Evolutionary Prediction of Manufacturing Costs in Tool Manufacturing

Mirko Ficko, Boštjan Vaupotič, Jože Balič

Abstract:

One of the most important factors in the offer for tool manufacture is the total manufacturing cost. Although the total manufacturing costs can be rather precisely determined by the cost analysis, this approach is not well applicable in tool-making due to cost and, particularly, time demand. Therefore, the authors propose a new approach to prediction of total manufacturing costs, which is based on case based-reasoning method and imitates the human expert. The system first abstracts from CAD-models the geometrical features, and then it calculates the similarities between the source cases and target case. The most similar cases are used for preparation of prediction by genetic programming. The genetic programming method provides the model connecting the individual geometrical features with the costs searched for. Regarding to the connections between geometrical features and tool cost of source cases the formula for calculation of tool cost of target case is being made. The experimental 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 tool manufacturing costs, case based reasoning, genetic programming*

1. Introduction

Quick response to business opportunity has been considered as one of the important factors to ensure company competitiveness. Therefore, new products must be more quickly developed, manufactured and introduced to the market. This fact is obvious for example in automotive industry, where the time to develop a car has been reduced from 60 months 10 years ago to 18 months today (Ding, Y. *et al.*, 2004). In such competitive conditions, where new products appear on the market within shorter time intervals the development time is shorter and shorter, the branch of industry busy with tool manufacture assumes a vital role. The capacity of the tool-making shop to respond quickly to the demand in today's competitive environment is a key factor of competitiveness.

The buyers of tools have a worked out idea about finished product, whereas the tool-makers are responsible for the tool design, preparation of the manufacturing technology and final manufacture of the tool. The first activity of tool making shop connected to new order is preparation of the offer. In most cases the offer itself is quite simple. Most often it comprises only business information, above all, the price. This information is of key importance for the economic success of the order both for the buyer and seller of tools. However in the multi-project environment, characteristics of the tool-making industry it is difficult to predict the total costs at execution of the order. It would be very useful to have a tool for preparation of total manufacturing costs. The paper tries to find a solution for this problem. Differently from other approaches, we have developed a system which imitates the natural intelligent system – expert for solving this problem.

This paper comprises five sections. The introductory section presents the problems of the tool-making industry occurring in preparation of the order. The second section discusses the cost prediction activity focusing on costs prediction in the tool-making companies. The third section presents the model of the cost prediction by intelligent methods. The subsections explain the individual components and working principles of that system. The fourth section deals with the use of the presented system on a problem and with the test results of the system. In the last section the results are discussed and the guidelines for future research indicated.

2. Present situation of cost determination

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 mostly 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.

2.2 From demand to order

Usually sheet metal stamping tools are made individually upon the order of costumer. Shortly after order the tool-makers must obtain the answer to the following questions within the shortest possible time:

1. Are we in a position to make the tool for the product concerned?
2. Do we have the means for the manufacture of that tool?
3. How much time do we need to be able to make the tool?
4. 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 (Fulder, T. et al., 2001). The answer to the third question is very important particularly in the tool-making activities since adhering to the delivery time is one of most important factors of success. However, it is often difficult to answer that question, since the answer depends on a variety of interconnected factors (Pahole, I. et al., 2003). In the process of agreeing the tool-makers usually do not have the chance to determine the tool manufacturing time since they are specified by the clients. The tool-making shop must answer like this: "The delivery time 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.

2.3 Problem of total cost determination

The tool manufacture is a complex process including a variety of personnel, machines and technologies. Therefore, specifying the manufacturing costs poses a serious problem. In addition, this activity is very time-limited. The tool manufacturing costs can be rather precisely analytically determined, but analyses require additional time and cause additional costs. The tool-makers can afford none of these. In answer to the demand the offer must be prepared as fast as possible, possibly within a few hours, but not later than in a few days.

Thus, the cost prediction is connected with quite a few difficulties. Most of the difficulties appear due to the dependence between quantity of information and the capability of cost prediction. The principal difficulties can be summarized as follows:

- It is hard to obtain a high-quality cost prediction from the design drawings, although in this stage of the product development it is the product target price which is the most important.
- For a sufficiently accurate cost price considerably more technological information is required.
- Cost prediction is connected with costs. Therefore, the cost prediction is not always economical (Wierda, L. S., 1990). It may happen that the prize of cost prediction is higher than the benefit of it.
- The information about costs is dynamical. Due to internal changes in the company and external changes in the economic environment the costs change.
- The cost prediction is limited to one company and one product only. A general rule, applicable everywhere cannot be contrived.
- Due to characteristics of the problem itself the cost prediction accuracy is often not satisfactory.

