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# Prediction of total manufacturing costs for stamping tool on the basis of CAD-model of finished product

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**Abstract**

One of the orientations of the tool-making industry is towards shortening the time from enquiry to the supply of tools. The tool-making shops must prepare within the shortest possible time an offer for the manufacturer of the tool based on the enquiry in the form of the CAD-model of the final product. For preparation of a proper offer, the values of certain technological features occurring in the manufacture of the tool are needed. Most frequently the tool manufacturer is interested in total cost for manufacture of the tool. Because of lack of time for making a detailed analysis the total costs of tool manufacture are predicted by the expert on the basis of the experience gathered during several years of work in this area. In our work, we conceived an intelligent system for predicting of total cost of the tool manufacture. We limited ourselves to tools for manufacture of sheet metal products by stamping; the system is based on the concept of case-based reasoning. On the basis of target and source cases, the system prepares the prediction of costs. The target case is the CAD-model in whose costs we are interested, whereas the source cases are the CAD-model of products, for which the tools had already been made, and the relevant total costs are known. The system first abstracts from CAD-models the geometrical features, and then it calculates the similarities between the source cases and target case. Then the most similar cases are used for preparation of prediction by genetic programming method. The genetic programming method provides the model connecting the individual geometrical features with total costs searched for. In the experimental work, we made a system adapted for predicting of tool costs used for tool manufacture on the basis of a theoretic model. The results show that the quality of predictions made by the intelligent system is comparable to the quality assured by the experienced expert.


*Keywords:* Prediction of costs; Tool-making; Stamping; CAD-model; Intelligent systems; Genetic programming

## 1. Introduction

In today's industry, where the costs play a very important role, the sheet metal products have replaced many products made by casting or forging. They have replaced also many complex composed products. The sheet metal products have become popular also due to low price, accuracy of dimensions, durability and favourable physical properties. Today, when new products appear on market within shorter time intervals and the development times are shorter, the branch of industry busy with tool manufacture assumes a vital role. The buyers of tools have a worked out idea about finished product, whereas the toolmakers are responsible for the tool design, preparation of the manufacturing technology and final manufacture of the tool.

The capacity of the tool-making shop to respond quickly to the enquiry is an important factor of competitivity. On the basis of the enquiry, it must obtain the answer to the following questions within the shortest possible time:

- Are we in a position to make the tool for the product concerned?
- Do we have the means for the manufacture of that tool?
- How much time do we need to be able to make the tool?
- How much the tool will cost?

The answers to the first two questions are rather trivial; if the company does not know the answers to these two questions it is probably better for it not to undertake the order at all. As the matter of fact the answers to these two questions are the result of cooperation between designers and technologist and depend on the state of skills and resources in the company [5]. The answer to the third question is very important

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particularly in the tool-making activities since adhering to the delivery times is one of the most important factors of success. However, it is often difficult to answer that question, since the answer depends on a variety of interconnected factors [12]. In the process of agreeing the toolmakers usually do not have the chance to determine the tool manufacturing times since they are specified by the clients. The tool-making shop must answer like this: “The delivery times can/cannot be met.” The answer to the fourth question, too, is very important, since only if it is precise, on the one hand the preparation of a competitive offer is possible and, on the other hand, undertaking jobs, bringing loss, is avoided. The tool price is limited upwards and downwards since the toolmakers cannot afford additional reserves in price because if the price is too high it is not competitive on the market and the order is not awarded. Contrarily, if the price is too low it brings loss to the company, which is not to the interest of the toolmaker.

In the stage prior to undertaking an order the tool-making shop is busy with the problem of specifying the technological features of tool. It has available scarce, usually only geometrical and physical information about the final product on the basis of which it must prepare its offer. The tool manufacture is a complex process including a variety of personnel, machines and technologies. Therefore, specifying the technological features, including the manufacturing costs, poses a serious problem. In addition, this activity is very time-limited. The output of this activity is of key importance for securing an order and for the business success of the order secured. The total costs increased for the expected profit are an important piece of information the company needs for negotiations with the tool buyer. The tool manufacturing costs can be rather precisely analytically determined, but analyses require additional time and cause additional costs. The toolmakers can afford none of these. In answer to the enquiry the offer must be prepared fastest possible, possibly within a few hours, but not later than in a few days – those times are specified by the client. However, the toolmakers try to avoid the additional costs of preparation of the offer which may not bring a new order at all.

