ISSN 1392 - 1207. MECHANIKA. 2009. Nr.4(78)

Intelligent model for painting process and cost forecasting

R. Mankute*, A. Bargelis**

**Kaunas University of Technology, Kęstučio 27, 44312 Kaunas, Lithuania, E-mail: rasa.mankute@ktu.lt*

***Kaunas University of Technology, Kęstučio 27, 44312 Kaunas, Lithuania, E-mail: algirdas.bargelis@ktu.lt*

1. Introduction

Products design tendency during the last 20 years shows domination painting versus galvanizing processes [1-3]. It is associated with generated paints of full color spectrum and conditionally simple process, in particular, applying powder painting technologies [4, 5]. Painting process belongs to the product finishing manufacturing operations and consists of mechanical and chemical actions. Chemical engineering and used materials are dangerous to the nature ecology and must be carried out carefully. At this point of view, powder-painting process has also advantages versus other coating processes [6, 7].

Quality of the painting process outlines the whole product value and its success in marketplaces. It depends on parts surface preparation before painting, used facility, tooling, paint color and type, production volume and employees skill. Surface preparation demands additional operations such as daubing and polishing for molded iron parts while stamped parts from sheet metal in most cases do not require any additional job before painting. There are automated powder painting lines for mass production and specialized facility set for batch painting processes. The various types of hangers, as tooling for the mentioned facilities in painting process are applied. The frequent exchange paint color and type increases the process set up time and eventually the total painting time. Production volume of a painting process and employees skill is a key factor choosing facility type.

The objective of this research is to develop an intelligent model for painting process and cost forecasting at the early stage of a new product design, which could help estimate an each design alternative. Painting process cost amounts from 7 to 18% of total product manufacturing cost [8] that is available to minimize searching decisions at the early product design stage.

2. Forecasting of painting process and cost at the early product design stage

2.1. Definition of part coating attributes

The main attributes of product coating are geometrical form, dimensions, mass and coating area of the parts and coating quality. Part mass and dimensions determine the painting facilities and tooling of the technological process, while area and requirements to painted surfaces quality – coating materials consumption and the painting process time. In mass or batch production when product design is totally finished, a part mass and coating area are defined as follows:

1. traditionally – formulas + calculator;
2. analytically – dependence of the parameters and derivative formulas;
3. analogically – parts-analogues, catalogues and data bases (DB);
4. automatically - using AutoCAD, Solid-Edge, SolidWorks, CATIA systems and so on, extracting and estimating separate design features from part 3D CAD model.

The mentioned methods, unfortunately, are not suitable at the early new product design stage when finished drawings and specifications are not available. The forecasting method of a coating area to the sheet metal products has been developed, which is proper when sheet tickness s is in interval from 0.5 to 3.0 mm. It was found the mathematical dependence among part coating area A and its mass M and sheet metal thickness s

$$A = 2 \cdot 10^{-6} \left(\frac{M}{s\,\rho} + k\sqrt{\frac{M\,s}{\rho}} \right) \tag{1}$$

where k is the coefficient estimating coating area and part geometrical form deviation, k = 1.05-2.0; ρ is density of the part material.

An influence of variety slots, holes and another design features size ratio with total part dimensions and area by coefficient k of the thin sheet metal parts is considered. Parametrical definition of dimensions mutation for internal rectangular slots is as follows

$$1 \le \frac{h\,l}{s\left(h+l\right)} \le k \tag{2}$$

where h is slot width, mm; l is slot length, mm.

Then l can be calculated:

$$\frac{s\,k}{h-k\,s} \le l \le \frac{k\,s\,h}{h-k\,s} \tag{3}$$

For the circular holes

$$1 \le \frac{d}{4\,s} \le k \tag{4}$$

where d is hole diameter, mm

$$4s \le d \le 4ks \tag{5}$$

The marginal dimensions according to the formulas (3) and (5) are presented in Tables 1 and 2.