If the findings about the problems appearing in determining the total manufacturing costs in tool manufacture are summarized it is found out that two basic problems are in question:

- lack of technological information about fulfilment of the order
- lack of time for preparation of cost analysis of the orders.

Lack of technological information is caused by the nature of make-to-order production, which is common in tool manufacturing: in the beginning, only the CAD model of the final product and practically no technological information is available and no sooner as on the end, when the tool has been finished and is ready for the manufacture of the final products, all technological information resulting from the tool manufacture process, is available. Therefore in the stage of securing the order not the determination but prediction of total costs of tool manufacture is at issue.

Most frequently, in tool manufacture, the experts with long-standing experience deal with prediction of cost of tool manufacture. 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 fast and without the necessary expert knowledge.

2.4 Cost prediction methods

As we mentioned before there has been developed many approximate cost prediction methods. They can be divided (Duverlie, P. and Castelain, J. M., 1999):

- Intuitive methods; based exclusively on the expert's capabilities
- Analogue 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.

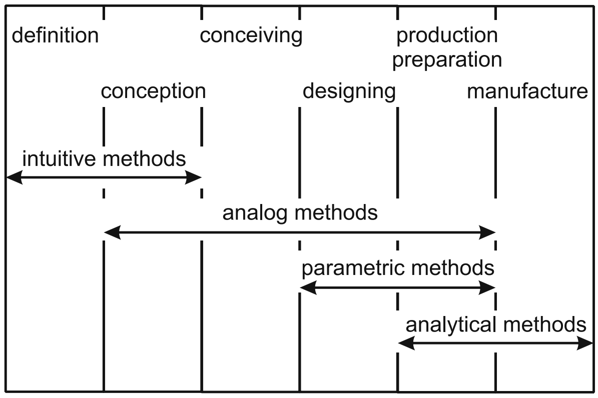

Figure 1: Area of use of cost prediction methods (adopted from Duverlie, P. and Castelain, J. M., 1999).

None of the above methods is appropriate in all stages of the development cycle. They differ in the requirements and area of use. Figure 1 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. 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.

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

3.1 Taking example by intuitive methods

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 toolmaking, but only those meeting the specific requirements of the tool-making industry for very fast and precise predictions. In the business environment of the tool-makers only the analogue and parametric methods are applicable and in no way the analytical ones. 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. That task is performed by experts with proper technical-economic knowledge. In this case the experts are experienced individuals having gathered in their work enough knowledge to be able to perform this task. When gathering experience they resorted to acquiring the knowledge by deliberate exercise in order to improve the effect, which according to Ericsson, K. A. and Charness, N. (1994) is the best method of recruiting the experts. However, in spite of optimal learning the future experts must do 10000 hours of deliberate exercise (Charness, N. and Schultetus, R.S. 1999) which in practice, implies 10 years of working experience in this area. Gradually, the expert develops the capability of rather good cost prediction. 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.

In all methods developed so far, besides intuitive prediction, 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 evolutionary 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 analogue and parametric methods. 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 data base. While the expert uses his intelligence for reasoning, the artificial system uses genetic programming method.

3.2 Case-based reasoning

The case based reasoning concept has been in use since mid eighties of the past century. It is based on the findings in psychology and adopts one of the solving processes 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 (Kolodner, J. K. et al., 1985). 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 (Strube, G. and Janetzko, D., 1990).

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 (Althoff, K. D. and B. Bartsch-Spörl, 1996). 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.

3.3 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 (Figure 2):

- o Collecting the geometrical and technological information in the computer data base.
- o Abstracting the geometrical features from the target case (CAD-model of product).
- o Selecting the most similar cases (source cases) from the data base.
- o Working out the formula for cost prediction.
- o 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. It is saved in the data base 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 for prediction of costs.

As soon as the system gets a new case, i.e., the problem description in the form of CAD-model, it must translate it into the form which is suitable for artificial system. We must be aware that by today's artificial intelligence it is impossible to treat the entire complex 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. 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 data base is calculated. The similarity is calculated as the distance between the final points of vectors in the vector space. The greater that distance the smaller is 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. Those isolated cases are the source cases for reasoning about the solution of the target case.

