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Intelligent modelling in manufacturing

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ABSTRACT

Purpose: Modeling of production systems is very important and makes optimization of complicated relation in production system possible. The purpose of this paper is introducing artificial techniques, like Genetic Algorithms in modeling and optimization of job shop scheduling in production environment and in programming of CNC machine tools.
Design/methodology/approach: Conventional methods are not suitable for solving such complicated problems. Therefore Artificial Intelligent method was used. We apply Genetic Algorithm method. Genetic Algorithms are computation methods owing their power in particular to autonomous mechanisms in biological evolution, such as selection, "survival of the fittest" (competition), and recombination.
Findings: In example solutions are developed for an optimization problem of job shop scheduling by natural selection. Thus no explicit knowledge was required about how to create a good solution: the evolutionary algorithm itself implicitly builds up knowledge about good solutions, and autonomously absorbs knowledge. CNC machining time was significant shorter by using GA method for NC programming.
Research limitations/implications: The system was developed for PC and tested in simulation process. It needs to be tested more in detail in the real manufacturing environment.
Practical implications: It is suitable for small and medium-sized companies. Human errors are avoid or at lover level. It is important for engineers in job – shops.
Originality/value: The present paper is a contribution to more intelligent systems in production environment. It used genetic based methods to solve engineering problem.
Keywords: Intelligent methods; GA; Job shop scheduling; CNC programming

1. Introduction - about the system

Integration of basic components into a combined unit is the basic principle followed by the nature since ever. The systems can be non-living, living, artificial or social systems [1]. Each system is a part of the environment under whose influence it develops. A common characteristic of the systems is that the conflict between the individual system and the environment leads to gradual lagging, regression or even destruction of the system. The defense mechanism by which the system tries to become harmonized with the environment is the evolution.

During evolution the system ripens and with its activities it simultaneously generates again and again new states of the environment to which the competitive systems and successors of the system itself must re-adapt themselves in the new life cycle. The novelties brought by the system into environment create new changes. The evolutionary ripening and growth of the system cause self-organizing integration or a centrally dictated linking of the basic components of the system.

2. Evolutionary optimization of the system

Optimization is a process of searching for the best solution in the space of possible solutions of the mathematical model describing the problem. So far, the conventional optimization methods have proved good, but they have many disadvantages. As they use deterministic operations, they can slide fast into the local optimum. In addition, the complex systems cannot be optimized with them efficiently. The evolutionary optimization processes differ from conventional optimization methods in that they use probabilistic principles (stochastic operations), therefore none of the above limitations applies to them. Figure 1 shows the general process of evolutionary optimization methods.

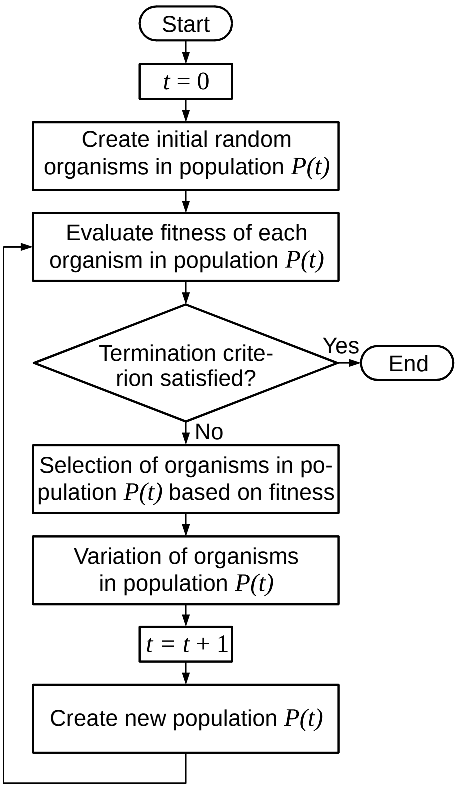

Fig. 1. Process of evolutionary optimization methods

3. Genetic alghoritm

Since their introduction genetic algorithms [2,3] were spread on almost all areas of research work. They proved to be an effective optimization tool for multicriterial and multiparametrical problems. Their power is in random guided search hidden in imitation of principles of natural evolution. To implement the genetic algorithm on a certain problem an individual and an environment in which the individual has to fit have to be prescribed. A common description of the individual is a binary code of an optimization variable(s). The environment in which the individual has to survive consists of constraints and rules of an optimization field and is presented by one or more optimization functions known also as fitness functions. A process of optimization runs in cycles in which new generations of individuals are created with increasing average fitness of a population. Increasing of average fitness is assure by genetic operators:

- Reproduction which assures that best fitted individuals are reproduced into next generation,
- Crossover where the reproduced individuals are crossed interchangeably, and
- Mutation which provides new, not yet evaluated individuals.

GA is a special example of evolutionary optimization methods, where a relatively poor set of information is written into the organisms. Figure 2 shows the most frequently used terms used in GA. The population consists of organisms. The organisms are points in the space of solutions. The organism has coordinates that are also called genes. It is characteristic of conventional GA that the organisms represent coded values of variables of the mathematical model. Coding of variables into fixed-length binary strings is most widespread. The binary representation of the organism is called genotype and the actual value of the organism is called phenotype. Figure 3 shows the population of four organisms. Each organism consists of five genes. The genotype of organism 1 is 01101, and the relevant phenotype is 13 [4].

