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A DIGITAL-AGE APPROACH OF MANUFACTURING OPTIMIZATION

Gabriel Frumuşanu, Alexandru Epureanu

[1]"Dunărea de Jos" University of Galaţi, Department of Manufacturing Engineering
Domnească Street 111, 800201 – Galaţi, Romania

Corresponding author: Gabriel Frumuşanu, gabriel.frumusanu@ugal.ro

Abstract: The problem of manufacturing process optimization is one of the most addressed issues across literature concerning the manufacturing field. Until now, this optimization has been based on indirect description of manufacturing, through prefabricated algorithmic models (be they analytical or numerical), as well as on information processing, by composing this kind of models. This is why the optimization is difficult and complicated, even in the case of the simplest processes. This paper presents a new approach of the manufacturing optimization concept, having as main defining aspects: *i)* The manufacturing process is regarded as decisional instead of physical process, *ii)* The optimization object is the manufacturing task, defined as product transition from current state up to final state, *iii)* The manufacturing model consists in a dataset, and, *iv)* The optimization problem solution consists in task configuring, task accomplishment, and task modeling. According to the new approach, the optimization result consists in the ensemble formed by an optimal structure (optimal configuration of the given task), an optimal process (optimal values of the process variables), and an optimal model (obtained by iterative rebuilding of the manufacturing model). The application of the proposed approach is sampled through a comparative illustration.

Key words: manufacturing optimization, digital modeling, decision making, comparative assessment, global optimization.

1. INTRODUCTION

To face the fierce competition on market exacerbated by globalization, the companies try hard to improve their manufacturing processes, and to obtain products of high quality, manufactured at competitive price, in increasingly restrictive terms of environmental impact and specific consumption of materials [1]. To reach these targets, it is highly important to work in optimal conditions.

In recent years, numerous studies on the issue of optimizing manufacturing processes have been developed, addressing a multitude of aspects (be they of technical, financial, commercial, environmental or other nature). Despite of the manufacturing environment complexity, the optimization problem was most of the times approached on the base of a unique criterion, derived from the above-mentioned objectives. Still, they are enough studies that considered multiple criteria (multi-criteria optimization), but without a unitary manner of associating them.

The most encountered criteria for manufacturing optimization are productivity [2, 3], cost [4, 5], manufactured surface roughness [6], cutting force magnitude [7], energy consumption [8, 9]. As optimization techniques, one can mention Genetic Algorithms [10, 11], Artificial Neural Networks [12, 13], Fuzzy Logic [14], Particle Swarm Optimization [15], etc.

It should be noticed that, manufacturing process optimization is frequently mixed up with cutting regime optimization and it is performed usually on the base of an analytical model of the objective-function. Most of the existing papers in this field deal with the actual execution of the product.

The conventional approach of manufacturing optimization is not enough adapted to the requirements specific to manufacturing process, because:

- Although a process should be optimized in its wholeness, frequently this cannot be done, because decisions concerning the process must be taken at successive levels, whilst the decision from a certain level cannot be taken before accomplishing the tasks from previous level,
- The tasks accomplished during the entire manufacturing process of a product (including ordering, design, planning, programming, and processing) have different natures and requirements, and

- The existence of a sometimes-high number of manufacturing tasks needing to be accomplished for obtaining a product leads to a huge number of variables to be monitored, hereby the dimensionality of the optimization problem passes over the available computational resources.

The challenge for this paper was to release a new approach for manufacturing optimization, adapted to the specificity of nowadays manufacturing environment, on one side, and to the opportunities created by generalized & accelerated digitalization process, on the other side.

This paper presents a new approach of the manufacturing optimization, having as main defining aspects: *i)* The manufacturing process is regarded as decisional instead of physical process, *ii)* The optimization object is the manufacturing task, defined as product transition from current state up to final state, *iii)* The manufacturing model consists in a dataset, and *iv)* The optimization problem solution consists in task configuring, task accomplishment, and task modeling. Next section introduces a new concept of manufacturing optimization. The third section presents a new approach of the manufacturing process. The fourth section proposes a procedure for implementing the new optimization concept. The fifth section deals with a comparative illustration, while the last one is for conclusion.