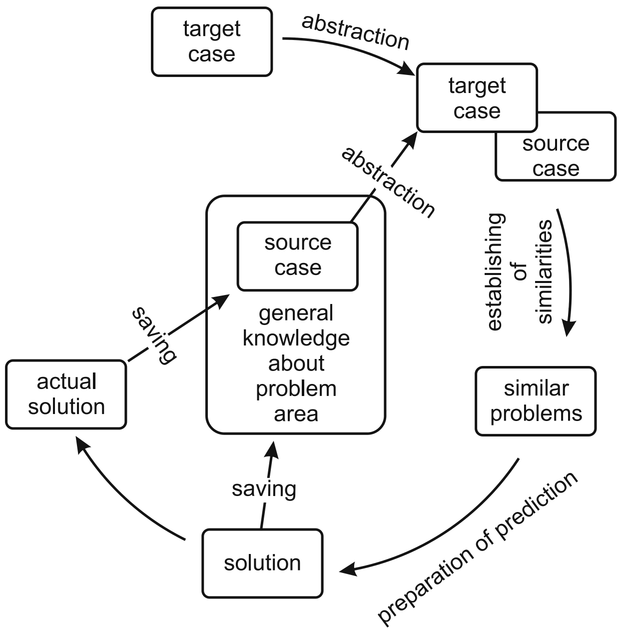

Figure 2. Case based reasoning cycle in predicting total costs.

For reasoning about the solution on the basis of similar cases the reasoning subsystem uses the artificial intelligence method – genetic programming. We decided on genetic programming because of its ability of robust forming of formula. Evolutionary methods are the most general approach to solving such problems. 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 data base. In our case, in the stage of adoption of solution the system uses the approach similar to parametric method. The result is the formula containing parameterized geometrical features of the finished product as variables.

3.4 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 description 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 mostly 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. It is in the nature of evolutionary methods that they work faster, if they have fewer terminals. In our case the terminals are the vector components.

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 reasoning 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.

As the system of cost prediction imitates the natural intelligent system – i.e. the human – the similarity, having the same meaning as in the every day 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, 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:

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

However, the similarity thus calculated is not a good enough criterion of similarity since the vector components 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. g_{cj} designates geometric feature c of case j. Multiplier d_j is:

$$d_j = \begin{Bmatrix} r_j \cdot \dfrac{1}{g_{cj}}; g_{cj} \neq 0 \\ 0; g_{cj} = 0 \end{Bmatrix} \tag{3}$$

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:

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

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

The number of selected cases depends on the number of similar cases. It's not adequate to select a case which is not similar at all and on other hand it's not adequate to make a prediction on the basis of a small number of cases. Therefore the first condition to make a good prediction is to have enough similar cases.

3.6 Reasoning with 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 1974 by Rechenberg in his work *Evolutionary strategies*. His work was then pursued by other researchers. Thus in 1975 John Holland developed genetic algorithms, and some 15 years later John Koza J. R. (1992) developed still the genetic programming. In these methods the evolution is used as an optimization process in which the organisms become increasingly adapted to environment in which they live (Kovačič, M. and Balič, J., 2003). Two main characteristics of evolutionary methods are: they do not search for the solution in the ways determined in advance (deterministic) and they simultaneously treat a variety of simple objects (Brezocnik, M. *et al.*, 2003). 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 (Koza, J. R., 1992). 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 repeated 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.

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 effected, 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 where $m<n$ applies:

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

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 multi-parametric function on the basis of known cases, written in programme language AutoLISP, has been used.

Procedure of solving by genetic programming is presented 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 formula in hand, the components of the transformed target vector are entered 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.

3.7 Automation of predicting

In order to make global prediction of total manufacturing costs efficiently the method must be automated to certain extent (Wierda, L. S., 1990), otherwise the method cannot produce up-to-date results due to changing environment. If the method is not automated, there are no reasons to use it, although it is time and cost non-demanding.

Automation must cover the acquisition and storing of data. The geometrical and technological data must be stored in suitably structured form. It is proper to use relation and object computer data bases. Also the module for finding the dependence between geometrical and technological features must be automated for efficient work. Consequently, such automated system must contain at least the data base for storing geometrical and technological data and the module for finding the dependence between geometrical and technological features.