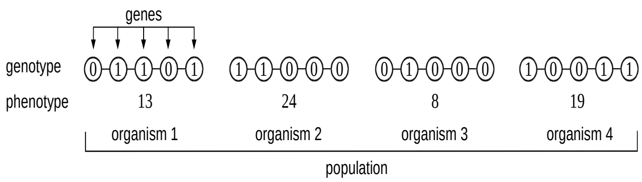

Fig. 2. Common terminology in genetic algorithms

Evaluation of organisms is the driving force of the evolutionary process. Quality of the individual organism is determined on the basis of its ability to solve the problem. A higher probability of cooperating in basic operations of the conventional GA (e.g., reproduction, crossover, and mutation) is prescribed to organisms (solutions) of higher quality. Thus, the fitter organisms more frequently transfer their genetic material into the next generation, whereas bad organisms slowly die away from the population.

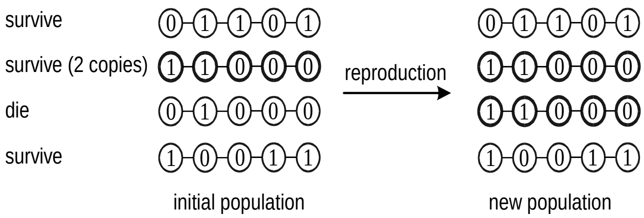

Fig. 3. Operation of reproduction in GA

Figure 3 shows also the operation of reproduction. Reproduction gives a higher probability of selection to organisms of higher quality. They are copied unchanged into the next generation.

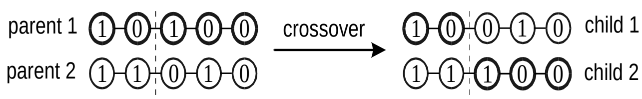

Fig. 4. Operation of crossover in GA

Figure 4 shows the operation of crossover. The crossover ensures the exchange of the genetic material between organisms. From two parental organisms two children result at the level of genotype. The selection of the crossover point, indicated by dashed line, is random.

Figure 5 shows the operation of mutation. Mutation at the level of the genotype randomly introduces new genetic material into organisms. The evolutionary development of organisms usually leads to better and better solutions. At the end, the population of identical (or at least very similar) organisms is obtained.

In literature it is possible to notice many variants of the conventional GA that are adapted to specific characteristics of the optimization problem dealt with. The variants particularly differ in representation of organisms and use of additional or modified genetic operations [3].

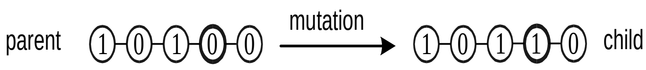

Fig. 5. Operation of mutation in GA

4. Optimisation

Optimization is the process of trying to find the best solution to a problem that may have many possible solutions. Most problems involve many variables that interact based on given formulas and constraints [3,5]. For example, a company may have three manufacturing plants, each manufacturing different quantities of different goods. Given the cost for each plant to produce each good, the costs for each plant to ship to each store, and the limitations of each plant, what is the optimal way to adequately meet the demand of local retail stores while minimizing the transportation costs? This is the sort of question that optimization tools are designed to answer.

Optimization often deals with searching for the combination that yields the most from given resources.

In the example above, each proposed solution would consist of a complete list of what goods made by what manufacturing plant get shipped in what truck to what retail store. Other examples of optimization problems include finding out how to produce the highest profit, the lowest cost, the most lives saved, the least noise in a circuit, the shortest route between a set of cities, or the most effective mix of advertising media purchases. An important subset of optimization problems involves scheduling, where the goals may include maximizing efficiency during a work shift or minimizing schedule conflicts of groups meeting at different times.

To increase the efficiency of any system, we must first understand how it behaves. This is why we construct a working model of the system. Models are necessary abstractions when studying complex systems, yet in order for the results to be applicable to the "real-world", the model must not oversimplify the cause-and-effect relationships between variables. Better software and increasingly powerful computers allow economists to build more realistic models of the economy, scientists to improve predictions of chemical reactions, and business people to increase the sensitivity of their corporate models.

5. Adaptation of GA

As interest swelled in academic circles, as serious computational power began moving its way into mainstream desktop machines and made design and maintenance of complex models easier [6]. The use of real numbers rather than bit string representations eliminated the difficult task of encoding and decoding chromosomes.

The popularity of the genetic algorithm is now growing exponentially, with seminars, books, magazine articles, and knowledgeable consultants popping up everywhere. Many companies employ genetic algorithms regularly to solve real-world problems, from brokerage firms to power plants, phone companies, restaurant chains, automobile manufacturers and television networks. In fact, there is a good chance that you have already indirectly used a genetic algorithm before.

6. Example 1 – job shop scheduling

A workshop needs to find the best way to schedule a set of jobs that can be broken down into steps that can be run on different machines. Each job (job 1, machine 1 = 11 to 55) is composed of five tasks (25 tasks), and the tasks must be completed in order. Each task must be done on a specific machine, and takes a specific amount of time to complete. There are five jobs and five machines [5].

Table 1.
Initial and optimized values

INITIAL VALUES					GA OPTIMIZED VALUES				
Task	Job/Mach.	Job	Mach.	Process Time	Task	Job/Mach	Job	Mach.	Process Time
1	11	1	1	64	12	32	3	2	70
2	12	1	2	66	16	41	4	1	54
3	13	1	3	31	3	13	1	3	31
4	14	1	4	85	11	31	3	1	74
5	15	1	5	44	24	54	5	4	15
6	21	2	1	7	25	55	5	5	91
7	22	2	2	69	7	22	2	2	69
8	23	2	3	68	4	14	1	4	85
9	24	2	4	14	14	34	3	4	1
10	25	2	5	18	18	43	4	3	98
11	31	3	1	74	5	15	1	5	44
12	32	3	2	70	23	53	5	3	10
13	33	3	3	60	15	35	3	5	90
14	34	3	4	1	6	21	2	1	7
15	35	3	5	90	8	23	2	3	68
16	41	4	1	54	10	25	2	5	18
17	42	4	2	45	19	44	4	4	76
18	43	4	3	98	9	24	2	4	14
19	44	4	4	76	2	12	1	2	66
20	45	4	5	13	21	51	5	1	80
21	51	5	1	80	13	33	3	3	60
22	52	5	2	45	17	42	4	2	45
23	53	5	3	10	22	52	5	2	45
24	54	5	4	15	1	11	1	1	64
25	55	5	5	91	20	45	4	5	13

Let the number of population be 50, the mutation rate 0,06 and the crossover rate 0,5. A group of the initial population is first produced randomly, then the reproduction, recombination and mutation operations are run repeatedly, based on the fitness of the individual until the GA converges.