2. THE PROPOSED CONCEPT OF MANUFACTURING OPTIMIZATION

We further present the distinctive features of the proposed manufacturing optimization concept.

- The manufacturing optimization refers to the digitalized, holistically monitored, decisional-modeled manufacturing process.

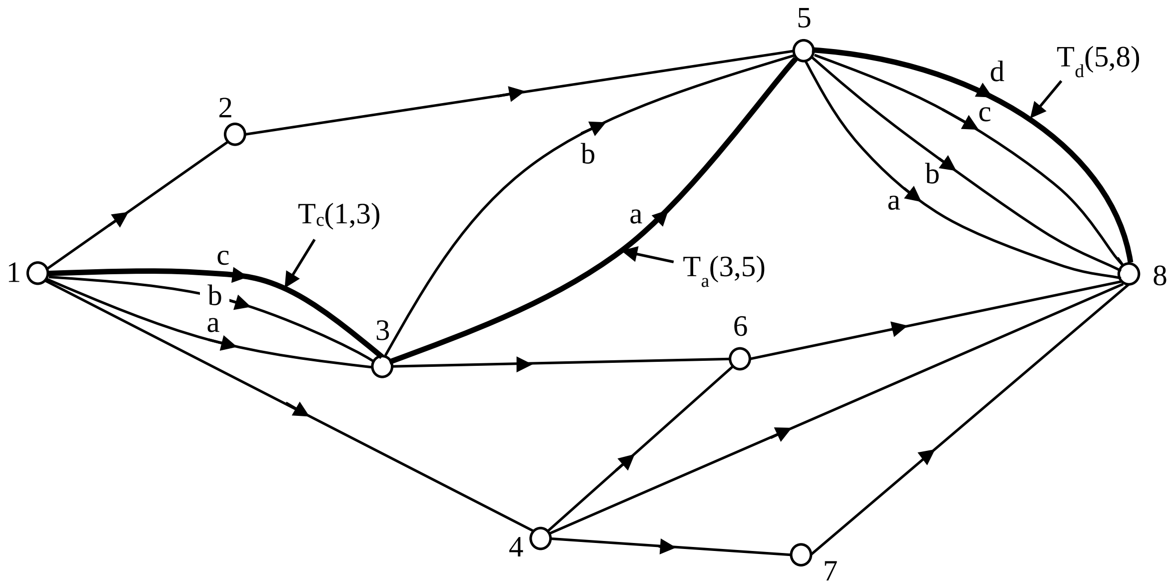
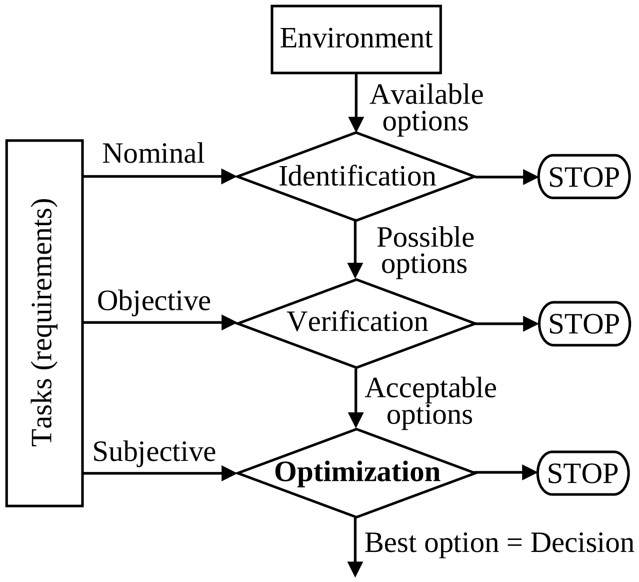


