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Intelligent automatic cutting-tool selections for turning operations

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Abstract
This paper introduces an intelligent system for selecting the best set of tools on the basis of a 3D CAD model and other relevant selection factors. An artificial intelligence method (neural networks) has been used for solving this complex classification problem. On the basis of the knowledge acquired during this process of learning, the system responds to new unknown examples in the manner nearest to the experience acquired during learning. This concept was used for the most widespread cutting process i.e. turning and the results reached are in conformity with expectations. The resulting solutions are comparable with the solutions given by experts. The system can be adapted for demand of practically users.

Keywords): *Cutting tools, Intelligent automatic selection, Intelligent systems, 3D CAD model, Neural networks.*

1. Introduction
Intensive technological development poses new and more demanding tasks for the economy again and again. Due to the increasing complexities of products, the need for higher exploitation, higher quality, and lower costs, production has changed very much over recent times [1]. Modern machine tools are highly demanding and highly automated. They require reliable system for generation of control data, monitoring and control of exploitation, constant modifications and modernization. They tend more and more towards complete autonomy.

The need for intelligent control system is expressed. Such system is shown on Figure 1. The system consists of common data base, processing module and input/output module with pre-processing and post-processing phase. The tasks of systems are: monitoring, collection of machining data, optimization of cutting procedures, DNC, CNC programming and collaboration with outside "world".

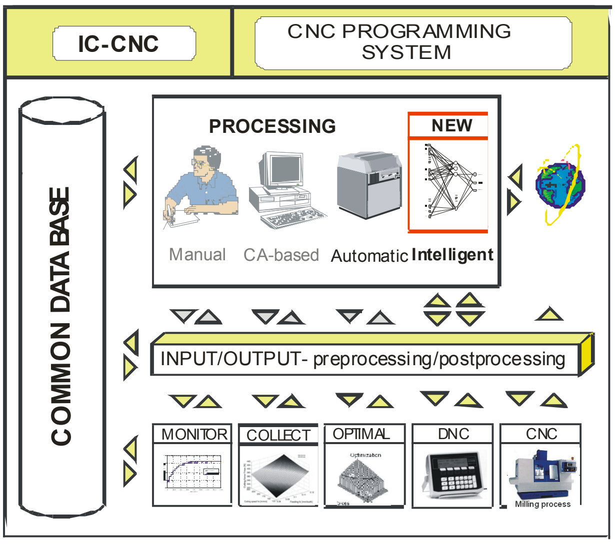

Figure 1. Intelligent system for CNC machining data generation

The selection of cutting conditions, cutting tools and optimization poses certain problems for which efficient and appropriate measures are necessary. Various systems for the automated selection of cutting tools have been developed, but they have never completely replaced the human (skilled

worker). Today's systems are using decision tables and decision trees for the automatic selection of cutting tools. The use of such systems is inflexible and inappropriate for today's manufacturing. In such systems the user's requirements must be completely defined, otherwise the design is incomplete and subject to errors. This knowledge is inaccessible, hard to understand, and extremely hard to modify without major changes to the programme. Therefore, it is difficult to adapt them to the specific needs of a company.
The complex intelligent system for optimization of machining (turning) using neural networks and genetic algorithms has been developed (Figure 2). Input information is CAD model of the component and the task is completely automatic optimum cutting tool selection and optimization of tool path (CNC programme) without any interference of the human into the system.

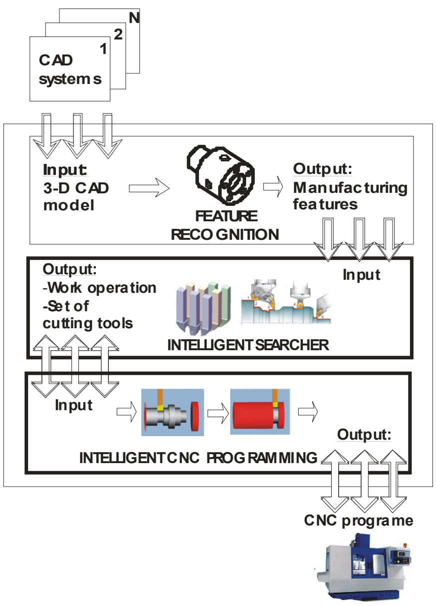

Figure 2: System structure of selection, optimization and programming

Intelligent CNC programming module has two main tasks:

- searching for space of possible solutions for CNC programme (GA driven), to avoid local maximum and
- optimization of tool path (NN driven) for searching for global maximum (optimal solution).

