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A Solution for Predicting the Timespan needed for Grinding Roller Bearing Rings

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INTRODUCTION

In the actual economic environment, the industrial manufacturers defined and implemented different development strategies based on cost saving principles, considering on one side the resources availability and rational consumption and, on the other side, production parameters improvement through lead time reduction in conditions of keeping the same quality for the produced and delivered goods.

The actual challenge is to find out a solution which can help the manufacturers to predict rapidly and with a high degree of precision the indicators of a given manufacturing process based on collected previous data and knowledge.

In this study it is presented a solution to predict the timespan needed for grinding the roller bearings rings based on the use of a database with data collected from the industrial environment by applying the specific algorithms of the Holistic Optimization Method (HOM). The HOM includes two algorithms: i) *the causal identification of a manufacturing process* and ii) *the comparative assessment among the already performed manufacturing cases*, recorded as instances database. The two algorithms can be used to estimate the values of different performance indicators of the processing processes. The solution presented in this study it is characterized by the fact that a decision must be made at any time during the manufacturing process by using both proposed algorithms.

The case study developed in this study for timespan prediction in the manufacturing process for grinding roller bearing rings, is validated based on a database with data collected from the industrial environment.

METHOD

The Holistic Optimization Method consists of two algorithms:

i. *The causal identification algorithm* targets to identify multiple forms of the same causal relation. The output of this action is the identification of the most suitable cause-variable set by which the effect-variable can be evaluated. The result is the causal links graph.

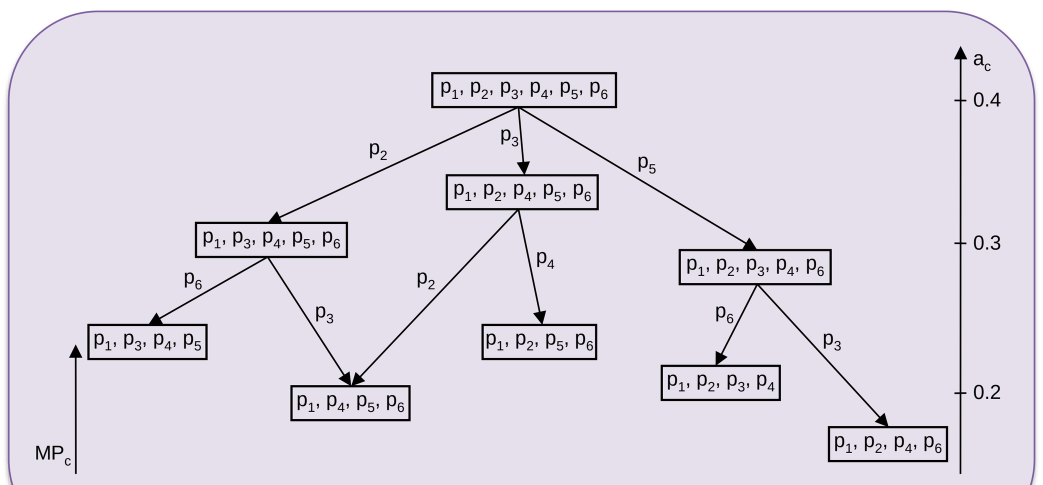

Figure 2. The generic causal links graph

ii. *The comparative assessment among the already performed manufacturing cases* is an innovative approach of the analysis of the potential optimal solutions, based on their hierarchization. This action aims to assist the decision making regarding the continuation of the manufacturing process at a certain decision level.