The results of experimental investigations of a part coating area definition according to the Eq. (1) showed that forecasting error fluctuates in the limit of ±5%. The investigated parts were made by stamping, moulding, bending and welding with various geometrical

Table 1

Marginal dimensions of rectangular slot length

Thickness s	Width h	Length l		
		k=1.5	k=1.95	k=2.0
2	5	2-7	4-17	4-20
2	6	2-6	2-11	2-12
2	7	2-5	2-8	2-9
2	8	2-4	2-7	2-8
2	9	2-4	2-6	2-7
2	10-20	2-4	2-5	2-5
2	20-100	2-3	2-4	2-4
3	7	2-12	5-35	6-42
3	8	2-10	3-21	3-24
3	9	2-9	2-16	2-18
3	10-20	2-6	2-10	2-9
3	20-100	2-5	2-7	2-7

Table 2

Marginal dimensions of hole

Thickness s	Diameter d		
	k=1.5	k=1.95	k=2.0
1	4-6	4-7	4-8
1.5	6-9	6-11	6-12
2	8-12	8-15	8-16
2.5	10-15	10-19	10-20
3	12-18	12-23	12-24

form and thickness mutations from 1 to 3 mm. Eq. (1), unfortunately, does not fit to prismatic and rotational form solid parts.

2.2. Definition of coating process parameters

The main coating parameters of technological process as working regimes, quantity of parts on the hanger, also available number of hangers in facility and quantity of workers and coating time are defined designing coating process. Real coating process (RCP) of each product is based on a typical process (TP), which is unique for coating process type, as painting, galvanizing or so on. TP contains all common coating process procedures as operations and their sequences, facilities, applied materials, working regimes and safety instructions. RCP takes the TP entire and defines the main coating attributes related with real parts peculiarities grounded on many factors as:

1. Coated part material and blank manufacturing method, surface roughness, geometrical form and coating area size.
2. Coating peculiarities:
   - coating type (powder or liquid painting, lacquer, galvanizing and so on;
   - coating material type;
   - coating thickness and layers quantity.
3. RCP technological process, operations and their sequence.

2.2.1. Calculation of painting labor time

There are two methods for painting time definition:

1. According to the comparative painting time consumption

$$T_d = \frac{N_T\, A}{60} \tag{6}$$

where T_d is product painting time, h; N_T is comparative painting time consumption, min/m^2, which depends on paint type, part geometrical form and painting quality; A is total painting area, m^2.

N_T for automated painting line is defined according to its speed

$$N_T = \frac{1}{v\, a} \tag{7}$$

where v is the speed of painting, m^2/min; a is the coefficient estimating useful painting area of a hanger (0.35-0.7).

$$a = \frac{x\, y}{X\, Y} n_x\, n_y \tag{8}$$

$$n_x = \left\lfloor \frac{X}{x + a_x} \right\rfloor \tag{9}$$

$$n_y = \left\rfloor \frac{Y}{y + a_y} \right\lfloor \tag{10}$$

where x is the length of painted product, mm; y is the height of painted product, mm; X is the length of painting area in line, mm; Y is the height of painting area in line, mm; n_x is the quantity of product columns in painting area; n_y is the quantity of product rows in painting area; a_x is the distance between products in columns; a_y is the distance between products in rows.

2. According to the functional dependencies

$$T_d = f_1(T_p, Q, A, P1, P2) \tag{11}$$

where T_p is a part transportation time to the painting cell, h; Q is quality of the painted surface; A is painting area, m^2; $P1$ is paint type; $P2$ is part material.

Mathematical Eq. (11) realizing into parametrical dependency is made using assumptions as follows:

1. part transportation time to the painting cell T_p and painting time T_d is different, i.e. these operations are carried out in series;
2. taking into account that Q = const, $P1$ = const and $P2$ = const;
3. the influence of variation variables mentioned in paragraph 2 on T_d can be evaluated by correction coefficients;
4. coating area A is a decisive factor directly influencing the value T_d and developing a forecasting model nomograms between T_d and A are created;
5. the logarithmic coordinates are used in nomograms, because they reduce the scatter of statistical data and the nomograms that are more precise can be created.