It can be claimed that the problem of prediction of the total manufacturing costs has not been satisfactorily solved. Prediction relies too much on subjective influences of the expert. It is evident that the described problem needs a better solution. A system is needed in the offering stage to be able to determine the tool manufacture costs directly from the CAD-model of the finished product fastly and without the necessary expert knowledge.

This paper comprises five sections. Section 1 presents the problems of the tool-making industry occurring in preparation of the order. Section 2 describes how today the cost prediction is effected in tool-making companies. Here, the cost determination methods known are discussed. Section 3 presents the model of the intelligent system for cost prediction. Sections 3.1–3.7 explain the individual components and working principles of that system. Section 4 deals with the use of the presented system on a concrete problem and with the test results of the system. In Section 5, the results are discussed and the guidelines for future researches indicated.

## 2. Present situation

Although many methods of prediction of the tool manufacturing costs have been developed, the intuitive cost prediction is most frequently used for the reasons stated in the introduction. It means that for prediction of the manufacturing costs toolmakers use particularly their experience acquired in manufacture of similar tools. That experience is gathered in the form of expert knowledge of the employees. Thus the offers are prepared by experts, well familiarized with the tool manufacture, in cooperation with tool designers and tool manufacturing method engineers. The expert works out the prediction on the basis of the product CAD-model observation and the scarce additional information. In a not quite clarified manner he relates the shape and the size with costs. Consequently the quality of the price thus obtained depends on subjective factors. Subjective human judgement has the predominant role in predicting the greatest share of costs.

### *2.1. Tool manufacturing costs*

The manufacturing costs are divided into the costs of materials, work, cooperation, design, manufacture, tests, measurements and transport. While some of these costs have the nature of fixed costs incurred in the manufacture of different tools of approximately same size, other costs can occur depending on the size and shape of finished product. Usually, fixed costs are simple to determine, whereas variable costs as a rule depend very much on the tool features. Out of the total costs the costs of work represent approximately one-half of all costs, therefore, for prediction of total costs it is of utmost importance to predict the required number of man-hours as accurately as possible. The work costs are all cost related to mechanical and manual work. They are expressed as work hours required for execution of the order and cost price of 1 h of work.

### *2.2. Cost prediction methods*

Most researches are concerned about the cost determination after finished manufacture and less about the cost prediction. Wierda [15] has divided the cost prediction methods into the global cost prediction and detailed cost prediction. The global and detailed cost prediction methods differ in speed, quantity of required information, costs and areas of use. The global cost prediction methods are useful in early determination of costs and where no time and means are available for determination of costs. Contrarily, the detailed cost prediction methods are useful in the precise cost analysis of the finished product.

When predicting the costs in early stages of product development we have to do with insufficient information about

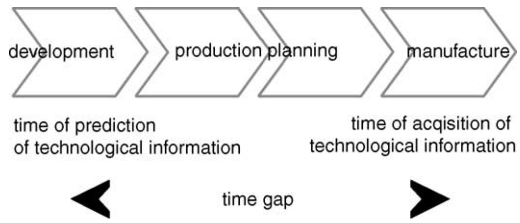


Fig. 1. Time gap between times of prediction and acquisition of technological information.

product and manufacturing technology. The methods differ particularly in volume of information they require. In early development stages considerably less technological information is available than later on when the product has been finished. Fig. 1 shows the gap between the time of prediction and the time of acquisition of technological information. Therefore in early development stages, in particularly the methods, requiring less information, are useful. These methods are mainly based on the expert's intuition and establishing of similarities. Later on in the development cycle the analog and parametric methods, often combined, are useful.

