Estimation of Roller Bearings Manufacturing Cost by Causal Identification and Comparative Assessment – Case Study Performed on Industrial Data

Gabriel Frumuşanu, Cezarina Afteni, and Viorel Păunoiu

***Abstract*—The conventional approach is not the best choice for optimizing the manufacturing process, because of its specific structure, and of the specific definition of the optimization problem in its case. During last years, the authors of this paper have developed the concept of holistic optimization and a method for its application in manufacturing process optimization. The method works on the base of two procedures, aiming the causal identification and the comparative assessment of the manufacturing jobs. This paper presents a validation of these procedures by applying them in the case of estimating the manufacturing cost of roller bearings. The case study used a database extracted from the industrial environment. Clusters of condition-variables being the most appropriate for evaluating the cost are determined, at first. Then, neighborhoods of the interrogated cases are extracted from the database and the proximity function is identified. The estimated ranking (hence the manufacturing cost) of the interrogated case is found on this base, eventually.**

***Index Terms*—Manufacturing cost estimation, comparative assessment, causal identification, roller bearings.**

I. Introduction

In the last years one of the most important problems in industries was cost saving. In engineering terms a bearing is defined "Any two surfaces rubbing against each other be it a bush or sleeve around a shaft or a flat surface moving over another flat surface".

The bearings can be produced in large quantities in the required quality and accuracy. They are used nearly everywhere, in industries such as automotive, aerospace, machine tools, mining, medical, agriculture.

A standard bearing is composed by four basic components an outer and inner ring, a number of Z rolling elements (ball and roll) and a plastic or metal sheet cage (see Fig. 1).

Bearings can be classified according to:

1) *The type of motion*, as for plain bearings, where the gliding motion takes place between the bearing and the supported part, and as for rolling bearings, where the rolling bodies describe a rolling motion;
2) *The direction* of bearing force *for* radial and thrust bearings;
3) *The function* in fixed bearings which can take up shearing forces and axial forces in both directions and in non-locating bearings which allows displacement in a longitudinal direction.

In the era of the mass customization, rapid and accurate estimation of the manufacturing cost improve the competitiveness of a product.

Fig. 1. Types of bearings.

The costs have become a major driver of business in many industries. The strong economic motivation for cost estimation and modeling comes from the requirement to know future manufacturing costs required in the quotation process.

There have been a number of researchers who studies on accurate cost estimation for manufacturing product.

In traditional system, the cost and price of product is calculated as follow:

1) Tracing: allocating direct material and direct payment to products and services.
2) Allocating overhead costs to products or services based on a definite attraction rate.
3) Calculating the cost and price of products, [1].

In [2] is described the development of a cost estimating methodology for predicting the cost of engineering design during the conceptual stages of product development. Cost estimated and cost engineering are separate disciplines yet inextricably linked. The cost estimating refers to a commercial business process that provides the customer with an estimate of product or service. The cost engineering is more involved and concerned with design trade studies ratherthan that of providing estimates for commercial proposals.

Shehab *et al*. develop in [3] an intelligent knowledge-based system that accomplishes an environment to assist inexperienced users to estimate the manufacturing cost modelling of a product at the conceptual design stage of the production cycle. The main function of the system, besides estimating the product cost, is to generate initial process planning includes generation and selection of machining processes, their sequence and their machining parameters.

The paper [4] presents a cost estimation methodology as well as a cost estimation model, which estimate the cost of products by relative comparison of the attributes of new product variants with the attributes of standard product variants.

In [5] the author investigate experimentally the applicability of neural networks for cost estimation in early

Manuscript received on February 20, 2020; revised May 1, 2020.

The authors are with the Manufacturing Engineering Department, Dunarea de Jos University of Galati, Romania (e-mail: gabriel.frumusanu@ ugal.ro, cezarina.afteni@ugal.ro, viorel.păunoiu@ ugal.ro).

DOI: 10.7763/IJMO.2020.V10.757

phases of product design. Experiments are based on pilot cost data from a manufacturing company.

Ma *et al* proposed in [6] a generic semantic model for the purpose of automatic cost estimation, and a new concept named cost feature is suggested. In this paper, they investigate a new manufacturing cost calculation model coherently throught the lifecycle of a product series, especially emphasizing at the conceptual design stage, which integrates three funtional sub-models: feature-based costing, data mining and semantic reasoning.