The GA computes how much time elapses between the start of the first scheduled task and the end of the last scheduled task. This total time is what we wish to minimize.

The initial values and the GA optimized values are summarized in Table 1, while figure 6 shows the total time before optimization with GA anf figure 7 total time after optimization with GA.

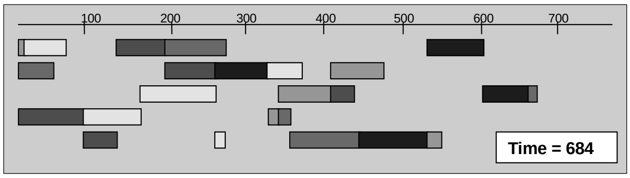

Fig. 6. The total time before optimization with GA
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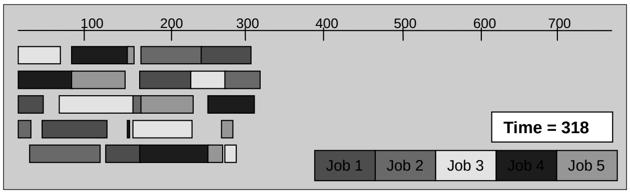


Fig. 7. The total time after optimization with GA

7. Example 2 – intelligent CNC programming

7.1. State of-the-art

In the year 1937 Turing proposed in his seminar paper, "On Computable Numbers, with an Application to the Entscheidungsproblem," appeared in Proceedings of the London Mathematical Society [7-11], the idea of an intelligent machine that could “think” like human being. In the 1950 article in the British philosophical journal Mind, Turing proposed what he called an "imitation test," later called the "Turing test", which is a measure for intelligence of the machine . That was a starting point for development of intelligent machine - computer. Since then artificial techniques and methods have been introduced in all fields of engineering activities, also in CAD/CAM systems. In recent researches genetic algorithms take more and more applications. They proved to be an effective optimisation tool for multicriterial and multiparametrical problems. Their power is in random guided search hidden in imitation of principles of natural evolution. Using genetic algorithms in computer-aided design and several ways in which they can solve difficult design problems is described in [9-11].

The most important part of intelligent CAM system is cutting tool-path generation for CNC machine tools. A lot of constrains, such as cutting tool geometry and material, cutting material, machining operation, machine tool, clamping device, wet or dry machining etc., must be taken into account to automatically generate an optimal tool-path. In state-of-the-arte research several main streams are observed:

- Incorporating artificial techniques into CAM system
- Modelling and control of various machine tool parameters, using artificial techniques
- Building the intelligence into CNC unit of machine tool.

For introducing the automatic and intelligent way of tool path generation new data exchange protocol is needed. The worldwide IMS research initiative is going on to develop a new data model entitled STEP-NC (ISO 14646 standard). Paper [10] provides a future view how this standard could be used in intelligent CAD/CAM systems.

Intelligent, artificial neural network based system for autonomous planning of turning operation is proposed in [11]. This system optimizes cutting conditions taking into account cutting tools, material of the workpiece and machine tool characteristics. Machining processes are predicted using adaptive system, which is able to set the parameters of neural networks. The output is a set of optimized machining parameters.

Kadono [12] describes a system and device for generating the tool path on NC machine tools and adequate NC control. The system at first recognizes the geometric feature of CAD model of the part and on the basis of preserved processing procedures (machining cycles, sub-programs) chooses the most suitable tool path. The system can choose only machining procedures, which have been previously defined as typical processing for particular sub-programs.

The research study [13] describes an autonomous, intelligent CAD/CAM programming system for the cutting device controller (CNC laser cutting machine tool), based on evolutionary methods. The CNC cutting system is able to autonomously optimise paths between cutting trajectories, determined by the product’s CAD model. The evolutionary method GA, which has been proved to be effective optimization tool for multicriterial and multiparametrical problems, was successfully implemented for autonomous laser cutting programming. The case study shows the machining costs reduction of 30 %. The programming phase – manufacturing planning and optimising was successfully fully automated.

The expert CAD/CAM system STATEXS for dimensioning, optimization and manufacture of gears and gearings is presented in [14-15]. The optimum dimensions of the gearing were determined using genetic algorithms, well suited to such problems especially because of their robustness and their ability to detect global extremes. After completion of the calculations and optimization of gears or gear pairs, there follows one of the most difficult operations, the manufacture of the product with theoretically determined and optimized properties. Genetic algorithm approach for the manufacture of various products with demanding shapes was used.

The paper [16] shows how with the help of artificial neural network (ANN), the prediction of milling tool-path strategy could be made in order to establish which milling path strategy or their sequence will show the best results for free surface machining, taking the set of technological constraints into account. The defined milling path strategies serve as input in the conventional

CAD/CAM programming system. Configuration of used neural network is presented, and the whole procedure is shown on an example of mould, for producing car lights bodies.

Literature [17] describes a learning method of a purpose made device. For this reason a special man-machine interface, which enables a dialog with the user and learning, is built-in into the control unit of the machine.