Therefore, different approximate methods of cost prediction have been developed [3]:

- Intuitive methods, based exclusively on the expert's capabilities;
- Analog methods, costs are evaluated on the basis of similarity with other products;
- Parametric methods, costs are evaluated on the basis of the product characteristics which are in the form of parameters (influencing factors);
- Analytical methods, costs are evaluated on the basis of the sum of the individual planned costs.

None of the above methods is appropriate in all stages of the development cycle. They differ in the requirements and area of use.

Fig. 2 shows the areas of the use of the cost prediction methods per product development cycle. It can be seen that intuitive methods are useful in early development stages. The intuitive cost prediction cannot be identified as method, since it is usually not result of planned work and does not comprise a procedure. Such prediction method does not require special preparation and is not demanding with respect to time and cost, but it is unreliable and needs a qualified expert.

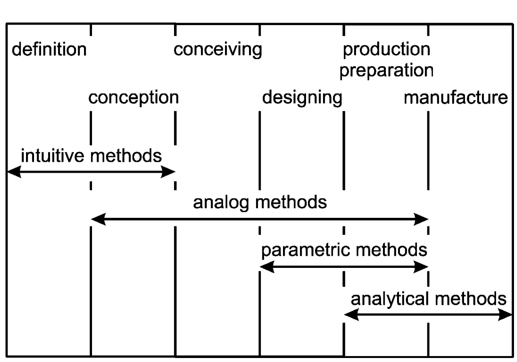


Fig. 2. Area of use of cost prediction methods (adopted from Ref. [3]).

Like the intuitive methods the other methods use the cost predictor's – expert's intuition to a large extent, but they are most frequently based on analytical work. Analog methods are useful since the time when approximate product dimensions and shape are known, however, they, too, are very unreliable just like the intuitive methods. They are based on the identification of similarity to other products or product parts for which the manufacturing technology and, consequently, the costs are known. Case-based reasoning is one of promising analog cost prediction methods [9]. In the stage of adapting the existing solution to a new case it uses the combination of different methods.

Parametric methods treat the product manufacture as a black box, i.e., they do not deal with the manufacturing technology but they try to parametrize the input data and relate them to cost into functional dependence. Those methods are very successful in combination with analog methods. The parametric methods use known physical values of product such as mass, volume and dimensions. They relate the technical characteristics of the product to the economic characteristics and apply only within one class of products. It is a great advantage that the functional dependence expressed with technical parameters ensures a clear insight into how the individual technical parameters influence the costs. Many difficulties occur in selecting the parameters and the form of function.

Analytical methods require much means and time, since in case of them the manufacturing technology is worked out and then the costs are predicted on the basis of the anticipated technology. They are based on analytically determined facts. However in case of these methods prediction is hardly concerned; as a matter of fact, the costs are analyzed. They predict the costs on the basis of a breakdown of the product manufacturing process into tasks and component parts [4]. Total costs are then calculated as the sum of cost of work and material. Actually, before a new product appears on market, the manufacturing costs and price are determined on basis of that method [6]. The use of the method gives accurate results, however detailed data on the product and the manufacturing technology are needed.

## 3. Model of intelligent system for prediction of tool manufacturing costs

It has been established that the toolmakers most frequently use the intuitive prediction of total manufacturing costs. Such cost prediction is used since it is not demanding with respect to time and cost. However, this approach is today obsolete and the problem requires a better solution. It is interesting that the cost prediction for the needs of preparation of offers in the customer multi-project environment has not yet been better solved, particularly if the importance of this activity from economic point of view is taken into account.

The cost prediction methods, enumerated in the previous section, do not regard the type of product. However, all the methods enumerated are not adequate in tool-making, but only those meeting the specific requirements of the tool-making industry for very fast and precise predictions. In the business environment of the toolmakers only the analog and parametric methods are applicable and in no way the analytical ones.

In all methods developed so far, difficulties are met, which have not yet been satisfactorily solved. Associations between geometrical information and tool manufacturing costs practically cannot be covered by deterministic methods. Therefore for the determination of dependence between the geometric features and the manufacturing costs the artificial intelligence methods have been used. By using these methods we have tried to avoid difficulties arising in describing the complex system by deterministic rules. We have conceived an intelligent system using the principle of operation of the analog and parametric methods. Thus the hybrid model of the case-based reasoning concept using the genetic programming method for reasoning has been formed.