Fig. 1. Graph of decisional options

- The manufacturing optimization aims to establish the manner to proceed in a given moment of manufacturing process deployment. The Figure 1 presents the graph of decisional options for a hypothetical process including eight possible states in which the product may retrieve. In four points (namely 1, 3, 4, and 5) process ongoing requires decisions to be made about the way to follow, each arc meaning a transition option between two product states. In the addressed example, the path 1-3-5-8 (composed by transition options $T_c(1,3)$, $T_a(3,5)$, and $T_d(5,8)$) means the optimal solution of the problem.
- The optimization is performed in the decision-making regarding the establishment of the way to follow. Figure 2 shows the decision-making diagram with its specific stages. At first there is the identification of the possible options for from the set of available options enabled by the existing environment. Then the acceptable options are found after verification of the objective requirements fulfilment. Finally, the optimization itself is performed, delivering the decision meaning the best option to proceed.
- The decision-making concerns the product transition from current up to final state and consists, in fact, in three decisions to be made (Figure 3). The first one is about the structure of the set of tasks resulted after initial task configuring. The second regards the execution tasks configuring in work programs, while the third is dedicated to the choice of the model to be used to find the optimization problem solution.



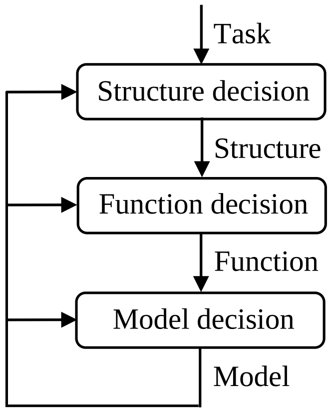


Fig. 2. Decision-making diagram

Fig. 3. Optimization problem solution

As conclusion, optimizing the manufacturing means the solving of optimization problems that appear in every decision-making action - be they referring to the structure of the process, the configuration of the system or the model of their interaction.

3. THE NEW APPROACH TO THE MANUFACTURING PROCESS

We here introduce the distinctive features of our approach to the manufacturing process.

3.1 The manufacturing task, ***T***, is approached as presented below.

- It is defined as the transition of product state from current up to the final one.
- It is described by:

- *Features,*

$$T_{features} = \{S, P, Q\}, \quad (1)$$

where S, concerning product state change, P – process performing, and Q – operating condition, are the task features and represent the elements of the defining metric of the task (through which the "manufacturing task" is distinguished from other tasks),

- *Attributes,*

$$T_{attributes} = \left\{\{S_i\}, \{P_j\}, \{Q_k\}\right\}, \quad (2)$$

which describe the features $\{S, P, Q\}$ and represent the elements of the qualitative metric of the task, and

- *Variables,*

$$T_{variables} = \{v_1, v_2, \dots\ v_i, \dots\ v_n\}, \quad (3)$$

where a variable means an attribute together with its criterion of evaluation (measuring unit), while its value is the value of the criterion. In other words, in the case of such a variable, not only the value can change, but also its meaning. For example, in the case of a turning task, the variable v_i may mean the maximum admissible value of the cutting speed, when the criterion of evaluation is m/min, while the value – the criterion level – could be 120. The variables represent the elements of the quantitative metric of the task.

- The digital description of the task is formally achieved by an ordered string of variables $\{v_1, v_2, \dots\ v_i, \dots\ v_n\}$.
- According to the role they play in task description, the values of variables from the first segment of the string represent the defining description of the task, from the second segment - qualitatively describe the task, while from the third segment - quantitatively describe the task. It should be noticed that the variables value is shown explicitly, while the meaning is implicitly understood through the values of previous variables.

According to the role they play in decision-making, the variables may be one of the types: Hypothesis-variable, $\hat{T}$; Decision-variable, $\bar{T}$, and Result-variable, $\tilde{T}$.

Any of them entirely determine a given task.

- The relationships among the decision variables may be:
  - Objective, formalized through a set of functions,

$$F(v_1, v_2, \dots\ v_i, \dots\ v_n) \sim 0, \tag{4}$$

where ~ 0 means $\{= 0 / < 0 / > 0\}$, and
  - Imposed, formalized through a system of equations

$$G(v_1, v_2, \dots\ v_i, \dots\ v_n) \sim a, \tag{5}$$

where $\sim a$ means $\{= a / < a / > a / \rightarrow a\}$, a being the parameter specifying a particularity.