Paper is organize in 8 chapters, including introduction, state of the art, presentation of new intelligent system, structure of the model, case study, conclusion and references.

2. State of the art

It has been proved that hitherto research and findings in the area of using artificial intelligence techniques in modern manufacturing systems have strongly contributed to an improvement in the necessary flexibility and efficiency required by modern manufacturing systems. Over recent years, neural networks and genetic algorithms has manifested a high potential for solving complex classification problems in the area of manufacturing systems [2].
In the early 1980's, research started in the area of tool or tool-set selection regarding certain operation or group of operations. The first attempts at automatic tool selection were modules using graphics and offering a catalogue of available cutting tools to the user [3], [4]. A higher-level of automation was proposed by Sanni [5]. In addition to the geometrical features, Vogel and Adlard [6] also included certain preferential tool criteria into tool-selection and added a new degree of automation. A further step-forward in automatic cutting-tool selection was made by Arezoo [7], who not only presented a system which found all the combinations of tool sets geometrically able to work a component, but also automatically selected the best tool set from the costs point of view. Similar modules using minimum operating-cost criteria for tool selection were also presented by certain authors [8], [9], [10].
The objective of cutting-tool selection in widespread cutting process-turning is to select the best tool holders and cutting inserts from the available cutting tool data bases. To this end, computer-aided tool-selection systems have been developed. In their model, Plummer and Hannam [11] considered the workpiece material and its profiled geometry. Giusti et al. [12] developed an expert module for tool-selection during turning operations. Chen et al. [13] developed an automatic tool-selection system for rough-turning on the CNC turning lathe. Chen and Hinduja [14] used the tool-selection process in order to check any tool-collision with the workpiece or machine during machining of the workpiece. Hinduja and Huang [15] performed research called OPPLAN in which they assumed that only one tool is used for the machining of slots and grooves. Maropoulos' and Hinduja's [16] system for tool balancing regulates the selected tools for working certain components on the turning centre, and optimizes tool-change strategy on the basis of manufacturing costs. Domazet [17] used a hybrid approach. Matos and Mesquita [18] focused on those combinatorial problems posed by tool-

selection for external turning operations. Kirana and Vineshe [19] developed a system method for selecting an ideal tool-set for a certain part, which could be integrated into process-planning systems. Fernandes and Raja [20] performed a tool-selection process for external and internal turning, but they only considered the operations of cylindrical and face-turning. Edalew et al. [21] developed a system that operated completely interactively and for information relating to the individual object such as, for example, the part's status, and the ordering of features and component materials to be included in the system. In their paper Mookherjee and Bhattacharyya [22] showed how manual searching can be replaced by an expert system which automatically selects the tool and/or cutting insert for turning, and the material and geometry, based on the client's requirements. Wang et al. [23] presented a new methodology covering the use of genetic algorithms for the selection of optimum cutting conditions and cutting-tools during turning operations with several tool passes, on the basis of extensive optimization criteria.

Automatic intelligent programming of machine tools was done in previous research by Ficko et al. [24], Balic et al. [25], [26]. This research leads to development of new CNC control unit with learning ability for machining centers [27].

Intelligent programming methods are very important in modeling of manufacturing systems, especially in Flexible manufacturing [28], [29].

By extensive examination of technical literature, it was discovered that a system for intelligent autonomous cutting-tool selection for turning operations, has not yet been developed.

3. Presentation of intelligent system

Proposed intelligent system is so conceived that it can select the most optimal cutting tool set on the basis of a 3D CAD model, and important selection parameters independently of human interference in the system. The system generate tool path for turning operations and it is capable of learning in order to work intelligently. However, learning only is insufficient. To be capable to learn at all, the system must have certain capabilities, such as sufficient memory capacities, concluding capacity (processor capacities), detecting capacities (input and output) etc. Further training requires some initial knowledge which is inherent in living systems. By training, the system's capacity is enhanced and its intelligence increased [30]. The neural networks used by described system have such capacities.

The system works in several stages (Figure 3) which cover the preparation of the 3D CAD model, the stock, the workpiece for rough-turning and the workpiece for finish-turning representing the final products, which are automatically formed. The recognition of features for roughing and finishing is also part of the system.