The so-called intelligent system is similar to the natural intelligent system, i.e., expert. Like the expert the system has the memory structured in the form of relation database. While the expert uses his intelligence for reasoning, the artificial system uses genetic programming method.

### 3.1. Case-based reasoning

The case-based reasoning concept has been in use since mid-1980s. It is based on the findings in psychology and adopts one of the problem-solving ways used by experts. Researchers in artificial intelligence have found out that this concept ensures working out of intelligent systems which are useful and non-exacting at a time [8]. As a matter of fact, this is one of the most universal manners of problem solving, used frequently by the human in his work. It uses the recognizing way to modelling and explaining the human approach to solving the problems in the areas where experience has a very important role [14].

In case-based reasoning it is assumed that interconnections between the descriptions of problems can be found. The knowledge about the area is saved in the form of cases similarly as the knowledge owned by the expert and not in the form of deterministic knowledge. The case is defined as the record of the problem and of its situation. It can be presented in the form of vector or as a complex composed object [1]. The target case is the description of the problem whose solution is searched for, whereas the source case is the description of the problem with known solution.

Fig. 3 shows the terminology and the principle of operation of the case-based reasoning applied to the problem being solved.

In our case, in the stage of adoption of solution the system uses the parametric method. The parametric dependence is obtained by the genetic programming method. The result is

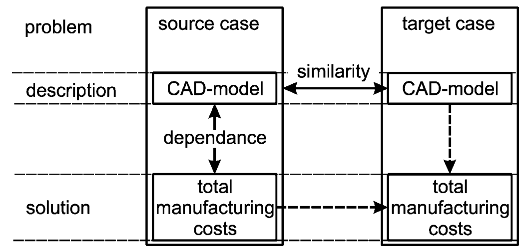


Fig. 3. Principle of working of case-based reasoning.

the formula containing parameterized geometrical features of the finished product as variables.

### 3.2. Description of model

The model is built on the basis of the improved model of the global cost prediction and the case-based reasoning concept. For preparing the prediction it uses the following steps:

- Collecting the geometrical and technological information in the computer database.
- Abstracting the geometrical features from the target case (CAD-model of product).
- Selecting the most similar cases (source cases) from the database.
- Working out the formula for cost prediction.
- Use of formula preparing the prediction.

Source cases are necessary for the use of case-based reasoning. Therefore, geometrical and technological information must be collected in the company. It is saved in the database as logically connected geometrical and technological information about the individual cases. Selection of the source cases most similar to the observed case facilitates searching for the dependence and preparation of the formula and ensures higher precision of the prediction. In the next step, the parametric dependence is prepared by system for genetic programming. In the last step the resulting parametric dependence is used like in the case of ordinary parametric method.

The worked out model of the intelligent system for cost prediction contains:

- Subsystem for collection of technological data;
- Subsystem for abstracting geometrical features;
- Subsystem for determination of similarity;
- Reasoning subsystem;
- Subsystem for use.

As soon as the system has obtained a new case, i.e., the problem description in the form of CAD-model for which it must predict the value of cost, it must bring it into the form which the system understands. We must be aware that by today's artificial intelligence it is impossible to treat the entire product model as perceived by the human. However, even the experts do not have in memory the complete information about the product but only the most important parts and summaries. The system first abstracts the geometrical features from the CAD-model. Most frequently, this means that the system isolates the physical properties, the quantity description of the product and the geometrical features from the CAD-model. Geometrical description of the product at the level of geometrical features is the most appropriate because in the individual geometrical features also the technological data significantly influencing the cost are hidden. Example: geometrical feature – hole in the stamped products requires a punch in the tool to make that hole. The output of abstraction of the CAD-model is a record of the problem in vector form. The individual features are comprised parametrically as components of that vector. In the next step, the similarity of the target case against other cases saved in the database is calculated. The similarity is calculated as the distance between the final points of vectors in the vector space. The greater the distance, the smaller the similarity between the two products. In the further step, those most similar cases, which are then the input into the reasoning subsystem, are chosen. For isolation of those most similar cases the absolute or relative criterion can be used. Those isolated cases are the source cases for reasoning about the solution of the target case.