Literature [18] describes the method for generating of NC programs. A special system saves the data about parts, belonging coordinates, characteristic junctions and time of assembly for single electronic components. The solution enables shortening of the time for the composition of NC programs and reduction of mistakes in preparing of programs.

Paper [19] presents so-called machining potential field method to generate tool paths. This field is constructed by considering the part and the cutter geometry, which represent the machining-oriented information on the part surface and allowed machining planning. The developed techniques can be used to automate the multi-axis tool path generation and to improve the machining efficiency of sculptured surface machining.

7.2. Basic model

Basic idea of the system was developed in past research work and is shown on Figure 8 [20-30]. The first step is geometrical feature recognition and classification. It is described in more detail in references [29-30]. Recognition and optimisation system consists of two main parts, and works in two stages. The process starts with processing of the CAD part model in order to analyse the shape and all characteristics of geometrical features.

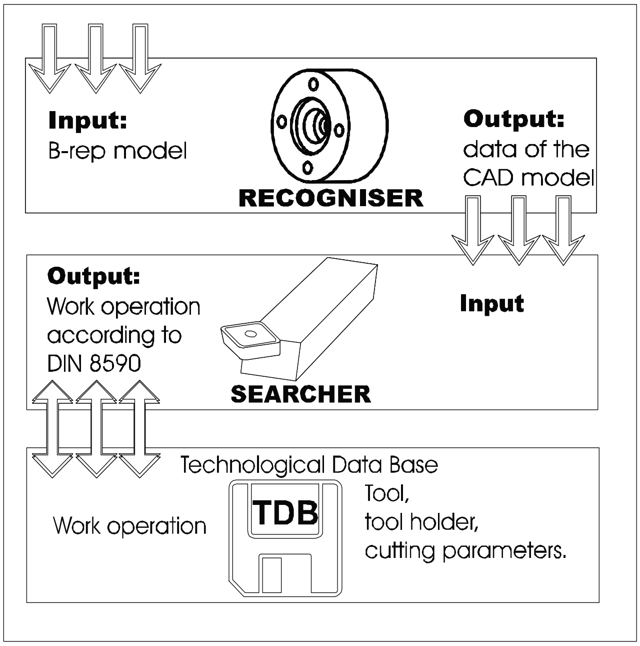


Fig. 8. Basic structure of the GA based model [28]

In this system the initial 3D-parts are represented by boundary representation (B-rep.). The Recogniser is able to recognise many different types of features out of which special attention is given to the recognition and classification of explicit features.

Output data of the first part from Recogniser represent the input for the next part, the Searcher. It takes the evaluated geometric data from the Recogniser and starts the search for the appropriate work operation through the technological database by comparing the original data from the model with the recommended data for the available tools stored in the production system. The structure of technological databases is defined by a work operation. It is systematically divided according to DIN standard (DIN 8580) depending on different working procedures. Its structure represents a complex optimisation environment in which the optimisation of a production can be done.

The new developed intelligent CAD/CAM system for programming of CNC machine tools is shown on Figure 9. The input in the system is a CAD model of the part.

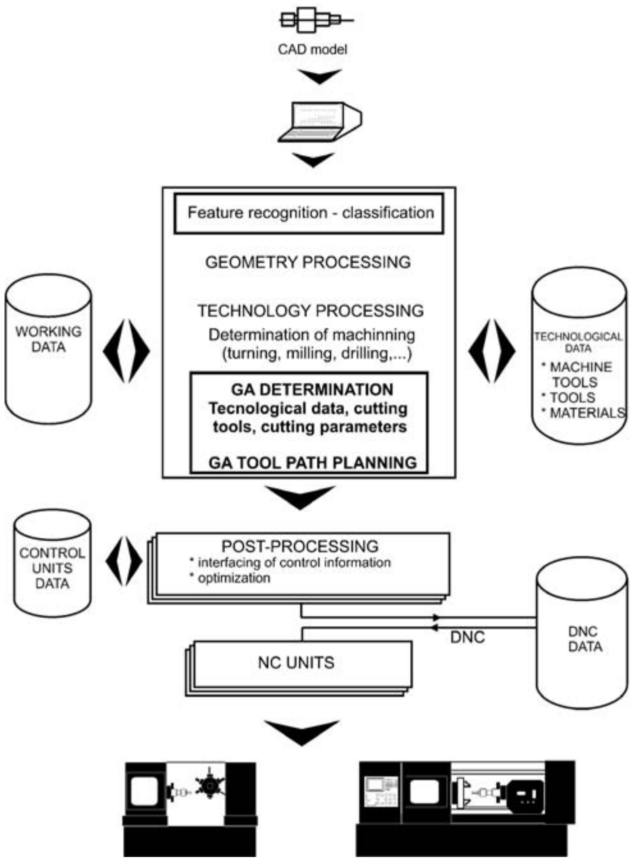


Fig. 9. Basic structure of intelligent CAD/CAM system

On the basis of recognised features the module for GA based determination of technological data is taken over in order to determine: cutting tools, cutting parameters (according to workpiece material and cutting tool material) and detailed tool path planning.

Afterwards post-processing takes palace and converted the tool-path data, which are at this stage neutral for the defined numerical control and machine tool.

7.3. Turning operation used in the model

Turning operations are classified according to the DIN 8580 standard [13, 31-32]. Allowed cutting tool movement in cutting is in the positive Z and X-axis. Outside length turning operations used in a developed model are:

- Turning along main z-axis (Figure 9-a),
- Crosswise turning along x-axis (Figure 9-b),
- Combination of both operations.

Allowed tool rapid (free) movement is in all directions while the cutting edge is not in contact with cutting material and could not cause the collision of cutting tool with workpiece.