3.2 The manufacturing job, ***J***, is approached as it follows.
- It refers to the options available to realize a certain generic change of product state, i.e., to accomplish a generic task.
- It is considered representative of a task family, where the tasks are related when they have the same values for a certain part of their variables.
- It is defined by a set of manufacturing variables, referred as job variables $J_{variables}$, which have the same value and is included in $T_{variables}$ of each component task, and is described by the other variables from $T_{variables}$, having different value for each component task of the job.
- A set of variables values $\{v_1, v_2, \dots\ v_i, \dots\ v_n\}$ of task variables $T_{variables}$ that obey a given set of F functions and a given system of G equations describe one of the tasks belonging to a certain family of tasks.

3.3 The manufacturing digital modeling has, according to the here-introduced approach, some specific features, further presented.
- The manufacturing model has $\hat{T}$ as hypothesis, while $\bar{T}$ and $\tilde{T}$ means the corresponding decision.
- The model is multi-level. Each level represents a job. Belonging relations exist among levels.
- Job model may be one of:
  - Elementary model *m*, formalized through a set of values of $T_{variables}$,
  - Implicit model *M*, formalized by a set of *N* elementary models *m*, and
  - Explicit models M_1, M_2, … M_c, formalized as *c* sets of elementary models *m*, where each explicit model has some of $T_{variables}$ variables as condition-variables, while other variables from $T_{variables}$ – as effect-variables. Each explicit model individualizes from the rest by concerning a different cluster of variables among T_1, T_2, … T_c.
- A given model is obtained by composing available models.

The models are used by applying the comparative assessment operation [16].

3.4 The manufacturing sequence (Figure 4) is considered to comprise three correlated actions.
- <u>Decision learning</u>, which consists in the *conversion of information* resulted from monitoring (formalized as multiple $\widetilde{T_n}$ and $\widetilde{T_\alpha}$) *into knowledge*, (formalized as corresponding job-models, in implicit form, M_n and M_α).
- <u>Decision making</u>, which consists of making the following types of decisions:
  - *Modeling decisions* related to the configuration of a job-model of implicit form, *M*, in *c* models of explicit form, M_1, M_2, … M_c,
  - *Planning decisions* that concern the configuration of the input task, $\widehat{T_n}$, into multiple output tasks, which may be execution tasks, $\widehat{T_\alpha}$, and/or released tasks, $\widehat{T_{n+1}}$, and
  - *Programming decisions* regarding the configuring of $\widehat{T_\alpha}$ execution tasks in programmed tasks, $\overline{T_\alpha}$.
- <u>Decision execution</u>, which means the conversion of the programmed task, $\overline{T_\alpha}$, into the accomplished task, $\widetilde{T_\alpha}$.

3.5 The manufacturing process is addressed as a recursive-holonic structure of manufacturing sequences. The recurrence relation is:

$$T_n = T_{input} \Rightarrow T_{output} = \{T_\alpha, T_{n+1}\}, \tag{6}$$

while the belonging relation is:

$$T_{n+1}, T_\alpha \in T_n. \tag{7}$$

3.6 Manufacturing calculus

We here suggest a possible mathematical representation of the manufacturing as an algebraic structure. This structure defines the digital approach of the manufacturing process and describes what could be possible entitled "digital management" (concerning the decision-making actions), "digital control" (concerning the decision-execution actions), and "digital monitoring" (concerning the decision-learning actions).

The main features of this structure are:

- Space: manufacturing process,
- Objects: variable, task, job,
- Object attributes: hypothesis, decision, result, implicit, explicit, reference, belonging,
- Operations: configuration (⇒), conversion (⇔), to which comparative assessment (~*R*) is added, where "~" may mean one of $\{=, <, >, \rightarrow\}$, while *R* is the reference,
- Operations properties: associativity, commutativity and neutral element, and
- Formalism: variable, *v*, matrix, *M*, function, *F*, equation, *G*.