In paper [7] is presented a mathematically advanced method for improving fidelity of cost estimation for an engineering system. The authors used a new methodology for analyzing a set of cost data available in the literature, and compared the new cost model to results from a neural network based analysis and to a cost regression model.

The paper [8] concerns a new approach of the finding optimal decisions at all stages of the manufacturing process. This approach involves estimating the results (for example the cost of a product) based on the values of a descriptive parameters by comparative assessment. The proposed method works in three successive stages, namely two preparatory stages, dedicated to the analysis of the past activity performed by the manufacturing system and to the identification of potential assessment tooling, and one operational stage for actually optimizing the decisions process, by comparative assessment.

In [9], the authors suggest a different approach in performing the comparative assessment, based on alternatives rankings. The rankings are assigned to potential alternatives, by reffering them to tha cases of already performed manufacturing activities, recorded as past instances database, after ranking criteria such as cost, timespan, consumed energy etc. The selection decision results by comparing potential alternativesrankings. They propose an expression for the distance-function together with an algorithm for actually finding the ranking of the analyzed alternative.

This paper presents a validation of two procedures, aiming the causal identification and the comparative assessment of the manufacturing jobs, by applying them in the case of estimating the manufacturing cost of roller bearings.

The case study used a database extracted from the industrial environment. Clusters of cause-variables being the most appropriate for evaluating the cost are determined, at first. Then, neighborhoods of the interrogated cases are extracted from the database and the proximity function is identified. The estimated ranking (hence the manufacturing cost) of the interrogated case is found on this base, eventually.

The paper is organized as follows: the second section presents a conventional cost modeling within a company producing bearings and bearing assemblies. Next section describes the two procedures, aiming the causal identification problem and the comparative assessment problem. The fourth section is dedicated to the validation of these procedures by applying them in the case of estimating the manufacturing cost of roller bearings. The last section presents the paper conclusion.

II. Conventional Cost Modeling

In order to adapt their strategies to the current economic situation, the companies developed their own algorithms for cost and price calculation.

Cost break down becomes a tool which helps sales people to understand the main cost components and also designer to observe the main influence of the technologies in the final cost of the product.

One important component in price calculation it is represented by the internal costs. These costs are determined taking into account the raw material consumption and related purchasing price and other auxiliary materials price including: tools, devices, measurement instructions and technological liquids. Supplementary to the mentioned components in the cost calculation other factors are: salaries costs, general expenses of the company (including taxes and other financial expenses).

In the actual economic environment, companies define their investment programs based on prediction of the sales, taking into account the estimated profits versus expenses. In the investment programs are included objectives mainly for technology up-grade or renew which become more and more sophisticated and consider also the impact of the process developed through the designed technology both on the environment and workers on one side and on the other side the impact of that technology on the cost and price of the product.

The price of the product influence finally the internal decision to manufacture one or another product, to accept one or another customer order and finally the main impact is on the customer to decide. Before to take a strategic decision regarding manufacturing and also the placing of orders it becomes very important to know and consider all the cost components and their values.

Some companies use in their marketing strategies the cost break down in order to explain to the potential customer how the product it is made and how the value is added through the main manufacturing process steps, starting with raw material receiving tell delivery of the product to end customer.

Also in some cases it is very important to consider the distribution costs which could influence the decision of the buyer/customer.

The total manufacturing cost (TMC) includes direct materials, direct labor, and overhead costs.

TMC	=	Direct materials cost
	(+)	Direct labor cost
	(+)	Overheads costs

The cost of direct materials is the cost of the materials used for the manufacturing of a product during a given period.

The cost of direct labor that contributes to the manufacturing of a product during a given period.

Overhead costs are the costs that are not directly related to the manufacturing of a product.

For example, we will be considering a company that produces bearings, for estimation of a total manufacturing cost of a certain type of bearing, namely *axial type bearing* with the dimensions: inner diameter D_i = 50 mm, outer diameter D_e = 110 mm and height L = 64 mm.

The cost of direct materials includes direct materials, the inventory at the beginning of the period and the inventory at the end period.

Cost of direct materials	
• Direct materials	28.32 um
• Inventory at the beginning of period	14.27 um
• Inventory at the end of period	(10.84 um)
Cost of direct materials	**31.75 um**

To calculate, the overhead costs, include the cost of indirect labor, the cost of indirect materials, the cost of salaries, the maintenance, the technology, the quality, the external services and repairs, the packing, taxes and depreciation, CGI, the external services.

