IOSUD –„DUNAREA DE JOS” UNIVERSITY OF GALATI
Doctoral School of Mechanical and Industrial Engineering

UNIVERSITAS
GALATIENSIS

DOCTORAL THESIS

- Abstract -

Holistic optimization of manufacturing process

PhD student,
Eng. Cezarina AFTENI

PhD supervisor,
Prof. dr. eng. Gabriel-Radu FRUMUȘANU

Seria I 4: Industrial Engineering Nr. 70
Galati, 2020

IOSUD - „DUNAREA DE JOS" UNIVERSITY OF GALATI

Doctoral School of Mechanical and Industrial Engineering

UNIVERSITAS GALATIENSIS

DOCTORAL THESIS

- Abstract -

Holistic optimization of manufacturing process

PhD student,
Eng. Cezarina AFTENI

Chairman,	Prof. dr. eng. Cătălin FETECĂU	"Dunarea de Jos" University of Galati
PhD supervisor,	Prof. dr. eng. Gabriel-Radu FRUMUȘANU	"Dunarea de Jos" University of Galati
Scientific referees:	Prof. dr. eng. ec. Cristian-Vasile DOICIN	Polytechnic University of Bucharest
	Prof. dr. eng. ec. Dumitru NEDELCU	"Gh. Asachi" Technical University of Iasi
	Prof. dr. eng. Cătălina MAIER	"Dunarea de Jos" University of Galati

Seria I 4: Industrial Engineering Nr. 70
Galati, 2020

Contents

Keywords: *optimization, holistic, manufacturing process, dynamic planning, comparative assessment, modeling, instances database, manufacturing performance, key features, modeling potential, identification.*

Introduction

The general objective of the studies undertaken in this thesis was the research in order to elaborate a new concept regarding the optimization of the manufacturing process – the holistic optimization, as well as the development of some original methods that allow the implementation of this concept in practice.

The holistic optimization concept was developed in direct connection to the requirements of manufacturing process optimization. The holistic optimization supposes, in general, to retake the optimization action at successive levels, any time this is necessary, namely, when new decisions should be taken.

In the vision presented in this thesis, the „holistic optimization" main issues are:

- *The optimization area* covers the entire life-cycle of optimization object. When this object is the manufacturing process, the life-cycle is comprised between product ordering (by the client) and product delivering (to the client).
- *The optimization goal* is to satisfy all optimization aspects, namely the best formalization of the optimization request, the best tooling for assessing the position of a potential solution relative to optimization goal, and the best solution for the optimization problem.
- *The optimization action* consists in providing the permanent optimization of decisions flow through which the manufacturing process ongoing is controlled.

Thesis specific objectives were:

- The extension of the optimization domain to the entire life-cycle of manufacturing process (from the product ordering until product delivering).
- To redefine the purpose of optimization, following the best formulation of the problem, the best tooling of the assessing, the best solution for the optimization request according to a predefined criterion/set of criteria.
- The modification the optimization character – dynamic character through the possibility of reconsidering it at any stage of the manufacturing process and at the same time flexible character through of the possibility of changing the format of the optimization problem and the objective function.
- To redefine the optimization space, by taking into account the causal relationships between the variables of the optimization problem.
- The replacement of the manufacturing process analytical modeling with causal modeling;
- The use of comparative assessment to select the optimal solution.

The doctoral thesis is structured in eight chapters, as follows:

- In **chapter 1,** entitled **„The state of the art regarding the manufacturing process optimization"**, the documentation of the current state regarding the approaches conserning the optimization of the manufacturing process performance is realized following the study of technical literature, scientific papers and doctoral theses in this field.
- In **chapter 2,** entitled **„Thesis objectives and research directions"**, some shortcomings in dealing with the problem of optimizing the manufacturing process are highlighted, a reconsideration of the concept of optimization is proposed, the research directions are defined and the research objectives are enounced.
- In **chapter 3,** entitled **„The concept methodology for holistic optimization of the manufacturing process"**, the holistic optimization concept in direct connection to the

requirements of manufacturing process optimization is presented and are identified the key features that describe the holistic optimization by referring it to conventional optimization. According to the holistic optimization concept, in this chapter, an original method for optimizing the manufacturing process is proposed.

- In **chapter 4,** entitled **„Method for structural identification of the manufacturing process"**, is developed a novel method that allows the structuring of its activities, at all levels involved (order acceptance, production planning, product design, processes planning and product processing), by elaborating the tree of specific activities. The relations between the manufacturing process stages and the afferent information circuit are revealed and the identification of the manufacturing process variants, at the level of each manufacturing activity is performed. The method aims to select the best variants at each level of the manufacturing activity, according to different optimization criteria (such as, for example, cost, timespan, energy consumption, and other critical consumption or combination combinations thereof).
- In **chapter 5,** entitled **„Method for causal identification of the manufacturing process"**, is developed an original method that allows multiple forms to be provided for one and same causal relationship. The method is designed with the purpose of being applied in the case of holistic optimization of the manufacturing process, before the comparative assessment of the results of the activities that can be selected at the level of a decision point in the manufacturing process graph. The method allows the identification of the most appropriate set of cause-variables, on the basis of which a effect-variable can be evaluated, depending on the specific conditions of a particular manufacturing process. The method purpose is to elaborate the tree of causal links.
- In **chapter 6,** entitled **„Method for comparative assessment of the manufacturing process alternatives"**, is developed a method that proposes an innovative approach in the analysis of potentially optimal solutions, based on their rankings. The method is designed to assist the selection of the optimal continuation variant for the manufacturing process, at a certain decision level. The comparative assessment of the potential alternatives is made by reffering them to the cases of already performed manufacturing processes. The application of the comparative assessment method is done after the causal identification completion, respectively after the adoption of a set of cause-variables describing the effect-variable of interest at the present moment, by applying the method presented in the previous chapter.
- In **chapter 7,** entitled **„Experimental validation"**, the method for holistic optimization of the manufacturing process is validated through numerical experiments, carried out as several case studies: *i)* structural identification in bearing manufacturing case, *ii)* causal identification and comparative assessment for the cost estimation of a turning operation – artificial instances database, *iii)* causal identification and comparative assessment for timespan estimation for bearing ring turning – database extracted from the industrial environment, and *iv)* causal identification and comparative assessment for the cost of roller bearing manufacturing – database extracted from the industrial environment.
- In **chapter 8,** entitled **„Final conclusions and original contributions"**, the original contributions of the thesis author are highlighted, the final conclusions of the doctoral thesis are drawn. Some future directions for capitalising the results of the researches and for extending their application are also presented.
- The paper ends there are presented the bibliographic resources, as well as the list of the papers published or presented by the author during her doctoral studies.

Chapter 1

The state of the art regarding the manufacturing process optimization

Within this chapter, a systematic analysis has been developed regarding the formulating and solving of optimization problems in general, and those related to the manufacturing process in particular. The state of the art regarding the approaches concerning the optimization of the manufacturing processes performance is realized following the study of technical literature, scientific papers and doctoral thesis in this field.