For reasoning about the solution on the basis of similar cases the reasoning subsystem uses the artificial intelligence method genetic programming. The genetic programming method forms the solution in accordance with evolutionary principles. Here the source case components are the programme terminals. For evaluation of the solution the system needs the value of costs the solutions of the most similar cases, therefore, in this step it transfers them from the database. The output of this subsystem is the dependence between geometrical features and costs, expressed by formula. The task of the subsystem for use is to apply that formula to the target case.

Fig. 4 shows operation of our model through case-based cycle.

### 3.3. Abstraction of CAD-model

For cost prediction much information, contained in the CAD-model, is excessive. This is the information having no influence on the manufacturing costs or having insignificant influence. It must be isolated not to hinder establishing of similarities and reasoning about solution. By abstracting the precise numerical descriptions in the form of CAD-model is reduced to the only one vector. That vector is called the case vector:

$$\vec{v}_p = \{g_1, g_2, g_3, \ldots, g_i, \ldots, g_n\} \tag{1}$$

The vector components from $g_1$ to $g_n$ are parametrically comprised individual geometrical features; however, the vector can contain also the known technological features and auxiliary data. Thus $g_1$ can be the thickness of sheet metal, $g_2$ the number of surfaces, etc. When selecting the vector components utmost attention is required, since it is desirable to describe the product with smallest possible number of components, i.e., as adequately as possible. We must be aware that the case vector is only a summary of presentation of the CAD-model and does not present the product completely.

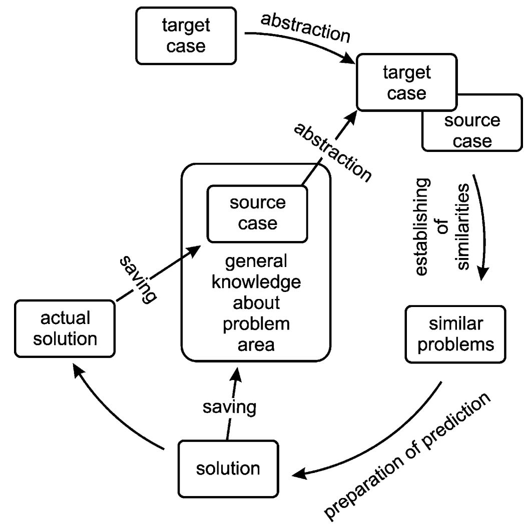


Fig. 4. Case-based reasoning cycle in predicting total costs.

### 3.4. Similarities of cases

As the system of intelligent cost prediction imitates the natural intelligent system – i.e. the human – the similarity, having the same meaning as in the everyday conversation, is introduced. Similarity is calculated on the basis of case vectors. The target case vector is compared with all vectors of source cases. Similarity is defined as the distance between the two final points of vectors. The smaller the distance is, the more the two products are similar.

$v_{cp}$ designates the target vector and $v_{pi}$ the vector of the source case $i$. Similarity $P_i$ between the vectors $v_{cp}$ and $v_{pi}$, or between the abstracted target and source case is equal to absolute value of difference between two vectors:

$$P_i = |\vec{v}_{cp} - \vec{v}_{pi}| \tag{2}$$

However, the similarity thus calculated is not a good enough criterion of similarity since the vector component have different value extents. Therefore when calculating the similarity $P$ all components must be normalized. When normalizing the components, the importance of the individual components or geometrical features can be considered. Therefore each component is multiplied by the normalization multiplier $d_j$, which can increase or decrease the influence of the individual component on the value of similarity. Multiplier $d_j$ is

$$d_j = \begin{cases} r_j \cdot \frac{1}{g_{cj}}, & g_{cj} \neq 0 \\ 0, & g_{cj} = 0 \end{cases} \tag{3}$$

The multiplier of influence of component $r_j$ can assume the values on the interval from 0 to 1.