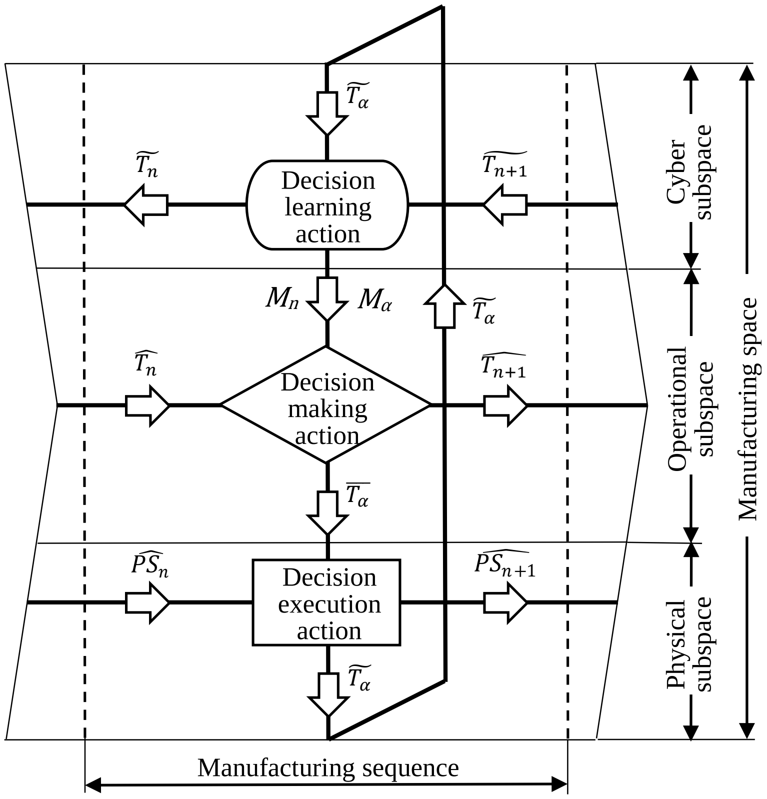


Fig. 4. Generic sequence of manufacturing

4. CONCEPT IMPLEMENTATION PROCEDURE

The conventional optimization procedure consists in approaching the manufacturing as physical process and refers to:

- *Hypothesis*, which means:
  - The model of causal relationships [17]: $X \Leftrightarrow Y$, where *X* are the condition-variables, while *Y* are the effect-variables
  - The optimization requirements: objective requirements and subjective requirements,
- *Conclusion*, which means the values of the condition-variables *X* and effect-variables *Y* that satisfy the optimization reqirements, and
- *Solution*, which consists in:
  - The delimitation of the existence domain for the searched solution (related to the satisfying of the objective requirements), and
  - The search for the solution, inside the delimited domain (related to the satisfying of the subjective requirements).

The proposed optimization procedure refers to:
a) Task defining as the transition of product state from current up to the final one, and
b) Manufacturing approaching as decisional process that includes:

- *Hypothesis* (given input), which means **the task**, described by the hypothesis-variable $\widehat{T}$,
- *Conclusion* (corresponding output), which now means **the best decision** concerning the task accomplishment, and
- *Solution* (searching mode), which consists of **model direct application**.

As follows, the manufacturing process structure is like the one presented in Figure 5, which samples the decisional structure corresponding to a manufacturing process consisting of three manufacturing sequences.
Here, $\widehat{T_1}$, $\widehat{T_2}$ and $\widehat{T_3}$ mean successive hypothesis, while $\{\overline{T_a}, \widehat{T_2}\}$, $\{\overline{T_b}, \widehat{T_3}\}$ and $\{\overline{T_c}, \overline{T_d}\}$ – decisions.