If we have to do with the manufacture of a great number of different products also the modules for finding similarities between the products and the modules for selecting the most influencing geometrical features – and/or CAD model abstracting are desirable.

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. For the first test we used the most general approach and from the target and source cases we abstracted the most recognizable geometrical features and not the features the features most influencing the variable searched for i. e. the total manufacturing costs. 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:

$$\vec{v}_i = \{R_i, U_i, SU_i, F_i, V_i, P_i, D_i, LRZ_i, LRN_i, LU_i, T_i, DI_i, DH_i, DV_i, K_i\} \tag{7}$$

Afterwards the similarity between the target and the source cases is calculated. Similarities were calculated on the basis of normalized vectors of cases. We selected five most similar cases as shown in Figure 3.

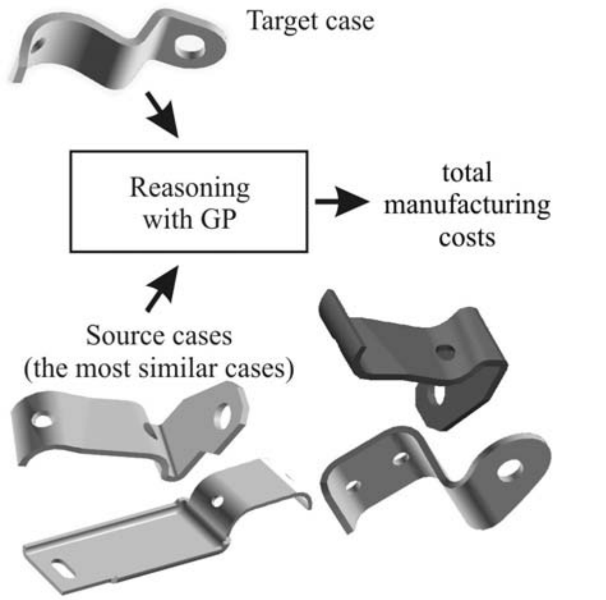

Figure 3. Source cases used in reasoning process by genetic programming.

Due to limitations of number of source cases and especially limitations of computation power we decreased number of vector components. In the next step we transformed the cases in such a way that we obtained the vectors of source cases which are of the form suitable for reasoning by means of genetic programming. The following transformation of the case vectors was effected:

$$\begin{aligned} &\vec{v}_{pi} \rightarrow \vec{v}'_{pi} \\ &\vec{v}_{pi} = \begin{Bmatrix} R_{pi}, U_{pi}, SU_{pi}, VI_{pi}, F_{pi}, V_{pi}, P_{pi}, \\ D_{pi}, LRZ_{pi}, LRN_{pi}, LU_{pi}, T_{pi}, DI_{pi}, H_{pi}, V_{pi} \end{Bmatrix} \\ &\vec{v}'_{pi} = \{SU_{pi}, P_{pi}, DI_{pi}, K_{pi}, t_{pi}\} \end{aligned} \tag{8}$$

The following actions were taken:

- 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*

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

Transformed source vectors and target vector, presented in Table 1, were obtained.

For reasoning the genetic programming system proposed by Miha Kovačič (M. Kovačič, 2003), was used. 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 adaptation; in the form of a list of transformed vectors.
- Determination of evolution parameters:
  - 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.

o 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:

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

Where t_s are the tool manufacturing costs.

Table 1. Example of data to be entered into reasoning system.

case	SU	P	DI	K	total manufacturing costs
target case	2,0	2259,0	59,1	0,3	*searched*
source cases	4,0	2909,0	59,0	1,1	305,0
	2,0	4235,0	67,6	0,4	298,2
	2,0	4632,0	82,1	1,2	324,3
	1,0	2461,0	59,2	0,2	300,0
	2,0	2155,0	47,4	0,3	365,3

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 2.

Table 2. Comparison of error of system and expert.

Prediction	Error [%]
Expert	3,60
System (Run 1)	3,63
System (Run 2)	1,59
System (Run 3)	9,89
System (Run 4)	4,45
System (Run 5)	0,52
System (Run 6)	7,42
System (Run 7)	1,17
System (Run 8)	2,33
System (Run 9)	6,36
System (Run 10)	10,56

In Table 2 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. Especially, if it is borne in mind the analysis of the influence of vector components on total manufacturing costs was not made. 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.

