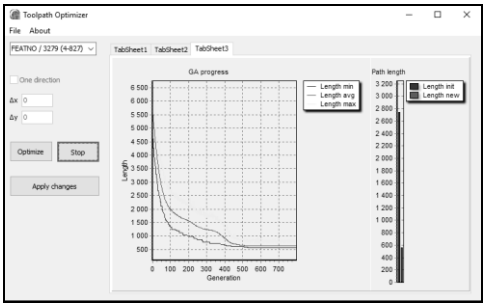


Fig. 8. Graphical flow of the optimisation process at the milling operation

4. CONCLUSION

To successfully address an optimisation problem, we must know optimisation methods and appropriately select the method we want to deploy to solve the problem in question. Although some methods resemble one another due to their work processes, they may not be equally suitable for solving the given task. Improper use of a method can reduce the resulting effect of its work; it can even lead to obtaining false results. TSP problem can be applied for some of the technological processes such as drilling, boring or local milling operations. Most of

the common CAM and CAD/CAM systems do not use any optimisation technique or use some kind of linear mathematics based technique for solving this task due to the computing time [7]. GA due to their efficiency can solve the mentioned problems in a few minutes instead of a long time (hours, days) with remarkable results. This article details optimisation of machining processes using out of the CAD/CAM system environment. This optimisation module may be used either directly or it can easily be modified in compliance with the users´ requirements. For example, it is possible to change the module of input and output data, which currently works only with the CL data field of CAD/CAM system Creo. The experiments were created to optimise processes of both boring and local milling. The results of these experiments show that genetic algorithm is a simple and effective method for solving complex optimisation problems. From the practical point of view, the application Toolpath Optimiser can be used in the pre-production phase with the aim to increase productivity and reduce production costs.

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