Similarity between the vectors of products is equal to:

$$P_{in} = \sqrt{\frac{1}{n} \cdot \sum_{j=1}^{n} d_j \cdot (g_{cj} - g_{pij})^2} \tag{4}$$

The similarity determined in this way has a value between 0 and 1. Here, lower value of $P_{in}$ means greater similarity.

### 3.5. Selection of the most similar source cases

Selection of the most similar cases is intended to increase the quality of the formula obtained by the genetic programming system. The formula applicable only for similar cases will be much easier to obtain than the universal formula. Usually, it will contain fewer terminals and will be more precise. When speaking about the most similar cases the cases are meant which are not equally similar all of them but they are ranked on the top of the scale of similar cases. For forming the formula by genetic programming method more cases are urgently needed.

### 3.6. Genetic programming

In the reasoning part of our system the genetic programming methods is used. In this environment, this method of evolutionary computation proves to be excellent. Together with preparation of input data on the basis of determination of similarity this method has proved to be efficient.

The idea of evolutionary computation was presented in 1960 by Rechenberg in his work "Evolutionary strategies" [13]. His work was then pursued by other researchers. Thus in 1975 Holland developed genetic algorithms [7], and some 15 years later Koza developed still the genetic programming [11]. In these methods the evolution is used as an optimization process in which the organisms become increasingly adapted to environment in which they live [10]. Two main characteristics of evolutionary methods are that they do not search for the solution in the ways determined in advance (deterministic) and that they simultaneously treat a variety of simple objects [2]. Structural solution is left to the evolutionary process. Because of the probabilistic nature of the evolutionary computation methods there is no guarantee that each evolution arrives at a satisfactory result.

In any evolutionary method we have to do with structures subject to adaptation. In conventional genetic algorithms and genetic programming a population of points is subject to adaptation in search space. In genetic programming hierarchically structured computer programmes are subject to adaptation [11]. The set of possible solutions in genetic programming is the set of all possible combinations of functions which can be composed in recursive way from the set of functions and from the set of terminals.

Solving of the problem starts with creation of a random population of solutions. In our case the solution is the formula for calculation of costs. This initial collection of problem solutions, which is usually created at random, is left to evolution. Each individual organism represents solution of the problem. Then the organisms are evaluated and greater probability of taking part in operations of selection and changes is assigned to those organisms which better solve a certain problem. By genetic operations of crossover, mutation and reproduction better and better solutions are then gradually approached from generation to generation. Reproduction is the basic way of continuation of a species of living organisms. Mutation is the component of evolution bringing novelties. Competition and selection are two processes always repeating where several organisms have available limited quantities of resources. Selection assures the survival of more successful members of the population and their passage in unchanged form into the next population. Changes influence one or several organisms and create the descendants from them. Selection results in a new generation which, again, is evaluated. The procedure is requested until the establishment criterion of the process has been fulfilled. This can be the greatest prescribed number of generations or the sufficient quality of solutions.

### 3.7. Preparation and use of formula

Because of the nature of genetic programming, preparation of a high-quality formula requires a high number of vectors of source cases, which actually means much source cases. In practice this condition is hard to meet. Only rarely a great number of very similar cases are available. Further, the case vector contains too many components. Many components mean many variables in formula and, of course, many terminals in the tree-like structure of the organisms. Together with the number of terminals also the computation exactingness increases. Preparation of the formula by genetic programming, containing many terminals and operators, is not rational with the computation power available today.

For these reasons the number of components of the case vectors must be reduced. Another abstraction is affected, but now the case vectors are abstracted in order to reduce the number of components. For reducing the number of components the following approaches are used:

- Components only slightly influencing the costs are isolated;
- Doubled components, i.e., components containing identical information are isolated;
- Computation operations between two or more components are carried out by uniting the information into one component.

Vectors of case $v_{ip}$, having the extent of size $n$ are transformed into converted vectors of $m$ scope:

$$\vec{v}_{ipk} \rightarrow \vec{v}\,'_{ipk} \tag{5}$$

where $v'_{ipk}$ is the transformed source vector of case $k$.