After mentioned consumptions, Eq. (11) turns into parametrical dependence [9]

$$T_d = T_p + T_o\, k_1\, k_2 \tag{12}$$

where T_o is painting operation time, h; k_1 is correction coefficient for painting quality (Q) estimation (k_1 =1, when quality is minimal; k_1 = 2.0-2.5, when quality is maximal); k_2 is correction coefficient for part material surfaces before painting ($P2$) estimation:

k_2 = 1 for parts produced from rolling steel,
k_2 = 1.2 for parts produced from forged steel,
k_2 = 1.5-1.7 for parts produced from molded iron.

$$lgT_o = m\; lgA + c \tag{13}$$

where m is the slope of a regression trend line; c is an intercept of a regression trend line.

Both constants m and c are defined experimentally applying results of considered case studies and companies' statistical data. Fig. 1 illustrates T_o definition nomogram for rolling sheet steel when painting quality is minimal.

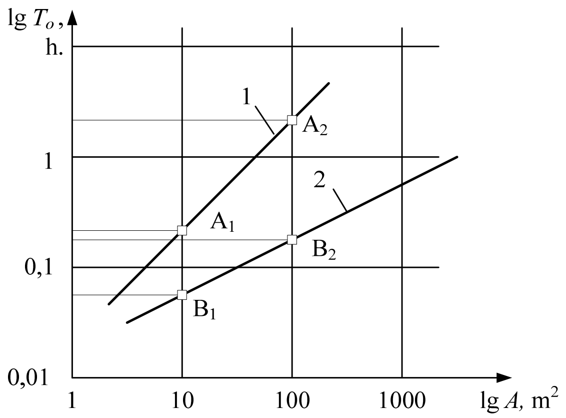

Fig. 1 Nomogram for painting time forecasting: *1* – Natural paints, *2* – synthetic paints

Part painting time in batch painting line is calculated as follows

$$T_d = n_w\, F_t \tag{14}$$

where n_w is quantity of operators according to the work places number in painting line; F_t is available working time of an operator per month, h.

2.2.2. Definition of paint materials consumption

Consumption of painting materials is calculated according to the comparative quota of each applied material. Consumption of paint's, the necessary additional components, and chemical materials for making fatless and washing operations are defined as follows

$$M_{pc} = N_M\, A k_3\, k_4 \tag{15}$$

where N_M is comparative quota of paint components consumption according to the painting process, kg/m^2; k_3, k_4 are correction coefficients estimating geometrical form and surface quality of the part. For the calculation of paints and lutes consumption, the layers quantity is considered

$$M_{pl} = N_M\, A k_3\, k_4\, n_l\, k_5 \tag{16}$$

where n_l is quantity of the layers; k_5 is the coefficient for estimation of material consumption reduction in further layers.

2.3. Forecasting of painting process and cost

By applying the peculiarities of painting process design and cost calculation and the acquired statistical data, a broad-brush parametric function is developed for forecasting painting cost C_P at an early product design or order engineering stage

$$C_P = \left(C_M + C_L\right) n\, k_6\, k_7 \tag{17}$$

where C_M is cost of paint materials, EUR; C_L is labor cost, EUR; n is quantity of parts or products; k_6 is the coefficient for estimating organization overheads (1.09–1.25); k_7 is the coefficient for estimating painting division overheads (1.05–1.15).

$$C_M = \left(N_{M1}\, C_{M1} + N_{M2}\, C_{M2}\right) A \tag{18}$$

where N_{M1} is comparative quota of paints consumption (0.15–0.25), kg/m^2; C_{M1} is paint cost, EUR/kg; N_{M2} is comparative quota of additional chemical materials consumption (0.015–0.25), kg/m^2; C_{M2} is additional chemical materials cost, EUR/kg.

$$C_L = \left(C_{FH} + C_{LH} + C_{EH}\right) T_d \tag{19}$$

where C_{FH} is facility depreciation per hour, EUR/h (Table 3); C_{LH} is operator cost per hour, EUR/h; C_{EH} is energy cost for facility control and painted parts drying, EUR/h.

$$C_{LH} = n_w\, t \tag{20}$$

where t is operator tariff, EUR/h.