The analysis of the bibliography was developed in the in the following directions:

- ✓ The type of optimization problem (e.g. unicriterial and multicriterial).
- ✓ The objective function (e.g. the productivity, the manufacturing cost, the manufactured surface roughness, the cutting force magnitude, the energy consumption, etc.).
- ✓ The solutioning methods (e.g. Genetic Algorithm GA, Artificial Neural Networks ANN, Particle Swarm Optimization PSO, Ant Colony Optimization ACO, Fuzzy Logic LF, Combinatorial techniques, etc.).

Also, the results of the research were analyzed related to manufacturing process planning and scheduling.

1.1. The optimization problem

The optimization, in essence, is the scientific option, which consists in the systematic elaboration and sorting of possible solutions of an engineering problem. The final goal of optimization is to select that solution, within the limits of a reference frame, defined by the conditions initially admitted or imposed, leads to the most convenient use of the resouces available for its materialization.

The optimization problem is a mathematical application for selecting a solution, out of a potential set, based on the evaluation of the objective function (functions).

An optimization problem supposes three components [1]:

- The objective function, to be extremized:

$$\min,\max f(X),\ X \in R^m, \tag{1.1}$$

- The variables vector, X:

$$X = \left(x_1, x_2, \ldots, x_m\right), \tag{1.2}$$

- The restrictions, having the form:

$$g\left(X\right) \le 0,\ \text{restrictions of inequality}, \tag{1.3}$$

$$h\left(X\right) = 0,\ \text{restrictions of equality}. \tag{1.4}$$

The need to optimize the manufacturing processes is justified by the existence of a great variety of technological methods and procedures, from which it is necessary to select the one that corresponds most to a certain criterion.

Many real problems require an optimal solution than a simple solution. Since decision problems require a yes/no answer, optimization problems require finding the best solution, differentiating the possible solutions.

1.1.1. Unicriterial optimization

By optimization are looking to be minimize (or maximize) an objective form function, [2]:

$$\varphi\left(x_1, x_2, \ldots, x_p\right) = f\left(x_1, x_2, \ldots, x_p\right) \rightarrow \min, \max. \tag{1.5}$$

In case of the manufacturing optimization problem, f - can be the productivity, the manufacturing cost, the manufactured surface roughness, the cutting force magnitude, the energy consumption, etc.

The unicriterial optimization has been addressed in the dedicated literature, for example, in the papers [3], [4]. For solving this problem in the papers [5], [6] deterministic, stochastic, heuristic and metaheuristic methods are presented.

1.1.2. Multicriterial optimization

The multicriterial optimization (also called multi-objective optimization, multi-performance optimization, or Pareto optimization) is an area of decision making with multiple criteria, can be defined as the problem of finding a vector of the decision variables that satisfies the restrictions and optimizes the objective vector, whose elements represent the objective functions, [2].

The Pareto concept, takes its name from Vilfredo Pareto (1848-1923), who used the concept in his studies on economic efficiency and income distribution, [7]. In figure 1.1 shows the Pareto curve (in red), for a minimization problem with two objectives (f_1, f_2). It is desired to identify those individuals who minimize both objectives f_1 and f_2. Any two individuals on the Pareto curve (A, B) are not-dominated, [8].

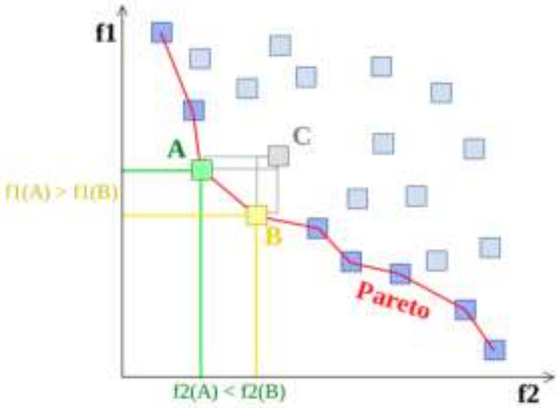


Figure 1.1. Pareto Front [8]

Multi-objective optimization methods can be grouped into four classes: no preference, a priori, a posteriori and interactive methods, [9].

Multicriterial optimization has been adressed in the specialty literature, e.g. [10], [11].

1.1.3. Multilevel optimization

In many decision-making processes there is a hierarchy of decision-makers and decisions are taken at different levels. The multilevel optimization focuses on the entire hierarchical structure. In terms of modeling, the field of restrictions associated with a multilevel optimization problem is implicitly determined by a number of optimization problems that must be solved in a predetermined sequence.

Multilevel optimization problems, in general, are mathematical programs that have a subset of the variables constrained to be an optimal solution for „other programs” parameterized by the remaining variables.

For example, a bilevel optimization problem can be defined as:

$$\min_{x \in X,\, y \in Y} F(x, y) \tag{1.6}$$

where: $y \in \arg\min_{z \in Y} f(x, z)$; $F, f : R^{n_x} \times R^{n_y}$, $X \subseteq R^{n_x}, Y \subseteq R^{n_y}$.

Multilevel optimization problemare hard to solve, [12]. One solving method is to reformulate multilevel optimization problem to optimization problems for which robust solution algorithm are available.

Evolutionary methods [13], though computationally demanding, could be an alternative tool to offset some of these difficulties and lead to an aproximate optimal solution

1.1.4. Multistage optimization

The multistage optimization generalizes standard optimization by modeling hierarchical decision problems, involving sequential/multistage decision processes.

The canonical problem to be solved, in minimization case, is:

$$\min_{x,y} \left(\sum_{t=1}^{T} f_t(x_t y_t) : (x_{t-1}, x_t, y_t) \in X_t, \forall t \right) \tag{1.7}$$

where: t means the time stage belonging to a set T of time stages, x_t is the vector of state variables and y_t – the local/stage vector of variables.

This type of problem can be solved by Branch and Bound algorithm, [14] and Benders' technique, [15].

1.2. Modern optimization techniques

Table 1.1 presents a summary of the study on the application of modern optimization techniques in solving the optimization problem of the manufacturing processes, according to dedicated literature.