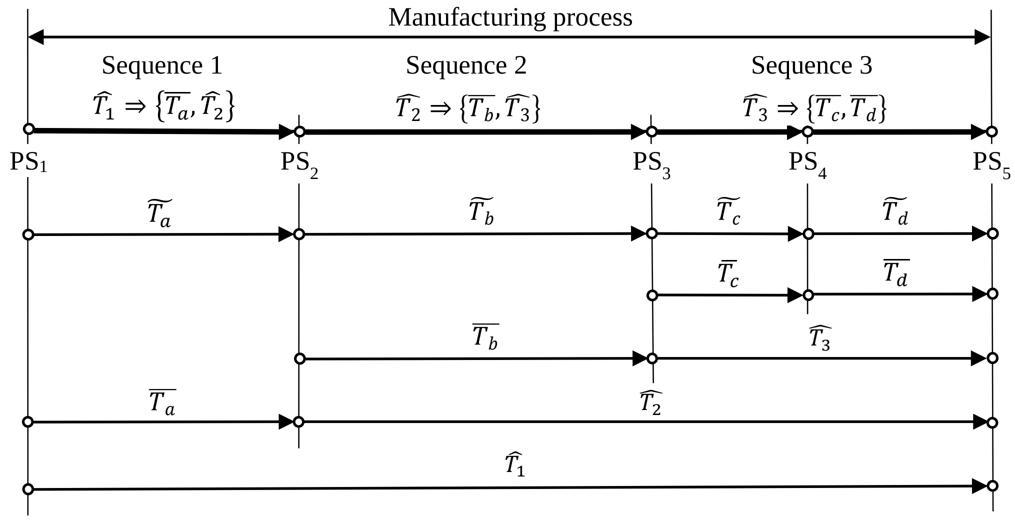


Fig. 5. Optimization of multi-sequence manufacturing process

<u>The obtained solution</u> consists of making decisions regarding:

- *Manufacturing model configuring*, which refers to the clustering of job variables:

$$T_{variables} \Rightarrow Best\ variable\ cluster, \tag{8}$$

Manufacturing process planning, which is about configuring the given task into execution tasks and released tasks:

$$\widehat{T_n} \Rightarrow \widehat{T_\alpha} \cup \widehat{T_{n+1}}, \tag{9}$$

- *Manufacturing system programming*, which refers to configuring the execution tasks into work programs:

$$\widehat{T_\alpha} \Rightarrow \overline{T_\alpha}\ . \tag{10}$$

For a better understanding of proposed optimization procedure, the distinctive features of the two approaches are comparatively presented in Table 1.

Table 1. Distinctive features of conventional vs. proposed optimization procedure

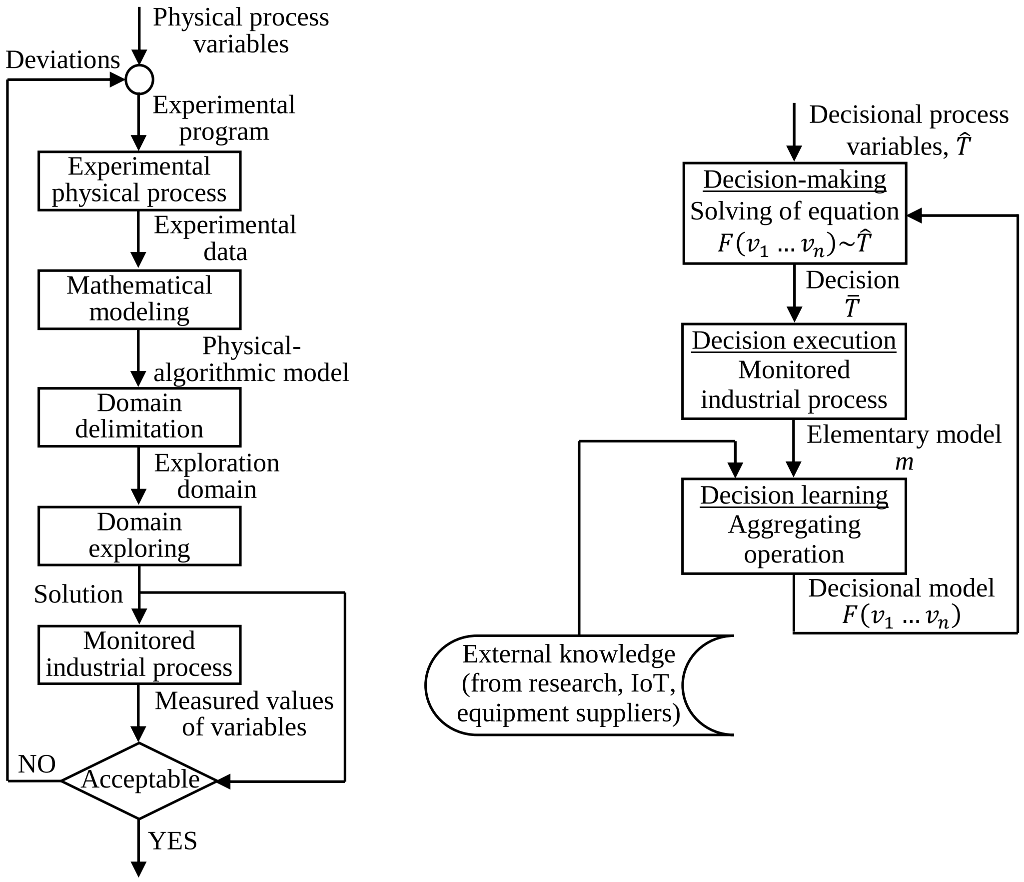
Feature	Conventional approach	Proposed approach
Optimization object	Manufacturing system operation in order to accomplish the given task	
Modeled state	Exploratory state	Optimal state
Model variables	Physical variables	Decisional variables
Model type	Algorithmic	Digital
Modeling source	Experimental data	Industrial data
Elementary model	Analytic relation	Numeric dataset
Optimization action	Domain exploration	Direct calculus
Definition of optimum	Extreme value of a given variable	Target value of a given variable