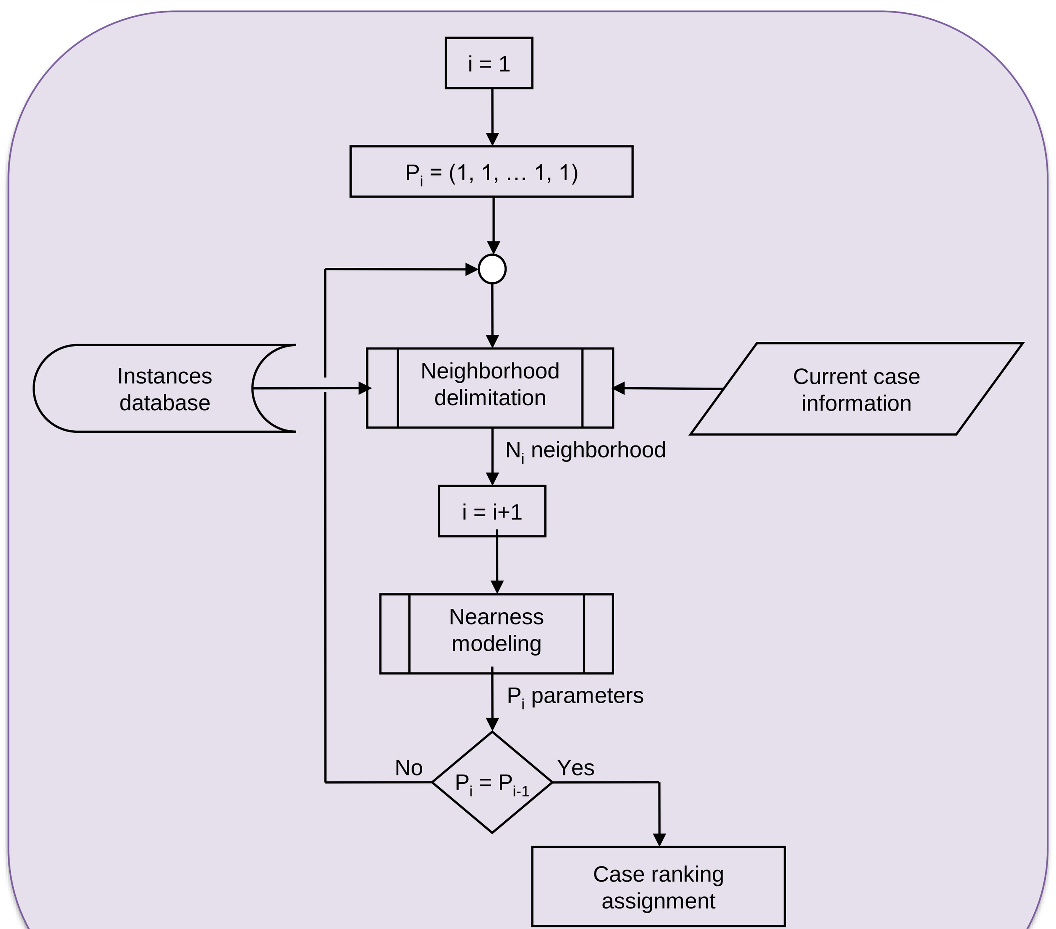

Figure 3. Comparative assessment algorithm

The efficiency of the method was validated through a case study for the manufacturing processes of some bearing components. A real database extracted from the industrial environment was used.

RESULTS & DISCUSSION

The simulation of the grinding phase's correlation with the timespan was developed in order to identify the most suitable set of causal-variables with the most important impact on the timespan.

❑ Causal identification

1. Process identification

- **Cause-variables:** the outer diameter of the ring, D_e, the inner diameter of the ring, D_i, the width of the ring, *l*, the weight of the ring, *g,* the machined surface roughness, R_a, the cutting speed, *v*, the feedrate, *f*, the grinding stone rotation speed, v_r, the cutting depth, *t*.
- **Effect-variable:** Timespan, *Ts* [min].

2. Data concatening

The values from the 10 columns were individually scaled in interval [0,1]. The database for the scaled values contains 77 instances.

3. Instances comparing

The scaled values from the 10 columns were compared separately. The database obtained for the fascicle it have $N = C_{77}^{2} = 2926$ beams.

4. Variables assessing

- *Dimensionality reduction*
  - ✓ Reference threshold: $h_{ref} = h_9 = 0.1342$, $h_{k\text{-}2} = h_6 = 0.2621$.

Table 1. Values of *Δi'* images dimension

Cause-variables	Successive steps for dimensionality reduction			
	Step 1	Step 2	Step 3	Step 4
D_e	0.1433	0.1433	-	-
D_i	0.1705	0.1705	0.6869	0.6869
l	0.1753	0.3352	0.3352	0.6940
g	0.1736	0.1736	0.1736	-
R_a	0.9122	0.9122	0.9122	0.9122
v_a	0.1179	-	-	-
f	0.7609	0.8043	0.8043	0.8043
v_r	0.4155	0.9251	0.9251	0.9251
t	0.2927	0.2927	0.2927	0.2927

The maximal cluster: [Di, l, Ra, f, v_r, t].