Table 3

Expression of the fixed parameters by facility cost

Parameter	Variable	Source of cost obtained by
Facility and working space cost	FW	Facility and space purchase cost
Facility depreciation per year	FD	$FW/8$
Facility maintenance cost per year	FN	Most comprehensive package
Average set up time cost per year	AS	One hour per shift
Total facility cost per year	FC	$FD + FN + AS$
Hours in operation per year	HY	12x21x16 = 4032
Facility cost per hour	C_{FH}	FC/HY
Part painting time	T_d	Developed model
Facility cost per part	FP	$C_{FH} \cdot T_d$

3. Structure of intelligent model for painting process and cost forecasting

The first version of the developed intelligent model software is programmed using Microsoft Excel programming language and is based on the process and manufacturing resources forecasting mathematical equations also the theory of chances and probability. It is used at the very early stage of new product and process design generating and estimating available alternatives. The developed alternatives are ranked according to the manufacturing cost.

The structure of developed model is presented in Fig. 2. It consists of 3 main subsystems:

1. Painting process data.
2. Forecasting.

Fig. 2 illustrates input and modeling data:

1. Variable data as item number, name, material, production volume, dimensions (thickness, length, width, diameter).
2. Data base that contains all necessary materials information as paints type, operations, equipment and applied tooling:
   - material cost, EUR/kg;
   - equipment cost, EUR/h;
   - applied tooling cost, EUR/unit;
   - paints type and cost, EUR/kg, etc.
3. Painting data:
   - k_1-k_7 – coefficients for correction;
   - m, c – coefficients of painting time definition nomograms.

