ISSN 1392 - 1207. MECHANIKA. 2011. 17(3): 300-305

Simulation of products classification system for manufacturing cost forecasting

A. Stasiškis*, D. Čikotienė, A. Bargelis*****
*Kaunas University of Technology, S. Daukanto 12, 35212 Panevėžys, Lithuania, E-mail: andrius.stasiskis@ktu.lt
**Šiauliai University, Vilniaus str. 141, 78222 Šiauliai , Lithuania, E-mail: dalia@tf.su.lt
***Kaunas University of Technology, Kęstučio 27, 44312 Kaunas, Lithuania, E-mail: algirdas.bargelis@ktu.lt

crossref http://dx.doi.org/10.5755/j01.mech.17.3.507

1. Introduction

Today's struggle competition in marketplace demands permanent increase of productivity through new products and processes development. The computerized actions of this task like CAD, CAPP, ERP, CAM and so on must make a strong support creating and implementing novelties. Product performance and cost are essential criteria in new product design. A key part of a product development cycle is the conceptual design phase that greatly influences the resulting performance, cost, quality, product manufacturability and life cycle parameters of the product life cycle [1]. In this phase it is necessary to forecast product or its part manufacturing time, cost and delivery time to market. The products' classification system could simplify solving of above mentioned tasks and seeking the best solutions of product's manufacturing cost and characteristics in the separate products' class level.

The research objective of this paper is creation of mechanical engineering products' classification system that could help improve and simplify its early stage development procedure, in particular, looking for better product performance and less manufacturing cost. The developed classification system was tested implementing it into laboratory and industry for new products and processes development in virtual reality.

2. Overview of objects classification methods

The mankind uses classification from ancient times. There are many classification methods in use [2]. All classification methods apply object parameters to characterize it. Parameters could be qualitative and quantitative. It is not difficult to classify object that has one or two parameters. It becomes rigid problem when the object has a lot of quantitative and qualitative parameters.

There are number of well known standard classification methods [3]:

- neural network method;
- nearest neighbour method;
- decision tree method;
- other methods.

Each method has its own advantages and disadvantages. The biggest advantage of neural network methods is that they can classify object with big number of parameters and with high parameter's value distribution. The disadvantage is that these methods are slow in both training and application.

Neural network learning procedures and statistical classification methods are applied and compared empirically in classification of multisource remote sensing data [4]. Reliability measures are introduced to rank the quality of the data sources. The data sources are then weighted according to these rankings in the statistical multisource classification.

The nearest neighbor method finds the closest object from training set to the object that should be classified and the decision is made that object belongs to the nearest neighbour class [5]. The Analytic Hierarchy Process (AHP) methodology is quite simple and easy to implement. But object parameters and features must be selected very carefully. Even one unsuitable parameter (that does not separate classes) could make the method fail. The presented research is for suppliers' selection for different manufacturing industries. It was concluded that AHP method works well in making decisions for many types of companies that involve different types of suppliers.

Axis-parallel decision tree methods are based on the tree with nodes in which each one parameter is compared with some value [6]. If a parameter has greater value one branch of tree is taken, and if the parameter has less value – other tree's branch is chosen. When the last node is passed the decision is made that object belongs to this certain class. This method is faster than the other above mentioned methods. The disadvantage of this method is that it is not flexible in parameter space.

Oblique decision tree methods have some advantages compared with axis-parallel method [7]. At each node the combination of some parameters is computed using a set of feature weights specific to that node and the sum is compared with a considered value. One branch of the tree is selected. When the last node is passed the decision is made that the object belongs to this certain class. It is more difficult method to realize comparing to axis-parallel decision tree methods. The main advantages of decision tree methods are that they are fast and use only a few parameters to classify the objects.

The reviewed research papers can not be directly applied for the classification of mechanical engineering products in their performance development and considering of economic manufacturing perspective. This research objective has been solved in this paper.

3. Classification system development

Mechanical product classification system has been developed adopting the above mentioned objects' classification methods. The integrated approach of new product and process creation has been used in this classification method development.

Aiming to accelerate both new product development and manufacturing engineering at the early stage of itself product and its components creation, the classification system could be used seeking minimization of development time and cost. It enables to reduce manufacturing engineering uncertainty classifying manufacturing products into separate classes according to the quantitative and qualitative parameters. Attributes such as mass, size, volume, power, speed and so on could be applied for products classification. Two means could be used to characterize an object by certain attribute. First: object k could be characterized by quantitative attribute b_{kl} (b means object mass or size or so on). Second: it is possible to affirm that $b_{kl} = 1$, if object k satisfies l attribute, and $b_{kl} = 0$, if object k does not satisfy this condition.