For the reasoning subsystem for the genetic programming method the input data are prepared in the form of a list of converted source vectors of cases with added values of costs and/or solutions. Now the input data for the reasoning subsystem have been prepared, the latter has yet to be set. For the reasoning subsystem the application for determining multiparametric function on the basis of known cases, written in programme language AutoLISP, has been used.

Solving by genetic programming is affected in the following steps:

- Determination of set of terminals; terminals are the components of the transformed case vectors and the real numbers created at random.
- Determination of set of basic functions; these are in particular the basic mathematical functions.
- Insertion of cases for calculation of adaptation; the cases are the lists of converted source case vectors.
- Determination of parameters of evolution; the evolution parameters are the number of organisms in the population, the maximum depth in crossover, the maximum depth in creation.
- Determination of criterion for stopping the evolution; for stopping of evolution the number of evaluated evolutions has been selected.

The output of reasoning subsystem is the functional dependence between components of the converted vector of the target case and costs. $t_c$ designates the solution of the target case, i.e. the solution of problem:

$$t_c = f(\vec{v}_c) = f(g_{c1}, g_{c2}, g_{c3}, \ldots, g_{cj}, \ldots, g_{cm}) \tag{6}$$

After having the functional dependence in hand, it must only be used. Then the components of the transformed target vector are inserted and thus the costs are calculated. It must be emphasized that this functional dependence applies only to this target case, thus the function obtained is usable only once.

## 4. Example and results

The input information into our model is the CAD-model of the final product, which is also the target case. The other input information into the model are the cases of tools already made. These CAD-models with costs are the source cases.

From CAD-model it is necessary first to abstract the data on the basis of which the case vectors will be determined and similarity between the source cases and the target case calculated. From CAD-models the following geometrical features have been identified:

- Number of geometrical features made by cutting (secondary features) – *R*;
- Number of geometrical features made by bending (secondary features) – *U*;
- Extent of bends – SU;
- Number of faces of CAD-model – *F*;
- Thickness of main geometrical feature – *D*;
- Surface area of main geometrical feature – *P*;
- Volume of main geometrical feature – *V*
- Total outside length of cutting of main geometrical feature – LRZ;
- Total inside length of cutting main geometrical feature – LRN;
- Total length of bending lines – LU;
- Number of triangles in STL-format – *T*;
- Greatest distance between two points of CAD-model – DI;
- Greatest distance between two points of CAD-model in direction of largest plane of CAD-model – DH;
- Greatest distance between two points of CAD-model in direction rectangular to largest plane of CAD-model – DV;
- Ratio between DV and DH – *K*.

After abstracting the features of all source cases and target case the case vectors for each case were obtained:

$$\vec{v}_i = \{R_i, U_i, \mathrm{SU}_i, F_i, V_i, P_i, D_i, \mathrm{LRZ}_i, \mathrm{LRN}_i, \mathrm{LU}_i, T_i, \mathrm{DI}_i, \mathrm{DH}_i, \mathrm{DV}_i, K_i\} \tag{7}$$

Afterwards the similarity between the target and the source cases is calculated. To select organisms for the use in the reasoning subsystem quality selection was used. Thus, only the cases or vectors of source products having the value of normalized similarity $P_{in} < 0.15$ were selected.

The following transformation of the case vectors was effected:

$$\begin{aligned} &\vec{v}_{pi} \to \vec{v}'_{pi}, \\ &\vec{v}_{pi} = \{R_{pi}, U_{pi}, \mathrm{SU}_{pi}, \mathrm{VI}_{pi}, F_{pi}, V_{pi}, P_{pi}, D_{pi}, \mathrm{LRZ}_{pi}, \mathrm{LRN}_{pi}, \mathrm{LU}_{pi}, T_{pi}, \mathrm{DI}_{pi}, H_{pi}, V_{pi}\}, \\ &\vec{v}'_{pi} = \{\mathrm{SU}_{pi}, P_{pi}, \mathrm{DI}_{pi}, K_{pi}, t_{pi}\} \end{aligned} \tag{8}$$