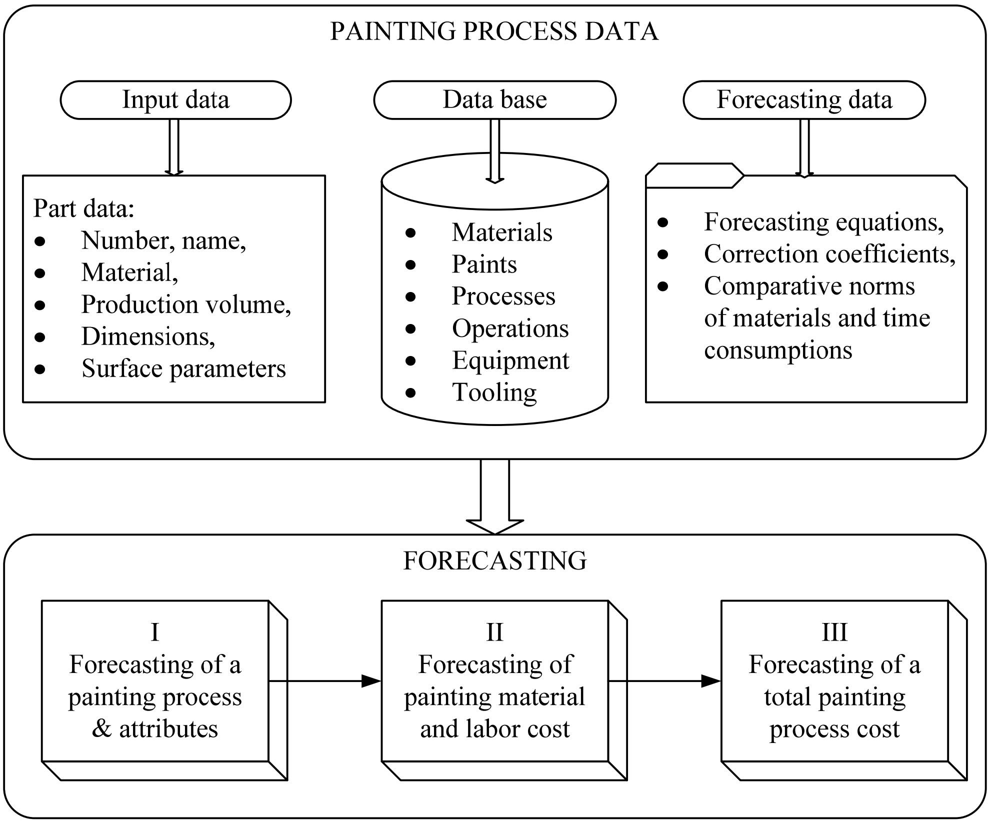

Fig. 2 The structure of developed intelligent painting process forecasting

4. Results and discussions

The developed model was tested in two Lithuanian manufacturing companies: company *AL* that exploits automated painting line and company *BP* – batch separate painting facilities. Typical mechanical components – gas cylinders and various sheet metal parts produced by CNC laser cutting, punching and bending operations have been taken. Table 4 illustrates applied parameters of the painting process and comparative quota of used materials. Data required for forecasting painting process and cost is presented in Table 5. Figs. 3 and 4 indicate the accuracy of forecasted attributes and painting cost respectively. The comparison of forecasted and real process data and cost pointed that error scatter mutates from 5.5 to 10.8%. The coefficient of error variation (COV) is equal to 5.58%.

The discussion of research results relates the purposeful use of a painting process structure, facilities and cost and quality. The developed model can help engineers

Table 4

Applied parameters in model testing

Parameter	Comparative quota	Value
Paints consumptions	N_{M1}, kg/m^2 (0.15-0.25)	0.2
	Cost C_{M1}, EUR/kg	5.21
Additional chemical materials	N_{M2}, kg/m^2 (0.015-0.05)	0.015
	Cost C_{M2}, EUR/kg	13.03
Paint materials cost total	EUR/m^2	1.24

Table 5

Forecasting data of painting process cost

Parameters		Batch production BP	Automated line AL
Coefficient for estimating organization overheads	k_6 (1.09-1.25)	1.12	1.12
Coefficient for estimating painting division overheads	k_7 (1.05-1.15)	1.05	1.05
Facility cost per hour	C_{FH}, EUR/h	25.2	143.7
Quantity of workers	n_w	2	4
Tariff	t, EUR/h	4.55	4.55
Labour cost per hour	C_{LH}, EUR/h	9.1	18.2
Energy cost per hour	C_{EH}, EUR/h	0.2	1.07
Painting speed	v, m^2/min	2.5	10
Coefficient estimating useful painting area	a (0.35-0.7)	0.37	0.4

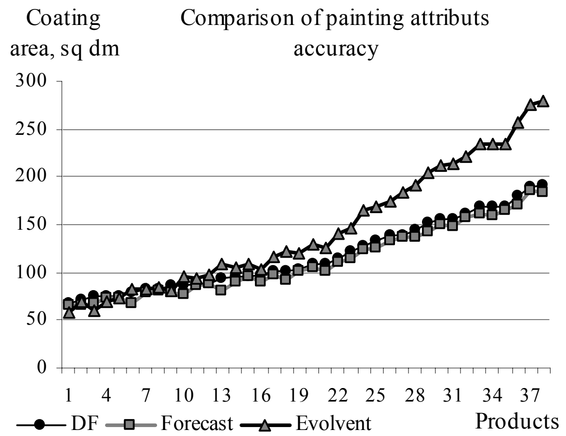

Fig. 3 The comparison of forecasted painting attributes accuracy

to choose the above-mentioned attributes in both the early new product design stage and new order engineering phase when an organization operates only in manufacturing field. The new product and process design is the essential task of the manufacturing organization that defines other areas of a company activity.