Description of the objects by means of the first or second case gives the matrix $B(m \times n)$ of the symbol b_{kl} where objects correspond to the lines and attributes – columns. Matrix B will be filled with different format numbers in first case and similarly with 0 and 1 in the second case. Matrix B in the first case should be changed into dimensionless matrix $\widetilde{B}$, where matrix $\widetilde{B}$ elements should be as follows:

The mean value of any column l

$$v_l = \sum_{k=1}^{m} b_{kl} / m \tag{1}$$

Mean square deviation g_l from the mean value could be calculated

$$g_l = \sqrt{\frac{\sum_{k=1}^{m} \left(b_{kl} - v_l\right)^2}{m}} \tag{2}$$

Then matrix $\widetilde{B}$ elements are

$$\tilde{b}_{kl} = b_{kl} / g_l \tag{3}$$

Also the weight factor vector $R(r_1, \ldots, r_1, \ldots, r_n)$ is used. It relates the importance of component characteristics with comparison with other attributes. The ratio of l_1 and l_2 is expressed as r_{l1} / r_{l2}.

Any class of products S_k differs from another one by the number of attributes or by their characteristics. Class S_k is defined by criterion of closeness of adjacent S_k; and criterion of exclusiveness and uniformity of adjacent S_k; generalized criterion which characterizes the level of exclusiveness and uniformity of all classes.

Closeness criterion of i–th and j–th object is designated d_{ij}. The calculation depends on matrix B type. If matrix B belongs to the second type, then

$$d_{ij} = \sum_{k=1}^{n} d_{ij}^{k} r_k \tag{4}$$

where k is attribute number; $d_{ij} = 1$ if i and j objects possess k attributes, i.e. $b_{ik} = 1$ and $b_{jk} = 1$; $d_{ij} = 0$ in all other cases.

If matrix B belongs to the first type, then

$$d_{ij} = \frac{1}{\sum_{k=1}^{n} \left(\widetilde{b}_{ik} - \widetilde{b}_{jk}\right)^2 r_k + 1}. \tag{5}$$

Bigger d_{ij} values correspond to more close objects. Values d_{ij} form up matrix D, which is called matrix of closeness.

Attribute of uniformity

$$d_{sk} = \sum d_{ij} \tag{6}$$

where $i, j \in S_k$.

Uniformity ought is divided into internal (in the class) and external. Internal uniformity could be expressed

$$W_k = \frac{d_{S_k}}{C_{S_k}^2} \tag{7}$$

where $C_{S_k}^2$ is the number of pairs of combinations of S_k class.

Closeness value of the S_k class objects is defined by W_k. But this is not sufficient for the class definition. It is necessary to know how class S_k is related with other objects of a lot Q. Suppose $\widetilde{S}_k$ is a lot of objects do not belonging to the class S_k; $d_{\widetilde{S}_k}$ is the sum of closeness between objects of class S_k and objects do not belonging to that class

$$d_{\widetilde{S}_k} = \sum d_{ij} \tag{8}$$

where $i \in S_k$, $j \in \widetilde{S}_k$.

External exclusiveness of the S_k class is characterized by the expression

$$\Psi_k = \frac{d_{\widetilde{S}_k}}{S_k \widetilde{S}_k} \tag{9}$$

which shows the closeness value of the S_k class objects to the objects not belonging to that class. Difference $F\left(S_k\right) = W_k - \Psi_k \rightarrow max$ is the best characteristic of both class and the quality of the classification.

Mechanical engineering products and their components using the proposed classification system are classified into separate classes applying the second type of matrix B. The matrix B of Lithuanian mechanical engineering products is shown in Table 1. The six different products and three types of mechanical engineering products' components are included in the developed matrix B. This matrix presents manufacturing companies where authors of the paper have made considerations of products performance and characteristics, processes capabilities and quality parameters, operations facilities, tooling and their interfacing both in the early stage of product and process development, and batch production stage. The carried out consideration on the modeling of manufacturing processes and manufacturing resources in virtual reality is based. Modeling objective was the creation and evaluation of some product and process alternatives. The modeling objective is searching the better alternative of new products and processes, and looking for higher productivity and quality. The forecasting models of processes and definition of manufacturing resources have been proposed and tested in laboratorial and real production conditions. The appropriate