After simplification the worked out formulas are casually very complicated. Entering the parameters and calculation of the variable searched for take place in an automated manner in the computer system, so that the complication of the formula does not make predicting difficulty and/or the formula need not be simplified at all.

5. Conclusion

This paper presents quite uncommon approach to cost prediction. We have decided on building intelligent system due to awareness that the problems treated cannot be adequately solved by deterministic approaches. Testing of the system has brought interesting insights and many future challenges. Already the hitherto results show that they are of good quality compared to those made by expert. It is hard to expect the system will make very precise predictions, since even experienced human 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 good prediction.

Our further research 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.

AUTHORS

Mirko Ficko*, **Boštjan Vaupotič**, **Jože Balič** – Laboratory for Intelligent Manufacturing Systems, Faculty of Mechanical Engineering, University of Maribor; Smetanova ulica 17, SI-2000 Maribor, Slovenia. Tel.:+386 2 220 1595. Fax.:+386 2 220 7990.
E-mail: mirko.ficko@uni-mb.si
* Corresponding author

REFERENCES

[1] K. D. Althoff, B. Bartsch-Spörl, "Decision Support for Case-Based Applications", *Wirtschaftsinformatik*, no. 38, 1996, pp. 8-16.
[2] M. Brezocnik, J. Balic, Z. Brezocnik, "Emergence of intelligence in next-generation manufacturing systems", *Robotics and Computer Integrated Manufacturing*, vol. 19, no. 1-2, 2003, pp 55-63.
[3] N. Charness, R.S. Schultetus, *Knowledge and Expertise, Handbook of Applied Cognition*, John Wiley & Sons: New York, 1999.
[4] Y. Ding, H. Lan, J. Hong, V. Wu, "An integrated manufacturing system for rapid tooling based on rapid prototyping", *Robotics and Computer-Integrated Manufacturing*, vol. 20, 2004, pp. 281-288.
[5] P. Duverlie, J. M. Castelain, Cost Estimation During Design Step, "Parametric Method versus

Case Based Reasoning Method", *International Journal of Advanced Manufacturing Technology*, vol. 15, no. 12, 1999, pp. 895-906.

[6] K. A. Ericsson, N. Charness, "Expert performance: its structure and acquisition", *American Psychologist*, 1994, vol. 49, pp. 725–47.

[7] T. Fulder, A. Polajnar, K. Pandža, "Sposobnost – orodjarna. Ideje – motor gospodarske rasti orodjarn". In: *Proceedings of Orodjarstvo*, 2001, Portorož, Slovenija.

[8] J. Holland, *Adaptation in Natural and Artificial Systems*, University of Michigan Press, Ann Arbor, 1975.

[9] J. K. Kolodner, R. Simpson, K. Sycara, "A Proces Model of Case-Based Reasoning". In: *Problem Solving, Proceedings IJCAI-85*, Morgan-Kaufmann, Los Angeles, 1985, pp. 284–290.

[10] M. Kovačič, J. Balič, "Evolutionary programming of a CNC cutting machine", *International journal of advanced manufacturing technology*, vol. 22, no. 1-2, 2003, pp. 118-124.

[11] J. R. Koza, *Genetic Programming: On the Programming of Computers by Means of Natural Selection*, MIT Press, Cambridge, 1992.

[12] I. Pahole, M. Ficko, I. Drstvenšek, J. Balič, "Optimisation of the flow of orders in a flexible manufacturing systems", *Strojniški vestnik*, vol. 49, no. 10, 2003, pp 499-508.

[13] I. Rechenberg, *Evolutionsstrategie: Optimierung technischer Systeme nach Prinzipien der biologischen Evolution*, Frommann-Holzboog Verlag, Stuttgart, 1974.

[14] G. Strube, D. Janetzko, „Episodisches Wissen und fallbasiertes Schließen: Aufgaben für die Wissendiagnostik und die Wissenpsychologie", *Sweicherische Zeitschrift für die Psychologie*, vol. 49, no. 4, 1990, pp. 211–221.

[15] L. S. Wierda, *Cost information tools for designers: a survey of problems and possibilities with an emphasis on mass produced sheet metal parts*, Delft University Press, Delft, 1990.