The intelligent model for painting process and cost forecasting is based on the integration of painting process attributes database, forecasting parametrical functions and rules. It gives good accuracy of forecasted painting area to sheet metal products with thickness from 0.5 to 3.0 mm. Practically, at the same interval fluctuates the error of cost because painting area does the main influence as cost value while the rest parameters are conditionally constants.

The method that has been described in this paper accomplishes the objective of this research. However, this is not the only method currently available. It has its advantages and disadvantages. The advantages are several: the developed an originated parametrical function for painting area forecasting, definition of painting process and cost in automated painting line and batch production painting cell. The main disadvantage – it does not fit to the solid parts. The developed model or its separate parts are implemented in industry of Lithuania.

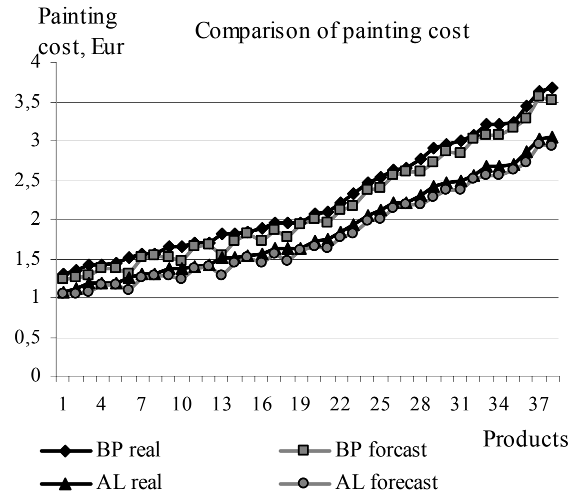

Fig. 4 The comparison of painting cost (BP – batch production, AL – automated line)

5. Conclusions and further research

The created intelligent model for painting process and cost forecasting is suitable to apply for research and practical needs in early product design stage or order engineering phase. It permits to avoid occurrences and mistakes in new product and process design seeking minimal manufacturing cost. The proposed model in order-handled manufacturing system can forecast painting process and cost with suitable accuracy. It was shown that fairly defining necessary manufacturing resources is available to win more orders.

Briefly, it is concluded as follows.

1. The forecasting error scatter of painting area at the early new product design stage where drawings and specifications are not available mutates from 5.5 to 10.8%.
2. The coefficient of error variation (COV) is equal to 5.58%.
3. It is shown that automated painting line with higher work productivity does not fit in batch production because of big manufacturing cost.
4. The developed methodology has been tested and validated for confirmation of the theoretical assumptions with the industrialists experience in companies and showed applicable results.

As a further work, it is planned to add the forecasting module for solid parts and integrate the developed model into Computer Integrated Manufacturing (CIM) system applying product modular design and agile manufacturing [10]. The marketing data and new orders wining procedure is very urgent in this task. The appropriate interfaces and programming modules for this task are necessary to develop.

Acknowledgement

This research was partially supported by the Lithuanian industrial science project “Intelligent functional model for product manufacturability” Nr 8339-2007.