Table 1

Mechanical engineering products' classifier (Matrix *B)*

Attributes												Class of components
Domestic appliances	Mechatronic component	Displaying image	Cooling device	Transport mean	Metal processing equipment	Part from metal	Part from plastic	Part from sheet metal	Has electronic parts	Die or presform	Producess compressed air	
1	1	1	0	0	0	1	1	1	1	0	0	TV & components
0	0	1	0	0	0	0	0	0	1	0	1	Compressors
1	1	0	1	0	0	1	1	1	1	0	0	Refrigerators
0	0	0	0	0	0	1	0	0	0	0	0	Solid metal mechanical parts
0	0	0	0	0	0	0	1	0	0	0	0	Non metal mechanical parts
0	0	0	0	0	0	1	0	1	0	0	0	Sheet metal parts
0	0	0	0	0	0	1	0	0	0	1	0	Dies & moulds
0	0	0	0	0	1	0	0	0	0	0	0	Machine tools & tooling
0	0	0	0	1	0	0	0	0	0	0	0	Transport means

software has been developed for manufacturing resources forecasting.

Next step in product classification is to classify components into subclasses. For the metal mechanical parts (fourth class, Table 1) five subclasses according to the part complexity have been chosen:

- very complex;
- complex;
- average;
- simple;
- very simple.

Part complexity is defined using design features classifier and design feature quantity. Design feature (DF) classifier is developed classifying them into rotational (1.1, 1.2, etc.), and nonrotational form (2.1, 2.2, etc.) [8]. In this research the object is described applying the first type matrix *B*, which is filled with different format numbers. The matrix is shown in Table 2.

Table 2

The number of DF in various subclasses of mechanical parts

Class of components	The number of DF, %									
	Rotational					Non rotational				
	1.1	1.2	1.3	1.4	1.5	2.1	2.2	2.3	2.4	2.5
Very complex	5	5	10	40	40	5	5	5	40	45
Complex	10	20	30	20	20	15	25	30	20	10
Average	50	25	15	5	5	30	25	17	25	3
Simple	70	25	5	0	0	60	30	10	0	0
Very simple	90	8	2	0	0	80	10	10	0	0

4. Research implementation

The created classifier of mechanical engineering products and components is implemented in laboratory and Lithuanian industry. It has two streams of application: 1) for new products design seeking better performance and manufacturing cost being in separate class level, and 2) for concurrent process design seeking less manufacturing cost and higher quality.

New product designers working in one separate class are able to acquire deep knowledge and best practice in narrow area of activity. It is easier to create systematical product design methodology solving trade-offs among product properties and characteristics, which is closely related with product's value. This research considers the second stream and is related with product manufacturing cost and quality at the early stage of development.

Trade-off between product performance and manufacturing cost in nowadays is becoming more and more important. Many alternatives are necessary to check finding the best final product and process solution. There are many jobs for process development at the early product development stage. One from some the newest proposals [9] is divided on the development of CAPP (Computer aided process planning) system for mechanical parts applying their dynamic classification and group technology. This development is for batch production, unfortunately, does not fit for early product design stage. In this stage product's designers prefer process and manufacturing cost forecasting methods because they are more effective and faster, and are giving sufficient accuracy of defined results. The process and manufacturing cost forecasting model [10] has been applied for developed classifier testing. Cost forecasting model was created applying competitive advanced manufacturing guidelines decreasing direct labor accounts [11] and assuming that total manufacturing cost consists of material, burden and labor costs. Iterating statistical data of various products latter cost and taking into account advanced manufacturing technologies, the total cost S is defined as follows

$$S = k_1 M + k_2 B + k_3 L \tag{10}$$

where M is material cost, B is burden cost, L is labor cost, k are weight coefficients, the values of which depend on product class and are defined experimentally.

Experiments and statistics showed that material cost ratio to the total product cost S comprise from 0.45 to 0.55 for compressors class products, while to the sheet metal products from 0.75 to 0.85. The dependence between total product manufacturing cost S and material cost M in relative money units for compressors class products is shown in Fig. 1 (assumption is made that material cost is equal to 1.0 conditional money unit). It can be also calculated as follows