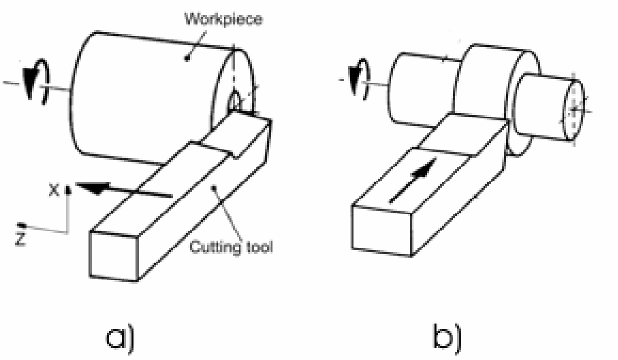


Fig. 9. Basic turning operations

The workpiece is rotational part for machining on lathes. Simple model is shown in Figure 10. It is representing by finished profile, while raw material (rough part) is representing by rough profile. Both profiles are previously defined in CAD system.

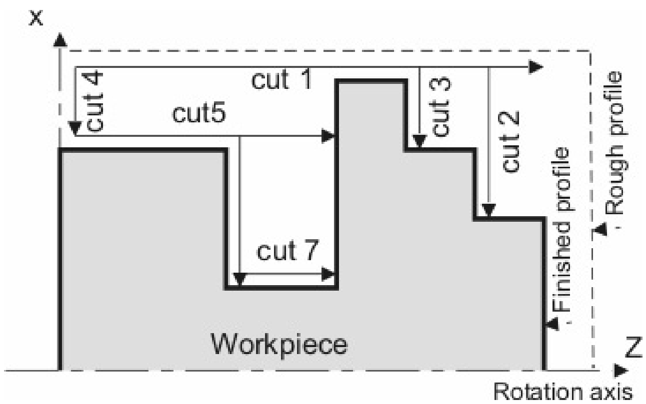


Fig. 10. Simple model of cutting tool path (single cuts)

The material, which will be removed, is split in several cuts named cut1, cut2, …cut7, according to allowed cutting tool movement. It is assumed that workpiece could be produced, applying this cutting tool movement on lathe. The task of the new system is to find out optimal combination of tool movements without any outside "intervention" of skilled CNC programmer.

7.4. GA model – coding

The position of workpiece and allowed tool movement is representing in the plane Z-X axis and divided in several small squares. One square represents allowed (discrete) tool sub-movement and could be free defined. Center point of the cutting tool edge is in the center of a square. The total cutting tool movement consists from several discrete sub-movements (Figure 11). This method is used in order to accelerate later on the GA process.

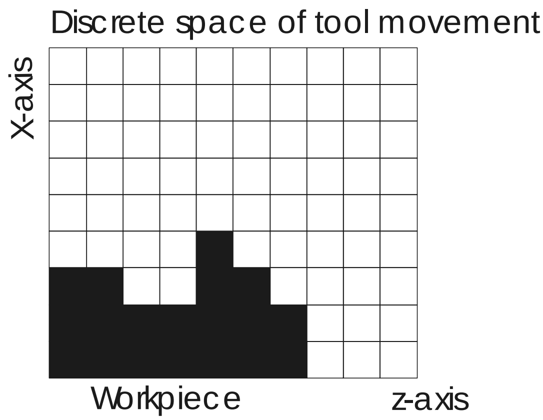


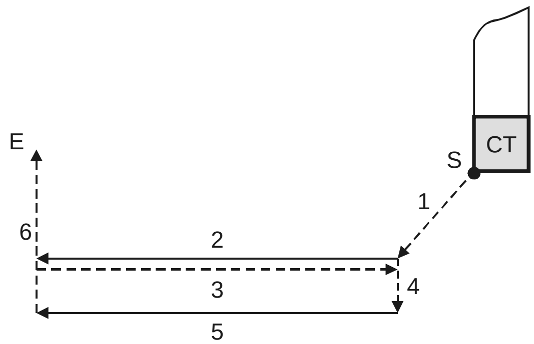
Fig. 11. Discrete nature of working space

A direct value coding is used, where every organism (chromosome) is a string of values and consists of several cuts (genes), which are randomly selected. Here is an example:

$$\text{Organism-n} = \{\text{cut-1; cut-2; cut-3; cut-4; cut-5; … cut-n}\} \qquad (1)$$

Each cut consist of a number of basic tool movements. A basic tool movement is a movement for one unit in the cutting direction. Each cut-n represents one tool path, where n is the number of cuts needed to remove all the material.

Typical cutting tool movement (tool path) is shown in Figure 12.



CT	- cutting tool
S	- starting point
E	- end point
1, 2,...6	- single movement of the cutting tool

Fig. 12. Typical cutting tool path in turning

In order to start the genetic algorithm two-parent organisms were randomly created; Parent-1 and Parent-2.

Parent-1 = {cut-1; cut-2; cut-3; cut-4; cut-5; cut-7; cut-6} (2)

Parent-2 = {<u>cut-6</u>; <u>cut-2</u>; <u>cut-3</u>; <u>cut-4</u>; <u>cut-5</u>; <u>cut-7</u>; <u>cut-1</u>} (3)

The set of cuts (genes) represents the movement of the cutting tool from the first cut (for example: cut-2) to the next cut (for example: cut-3) in parent 1 organism (equation 2). The first gene (cut1) is always the starting point and the last one (cut-n) the end point of the cutting tool movement.

7.5. GA model – genetic operations

The next step after the coding of organism is applying of genetic operations. The crossover selects cuts (genes) from parent organism (chromosome) and creates a new one, a named child or offspring. The crossover point was randomly chosen and everything before this point was copied from Parent-1, and then everything after the crossover point was copied from Parent-2.