Table 1.1. A summary of the study on the application of modern optimization techniques

Modern optimization techniques	***Bibliographic reference***
Genetic Algorithm GA	[16]–[22]
Artificial Neural Networks ANN	[23]–[25]
Particle Swarm Optimization PSO	[18], [26]–[29]
Ant Colony Optimization ACO	[26], [30]–[34]
Fuzzy Logic LF	[30], [35]–[37]
Combinatorial techniques	[38]

1.7. Conclusions regarding the state of the art

Following the bibliography analysis, from the national, as well as the international dedicated literature, on the topic adressed in the thesis, namely, the manufacturing process optimization, the following conclusions can be formulated:

1. There is an impressive amount of studies and researches in the field, which took into account different objectives related to the manufacturing processes, the solutions being developed based on a wide variety of optimization methods/techniques.
2. The manufacturing processes optimization follows a multitude of aspects, whether technical, financial, commercial, economic, environmental or of another nature.
3. The approach of the optimization problem is often unicriterial (derived from the objectives listed above), although the actual manufacturing environment is complex and can be subjected to optimization according to multicriterial optimization. However, there are enough studies that consider multiple objectives (multicriterial optimization), without the way in which they were associated to be unitary.
4. The most common optimization criteria are: the productivity, the manufacturing cost, the manufactured surface roughness, the cutting force magnitude, the energy consumption, etc.
5. The most of the studied used one of the following optimization methods/techniques: Genetic Algorithm, Artificial Neural Networks, Particle Swarm Optimization, Ant Colony Optimization, Fuzzy Logic, Combinatorial techniques, etc.
6. In some situations, improved optimization techniques have been implemented such as: Improved Genetic Algorithm IGA, Multi Objective Genetic Algorithm MOGA, Hybrid Particle Swarm Optimization HPSO, which has allowed the identification of high quality optimal solutions in the production planning phase.
7. In many situations, the manufacturing process optimization is confused with the cutting regime parameters optimization. This is usually done by using an analytical model of the objective function.
8. The manufacturing process scheduling, necessary for the processing of a product within a production section, can be carried out with the help of dedicated methods that aim at minimizing resource consumption and the average processing time, respectively maximizing the productivity.
9. In most cases, the manufacturing processes planning is approached separately from the manufacturing processes sheduling.
10. The vast majority of the existing papers refer to the optimization of the actual execution stage (processing) of the product.

Chapter 2

Thesis objectives and research directions

Some shortcomings in dealing with the problem of manufacturing process optimization are highlighted on the base of the conclusions presented in chapter 1:

1. The optimization domain does not cover the entire life-cycle of optimization object. When this object is the manufacturing process, the life-cycle is comprised between product ordering (by the client) and product delivering (to the client).
2. The purpose of optimization, is defined unilaterally/narrowly, reffering only to the best sollution solution for the optimization problem, according to a predefined criterion/set of criteria.
3. The conventional optimization is not sufficiently adapted to the specific requirements of manufacturing processes, because:
   3.1. Although the process must be optimized in its wholeness, but often this is not feasible from the beginning; successive decisions should be taken during the process, while the decision from a given level cannot be taken before establishing the job from previous level.
   3.2. The jobs performed during the manufacturing process (which included the stages: bidding-negotiating-acceptance order, product design, process planning, jobs scheduling) have different natures, at the same time, their exigencies are diverse.
   3.3. The effect-variables of a certain job, which should be used for evaluating a given effect from the process end, are not precisely known; moreover, they must be selected from a set of measurable variables specific to the job, which are not necessarily independent.
   3.4. The causal relations either between the cause-variables or between the cause-variables and the effect-variables are not a priori known.
   3.5. The possible existence of a high number of jobs needed for obtaining the product involves a too large number of variables to be managed – the dimensionality of the optimization problem to be solved is too large for the existing computational resources.

Research directions

Starting from the above shown shortcomings, a reconsideration of the concept of the manufacturing process optimization, is proposed by addressing the following research directions:

- The extension of the optimization domain to the entire life-cycle of manufacturing process, from ordering products, going through production planning, product design, process planning and product processing, to product delivery.
- To redefine the purpose of optimization, which will mean, simultaneously: the best formulation of the problem, the best tooling of the assessing, as well as, obviously, the best solution for the optimization request.
- The modification the optimization character – dynamic character (through the possibility of reconsidering it at any stage of the manufacturing process) and at the same time flexible character (through of the possibility of changing the format of the optimization problem and the objective function).

- To redefine the optimization space, by taking into account the causal relationships between the variables of the optimization problem.
- The replacement of the manufacturing process analytical modeling with causal modeling;
- The use of comparative assessment to select the optimal solution.

Thesis objectives

In connection with the reconsideration of the concept of manufacturing process optimization and its implementation, the research objectives presented in the thesis were, in particular:

- Development of the concept for manufacturing process holistic optimization and concept theoretical underlying by: specification of the approach character, definition of formalism, and position compared to conventional optimization.
- Development of the method for dynamic optimal planning of the manufacturing process (able to minimize the time and effort consumed by making decisions adapted to market conditions) and of an algorithm for this method application.
- Development of the method for manufacturing process structural identification (that allows the structuring of its activities, at all levels involved: order acceptance, production planning, product design, processes planning and product processing), by elaborating the tree of specific activities. The relations between the manufacturing process stages and the afferent information circuit are revealed and the identification of the manufacturing process variants, at the level of each manufacturing activity, is performed.
- Development of the method for manufacturing process causal identification, that allows multiple forms to be provided for one and same causal relationship. The most suitable for solving a comparative asssessment problem can be selected among them. Method output is the causal links tree (that gives the possibility of selecting, each time, the most suitable set of cause-variables for effect modeling). An algorithm for applying this method should also be developed.
- Development of the method for comparative assessment of the manufacturing process alternatives (that proposes an innovative approach in the analysis of potentially optimal solutions, based on their rankings) and development of an algorithm for method application.
- Exemplifying the method for structural identification in bearing manufacturing, in a case study aiming at making the manufacturing graph, including levels, technologies and decision-making steps related to each identification level.
- Validation and evaluation of the method for causal identification and testing of both method for comparative assessment, and algorithm for alternatives rankings assessment in three case studies:
    - with artificial instances database, in a turning operation case, having as objective function the cost;
    - with database extracted from the industrial environment, in a bearing ring turning case, having as objective function the timespan;
    - with database extracted from the industrial environment, cu date reale, in a roller bearing manufacturing case, having as objective function the cost.

Chapter 3

The concept methodology for holistic optimization of the manufacturing process

Within this chapter, the holistic optimization concept in direct connection to the requirements of manufacturing process optimization is presented and the key features that describe the holistic optimization are identified, by referring to conventional optimization. According to the holistic optimization concept, in this chapter, an original method for optimizing the manufacturing process is proposed. According to it, the step of the „zoom and pick” algorithm are presented.

3.1. Holistic optimization – a new approach

According to here presented vision, the „holistic optimization” main issues are:

- *The optimization area* covers the entire life-cycle of optimization object. When this object is the manufacturing process, the life-cycle is comprised between product ordering (by the client) and product delivering (to the client).
- *The optimization goal* is to satisfy all optimization aspects, namely the best formalization of the optimization request, the best tooling for assessing the position of a potential solution relative to optimization goal, and the best solution for the optimization problem.
- *The optimization action* consists in providing the permanent optimization of decisions flow through which the manufacturing process ongoing is controlled.