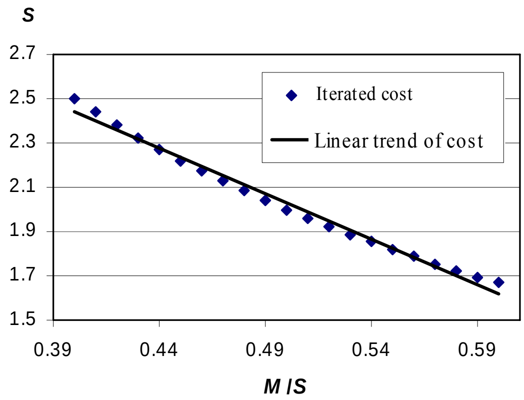

Fig.1. Relation between total product manufacturing cost and material cost

$$S = -4.1087M + 4.0845 \tag{11}$$

The material consumption rate M_1 on the product mass m is defined as follows [10]

$$M_1 = a_1 m + c \tag{12}$$

where a_1 and c constants (for sheet metal products 1.18 and -0.42, while for forged steel parts 1.21 and -0.39).

5. Results and discussions

5.1 Forecasting cost of solid metal mechanical part

The mechanical part – compressor's crankshaft (Fig. 2) has been chosen as an example for the developed classifier testing.

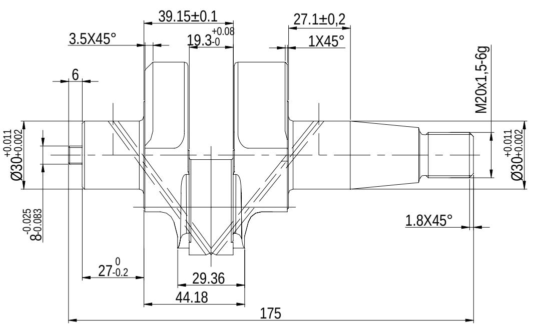

Fig. 2 Compressor's crankshaft

The part which mass 1.78 kg, is manufactured from a forged work piece. The closeness matrix D of compressor's crankshaft is found

$$D = \begin{vmatrix} 0 & 0 & 0 & 1 & 1 & 1 & 1 & 0 & 0 & 0 & 1 & 1 \\ 1 & 1 & 0 & 1 & 1 & 1 & 0 & 1 & 1 & 0 & 1 & 0 \\ 0 & 0 & 1 & 0 & 1 & 1 & 1 & 0 & 0 & 0 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 0 & 0 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 0 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 0 & 1 \\ 1 & 1 & 1 & 1 & 1 & 0 & 0 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 0 & 1 & 0 & 1 & 1 & 1 & 1 & 1 \end{vmatrix}$$

Closeness criteria according to the matrix data are defined (transformed into horizontal row) as follows

$$d_{ij} = \begin{vmatrix} 6 & 9 & 6 & 12 & 10 & 11 & 11 & 10 & 10 \end{vmatrix}.$$

As results show, the biggest closeness criterion is 13, so the part belongs to "Mechanical part" class (Table 1). The next step in mechanical product classification is to classify component into subclasses. The DF number of crankshaft is defined

$$D = \begin{vmatrix} 50 & 20 & 30 & 0 & 0 & 14.3 & 57.1 & 0 & 28.6 & 0 \end{vmatrix}$$

The closeness criteria

$$d_{ij} = \begin{vmatrix} 0.0001034 \\ 0.0002048 \\ 0.0003921 \\ 0.0001910 \\ 0.0001109 \end{vmatrix}$$

As results show, the biggest closeness criteria are 0.0003921 and part belongs to "Average" class of parts complexity. Such classification enables designer to use typical manufacturing process planning and forecast manufacturing costs according to the part complexity class. The comparison forecasted and experimental data are illustrated in Table 3.

Table 3

The comparison of forecasted and experimental data

Product name	Forecasted cost, €	Experimental cost, €
Crankshaft	6.56	6.05
Compressor 1	24.24	23.54
Compressor 2	23.56	25.56
Compressor 3	31.88	36.52
Compressor 4	36.55	46.63
Compressor 5	45.81	52.44

5.2 Forecasting product's process and manufacturing cost

As a case study 2 compressor class product has been chosen (Table 1). This product is applied as auto compressor in trucks and buses. There are classified some products' types in accordance of their properties and characteristics (Table 4). Over 26 different modifications of compressors are produced in Lithuanian company X through past twenty years. They are used mostly in trucks like: MAZ, KAMAZ, VOLVO, IVECO, MANN, SCANIA and busses IKARUS. In this case study five different truck compressors have been considered. The S has been forecasted by equation (11) and experimental data by statistics.