Overhead costs	
• Indirect labor	2.52 um
• Indirect materials	2.30 um
• Salaries	11.35 um
• Maintenance	2.50 um
• Technology	0.72 um
• Quality	1.93 um
• External services and repairs	1.34 um
• Packing	1.83 um
• Taxes	3.21 um
• Depreciation	9.00 um
• CGI	29.69 um
• External services	2.92 um
Overhead costs	**69.31 um**

The TMC is calculating by adding the cost of direct materials, the cost of direct labor and the overhead costs.

Total manufacturing cost	
• Cost of direct materials	31.75 um
• Direct labor	14.27 um
• Overhead costs	69.31 um
Total manufacturing cost	**115.33 um**

The traditional cost-estimation techniques known as single price estimating models, elemental estimating, operational estimating and resource related methods are also replaced by advanced cost estimating systems known as casual empirical models, regression models, simulation models and expert systems that use hardware and software to convert data into appropriate information for the ultimate users.

III. Proposed Method for Cost Estimation

The method works on the base of two procedures:

- The causal identification,
- The comparative assessment.
- The causal identification

The method of identifying causal links in the manufacturing process [10] is useful for finding the most appropriate pattern structure for a particular manufacturing activity/process. The facility of the method aims at identifying the groups of variables with potential for application in the modeling of the activity/process. The primary objective of applying the method is to allow the selection of variables, the most influential, easy to measure, and as few as possible, such as the resulting least complex model, according to the predicted estimate of precision. The method utilizes the past case studies relating to the manufacturing system, registered as a database, to reveal the causal links between the variables that characterize the development of the manufacturing processes on the considered system.

Applying the method for case-based identification of causal links in the manufacturing process involves several successive stages (see Fig. 2).

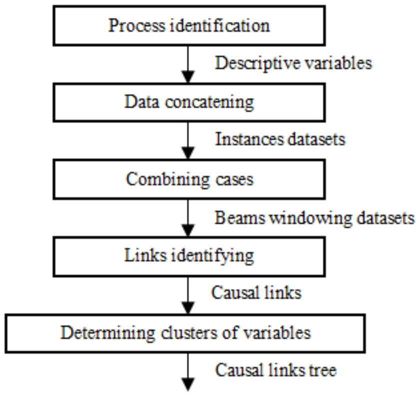


Fig. 2. The algorithm of the proposed method.

A. Process Identification

The first step of the algorithm involves analyzing the variant of target - manufacturing process to choose the variables that characterize its achievement. It then defines the set of variables (both cause- and effect-variables) with potential in process modeling.

B. Data Concatening

The purpose of the stage is to generate the database of previous cases, regarding the manufacturing process variant considered. Several cases refer to same type of activity if they can be characterized by the same cause-variables and effect-variables.

Three actions are necessary in order to do data concatening, namely clustering, updating and homogenization.

C. Instances Comparing

The method of identifying causal links is based on the idea, that if there is a causal link between two or more variables, the variance of a cause-variable will be reflected and therefore measured by an appropriate metric in a variation of another cause- and/or effect-variables.

D. Variables Assessing

This step aims to assess the cause-variables in order to find the ones having potential for evaluating the given effect-variable.

Variables assessing is performed by applying two algorithms, namely:

- The algorithm for dimensionality reduction,
- The algorithm for assessing the modeling potential of variables.

E. Causal Models Identifying

This can be realized by successively and repetitively applying a couple of algorithms, namely:

- The algorithm for generating smaller clusters,
- The algorithm for assessing the modeling potential of a cluster.

F. Causal Links Tree

The selection of the most suitable cluster of cause-variables with which can be describing the effect is made with the help of intuitive representation called the *causal links tree* (see Fig. 3).

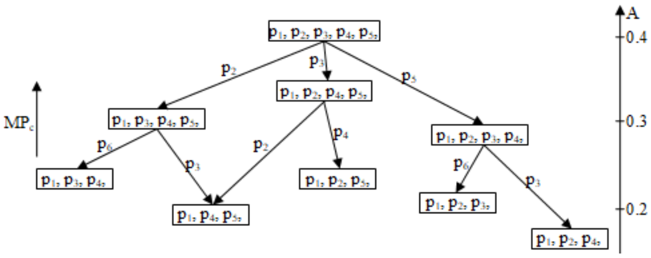


Fig. 3. The generic causal links tree [10].