After crossover two new chromosomes (Child-1 and Child-2) are created. They are exemplified below (4 and 5):

CHILD-1 = {cut-6; cut-2; cut-3; cut-4; cut-5; cut-7; cut-6} (4)

CHILD-2 = {cut-1; cut-2; cut-3; cut-4; cut-5; cut-7; cut-1} (5)

The next step is mutation, which prevents that all solutions in population will fall into a local optimum of solved problems. Mutation procedure takes place randomly and creates a new child – offspring (equation 7) from the original one (equation 6). In encoding we can switch a few randomly chosen bits from 1 to 0 or from 0 to 1.

Before mutation:

CHILD 1 = {Cut-6; cut-2; cut-4; cut-4; cut-5; cut7-cut6} (6)

After mutation:

CHILD 1 = {Cut-6; cut-5; cut-4; cut-4; cut-2; cut-7; cut-6} (7)

7.6. GA model – rules, constraints and fitness function

The sum of all cutting tool movements (Figure 8) represents a randomly created NC program for machining of a particular part for one run of the GA. For the next run the NC program will be different from the previous one in the number of steps needed for the machining of the part.

During the evaluation of calculated results (generated NC programs) several rules and constraints, which represent the fitness function, were taken into account:

- Rapid (fast) cutting tool movement
  - Rapid tool movement is allowed in all directions, which are inside the working space and are "free" of collision with workpiece (see also description under subsection c).
- Cutting movement – machining is allowed only in directions of + Z and –X axis
- Collision of cutting tool with a workpiece
  - Collision of cutting tool with workpiece is carrying out in the way that all tool movements are continuously monitoring. In this process also reduction of workpiece profile due to cutting of chips is taken into account. All not allowed position of cutting tool caused alarm. Only collision free movement are marked as good.
- Reduction of the un-clamping sequences to a minimum
  - New clamping sequence is generated if cutting procedure (generated NC program) does not remove all materials. Only NC programs with lowest number of clamping sequences is marked as good. The best machining strategy by turning is clamping of workpiece in only one sequence.
- Remember the region of material, which was already cut in previous tool movement
  - All toll movements are recorded and saved for a next run of GA. If GA procedure detect previous tool cutting movement next tool movement will be generated from this stage. In this way GA can know the material, previously remove from a workpiece.
- Reduce the machining time to a minimum.
  - Machining time is calculated from tool movement, taken cutting and rapid movement into account. Tool movement where collision of cutting tool occur is not taken as good.

7.7. Programming of CNC turning

Experiment study was made for turning operation of rotational part (Figure 13). CNC programmes were made by commercial CAD/CAM system [31].

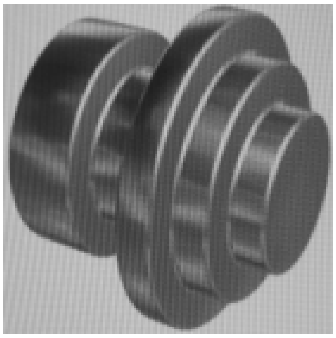


Fig. 13. CAD model of turning part

Programming of the same parts was done with newly developed GA based system. Definition of raw part, starting point and end point of tool movements are the same as in conventional CNC programming. After this definition the GA process is started generating a set of CNC programs.

The main goal of GA optimisation is to generate the shortest tool-path for machining of a part. Each cut or tool path consist of several basic tool movements. The number of basic tool movements needed to produce the part is a measure for efficiency of CNC programming system. Minor numbers of tool movement means higher efficiency and shorter machining time which results in decreasing production costs. Figure 14 shows various stages of turning, taken during simulation of GA prodess.

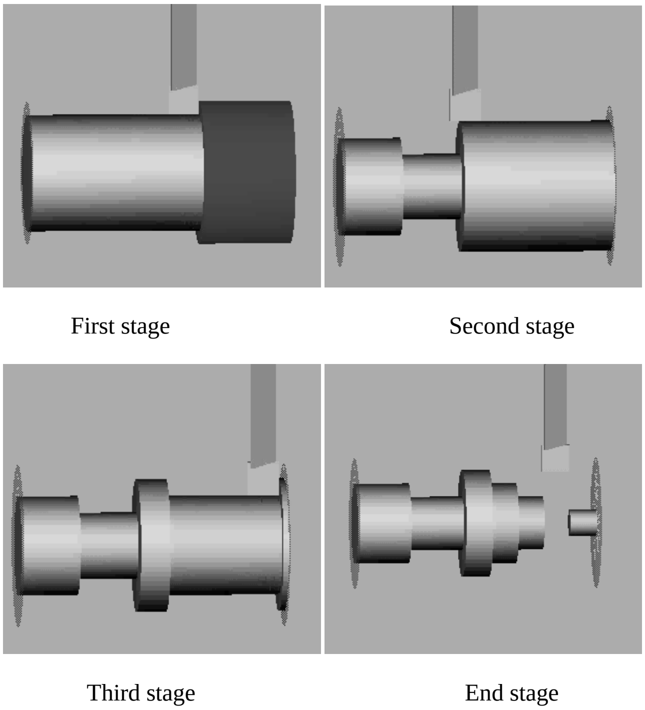


Fig. 14. Simulation of GA based toll path generation

7.8. Programing of CNC milling

Case study also was made for milling of prismatic parts (Figure 15). CNC program was made by the skilled CNC engineer using commercial CAD/CAM system. Programming of the same parts was done with newly developed GA based system. Definition of raw part, starting point and end point of tool movements are the same as in conventional CNC programming. After this definition the GA process is started generating a set of CNC programs for milling. The system prepares the NC program of the length of 33 steps for that fixing within a relatively short time [33].