5. COMPARATIVE ILLUSTRATION

For a better understanding of the manner in which the proposed optimization should be performed, we further present a comparative illustration between the application flowcharts of conventional vs. proposed approaches (Figure 6). The case of optimizing a manufacturing process afferent to a task accopmlishment (as previously defined) is addressed.
On one side, the steps of the manufacturing optimization in the conventional approach, as well as the results after each such step are shown in Figure 6-a, in their logical succession.
On the other side, the optimization of manufacturing approached as decisional process, by solving the equation:

$$F(v_1 \dots v_n) \sim \hat{T} \tag{11}$$

is represented in Figure 6-b, through its three main stages.



a) b)

Fig. 6. Comparative illustration: a – conventional approach; b – proposed approach

Table 2 samples the building of a physical-algorithmic model to optimize the turning of a cylindrical part having *D* diameter and *L* length, while Table 3 samples the decisional-digital model (the function *F*) obtained by composing available models (as previously exposed in this paper), when solving the same problem. Table 4 shows a possible statement of this optimization problem (the hypothesis-variable $\hat{T}$).

Table 2. Physical-algorithmic model

Physical-algorithmic model variables													
L	D	A	M	R	v	f	t	F	P	V	C	TS	E

Variables meaning is the following: 1 – part length, *L*, 2 – part diameter, *D*, 3 – part accuracy level, *A*, 4 – mechanical properties of part material, *M*, 5 – part stiffness, *S*, 6 – cutting speed, *v*, 7 – feed, *f*, 8 – cutting depth, *t*, 9 – cutting force, *F*, 10 – power absorbed by lathe, *P*, 11 – volume of removed chips, *V*. Other three parameters were selected as effect variables: 12 – manufacturing cost, *C*, 13 – timespan, *TS*, 14 – consumed energy, *E*.

$$t = \frac{5.1 \cdot R - 0.1 \cdot A}{10}\ [mm] \qquad f = \frac{4.4 - 0.4 \cdot A}{10}\ [mm/rot] \qquad v = \frac{C_v}{f^{0.3} \cdot t^{0.2} \cdot T^m}\left(\frac{10}{M} \cdot x_v + \frac{S}{10} \cdot y_v\right)\ [m/min]$$

$$F = C_F \cdot f^{0.8} \cdot t\left(x_F + \frac{M}{10} \cdot y_F\right)\ [N] \qquad P = \frac{F \cdot v}{6000} \cdot \frac{1}{\eta}\ [KW] \qquad V = \frac{\pi \cdot D \cdot L \cdot t}{1000}\ [cm^3]$$

$$C = \frac{V}{v \cdot f \cdot t}\left[\left(1 + k + \frac{\tau_{sr}}{T}\right)c_\tau + \frac{\tau_{sr} \cdot c_\tau + c_s}{T} + \frac{P \cdot c_e}{60}\right]\ [Euro] \qquad TS = \frac{V}{v \cdot f \cdot t}\left(1 + k + \frac{\tau_{sr}}{T}\right)\ [min] \qquad E = \frac{P \cdot V}{v \cdot f \cdot t} \cdot \frac{1}{60}\ [KWh]$$