1) The comparative assessment

The method of comparative assessment in the manufacturing process proposes an innovative approach in the analysis of potentially optimal solutions, based on their rankings.

The comparative assessment means to establish rankings for two or more alternatives to proceed, after given criterion (e.g. cost, time span, consumed energy etc.).

The comparative assessment of potential alternatives it is done by referring them to the cases of manufacturing processes already carried out, whose parameters have been registered in the past instances database, [11].

The algorithm after which the appropriate ranking is assigned to a given alternative (further referred as *current case*) by comparing it to the cases recorded in *Instances database* is illustrated in Fig. 4.

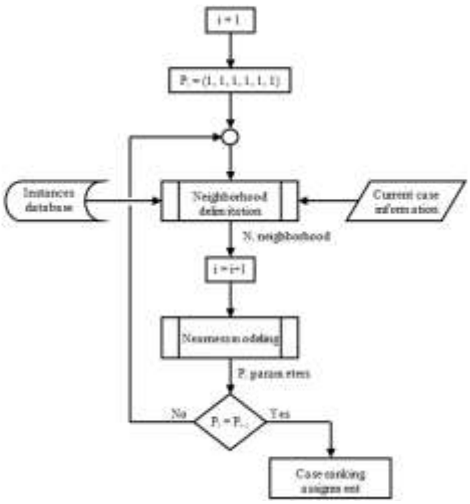


Fig. 4. Ranking assignment algorithm [11].

The algorithm works on the base of two procedures, especially conceived in this purpose:

- *Neigh*borhood delimitation,
- *Nearness* modeling.

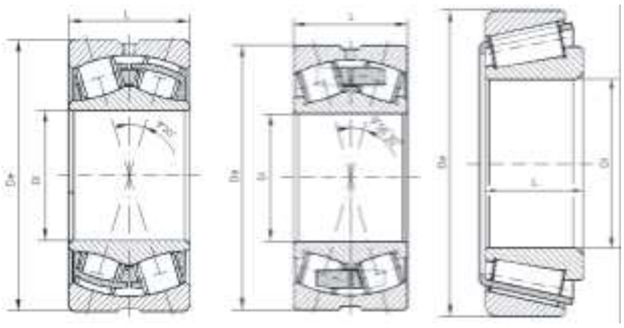
The procedure for *neighborhood delimitation* to find a neighborhood profile of a potential case through successive comparisons with cases of processes already carried out (with known results). The objective is to select from the instances database, the set of instances that corresponds to a given neighborhood profile.

The procedure for *nearness modeling* aims that, after a delimiting the current neighborhood N_i of the current case, the nearness between included cases is modeled in order to find a more expression of the nearness function. The modeling is proposed to be performed by nonlinear multiple regression.

Both procedures are successively run until two consecutive forms of nearness parameters.

IV. Cost Estimation for the Roller Bearing - Case Study Performed on Industrial Data

The roller bearings (Fig. 5) manufacturing cost was estimated by using the above proposed method in the case of a database extracted from the industrial environment.



a) b) c)

Fig. 5. Profile of the bearing.

A. The Causal Identification

For the application of the method by this procedure, the steps of the algorithm presented in previous section were followed.

B. Process Identification

The next set of nine cause-variables was considered as having potential in modeling the manufacturing process, namely:

- the bearing exterior diameters, D_e;
- the bearing interior diameters, D_i;
- the bearing width, L;
- the bearing weight, m;
- dynamic capacity, C_d;
- static capacity, C_s;
- limit speed under greasing conditions, n_1;
- limit speed under oil conditions n_2,
- the complexity index I_c.

The cost of the bearing was selected as effect-variable.

C. Data Concatening

The collected database has 141 instances, some of them being sampled in Tables I-A and I-B, before and after homogenization, respectively.

TABLE I-A: Real Instances Dataset (Actual Values, Excerpt)

Instance crt. no.	D_e [mm]	D_i [mm]	L [mm]	m [kg]	C_d [kN]	C_s [kN]	n_1 [min^{-1}]	n_2 [min^{-1}]	I_c [-]	C [lei]
1	110	60	47	1.496	77.4	209	7.76	1900	2800	61.65
2	140	65	79	4.858	176	424	8.36	1300	1800	184.41
3	78	58	22	0.421	88	285	9.32	1400	4000	33.66
4	125	70	40	2.106	153	341	6.36	1400	1900	85.56
5	35	20	10	0.041	14.9	26.6	4.16	5300	7000	8.53
. . .	. . . .									