3.2. Formalism (domain, variables, criteria, restrictions)

The formalism of the holistic optimization method is presented below:

- ***The optimization domain*** – if the conventional optimization acting in an Euclidian space R^n, consisting of *n* real variables, the holistic optimization is performed inside a so-called causal space V^m (figure 3.1), consisting generally of *m* cause-variables and the relations of dependence between them.
- ***The optimization variables*** are decisions to be taken, regarding both the optimized object and the optimization problem. The value of such a variable is an action that must be performed. In the case of conventional optimization, the variables are independent and numerical, while in the holistic optimization they are interdependent and logical. Interdependent variables because the decision to be made depends at one point on the previous decisions and determines the following decisions. In conventional optimization, the evaluation of the effect-variables is absolute, unlike this, in holistic optimization the evaluation of the effect-variables is comparative.

In order to understand more easily how holistic optimization works, the causal space of the optimized object is presented in figure 3.1.

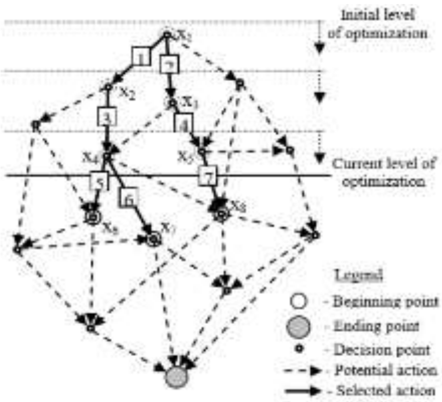


Figure 3.1. Causal space of the optimized object

- ***The optimization criterion*** – as already mentioned, it can be changed at each successive level optimization. For example, in the holistic optimization case of manufacturing process, the cost, the timespan, or combination between them can be considered as an aptimization criterion. Obviously, at one point, several criteria can be considered simultaneously (the format of the optimization problem changing from standard to multi-objective).
- ***The optimization restrictions*** – in addition to the restrictions according to the conventional optimization theory (regarding the areas in which the variables can be located), in tge holistic optimization case, two restrictive parameters are defined regarding the selection of the actions to be taken, namely the admissibility and accuracy levels. The first refers to the number of actions selected in relation to the total number of potential actions in a decision point. The second concerns the threshould from which the effects of two decisions must differ, in order to consider that they lead to different effects.

3.3. Optimization techniques

Among the classical techniques related to optimization, holistic optimization takes on specific elements from: the multistage optimization, the predictive analysis, and the combinatorial optimization.

The multistage optimization generalized standard optimization by modeling hierarchical decision problems, involving sequential/multi-stage decision processes. This type of problem can be solved by Branch and Bound algorithm [14] and Benders' technique, [15].

The predictive analysis is an area of statistics that deals with extraction information from data and using it to predict trends and behavior patterns, [39]. The core of predictive analytics refief on capturing relationships between cause- and effect-variables from past occurrences, and exploiting them to predict the unknown outcome.

An optimization problem is *combinatorial character* if each a variables can independently take a number of previously known numerical values, for examples, values integers, non-negatives below a given threshold or only values 0 or 1, [40].

3.4. Algorithm of the holistic optimization method

The method is applied on three stages, namely: *i)* the past activity, *ii)* the assessment tooling, and *iii)* the current process.

1. *The past activity*

The objective of this stage is to describe the past activity in a format appropriate to holistic optimization. In this purpose, the activity structure is analysed in order to reveal the potential zoom levels, meaning levels of the activity where specific actions determining the activity course take part. The ensemble of jobs following to be accomplished starting from such a zoom level up to the process final forms a typical job. More potential typical jobs can be identified, then, at each zoom level. New zoom levels can be found along a given typical job, while new typical jobs (of lower complexity) start from these new levels, and so on. Hereby, each typical job involves, in general, the accomplishment of a succession of other typical jobs (having smaller and smaller levels, in accordance with zoom levels).

An instances dataset, resulted by recording the past instances concerning a given typical job, should be associated to this job. Causal models of the typical job should be identified by processing the information from such instances dataset.

At this stage, the method application result consists in identifying the zoom levels, the potential typical jobs, and, for each such job, the corresponding instances dataset and the identified causal models.

2. *The assessment tooling*

In holistic optimization, the optimization request format it is not predefined. In fact, the desiderate formalization is part of the optimization problem solving.

In manufacturing, the managerial policy imposes the desiderate concerning the process. This can be different for different products. More than that, the desiderate may change in time even for the same product. At the same time, the desiderate reaching can be assessed after diverse criteria, specific objective functions (effect-variables) can be assigned for each criterion, and for evaluating such a function different sets of arguments (independent description-variables) can be used. For this reason, the presented method requires this stage for identifying the potential goals, criteria, functions and arguments, among which the most suitable ones will be selected, according to method algorithm presented below.

3. *The current process*

The proposed holistic optimization method avoids the mentioned difficulties. According to the method, current process “zoom and pick” consists in successively performing the following loop of actions:

- Go forward until meeting the next zoom level.
- Identify the optimization variables (decisions to be taken) and their values (potential typical jobs).
- Adopt the goal according to optimization desiderate and, corresponding to it, the optimization criteria (see stage 2).
- Formalize the criteria by selecting the function (job effect-variable) of interest and the most suitable arguments (job description-variables), the imposed restrictions and the appropriate format of the current optimization problem (also see stage 2).
- Make the comparative assessment of selected typical jobs.
- Discard the uncompetitive typical jobs.
- Assess the optimization uncertainty vs. optimization accuracy (which must be set at optimization beginning), for each remaining job. If an acceptable result shows for at least one of the remaining jobs, then this is considered optimal and the optimization is stopped. Otherwise, retake the succession of steps from the beginning.

3.5. Actions for current activity evaluation

The most important actions, based on which the current activity is evaluated are: *i)* the structural identification, *ii)* the causal identification, and *iii)* the comparative assessment.

1. ***The structural identification*** allows the structuring of its activities, at all levels involved (order acceptance, production planning, product design, process planning and product processing). At the level of each manufacturing activity to slect the best variants, according to different optimization criteria (such as, for example, cost, timespan, energy consumption, other critical consumption or combinations thereof).

2. ***The causal identification*** aims to identify variables groups with potential for application in the modeling of the activity/process. The causal identification allows the selection of the most influent, easier to be measured and a few as possible cause-variables, such as the resulted model has the lowest complexity, according to the required accuracy; finding multiple forms for one and the some causal relationship, among which the user can select the one that is best for solving the comparative assessment problem.

3. ***The comparative assessment*** means yo establish rankings for two or more alternatives to proceed after a given criterion. The rankings is assigning to potential alternatives, by reffering them to past manufacturing activities cases recorded in an instances database. For two (or more) potential alternatives in order to compare them after an criterion, the precise value of criterion is not need to know, instead of this, the comparison is easier to make by finding neighborhoods of already performed cases (with know results) to which each potential alternatives belongs. The definition of the nearness between two cases, which should be assessed starting from the values of cases known effect is the key-issue of comparative assessment. The ranking of a certain potential case results by analyzing the nearness between it and the ones from instances dataset (sorted after the targeted criterion).