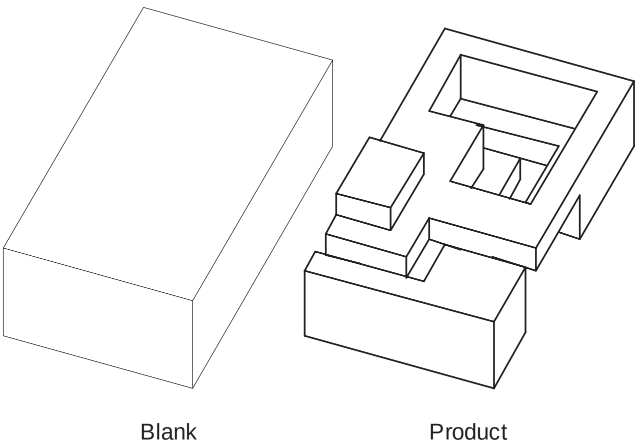


Fig. 15. Blank part and the product

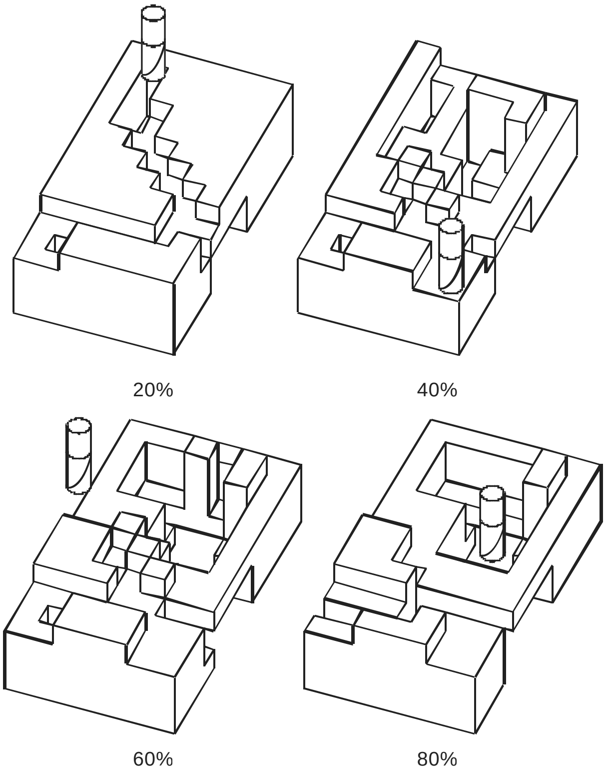


Fig. 16. Best milling tool path in generation 0

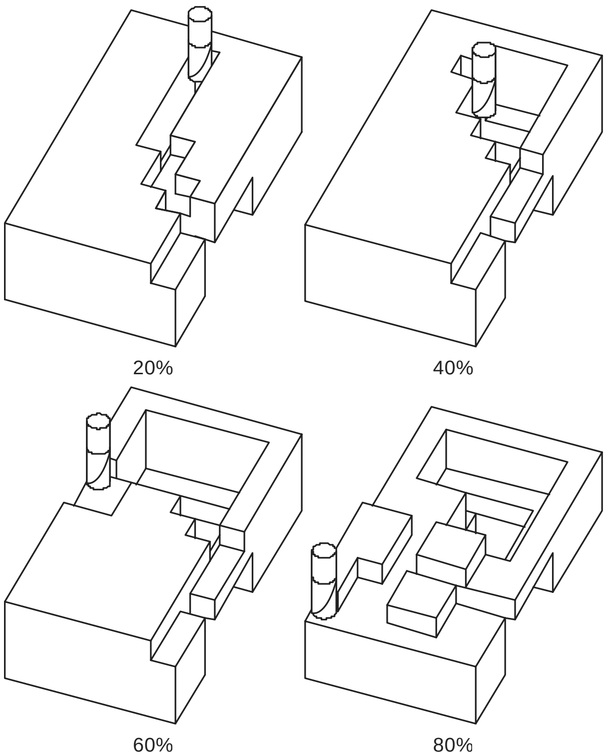


Fig. 17. Best CNC program of civilization

In the initial generation – generation 0 the NC programs are randomly created. Figure 16 shows the machining (percentage of length of the machining path) according to the best NC program created in generation 0. the path length of the best NC program in generation 0 amounts to 257 steps, which is less than the tool path length in case of conventional machining type. The tool holder did not hit the workpiece.

Figure 17 shows the tool travel with respect to the best program of the generation 45, where the best NC program of the civilization appeared. The path length of the best NC program in the civilization amounts to 137 steps, which means that productivity was increased for as much as 47.90% if compared with the conventional machining.

8. Conclusions

The paper presents the development and use of artificial intelligence, evolutionary methods, (genetic algorithms) in organization of manufacturing systems and prorgamming of CNC machine tools.

Due to complexity of the problems and size of the solution searching space we used the genetic algorithm method imitating the biological evolution of living beings. The system is capable of autonomously planning the machining technology, detecting the machined and un-machined workpiece areas, planning and optimizing the tool working and feeding motions, detecting the collisions and verifying whether the product cannot be completely machined on a certain machine.

According to our research experience, the genetic algorithms described in this paper are very suitable for optimization of technical, economic, scientific, chemical and business models. Implementations of genetic algorithms could provide an innovative and interactive decision making technique for adaptive scheduling in practical manufacturing applications. Justification and implementation of GA schemes for scheduling are discussed and compared.

The key advantage of the newly developed CAD/CAM model is introduction of GA based algorithm to generate rough and finished tool path strategy for machining of rotational parts on CNC lathe. The efficiency of this algorithm has been demonstrated, and it results in a significant reduction (up to 20 %) on machining time. The system is autonomic, intelligent, robust, user friendly, organized as distributed and it is not centrally controlled.