TABLE I-B: REAL INSTANCES DATASET (SCALED VALUES, EXCERPT)

Instance crt. no.	D_e	D_i	L	m	C_d	C_s	n_1	n_2	I_c	C
1	0.518	0.357	0.413	0.131	0.18	0.137	0.624	0.218	0.205	0.151
2	0.698	0.392	0.760	0.432	0.445	0.288	0.724	0.120	0.076	0.489
3	0.325	0.342	0.141	0.035	0.209	0.19	0.885	0.136	0.358	0.074
4	0.608	0.428	0.336	0.186	0.383	0.23	0.389	0.136	0.089	0.217
5	0.066	0.071	0.010	0.001	0.013	0.008	0.020	0.771	0.743	0.004
. . .	. . . .									

D. Instances Comparing

This time, the beams database generated with the Matlab application has $N = C_{141}^{2} = 9870$ beams. Several beams are sampled in Table II.

TABLE II: BEAMS DATABASE (EXCERPT)

Fascicul	δD_e	δD_i	δL	δm	δC_d	δC_s	δn_1	δn_2	δI_c	δC
(1,2)	0.180	0.03	0.347	0.3	0.264	0.151	0.1	0.097	0.128	0.338
(1,3)	0.481	0.5	0.021	0.263	0.28	0.23	0.302	0.13	0.153	0.106
(1,4)	0.09	0.071	0.07	0.05	0.202	0.092	0.234	0.081	0.115	0.065
(1,5)	0.451	0.285	0.402	0.13	0.167	0.128	0.604	0.55	0.538	0.146
(1,6)	0.030	0.114	0.336	0.056	0.17	0.268	0.34	0.065	0.064	0.015
. . .	. . . .									

E. Variables Assessing

1) Dimensionality reduction

At first, the references threshold has been to $h_{ref} = h_7 = 0.2097$, hence $h_{k-2} = h_5 = 0.3276$. According to the algorithm, windows having $H = 0$ and $h = h_{ref}$ were considered for the beams components corresponding to eight of the nine cause-variables, while for the ninety the image dimension Δ_i was measured (i = 1, 2, ... 9, successively). The values obtained for Δ_i, by using a dedicated MatLab application, are shown in Table III. As it can be noticed, $\Delta_{\min} = 0.2179$, corresponding to variable I_c, hence one of them may be discarded. At Step 2, the action from previous step is repeated for the remaining eight cause-variables and another one is discarded, namely D_e, and so on. After Step 3, $\Delta_{\min} = 0.3209 > h_5$, so the six cause-variables remaining until here can be considered relative independent and the maximal cluster is [D_i, L, m, C_d, n_1, n_2].

TABLE III: IMAGES DIMENSIONS Δ_i AND $\Delta_{\min}$

Condition variable	Successive steps of dimensionality reduction			
	Step 1	Step 2	Step 3	Step 4
D_e	0.28915662	0.28915662	-	-
D_i	0.39285714	0.39285714	0.78571428	0.78571428
L	0.52173913	0.52173913	0.54347826	0.55434782
m	0.35587761	0.35587761	0.35587761	0.51171944
C_d	0.35924932	0.35924932	0.35924932	0.60321715
C_s	0.32090077	0.32090077	0.32090077	-
n_1	0.92281879	0.92281879	0.92281879	0.92281879
n_2	0.35830618	0.53745928	0.61889250	0.61889250
I_c	0.21794871	-	-	-

F. Assessment of Variables Modeling Potential

The criteria for assessing the modeling potential have been determinates for each cause-variable of the maximal cluster, according to the algorithm above presented, by calculating the values of a, b, and *RMSE*, after considering the cost C as effect-variable. The results obtained with the help of Curve fitting tool from MatLab are presented in Table IV.

TABLE IV: THE VALUES OF a, b AND *RMSE*

	D_i	L	m	C_d	n_1	n_2
a	0.1272	0.2241	0.05765	0.0041	0.02191	0.3234
b	0.0445	0.03765	0.04864	0.05269	0.04961	0.03479
RMSE	0.0011	0.00058	0.00176	0.00112	0.00185	0.00171

G. Causal Models Identifying

The *MC* (assessed through the values of b) was adopted as criterion for selecting the cause-variables to be discarded when generating smaller clusters. Three clusters with 5 cause-variables each has been generated from the maximal cluster in the first stage. Then, two clusters with 4 cause-variables resulted from each of these three, in the second stage. Finally, two clusters of 3 cause-variables were obtained from each cluster with 5 variables. After assessing clusters potential in order to identify causal models, the process of generating smaller clusters had to be stopped at the level of 3-variables clusters. Variables selection and resulted clusters are presented in Tables V-A, B and C.