- *Assessing the modeling potential of variables*

The characteristics:

- the modeling power MP - a
- the modeling capacity MC - b
- the modeling unevenness MU - RMSE

MatLab modeling → Curve fitting tool (cftool)

Table 2. Values of the characteristics for modelling capacity

	D_i	l	R_a	f	v_r	t
a	0.1883	0.2208	0.0714	0.0077	0.00085	0.1726
b	0.0254	0.0261	0.0407	0.1308	0.0399	0.0326
RMSE	0.0072	0.0024	0.0037	0.00068	0.00068	0.00027

5. Causal models identification

- *Generating smaller clusters*

Table 3. Generation of 6, 5, 4 - variables clusters

Variables	D_i	l	R_a	f	v_r	t
b	0.0254	0.0261	0.0407	0.1308	0.0399	0.0326
Resulted clusters	[D_i, l, R_a, v_r, t]	[D_i, l, f, v_r, t]				

Variables	D_i	l	R_a	v_r	t
b	0.0424	0.0306	0.0384	0.0428	0.0319
Resulted clusters	[D_i, l, R_a, t]	[l, R_a, v_r, t]			

Variables	D_i	l	f	v_r	t
b	0.0507	0.0443	0.057	0.0569	0.0535
Resulted clusters	[D_i, l, f, t]	[D_i, l, v_r, t]			

Variables	D_i	l	R_a	t
b	0.0322	0.0349	0.0461	0.0445
Resulted clusters	[D_i, l, R_a]	[D_i, l, t]		

Variables	l	R_a	v_r	t
b	0.0307	0.0315	0.0475	0.0115
Resulted clusters	[l, R_a, t]	[l, v_r, t]		

Variables	D_i	l	f	t
b	0.036	0.0319	0.0494	0.0377
Resulted clusters	[D_i, l, f]	[D_i, l, t]		

Variables	D_i	l	v_r	t
b	0.0471	0.0391	0.0489	0.0469
Resulted clusters	[D_i, l, t]	[l, v_r, t]		

- *Assessing the modeling potential cluster*

The characteristics:

- the modeling power MP - a_c
- the modeling capacity MC - b_c
- the modeling unevenness MU - RMSE

MatLab modeling → Curve fitting tool (cftool)

Set of cause-variables	a_c	b_c	RMSE
[D_i, l, R_a, f, v_r, t]	0.0611	0.08703	0.0796
[D_i, l, R_a, v_r, t]	0.0793	0.0837	0.0806
[D_i, l, f, v_r, t]	0.3205	0.0481	0.0268
[D_i, l, R_a, t]	0.0705	0.0821	0.0816
[l, R_a, v_r, t]	0.3684	0.0806	0.0789
[D_i, l, f, t]	0.3535	0.0424	0.0266
[D_i, l, v_r, t]	0.3047	0.0466	0.0271
[D_i, l, R_a]	0.3752	0.03901	0.0204
[D_i, l, t]	0.3891	0.0326	0.0219
[l, R_a, t]	0.651	0.0386	0.0292
[l, v_r, t]	0.5902	0.0459	0.0159
[D_i, l, f]	0.393	0.0359	0.018

❑ Comparative assessment

MatLab modeling → Nonlinear multiple regression

1. Case ranking

Actual case	pivot
$D_{i1} = 0.3$	$D_{iv1} = 0.27903$
$l_1 = 0.7$	$l_{v1} = 0.69646$
$R_{a1} = 0.5$	$R_{av1} = 0.48360$
$t_1 = 0.45$	$t_{v1} = 0.47986$
$Ts_1 =$?	$Ts_{v1} = 0.42490$

$\Delta Ts_1 = 0.00391$

$\Delta Ts_1 = Ts_1 - Ts_{v1} \Rightarrow Ts_1 = 0.42881$

Ranking: $R_1 = 56$

2. Comparative assessement

Second case	pivot
$D_{i2} = 0.6$	$D_{iv2} = 0.59238$
$l_2 = 0.3$	$l_{v2} = 0.27930$
$R_{a2} = 0.75$	$R_{av2} = 0.73795$
$t_2 = 0.25$	$t_{v2} = 0.25873$
$Ts_2 =$?	$Ts_{v2} = 0.23330$

$\Delta Ts_2 = 0.00147$

$\Delta Ts_2 = Ts_2 - Ts_{v2} \Rightarrow Ts_2 = 0.23330$

Ranking: $R_2 = 50$

CONCLUSION

- In recent years the technologies have registered a rapidly development, with an important impact on company activities and on manufacturing process.
- In actual aproaches, the optimisation models are in general analitical and the evaluation of the results is direct.
- Here optimization means the assurance of the optimum in each stage of a manufacturing process. This purpose can be reached by optimization of the decision flow, which helps to control the manufacturing process. The optimization target should be cosidered as reference, while the decission means a control variable.
- The application of proposed method shows good results in the case of the database generated with data from the industrial field.
- The usage of a Matlab modeling application could help companies to reduce the time spent on discussion „make or buy" type, by considering past experience and results.

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