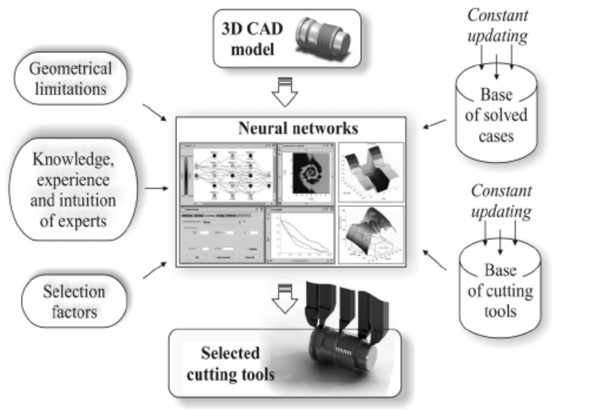

Figure 3. Tasks of the system for intelligent cutting tool selection

4. Structure of the model

Figure 4 shows the sequence of the individual steps executed for solving the problem.

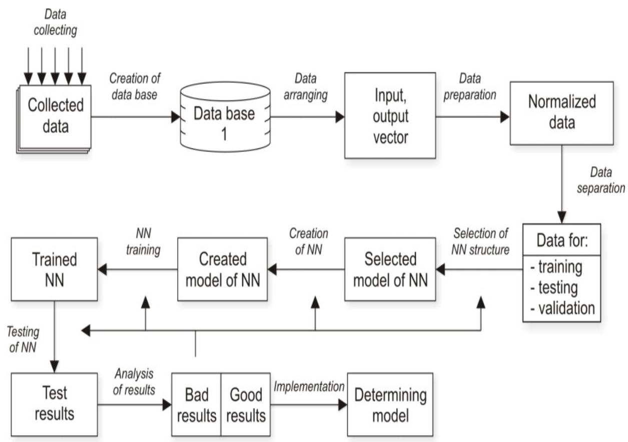

Figure 4: Model creation process

4.1 Data collection

The training data are of vital importance for the building of a neural network model. On this basis the model learns, and then successfully solves new tasks. According to expert judgements and theoretical facts, the workpiece geometrical features, workpiece material, and required surface quality were selected as the key data influencing cutting-tool selection during the training process. The necessary training data for designing the neural network model were obtained on the basis of solved problems which are important source of knowledge. Geometrical features data from different workpieces (200 in total) were collected.

A data-base is created for the purpose of neural network training. It consist of four units, ach unit contains the relationships between the geometrical features, workpiece material, quality of the required surface, and other selection parameters on the one hand, and between the cutting tools on the other. Figure 5 shows the limitations on the approach and/or exit angle on the workpiece for one of the cutting tools in turning.

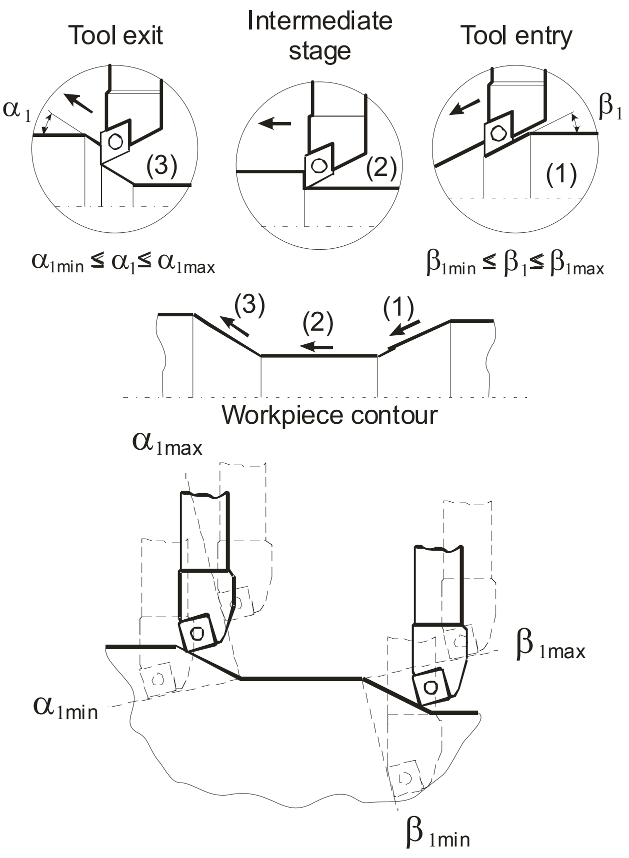

Figure 5. Tool entry and exit and max. and/or min. approach and/or exit angle on workpiece

5. Case study

This section presents the functioning and efficiency of the system. After training and testing, four neural networks are ready to be applied to the real environment. The workpiece (3D CAD model) should be suitable for the external turning operation.

The selection of adequate cutting-tools for a product's manufacture requires familiarization with all the product's geometrical properties. The turning process is usually carried out in two stages, rough and finish-turning, the geometrical features must be known for the final product as well as for the semi-finished product. Thus, the semi-finished product, obtained after rough-turning, and the stock required for the manufacture of such a product were automatically created from the basic 3D CAD model simultaneously representing the final product and/or containing the geometrical features for finish turning (Figure 6).