Table 4

The main parameters of different compressors

Compressor	Number of cylinders	Mass, kg	Volume, cm^3	Manufacturing time, h
No. 1	2	13.8	214	2.22
No. 2	2	13.6	214	2.62
No. 3	2	12.8	214	3.88
No. 4	1	9.9	306	5.27
No. 5	1	12.3	306	5.57

The modelling procedure of forecasting cost of mechanical products and their parts with interaction among all manufacturing system elements is related. Manufacturing system elements as product and part design, available suppliers of materials, partners and customers interact during whole forecasting process. It shows the dynamic of change itself manufacturing process and its cost fluctuation, and can be visible at the early design stage. Developers can react and do influence to digital numbers of cost having data of whole manufacturing system. The modelling methodology of interaction among elements in complicated technical system [12] has been applied in this research.

The slope and intercept of regression equation (11) have been defined by iterating and comparing the industrial statistical data and analytical calculations of compressor manufacturing process alternatives and cost.

6. Conclusions and further research

The products classification system and manufacturing cost analysis has helped to identify where the major material, workforce and burden sources of cost for new product and process development at the early stage are to be found. Both actions the product and process development must be carried out applying concurrent engineering methodology and increasing designers training, in particular, seeking collaborative design principles. The main task of product and process designers is to solve all appearing trade-offs in early stage because decisions in this stage make leading influence on the manufacturing cost and quality. Products' classification into different class levels can greatly decrease the number of trade-offs and release engineers job because they work in very specialised area and are able to acquire deeper domain engineering knowledge.

The developed products' classification system presents an intelligent attribution of different technical objects to the separate class level according to their parameters and properties. It helps to decrease the manufacturing cost for products being separated in one and the same class level. The developed forecasting model of compressor class products manufacturing cost accomplishes the research objective. It has its advantages and disadvantages. The advantages are several: the originated products' classification system has been simultaneously used for product and process design taking into account the qualitative and quantitative parameters of their design features (DF). The mathematical formalization of forecasting model, particularly regression expressions, aligns the manufacturing cost of the each process alternative for products being separated on the same class level. The principal shortcoming of the developed system is the applied interactive regime of data input for new product that is to be classified.

Briefly it is concluded as followsю

1. The created intelligent products classification system can help finding new ideas and decreasing the product and process development time and cost.

2. The developed manufacturing cost forecasting model composes the minimal error of manufacturing cost 2.89% and biggest error 21.62%.

3. The developed forecasting model has been tested and validated for confirmation of the theoretical consumptions with the industrialists experience without any additional preparation at the early design stage and has potential capability to be increased of the forecasting model accuracy.

4. The developed products classification system and manufacturing cost forecasting model help to disclose the regularity of changes the cost by changing the structure of product and process or use the strategy 'make or buy' finding cheaper partners.

Future research will be focused on the modelling process iterations amendment and generation of better products' and processes' alternatives. These actions on closely collaboration among big range specialists and experts in industrial and academia organizations must be grounded. For increase of the collaboration efficiency, the web-based system when new products' developers, suppliers, manufacturers and partners are located in different organizations and countries is planned to use. Appropriate portal could help to acquire experience, good practice and methods of various nations' creativity and work culture seeking improved competitiveness, productivity and benefit for all business partners.

Acknowledgement

This research was partially supported by contract with industry No 8467-2008 "Development of knowledge base for productivity increasing of CNC Laser cutting and punching machines".

References

1. **Hundal, M.S.** 1997. Systematic Mechanical Designing: A Cost and Management Perspective. New York: ASME Press. 562p.
2. http://sundog.stsci.edu/rick/SCMA/node2.html (visited 07 January 2010)
3. **Dai, W.L.; Li, D.C.** 2010. Applying systematic diagnosis and product classification approaches to solve multiply products operational issues in shop-floor integration systems, Expert systems with applications 37(9): 6373-6380.
4. **Benediktsson, J.A.; Swain, P.H.; Ersoy, O.K.** 1990. Neural network approaches versus statistical methods in classification of multisource remote sensing data, IEEE Transactions on geoscience and remote sensing 28(4): 540-552.
5. **Tahriri, F.; Osman, M.R.; Ali, A.; Yusuff, R.M.** 2008. A review of supplier selection methods in manufacturing industries, Suranaree Journal of Science and Technology 15 (3): 201-208.
6. **Fayyad, U.M.; Irani, K.B.** 1993. Multi-interval discretization of continuous valued attributes for classification learning. In R. Bajcsy (Ed.), Proc. of the 13 International Joint Conference on Artificial Intelligence: 1022-1027.
7. **Bayardo, R.J.Jr.** 1997. Brute-force mining of high-confidence classification rules. Proc. of the Third International Conference on Knowledge Discovery and Data Mining: 123-126.
8. **Bargelis, A.** Design for process capability and capacity at the product conception stage. Proceedings of 19th Int. Con. On Production Research "The Development of Collaborative Production and Service Systems in