TABLE V-A: GENERATION OF 5-VARIABLES CLUSTERS

Variables	D_i	L	m	C_d	n_1	n_2
b	0.0352	0.0283	0.0179	0.02651	0.04707	0.0509
Resulted clusters	[D_i, L, m, C_d, n_1]			[D_i, L, m, C_d, n_2]		

TABLE V-B: GENERATION OF 4-VARIABLES CLUSTERS

Variables	D_i	L	m	C_d	n_1
b	0.03625	0.02628	0.01739	0.02499	0.04405
Resulted clusters	[D_i, L, m, C_d]			[L, m, C_d, n_1]	
Variables	D_i	L	m	C_d	n_2
b	0.03552	0.02651	0.01663	0.02167	0.04639
Resulted clusters	[D_i, L, m, C_d]			[L, m, C_d, n_2]	

TABLE V-C: GENERATION OF 3-VARIABLES CLUSTERS

Variables	D_i	L	m	C_d
b	0.03384	0.02441	0.01748	0.01816
Resulted clusters	[D_i, m, C_d]		[L, m, C_d]	
Variables	L	m	C_d	n_1
b	0.03452	0.01986	0.02605	0.05446
Resulted clusters	[m, Cd, n_1]		[L, m, C_d]	
Variables	L	m	C_d	n_2
b	0.03896	0.01571	0.01366	0.06395
Resulted clusters	[m, Cd, n_2]		[L, m, C_d]	

Finally, they resulted only 4 (instead of 6) distinct clusters with 3 variables and 3 (instead of 6) clusters with 4 variables. Hereby, the causal tree will be formed from 1 + 2 + 3 + 4 = 10 clusters.

TABLE VI: THE VALUES OF a_c, b_c AND RMSE

Condition-variables from cluster	a_c	b_c	RMSE
[D_i, L, m, C_d, n_1, n_2]	0.7988	0.004066	0.007391
[D_i, L, m, C_d, n_1]	0.7748	0.002467	0.008119
[L, m, C_d, n_1, n_2]	0.8605	-0.001428	0.009931
[D_i, L, m, C_d]	0.8438	-0.00216	0.01061
[L, m, C_d, n_1]	0.7602	0.01108	0.004584
[L, m, C_d, n_2]	0.8323	0.01133	0.009419
[D_i, m, C_d]	0.8858	0.003786	0.006537
[L, m, C_d]	0.8635	0.005654	0.00775
[m, C_d, n_1]	0.7895	0.01235	0.002351
[m, C_d, n_2]	0.9038	0.01406	0.005238

H. Assessment of Clusters Modeling Potential

After finding the clusters of cause-variables that will compose the causal tree, the values of a_c, b_c and *RMSE* were found with Curve fitting tool from MatLab. These values are presented in Table VI.

I. Causal Link Tree

The causal tree drawn after MC_c criterion is depicted in Fig. 6.

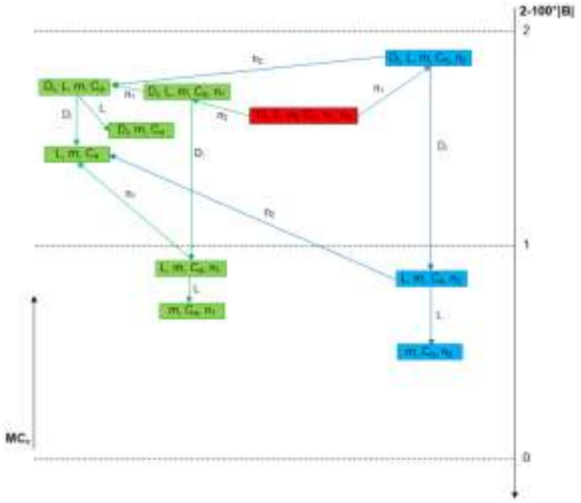


Fig. 6. Causal tree drawn after criterion MC_c

J. The Comparative Assessment

For application of the method by this procedure in the case for the cluster with four cause-variables [L, m, C_d, n_2] of a database extracted from the industrial environment for estimation of roller bearings manufacturing cost.