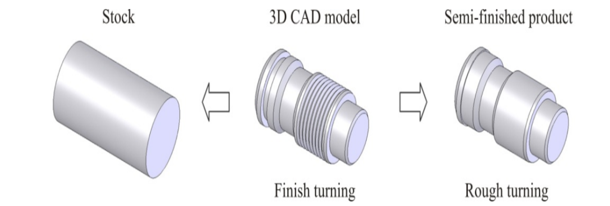

Figure 6. Automatic creation of stock and semi-finished products

On the 3D CAD models the individual geometrical features of which they consist could be included. In presented case, the specific geometrical features and/or higher geometrical elements defined by means of the API interface are needed. The case study is limited to external-turning because of clarity and complexity, but the system ensures a simple inclusion of internal-turning, and other specific turning methods, too. The geometrical features needed for the system are located in two-dimensional cross-sections of 3D CAD models. The tool-geometry determines which workpiece part can be worked with that tool and what cannot be manufactured. Consequently, only a certain type of cutting-tool can be used for the manufacture of a certain shape of workpiece. Thus the feature recognition covered those features determining the approach and/or exit angle (Figure 5). On the cutting-tool, this limitation is determined by the tool's cutting-edge angle and the nose angle. Thus, the outline of the half cross-section of the product for finish-machining is the tool path for finish machining, while the outline of the semi-finished product is the path for rough-machining (Figure 7).

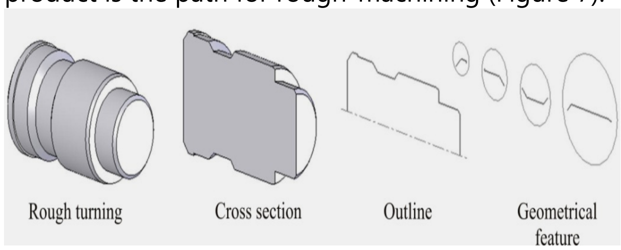

Figure 7. Geometrical features of semi-finished product

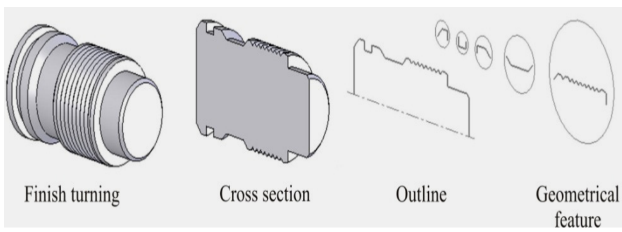

Figure 8: Geometrical features of final product

As geometrical features determining the possibility of the cutting-tool entry and exit are the key feature, an algorithm for recognizing such geometrical features and/or higher geometrical elements was created (Figure 7 and Figure 8).

The recognized geometrical features, the required surface quality and the material are also collected in Excel tables. The data are automatically normalized and transformed into suitable record for entering into neural networks. On the basis of these data the neural networks select suitable cutting-tool sets for rough and finish-turning, and determines the optimum sequence. The outputs of the first neural-network are the possible tools for rough-turning (Figure 9) and the outputs from the second-neural network are the cutting tools for finish-turning (Figure 10).

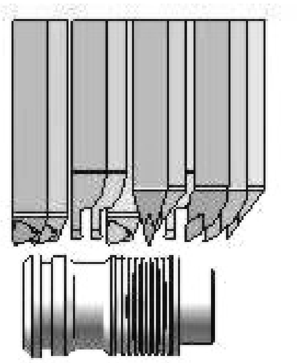

Figure 9. Selection of all possible tools

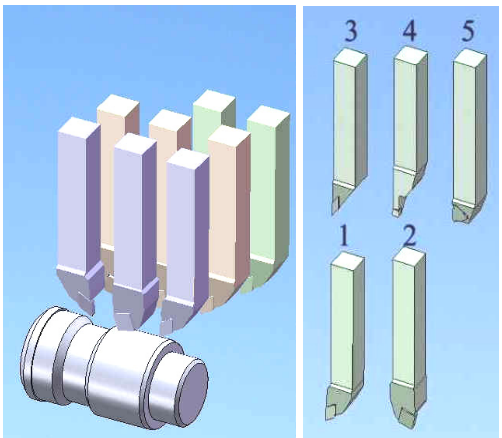

Figure 10: Tool selection (left) and optimized set (right)

The obtained results represent all cutting tool sets from the cutting tools data base which can machine the workpiece for roughing and for finishing operation. These results with appurtenant geometrical features are entered into the third and fourth neural networks by classifying the most optimal tool set.