References

1. **Oehme, R.** Painting Technology – Mankind and Environment. -Fat Science Technology, 1991, v.93, iss.2, p.72-75.
2. **Vanbiemen, W., Oldenburger, J.** More Efficient Spraying Techniques. -JOCCA – Surface Coatings International, 1993, v.76, iss.8, p.318-320.
3. Guide to Cleaner Technologies - Organic Coating Replacements. US Environmental Protection Agency, Office of Research and Development, September 1994, 95 p., http://www.p2pays.org/ref/02/01049.pdf [visited 26 June 2009].
4. Powder coatings: Technology of the Future, Here Today. An Overview of Powder Coating Materials, Equipment and Applications. – The Powder Coating Institute, Alexandria, issued 2/1994, http://www.owr.ehnr.state.nc.us/ref/10/09791.pdf [visited 26 June 2009].
5. **Almeida, E.** New anti-corrosive painting technologies at the beginning of the 21st century. -Journal of Coatings Technology, 2000, v.72, iss.911, p.73-84.
6. Pollution Prevention in Metal Painting and Coating Operations. – A Manual for Pollution Prevention Technical Assistance Providers, Northeast Waste Management Officials' Association, April 1998, 169p. http://www.p2pays.org/ref/01/00777 [visited 26 June 2009].
7. **Gorlach, IA.** Development of the thermal spraying process for anticorrosion surface protection. -Proceedings of International Multiconference of Engineers and Computer Scientists IMECS 2008, March 19-21, 2008 Hong Kong, v.I&II, book series: Lecture Notes in Engineering and Computer Science, p.1831-1836.
8. **Čikotienė, D., Bargelis, A.** Process modeling for quality in order-handled manufacturing system. -Mechanika. -Kaunas: Technologija, 2009, Nr.1(75), p.47-55.
9. **Bargelis, A., Mankutė, R., Stockton, D.** Product manufacturing cost calculation at the concept design stage. -Advances in Manufacturing Technology IX. Proceedings of the Eleventh National Conference on Manufacturing Research, ISBN 0 7484 0400 7. -London: Taylor & Francis, 12-14 September, 1995, p.609-612.
10. **Kässi, T., Leisti, S., Puheloinen, T.** Impact of product modular design on agile manufacturing. -Mechanika. -Kaunas: Technologija, 2008, Nr.6(74), p.56-62.

R. Mankutė, A. Bargelis

INTELEKTUALUS MODELIS DAŽYMO PROCESAMS IR SĄNAUDOMS PROGNOZUOTI

R e z i u m ė

Straipsnyje pateikta intelektualaus modelio dažymo procesams ir gamybos sąnaudoms prognozuoti struktūra ir matematinis formalizavimas. Modelis naudotinas ankstyvojoje naujo gaminio projektavimo stadijoje, ieškant gaminio konstrukcijos alternatyvos, geriausios pagal dažymo proceso sąnaudas. Sukurtas intelektualus modelis padeda greitai parinkti tinkamiausią dažymo proceso technologiją, įrenginius ir prognozuoti sąnaudas. Tyrimais nustatyta, kad dažymo proceso sąnaudų prognozavimo paklaidos svyruoja nuo 5.5 % iki 10.8 %.

R. Mankutė, A. Bargelis

INTELLIGENT MODEL FOR PAINTING PROCESS AND COST FORECASTING

S u m m a r y

In this paper the structure and mathematical formalization of intelligent model for painting processes and cost forecasting is presented. This model can be applied in the early product design stage generating various alternatives of product structure and seeking the best one according to painting process cost. Developed intelligent model is helpful for fast selection of best painting technology process, equipment and for forecasting of process cost. Research showed the dispersion of painting process forecasted cost – from 5.5 % to 10.8 %.

Р. Манкуте, А. Баргялис

ИНТЕЛЛЕКТУАЛЬНАЯ МОДЕЛЬ ДЛЯ ПРОГНОЗИРОВАНИЯ ПРОЦЕССОВ ОКРАСКИ И РАСХОДА ЗАТРАТ

Р е з ю м е

В публикации представлена структура и математическая формализация интеллектуальной модели для прогнозирования процессов окраски и их расходов. Эта модель предназначена для генерации различных альтернатив конструкции изделия и поиска лучшей по расходу затрат процесса окраски на ранней стадии проектирования. Создана интеллектуальная модель помогает быстро выбрать самую подходящую технологию окраски, оборудование и прогнозировать расходы затрат процесса. Исследования показали, что разброс погрешности прогнозирования расходов процесса окраски изменяется от 5.5 % до 10.8 %.

Received June 08, 2009
Accepted August 21, 2009

DOI: 10.5755/j02.mech.15271