References

[1] M. Brezocnik, J. Balic, A genetic programming approach for modeling of self-organizing assembly systems, Proceedings of the IAD' 98, IFAC workshop, Bled, Slovenia, 1998.

[2] J.N. Holland, Adaptation in natural and artificial systems, University of Michigan, 1975.

[3] D.E. Goldberg, Genetic algorithms in search, optimization, and machine learning, Addison-Wesley, Reading, Massachusetts, 1989.

[4] M. Brezocnik, J. Balic, Comparison of genetic programming with genetic algorithm, Proceedings of the DMMI' 97, Portoroz, Slovenia, 1997.

[5] F. Čus, M. Milfelner, U. Župerl, Sodobne metode optimiranja v proizvodnih procesih, 21. znanstvena konferenca o razvoju organizacijskih ved, Portorož, Management in Evropska unija 2 (2002) 820-829.

[6] A. Levy, Artificial Life, New York: Pantheon, 1992.

[7] P. Gray, Alan Turing, Time 153 (1999)147-150.

[8] R. Kurzweil, The paradigms and paradoxes of intelligence, Pt 2: The Church-Turing thesis, Library Journal 117 (1992) 73-74.

[9] G. Renner, A. Ekárt, A. Genetic algorithms in computer aided design, Computer-Aided Design 35 (2003) 709-726.

[10] R. Rosso, R. Allen, S. Newman, Future issues for CAD/CAM and intelligent CNC manufacture, from www.staff.lboro.ac.uk 2004.

[11] T. Matsumura, T. Obikawa, T. Shirakashi, E. Usui, Autonomous turning operation planning with adaptive prediction of tool wear and surface-roughness, Journal of Manufacturing Systems 12 (1993) 253-262.

[12] M. Kadono, Tool path data generation apparatus for NC machine tool and numerical controller, provided with: Patent Nr. US2001/0000805 A1, 2001.

[13] M. Kovacic, J. Balic, Evolutionary programming of a CNC cutting machine, International journal of advanced manufacturing technology 22 (2003) 118-124.

[14] B. Abersek, J. Flasker, J. Balic, Expert system for designing and manufacturing of a gear box, Expert systems with applications 11 (1996) 397-405.

[15] J. Balic, B. Abersek, Model of an integrated intelligent design and manufacturing system, Journal of intelligent manufacturing 4 (1997) 263-270.

[16] J. Balic, M. Korosec, Intelligent tool path generation for milling of free surfaces using neural networks, International journal of machine tool and manufacture 42 (2002) 1171-1179.

[17] T. Kamioka, H. Mochizuki, Learning promotion method on tool and learning promotion type machine, Patent JP2001034155, 2001.

[18] K. Nemoto, M. Kyoichi, H. Yamaguchi, H. Sugimoto, H.; Hasegawa, NC data generation device and its method, Patent JP11242510, 1999.

[19] CJ. Chiou, YS. Lee, A machining potential field approach to tool path generation for multi-axis sculptured surface machining, Computer-Aided Design 34 (2002) 357-371.

[20] J. Steven, I. Liang, L. Rogelio, L. Heker, R. Landers, Machining process monitoring and control: the state-of-the-arte research, Proceedings of the IMECE 2002, ASME International mechanical Engineering Congress & Exposition, New Orleans, 2002.

[21] K. Meissner, Anwendung Genetischer Algorithmen zur Optimierung von Fertigungsprozessen, Proceedings of the 5th International DAAAM Symposium, Maribor, 1994.

[22] V. Tandon, H. El-Mounayri, H. Kishawy, NC end milling optimization using evolutionary computation, International journal of machine tool and manufacture 42 (2002) 595-605.

[23] K. Kato, T. Momochi, Numerical controller for machining tool with learning function - combines learning program with entered program to produce resulting processing, Patent DE4011591, 1998.

[24] J. Balic, CNC control unit with learning ability for machining centers, Patent SI 21200 A, Patent application US 2003/0187624A1, 2003.

[25] Y. Liu, L. Zuo, T. Cheng, C. Wang, Development of an open parallel intelligent CNC milling system: Part 1, System structure, International Journal of Advanced Manufacturing Technology 16 (2000) 537-541.
[26] Y, Liu, C. Wang, Neural network adaptive control and optimization in the milling process, International Journal of Advanced Manufacturing Technology 15 (1999) 791-795.
[27] I. Chang, J. Deng, S. Chan, A next generation machining system based on NC feature unit and real-time tool path generation, International Journal of Advanced Manufacturing Technology 16 (2000) 889-901.
[28] I. Drstvensek, M. Brezocnik, J. Balic, GA work operation determination based on feature recognition, Annals of DAAAM for 1999, Proceedings of the 10th International DAAAM Symposium, Vienna University of Technology, (1999) 129-130.
[29] I. Drstvensek, I. Pahole, J. Balic, A model of data flow in lower CIM levels, Journal of Materials Processing Technology 157-158 (2004) 123-130.
[30] I. Drstvensek, M. Brezocnik, CAP integration interface based on GA work determination operation, Proceedings of the 8th International Scientific Conference "Achievements in Mechanical and Materials Engineering" AMME'99, Gliwice-Rydzyna-Pawłowice-Rokosowo, Poland, (1999) 189-192.
[31] J. Balic, M. Kovacic, B. Vaupotic, Intelligent programming of CNC turning operations using genetic algorithm, Journal of Intelligent Manufacturing 17/3 (2006) 331-340.
[32] J. Balic, Model of automated computer aided NC machine tools programming. Journal of Achievements in Materials and Manufacturing Engineering 17 (2006) 309-312.
[33] J. Balic, Intelligent CAD/CAM systems for CNC programming - an overview. Advanced Product Engineering Management 1/1 (2006) 13-22.