Within the thesis, specific methods have been developed for carrying out these actions. The three methods from above will be further presented in detail, in the following chapters.

Chapter 4

Method for structural identification of the manufacturing process

Within this chapter, a method for structural identification of the manufacturing process is developed. It allows the structuring of the activities, at all levels involved (order acceptance, production planning, product design, processes planning and product processing), by elaborating the tree of specific activities (the relations between the manufacturing process stages and the afferent information circuit are revealed). The identification of the manufacturing process alternatives, at the level of each manufacturing activity is also performed.

The method aims to select the best alternatives at each level of the manufacturing activity, according to different optimization criteria (such as, for example, cost, timespan, energy consumption, and other critical consumption or combination combinations thereof).

Following the selection of the best alternatives from each level of the manufacturing activity, the optimal technological path is obtained for obtaining the considered product.

4.1. The manufacturing process levels

The manufacturing process will be further considered as composed by activities structured on five successive levels (order acceptance, production planning, product design, processes planning and product processing).

The tree of specific activities that reflect the relationships between the activities at different levels of the manufacturing process, which will be subjected to holistic optimization, as well as the related information circuit are exemplified in figure 4.1.

In figure 4.1 at level A these are three potential activities A1, A2 and A3, of the three activities are selected , according to the method, only two that lead according to previous experience to the best results (lower cost, highest profit, etc.), namely A1 and A2. For each of the selected activities, at level B there are four potential activities B1, B2 for A1, B3, B4 for A2, of which only two are selected, namely B1 and B4. Further, the procedure is applied similar to level E.

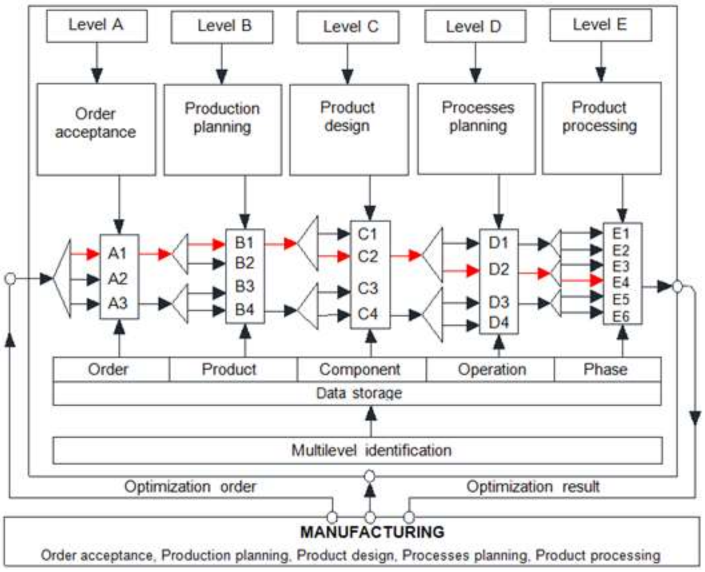


Figure 4.1. Holistic optimization of manufacturing process – block diagram –

Thus, following the successive evaluations and selections of the activities from the different levels of the manufacturing process, an optimal technological path is obtained for the considered manufacturing process, which includes activities A1, B1, C2, D2 and E4 (marked in red in figure 4.1).

4.2. Activities identification at each process level

The generic manufacturing process can be described by means of activity objects (these can be, at the different levels of the process: order, product, component, operation phase).

The result of the manufacturing process identification consists in proposed method case from the manufacturing process activity chain. Such a chain is exemplified in detailed representation in figure 4.2-a or synthetic in figure 4.2-b

The problem addressed in this chapter can be formulated now as the selection, from manufacturing graph, of the optimal manufacturing path, according to a flexible criterion/set of criteria.

As it can be easily observed, the manufacturing graph may be very complex. Frequently, the structure of activities needing to be performed in order to cover the manufacturing path is also complicated. Moreover, the evaluation of path effect by decomposing the typical activities in basic nominal activities, finding the effect for each of them and, finally, cumulating these effects is also a difficult task.

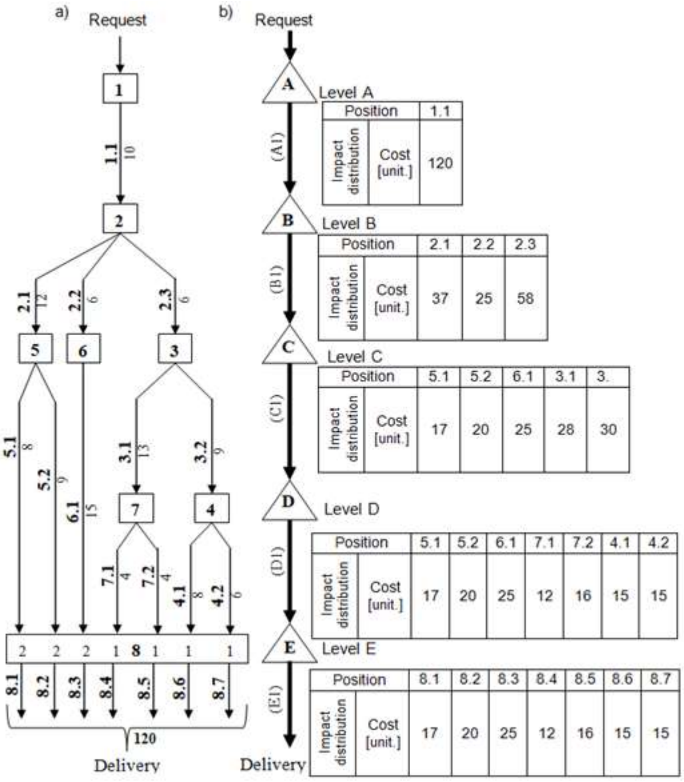


Figure 4.2. The activity chain for a manufacturing process variant

4.3. Alternatives for activities accomplishment

At a manufacturing process level, in general, there may be several variants of the process.

Figure 4.3 shows a manufacturing process for which these are several variants at each level. It should be noticed that for actually accomplishing the process, it is enough to follow a single path only. The ensembles of all potential paths that can be used for obtaining the product form the manufacturing process graph (figure 4.3).

The optimal manufacturing graph can be chosen according to the criterion followed, according to the values obtained; thus, three possible variants are exemplified: *i)* variant 1: after minimum value for cost, *ii)* variant 2: after minimum value for time, and *iii)* variant 3: after a combination of the two criteria, the cost, the variant marked with red in figure 4.3.