Optimal tool set is input in the GA based intelligent CNC programming system. The task of this system is to generate tool path for turning operation. The basic idea of the proposed concept system is sown of Figure 11. Blank, product and the relevant chips are discretized into squares. The tool of one square thickness in turning can move discretely up, down, left and right, whereas it cuts only to left or downwards. The material to be taken off is divided into several cuts consisting of chips. For example, the *cut-1* in the bottom of Figure 10 consists of 9 chips, the *cut-2* and the *cut-3* consist of 4 chips each, the *cut-4* of 2 chips etc.

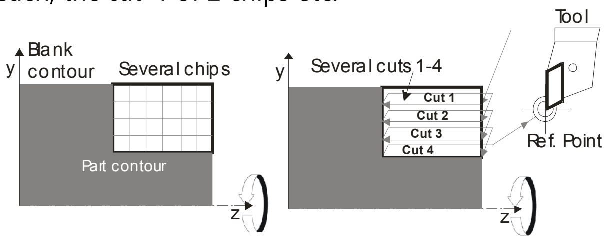

Figure 11. Representation of GA based CNC programming

Each set of cuts undergoing GA based procedure, which is representing in pseudo code on Figure 12.

```
begin
   check_consistence every_step
   check_collision every_step
   move from start_point to first_cutting_of_first_cut
   cut first_cut while cuttings_of_first_cut_consist
   for i=2 to i=number_of_cuts do
         begin
              while (not next_consistent_cut)
                   select next_consistent_cut
              move
                   from
                   last_consistent_cutting_of_
                   last_consistent_cut
                   to
                   first_consistent_cutting_of_
                   next_consistent_cut
              while cuttings_of_next_consistent_cut_consist
                   cut next_consistent_cut
         end
   move
         from
         last_consistent_cutting_of_last_consistent_cut
         to
         finish_point
   print
     collision_number, NC_program, NC_program_length
end
```

Figure 12: GA procedure evaluation in pseudo code

The results (cutting tool path on Figure 13) were compared with the selection of the expert who indicated two identical sets of optimum tools. It can be concluded that the system is capable of classifying intelligently the most adequate cutting-tool set similarly as an expert with 20 years of experience, can whilst it learns and expresses some degree of intelligence.

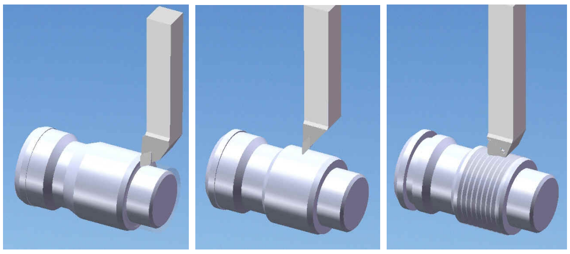

Figure 13. Generated cutting tool path

6. Conclusion

This research shows the integration of artificial intelligence into the production process. Neural networks have been used for classification of the most adequate cutting-tool. Thus, the necessary flexibility and efficiency required by modern manufacturing systems have been improved. Reconfigurability has been improved, flexibility, speed and accuracy have been increased, and full autonomy has been reached.

It can be established that the integration of neural networks in the process of searching for the most suitable tools is been a very good method. A very high-level of classification was reached. Each newly-solved example is stored in the base so that the networks permanently learn and gain knowledge and experience similar to the human expert. Conventional programming has been replaced with the use of neural networks by learning with examples, characteristic of which is the adaptiveness. Such system functions are flexibly and fully autonomous. Thus, the disadvantages of the systems used hitherto for the automatic selection of cutting tools can be avoided.

A disadvantage of such a system is the time-consuming creation of the cutting tool data base with appurtenant geometrical features, and the requirement for good familiarization with the cutting-theory. It would be appropriate to orient future research towards the design of an improved system for other turning operations, such as internal-turning and special-turning processes, with any geometrical features, selection factors, and searching for appurtenant cutting tools, with the capacity of data pumping out of the tool maker's cutting tool data base.

7. Denotation

3D - three dimension
CAD - Computer-Aided Design
CNC - Compute Numerical Control
DNC - Direct Numerical Control
GA - Genetic Algorithm
NN - Neural network

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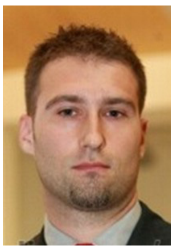

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