Emergent Economics", Valparaiso, Chile, July 29 – August 02, 2007, Electronic source, 6 p.
9. **Kuric, I.; Kuba, J.** 2007. New methods of product classification for computer aided process planning systems. Eng. Rev., 27(1): 13-17.
10. **Čikotienė, D.; Bargelis A.** 2009. Process modeling for quality in order-handled manufacturing system, Mechanika 1(75): 47-55.
11. **Mize, J. H., Glen, P.** 1989. Some fundamentals of integrated manufacturing. In Proceedings of Int. Con. Industrial Engineering, Toronto, Canada: 575-580.
12. **Silevičius, H.** 2011. Modeling the interaction of transport system elements, Transport 26(1): 20-34.

A. Stasiškis, D. Čikotienė, A. Bargelis

GAMINIŲ KLASIFIKAVIMO SISTEMOS PROCESUI IR GAMYBOS SĄNAUDOMS PROGNOZUOTI SUKŪRIMAS

R e z i u m ė

Straipsnyje pateikta gaminių klasifikavimo sistema, kuri yra esminis veiksnys geriausioms gaminio savybėms ir charakteristikoms rasti bei galimam gamintojui nustatyti esamose gamybos įmonėse. Sukurta sistema gali padėti klasifikuoti skirtingus panašios paskirties ir funkcijų gaminius į atskiras klases pagal jų charakteristikas ir savybes. Klasifikavimo procedūra pagrįsta dialogine duomenų įvestimi ir naudoja tokius objektų požymius, kaip masė, dydis, tūris, galia, greitis ir pan. Gaminiams, esantiems toje pačioje klasėje, buvo sukurtas gamybos sąnaudų prognozavimo modelis, pagrįstas matematinės regresijos lygtimi. Sukurtoji klasifikavimo sistema ir gamybos išteklių prognozavimo modelis išbandyti bei patvirtinti laboratorijoje ir pramonėje. Mokslinių tyrimų rezultatai įdiegti virtualios gamybos sistemoje ir taikomi ankstyvoje naujo gaminio ir jo gamybos proceso konstravimo stadijoje.

A. Stasiškis, D. Čikotienė, A. Bargelis

SIMULATION OF PRODUCTS CLASSIFICATION SYSTEM FOR MANUFACTURING COST FORECASTING

S u m m a r y

This paper deals with product classification system, which is an essential factor to find proper product's performance and manufacturing cost, and potential manufacturer in production enterprises. The developed system can help classifying different products with similar purpose and functions on the separate class level in accordance of their characteristics and properties. The classification procedure is based on the data input at the interactive regime and applies attributes such as object mass, size, volume, power, speed and so on. For products that fall on the same class, the forecasting model of manufacturing cost has been developed. Forecasting model is grounded on the mathematical regression equation. The developed classification system and manufacturing resources forecasting model have been tested and validated in both laboratory and industry. The proposed research creations have been implemented in virtual manufacturing system and employed at the early stage of new product and process development stage.

А. Стасишкис, D. Чикотене, А. Баргялис

СОЗДАНИЕ СИСТЕМЫ КЛАССИФИКАЦИИ ДЛЯ ПРОГНОЗИРОВАНИЯ ТЕХНОЛОГИИ И СТОИМОСТИ ПРОИЗВОДСТВА

Р е з ю м е

В статье рассматривается система классификации продуктов, которая является важным фактором, для определения характеристики продукта и возможного производителя среди производственных предприятий. Разработанная система предназначена для классификации различных продуктов с аналогичным назначением и функциями в отдельные классы в зависимости от характеристик и свойств. Процедура классификации основана на интерактивном вводе данных и использовании атрибутов объектов, таких как масса, размер, объем, мощность, скорость и так далее. Для продуктов, того же класса, разработана модель прогноза стоимости производства на основе уравнения регрессии. Разработанная система классификации и прогнозирования производственных ресурсов была проверена и подтверждена в лаборатории и в промышленности. Предлагаемые исследование внедрена в виртуальную систему производства и применяется в начальной стадии проектирования нового продукта и технологического процесса.

Received December 14, 2010
Accepted May 19, 2011