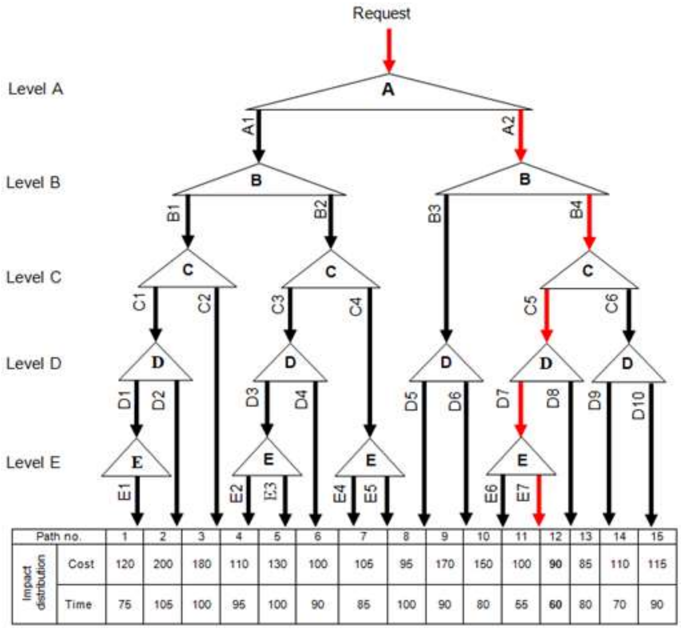


Figure 4.3. Manufacturing process graph

Chapter 5

Method for causal identification of the manufacturing process

Within this chapter, a method for causal identification of the manufacturing process is developed, allowing multiple forms to be provided for one and same causal relationship. The method is designed with the purpose of being applied in the case of holistic optimization of the manufacturing process, before the comparative assessment of the results of the activities that can be selected at the level of a decision point from the manufacturing process graph. The method allows the identification of the most appropriate set of cause-variables, on the basis of which a effect-variable can be evaluated, depending on the specific conditions of a particular manufacturing process. The method purpose is to elaborate the *tree of causal links, what can be considered a system of decision-making* ("Decision Support System, DSS", [41]). The method works based on the existing information by processing a database associated with the manufacturing process ("Instances-based learning, IBL", [42]) and involves going through several successive stages. The specific actions related to each stage are: *i)* process identification, *ii)* data concatening, *iii)* instances comparing, *iv)* variables assessing and *v)* causal models identification.

5.1. General considerations

The manufacturing process comprises the whole set of activities through which the product (no matter if physical object or service) subjected by a certain market request is realized, these activities purpose is to accomplish specific tasks. According to its purpose and in connection to the level inside the manufacturing process, the task might mean a market request, an order, a job, a process plan or a part program (figure 5.1).

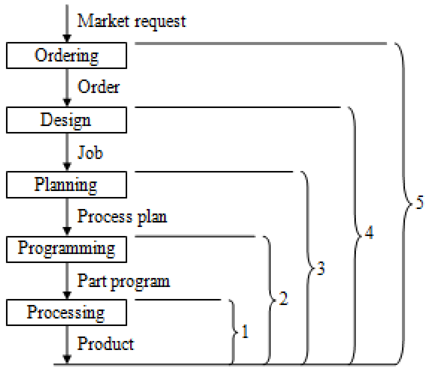


Figure 5.1. Effective manufacturing process activities

The support enabling to perform the manufacturing process is generically called *manufacturing system*. Depending on the specific process (e.g. 1 ... 5, figure 5.1), the manufacturing system can be addressed in different manners, at different levels.

The need for evaluation appears whenever: *i)* an analysis „what if" is performed to adopt an alternative to proceed in manufacturing process case, and *ii)* the characteristics of the task that have the greatest impact on the effect (objective) must be determined in order to effectively control the manufacturing process.

This evaluation requires the existence of a model, therefore, finding the model of considered process is a matter of general interest. However, such a model can be complicated, involving many variables, so finding it is difficult. In additional, the applicability of the model is limited – if the premises on which the model was determined are modified, it may become useless or, at best case – inaccurate.

Model construction involves two stages:

1. Model structure establishment, which means, first of all, the selection of the cause-variables by which the effect-variable can be evaluated and based on which the future model will be built (which supposes, at first, the selection of model variables).
2. Model formalization (through the concrete relation linking the effect-variable to the cause-variables) – for example, starting from a parametric model, the parametric values are adjusted until the model properly expresses, in a quantitative way, the causal link.

While a large number of techniques for accomplishing the second stage are available in dedicated literature [43]–[45]. The papers addressing the first stage can also be highlighted, based on different features selection techniques [46]. However, establishing the structure of the model based on determining causal link has been addressed until now, to the best of our knowledge. In our view, highlighting the causal links must be based on the causal identification of the process under consideration.

The method uses the past case studies relating to the manufacturing system, registered as a database, to reveal the causal links between the variables that characterize the process development on the considered manufacturing system.

5.2. Algorithm of the causal identification method

The objective of the method is to elaborate the tree of causal links, facilitating each time choosing the set of causa-variables that is most suitable for modeling a particular effect. The causal links tree can be further integrated into manufacturing decision support system (DSS). The application of the proposed causal identification method for manufacturing process modeling involves several succesive stages (figure 5.2). The specific actions to be performed at each stage are presented in the following sub-chapters.

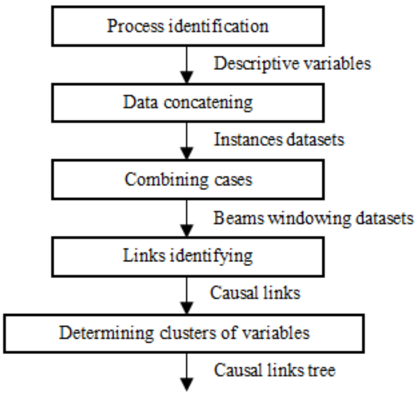


Figure 5.2. Algorithm of the causal identification method

5.3. Process identification

The first step of the alghorithm involves analyzing the targeted manufacturing process, in order to choose the variables that characterize its achievement. Thus, the set of variables (both cause- and effect-variables) with potential in process modeling is defined.

5.4. Data concatening

The purpose of this stage is to generate the database of previous cases, regarding the considered manufacturing process alternatives. 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. The c*lustering* deals with selection from instances collection that refer to given process and aiming to build the *instances database*. The *updating* of variables values is necessary due to the inherent changes intervening since the instances has been recorded. The *homogenization* aims to make the instances comparable, by scaling the values of each variable to values comprised between 1 and 0. In order to achieve the variable scaling, a Matlab application was developed.

After running the scalling algorithm, the scaled values of the variables must be stored (for example, in a new file in Microsoft Excel.