The following transformation of the case vectors was effected:

- components SU, *P*, DI were transferred;
- components *R*, *U*, VI, *F*, *V*, *D*, LRZ, LRN, LU, *T*, *H*, *V* were removed;
- components DH in DV were transformed into *K*.

$$K = \frac{\mathrm{DV}}{\mathrm{DH}} \tag{9}$$

After transformation of the selected vectors the genetic programming system was prepared in following steps:

- Determination of set of terminals; in our case the terminals are SU, *P*, DI and *K*.
- Determination of set of primitive functions; the basic mathematical operations, i.e., addition, subtraction, multiplication and division were selected.
- Insertion of cases for calculation of adoption; in the form of a list of transformed vectors.
- Determination of evolution parameters:

Table 1
Comparison of error of system and expert

| Prediction | Error (%) |
|---|---|
| Expert | 3.60 |
| System | |
| Run 1 | 3.63 |
| Run 2 | 1.59 |
| Run 3 | 9.89 |
| Run 4 | 4.45 |
| Run 5 | 0.52 |
| Run 6 | 7.42 |
| Run 7 | 1.17 |
| Run 8 | 2.33 |
| Run 9 | 6.36 |
| Run 10 | 10.56 |

- ○ Number of organisms in population is 2000;
- ○ Maximum depth in creation is 8;
- ○ Maximum depth in crossover is 15;
- ○ Probability of crossover on cells and organs is 0.7;
- ○ Probability of crossover on organs is 0.2.

- Determination of criterion for stopping of evolution; the greatest number of generations is 200.

After inserting of data and adjusting of all parameters of genetic programming the evolution was run a few times. The results obtained were in the form of functional dependence between the components of the transformed vector of product and costs:

$$t_s = f(\mathrm{SU}, P, \mathrm{DI}, K) \tag{10}$$

where $t_s$ are the tool manufacturing costs.

Example: after simplification one of the functional dependences between the geometrical features SU, $P$, DI, $K$ and costs $t_s$, worked out by the genetic programming methods is equal to

$$t_s = 105189 - 1235 \cdot \mathrm{DI} + 2701 \cdot K - 16 \cdot \mathrm{DI} \cdot K - \mathrm{DI} \cdot K^2 + 1190 \cdot P - 8 \cdot \mathrm{DI} \cdot P - \mathrm{DI} \cdot K \cdot P \tag{11}$$

We several times ran the evolution and each time the genetic programming system worked out a formula. The formulas were more or less complicated; the comparison of quality of prediction of our system and expert is shown in Table 1.

In Table 1 it can be seen that the quality of prediction of the expert and of our system are somehow comparable. The average error committed by our system is 4.79%. Although the error is higher than that of the expert, the results can be considered to be satisfactory. Experience shows that a qualified expert commits up to 15% of error. From this point of view the predictions can be considered as good taking into account that they have been made by an artificial system not having the capacity of intuition.

## 5. Conclusion

We have conceived a general concept of the intelligent system for predicting total manufacturing costs of tools on the basis of the CAD-model of the finished product. We have decided on building intelligent system due to awareness that the problems treated cannot be solved by deterministic approaches. The system built on the basis of our model is viewed as useful particularly in preparation of offers for the manufacture of tools on the basis of CAD-model of the finished product.

Testing of the system has brought interesting insights and many future challenges. Already the hitherto results show that the latter are of similar quality as if offered by expert. It would be too much to expect that the system will make very precise predictions, since even experienced experts cannot do that. It must be borne in mind that the tool manufacturing takes place in changing environment where also rules of chaos apply. The objective of our model is not to surpass the expert but to support him and maybe to replace him in the future. It can be established that the system is capable to work out a high-quality prediction. However we must be aware that enough properly similar cases are needed for the prediction of adequate quality.

Our further researches will be oriented towards making a system capable to abstract and to convert intelligently the data into a form suitable for processing by genetic programming. It is expected that with the increase of the computer power also the capacity and usability of the system will increase. In the future the system can be adapted for predicting the manufacturing costs of other types of forming tools.

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