The database has five columns (first four for L, m, C_d and n_2 cause-variables and the last for C effect-variable) and n = 141 lines.

K. Case Ranking Assignment

We supposed the current case (L_1 = 0.4, m_1 = 0.2, C_{d1} = 0.5, n_{21} = 0.15), needing to be ranked relative to the instances database from above. At first, the pivot (L_{v1} = 0.38043, m_{v1} = 0.20987, C_{dv1} = 0.46648, n_{2v1} = 0.12052, C_{v1} = 0.27999) has been chosen from instances database. Then, the algorithm for case ranking assignment has been iteratively run, the results being presented in Tables 6 and 7. The modeling by nonlinear multiple regression has been performed in MatLab (*Optimization tools* package).

The values for ε parameter have been selected at each iteration such as the current case neighborhood includes the same number of cases (here, 12 cases). The quality of modeling the cases neighborhood by nonlinear multiple regression is revealed by calculating the *Root Mean Square Error* (*RMSE*) parameter, well-known in Statistics. As one can easily notice, the algorithm stabilizes rapidly, after only two iterations – the three iterations give same results as the previous one.

As consequence, relation (6) can be used (in the form resulted after last modeling by multiple nonlinear regression) for calculating $\Delta C_1 = C_1 - C_{v1}$. The obtained value is ΔC_1 = -0.00172, hereby C_1 = 0.27827 and considered case ranking is R_1 = 108.

L. Actual Comparative Assessment

Let us consider two different current cases: first is the one addressed in previous section, while second is (L_2 = 0.7, m_2 = 0.35, C_{d2} = 0.4, n_{22} = 0.2). The problem to be solved is the selection, between the two cases, of the one with the smallest value of the effect-variable.

The algorithm for case ranking assignment is applied once again, for second potential case, to which the pivot (L_{v2} = 0.68478, m_{v2} = 0.34693, C_{dv2} = 0.36997, n_{v2} = 0.16938, T_{v2} = 0.31331) is associated from the same instances database. This time, the algorithm stabilizes after only one iteration – the second iteration gives the same results as the previous one. In the same manner as above, we find ΔC_2 = -0.00138, C_2 = 0.31470 and case ranking is R_2 = 114.

In conditions of the addressed problem, we have $R_2 > R_1$, so the solution to the problem is to selected the first case.

V. Conclusion

At the end of research presented in this paper, the following conclusions can be drawn:

- Compared to the traditional cost estimation method, which requires laborious calculations, estimating the cost by the proposed method proves to be simple and efficient.
- By causal identification, the number of cause-variables needed to evaluate the cost of roller bearing manufacturing is reduced substantially: instead of the ten variables a maximum clusters of six cause-variables has been identified [D_i, L, m, C_d, n_1, n_2], that shows very good potential for price modeling in the case of bearing production (b_c = 0.004066).
- Also, the clusters of three cause-variables has been identified that model the cost well enough [m, C_d, n_2], a significantly simpler solution for doing the same thing with reasonable good results (b_c = 0.01406).
- As can be seen from Table VI, in two cases the value for b_c resulted negative. This can be explained by the static character of the method, which, for a smaller number of cases, can lead to such results. To overcome this disadvantage, in the representation of the tree causal link, the absolute value of b_c was used in both cases.
- Comparative assessment cost provides plausible results, after a very small number of iterations (2).

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

GF conceived of the presented idea, and verified the case study results. CA performed simulations, collected and analyzed data and wrote the paper with input from all authors. VP aided in interpreting the results. All authors read and approved the final paper.

Acknowledgement

This work was supported by the Romanian Ministry of Research and Innovation, CCCDI – UEFISCDI, project number PN-III-P1-1.2-PCCDI-2017-0446 / *Intelligent manufacturing technologies for advanced production of parts from automobiles and aeronautics industries* (TFI PMAIAA) - 82 PCCDI/2018, within PNCDI III.

References

[1] F. Kowsari, "Changing in costing models from traditional to performance focused activity based costing (PFABC) activity based costing 2 time driven activity based costing 3 performance focused activity based Costing," *Eur. Online J. Nat. Soc. Sci.*, vol. 2, no. 3, pp. 2497-2508, 2013.

[2] R. Roy, S. Kelvesjo, S. Forsberg, and C. Rush, "Quantitative and qualitative cost estimating for engineering design," *J. Eng. Des.*, vol. 12, nr. 2, pp. 147-162, 2001.