5.5. Instances comparing

The method of causal identification 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. The core idea in finding causal models is to look for relations between the variations of cause- and effect-variables (denote by p_i respective q_j), instead to see each instance as event that illustrates the causal relation between these variables. Variables variations can be revealed by instances comparing. The comparison of k^{th} and l^{th} instances from a certain dataset means to calculate the differences $\delta p_i(k,l)$ and $\delta q_j(k,l)$ between their corresponding variables:

$$\delta p_i\left(k,l\right)=\left|p_{ik}-p_{il}\right|,\ i=1\ldots n_p \text{ și } \delta q_j\left(k,l\right)=\left|q_{jk}-q_{jl}\right|,\ j=1\ldots n_q \tag{5.1}$$

In relation (5.1) n_p and n_q represent the number of cause- respective effect-variables. The result of such a comparison will be further referred as *beam*(k, l). It consists in the reunion of the vectors $\delta p_i(k,l)$ and $\delta q_j(k,l)$. Hereby, the beam(k, l) includes *beam components* (more specific, n_p *cause-components* and n_q *effect-components*).

The instances, as well as the beams resulted by their comparing have identical dimension and similar structure. Thus, from instances as $\left(p_1,p_2,\ldots p_i,\ldots p_{n_p},q_1,q_2,\ldots,q_j,\ldots q_{n_q}\right)$ result beams of the same structure, $\left(\delta p_1,\delta p_2,\ldots\delta p_i,\ldots\delta p_{n_p},\delta q_1,\delta q_2,\ldots\delta q_j,\ldots\delta q_{n_q}\right)$. For this reason, it will be hereinafter made a natural correspondence between the cause-variable p_i and the cause-component δp_i, as well as between the effect-variable q_j and the effect-component δq_j. Obviously, each instance from the n composing the dataset can be compared to all other n–1. The ensemble of beams resulting after making all possible comparisons represents the *beams dataset*.

Because the beam(k, l) and beam(l, k) are identical (with k, l = 1...n), only one of them is recorded. Hereby, the beams dataset has $N=C_n^2$ lines.

5.6. Variables assessing

The purpose of this step is to find and evaluate the dependency relationships between variables with the potential to describe the causal relationship between the cause-variables and the effect-variable. This can be done from an existing *beam database*, using an original technique developed for this purpose, namely *beams windowing*, described below.

The elementary action in beams windowing is the *windowing sequence*, which means to impose restrained domains ("*windows*") for one or more of the beams components corresponding to analyzed variables, while the domains ("*images*") that consequently result for each of the other beam components are measured. The ensemble of beams concomitantly passing through all considered windows will be further called *strand of beams.*

The *windowing algorithm* can be now defined as windowing sequences series, but where unlike windowing program, the values of current sequence variables depend on their values from the previous section(s).

The identification of causal links is done by strand evaluating, which consists in the successive application of two procedures:

- *The procedure for dimensionality reduction*, for eliminating the cause-variables with a high dependence on other cause-variables;
- *The procedure for assessing the modeling potential* of each remaining cause-variable.

The result of applying the first procedure is the cause-variables maxim cluster. Starting from this, based on the values of the specific characteristics that characterize the cause-variables in terms of their modeling capacity, a sub-clusters of the maximal cluster can be generated (simply called clusters).

The algorithms of the procedure are presented below, by exemplifying their application in the case of the elementary problem, corresponding to the situation of a set of *m* cause-variables related to a single *q* effect-variable.

5.6.1. Algorithm for dimensionality reduction

Knowing that all variables (cause and effect) take values in the interval [0, 1], we take into account a predefined series of thresholds, h_k, heights (shown in figure 5.3) form a geometric progression, for example:

$$h_k = 0.8^k,\ k = 0, 1, 2\ldots \tag{5.2}$$

One of these thresholds, denoted by h_{ref}, is set as reference. Its selection depends on the extension of beams database (e.g. $h_{ref} = h_7 = 0.2097$).

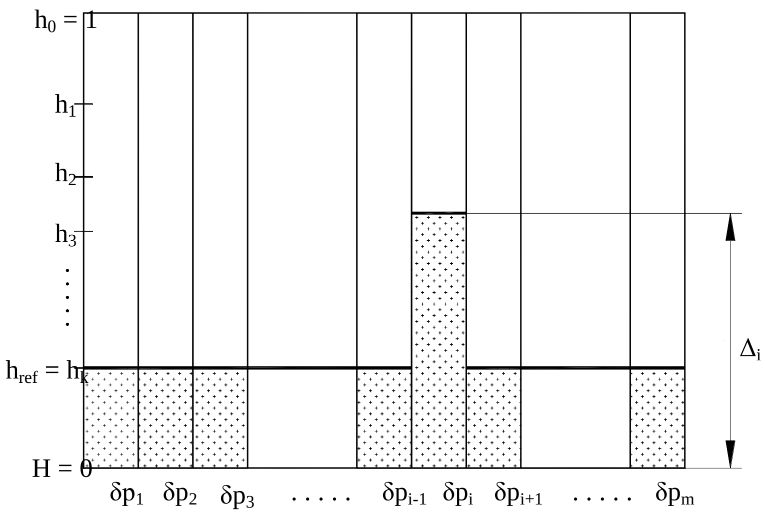


Figure 5.3. The windowing sequence applied for the cause-variable δp_i

The algorithm aims to discard the cause-variables having high degree of dependence on other cause-variables, and consists in the following actions:

- Windows having H = 0 and $h = h_{ref}$ are imposed to (m-1) of the cause-variable, excepting the i^{th} one, for which the image dimension Δ_i is measured (figure 5.3). Obviously, there are m possibilities to do this (i = 1, 2, ... m).
- The windowing sequence from above is run for each of the m cause-variables, hence m values of Δ_i will result.
- After that, the value of $\Delta_{min} = \min(\Delta_i)_{i=1,2,...m}$ is determined. If $\Delta_{min} < h_{k-1}(h_{ref} = h_k)$, then the cause-variable to which Δ_{min} corresponds can be considered as highly dependent on the other cause-variables, and it may be discarded.
- The set of remaining cause-variables is repetitively submitted to the previous three actions until the current value of Δ_{min} becomes higher than h_{k-1}. The last set of cause-variables, forms *the maximal cluster of variables.* These cause-variables can be considered relatively independent of each other and can be used to the effect modeling of q.

5.6.2. Algorithm for assessing the modeling potential of variables

Regardless of whether it is determined within the maximal cluster of cause-variables or one of its sub-clusters, the modeling potential refers to cause-variable and means their potential to model a certain effect-variables. Three criteria, below presented, can assess the modeling potential of a cause-variables belonging to a given cluster:

- ***The modeling power MP***, which shows how much the cause-variable variation is found in the effect-variable variation.
- ***The modeling capacity MC***, meaning the measure which the cause-variable is able to describe the effect-variable, itself only.
- ***The modeling unevenness MU***, reflecting the variability of the relation between cause- and effect-variables.

- Windows having H = 0 and $h = h_{ref}$ are imposed to (n–1) cause-variables corresponding to variables from considered cluster, excepting the i^{th} one, for which we impose a window whose dimension is successively modified from h_0 = 1, h_1, h_2 ... h_j, ... up to $h_k = h_{ref}$. An image of effect-variable δq having the dimension Δ_{ij}, j = 1, 2, ... k, corresponds to h_j dimension of the window imposed to δp_i (see figure 5.4, where j = 3).