In relations from above, C_v, x_v, y_v, C_F, x_F, y_F are constants, η means lathe efficiency ratio, *k* – the ratio between auxiliary and cutting times, τ_{sr} – tool changing time [min], *T* – tool durability [min], c_τ – wage specific cost, [Euro/min], c_s – expenses for tool usage between consecutive sharpenings [Euro], c_e – energy price [Euro/KWh]. Part dimensions *L* and *D* are expressed in mm.

Table 3. Decisional-digital model

Decisional-digital model variables									
v_1	v_2	v_3	v_4	v_5	v_6	v_7	v_8	v_9	v_{10}
Hypothesis, $\hat{T}$, Decision, $\bar{T}$, Result, $\tilde{T}$									
Variables meaning is the following: v_1 – machining procedure, v_2 – minimum cutting speed [m/min], v_3 - maximum cutting speed [m/min], v_4 – minimum acuracy level, v_5 - maximum cutting force [N], v_6 – set cutting speed [m/min], v_7 – set feed [mm/rot], v_8 – resulted manufacturing cost [Euro], v_9 – resulted timespan [min], v_{10} – resulted consume of energy [KWh].									
1	50	200	4	200	185	0.15	1.35	2.43	0.07
2	100	200	3	400	154	0.72	2.55	1.64	0.83
1	80	150	6	150	126	0.19	10.34	18.7	0.4
1	40	120	7	100	88	0.11	12.1	21.95	0.31
1	100	180	7	120	176	0.04	13.79	24.98	0.41
3	30	80	2	90	75	0.08	1.67	5.23	0.06

Table 4. Statement of the optimization problem

Task variables	Hypothesis of the optimization problem $\hat{T}$			
	Objective requirements (restrictions)			Subjective requirements (criteria)
Variable	=	>	<	→
v_1	1			
v_2		70		
v_3			190	
v_4		5		
v_5			160	
v_6				
v_7				
v_8				10
v_9				
v_{10}				

6. CONCLUSIONS

A digital-age manufacturing optimization can be achieved as explained below.

- Defining the manufacturing task as transition of the product state, from the current state up to the final state.
- Defining the object of optimization as the fulfillment of a task.
- Approaching the manufacturing process as a decisional process, in which *i)* a decisional sequence is triggered by the receipt of a task to be completed and *ii)* the decisional sequence consists of three actions: decision-making, decision execution, and decision learning actions.
- Approaching the optimization as the last step of decision-making action. This step consists in identifying the best option among the acceptable ones, where the option can be: *i)* configuring the received task as a set of new tasks, the fulfillment of which should be equivalent to its fulfillment, as well as *ii)* configuring the received task as a set of work programs, the execution of which should be equivalent to its fulfillment.
- Building, through a learning action, of the digital-decisional model of the manufacturing process, $\boldsymbol{F(v_1 \dots v_n) = 0}$, whose variables, $\{\boldsymbol{v_1, v_2 \dots v_n}\}$ are of three types: hypothesis-, decision-, and execution-variables, $\hat{\boldsymbol{T}}$, $\bar{\boldsymbol{T}}$, and $\tilde{\boldsymbol{T}}$ type, respectively.
- Optimizing the manufacturing task fulfillment, by solving the equation $\boldsymbol{F(v_1 \dots v_n) \sim \hat{T}}$, through a comparative-assessment operation.

To optimize the manufacturing process, the following are required:

- On-machine measurement,
- Holistic monitoring, and
- Online learning.

The main expected benefits are those generated by:

- Simplifying procedures, improving quality, and increasing the efficiency of manufacturing administration, including manufacturing management and control,
- Increasing the synergy resulting from the integration of cyber and physical components of the manufacturing system, and
- Better using the opportunities provided by digital technologies and systems.

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