[3] H. Shehab and E. M. Abdalla, "Manufacturing cost modelling for concurrent product development," *Robot. Comput. Integr. Manuf.*, vol. 17, no. 4, pp. 341-353, 2001.

[4] Y. Hooshmand, P. Köhler, and A. K. Krumm, "Cost estimation in engineer-to-order manufacturing," *Open Eng.*, vol. 6, no. 1, pp. 22-34, 2016.

[5] J. Bode, "Neural networks for cost estimation: Simulations and pilot application," *Int. J. Prod. Res.*, vol. 38, no. 6, pp. 1231-1254, 2010.

[6] Y. S. Ma, N. Sajadfar, and L. C. Triana, "A feature-based semantic model for automatic product cost estimation," *IACSIT Int. J. Eng. Technol.*, vol. 6, no. 2, pp. 109-113, 2014.

[7] J. Colombi, M. J. Miller, E. Michael, S. Michael, J. M. Grogan, and L. S. David, "Model based systems engineering with department of defense architectural framework," *Syst. Eng.*, vol. 14, no. 3, pp. 305-326, 2012.

[8] C. Afteni, G. Frumuşanu, and A. Epureanu, "Method for holistic optimization of the manufacturing process," *Int. J. Model. Optim.*, vol. 9, no. 5, pp. 265-270, 2019.

[9] C. Afteni, G. Frumuşanu, and A. Epureanu, "Instance-based comparative assessment with application in manufacturing," in *Porc. IOP Conf. Ser. Mater. Sci. Eng. Pap.*, 2018.

[10] C. A. and A. E. G. R. Frumusanu, "Causal identification of the manufacturing system," *J. Manuf. Sci. Eng.*, 2019.

[11] C. Afteni, G. Frumuşanu, and A Epureanu, "Instance-based comparative assessment with application in manufacturing," in *Porc. IOP Conf. Ser. Mater. Sci. Eng.*, vol. 400, no. 042001, pp. 0-8, 2018.

Gabriel Frumuşanu was born in Galaţi, Romania, in 1964. He received his bachelor in 1988, the PhD in 1999, the Habilitation in 2016, in industrial engineering at Dunărea de Jos University of Galaţi, Romania.

He is currently a professor at Dunărea de Jos University of Galaţi, Romania, and the head of the Manufacturing Engineering Department. He published over 150 scientific articles, some of them in prestigious journals. He owns 5 patents. He participated at numerous International conferences (Spain, Hungary, Tunisia, Israel, Moldova and Romania). His research interests are in machining systems control, cutting tools profiling and environmental impact of the manufacturing process. Prof. Frumuşanu is a member of UASTRO, AUIF and of editorial boards - Proceedings in Manufacturing Systems journal (Romanian Academy), the Annals of Dunărea de Jos University, Fascicle V.

Cezarina Afteni was born in Galati, Romania, on December 02, 1990. She received her bachelor in economical engineering in 2014 and the master in quality management in industrial engineering from Dunărea de Jos University of Galati, Romania, in 2016.

She is currently a PhD student at Dunărea de Jos University of Galati, Romania, in the Manufacturing Engineering Department. Her research interests are mainly related to optimization problems by integrating process planning and scheduling.

Ms. Afteni is involved in different research works from industrial environment. The main objectives developed within this colaboration are: lead time improvement in bearing manufacturing process and optimization of process chain in case of grinding and hard turning processes.

Viorel Paunoiu was born in Galati, Romania, in 1959. He is a professor of mechanical engineering at Dunarea de Jos University of Galati (1987-present), Faculty of Engineering. Manufacturing Engineering Department is main academic competences are technologies and equipment's for metal forming; numerical simulation of sheet metal forming; control and inspection in sheet metal forming; energetic phenomenon's studies in metal forming (deep drawing, flow forming, extrusion). Prof. Paunoiu participated as the director or a member in over 35 research projects supported by Romanian Ministry of Education and Science; author/co-author of over 10 scientific or didactic books; over 120 scientific papers written or co-authored by him and they are published to International/National Conferences proceedings (France, Hungary, Poland, USA, Moldavia, Italy) and Journals; author/co-author of 3 patents. He was the editor of the journal The Annals of Dunarea de Jos University of Galati, Fascicle V, Technologies in Machine Building (2008-2019). He is the founder and co-chairman of the International Conference NEWTECH – Advanced Manufacturing Engineering and Technologies (2009-present).