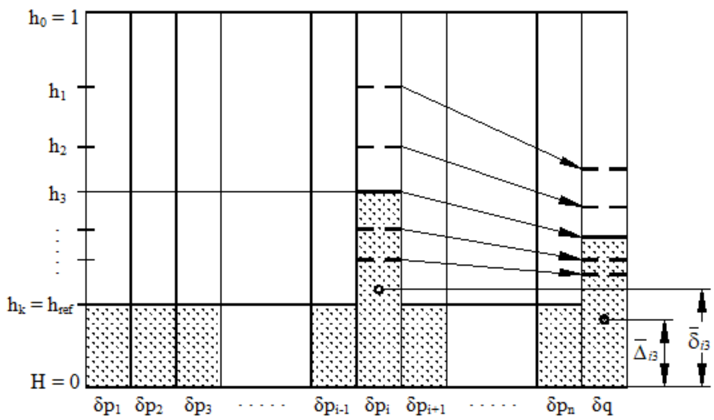


Figure 5.4. Assessment of p_i modeling potential

- In the case of the window having the dimension h_j imposed to δp_i component, the strand of beams passing through it and other (n-1) windows (for which $h = h_{ref}$) has the cardinal N_{ij}. Then, the average values $\bar{\delta}_{ij}$ and $\bar{\Delta}_{ij}$ are calculated as:

$$\overline{\delta}_{ij} = \frac{1}{N_{ij}} \sum_{l=1}^{N_{ij}} \delta p_{il} \tag{5.3}$$

$$\overline{\Delta}_{ij} = \frac{1}{N_{ij}} \sum_{l=1}^{N_{ij}} \delta q_{l} \tag{5.4}$$

where δp_{il} and δq_l mean the values of δp_i and δq corresponding to the l^{th} beam passing through the considered set of windows.

- A linear regression, having the shape:

$$y = a \cdot x + b \tag{5.5}$$

is fitted to the set of points $C_j\left(\overline{\delta}_{ij}, \overline{\Delta}_{ij}\right)_{j=1, 2, \ldots, k}$, the Root Mean Square Error (RMSE) being also calculated. Thus, the attributes of the modeling potential can be characterized by the values *a* (*MP*), 1-*b* (*MC*) and RMSE (*MU*). It should be noted that the values of these three characteristics are relative because they depend on the composition of the variables cluster to which they belong. In other words, the same cause-variables may show a different modeling potential if they are evaluated within different variables clusters.

5.7. Causal models identification

The use of modeling potential characteristics defined in the previous chapters for the cause-variables can be extended to the case of the variable clusters, after the necessary adaptations have been made. Let us consider the case of a causal model whose maximal cluster has n_{mc} cause-variables, p_1, p_2, ... p_{nmc}. This should have, at least in principle, the highest potential of modeling the effect-variable *q*. However, they might be encountered situations when the values for one or more of cluster variables are not available, or, as well, it might be useless a complicated model, involving all variables from the maximal cluster. In both cases, the solution is to use a causal model defined by fewer cause-variables. According to the presented method, the selection of the most suitable such a model supposes to identify multiple causal models concerning *q*. This can be realized by successively and repetitively applying a couple of algorithms, namely *i)* the algorithm for generating smaller clusters, and *ii)* the algorithm for assessing the modeling potential of a cluster.

5.7.1. Algorithm for generating smaller clusters

Let us suppose we have to deal with a cluster with n_c cause-variables (which may be in particular the maximal cluster, when $n_c = n_{mc}$). Any of them might be discarded in order to obtain a cluster with (n_c-1) variables, hence n_c clusters may result. If now, from each smaller cluster we discard another cause-variable, the total number of distinct clusters with (n_c-2) cause-variables that could be obtained is $n_c(n_c-1)$. Obviously, after only few steps of generating smaller clusters by discarding variables one by one, a very large number of clusters will result, which complicates very much the problem of assessing the potential for all of them. A reasonable solution is to consider only a part of the possible eliminations, more specific – to discard, at each level, only the cause-variables with lower modeling potential. The algorithm applied in this purpose, has three steps:

- Each of the n_c cause-variables is analyzed after a selected criterion for assessing the modeling potential (MP, MC or MU).
- The number of cause-variables to be discarded is established in concordance to the exigencies of the addressed modeling problem.
- After finding the n_d cause-variables with lowest modeling potential, n_d clusters with (n_c-1) variables are generated by discarding them separately, one by one.

5.7.2. Algorithm for assessing the modeling potential of a cluster

For evaluating the modeling potential of a variables cluster, a specific algorithm has been developed. The algorithm purpose is to assess the potential of a given cluster of cause-variables for modeling the considered effect-variable. The application of criteria defined in previous subsection (MP, MC and MU) can be extended from assessing cause-variables to assessing clusters of cause-variables, in what concerns their modeling potential, after making the needed adaptations. In the case of a cluster, the values of criteria (denoted by MP_c, MC_c and MU_c), result by applying the following algorithm:

- Windows having $H = 0$ and dimension successively modified from $h_0 = 1$, h_1, h_2 ... h_j ... up to $h_k = h_{ref}$ are concomitantly imposed to all n_c beams components corresponding to the cause-variables from cluster. An image of the beam component corresponding to effect-component δq, having the dimension Δ_j, $j = 1, 2, ... k$ results for each dimension h_j of the window (see figure 5.5, where $j = 3$).

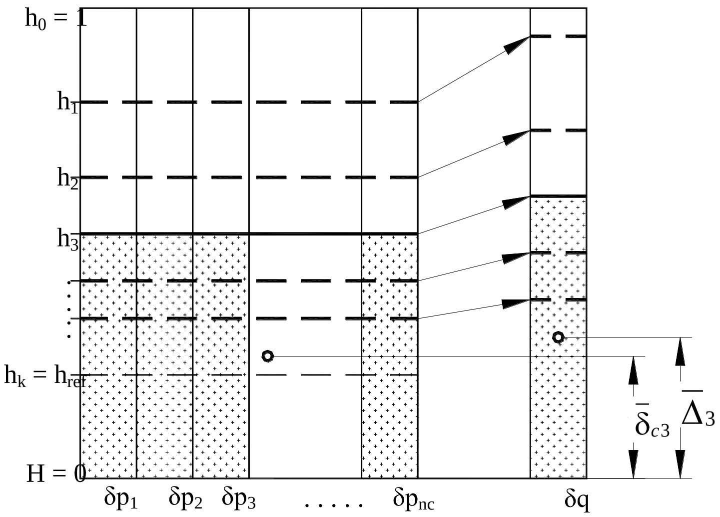


Figure 5.5. Assessment of cluster modeling potential

- When the windows imposed to cause-components have the dimension h_j, the strand of beams passing through them has the cardinal N_j. The average values $\bar{\delta}_{cj}$ and $\bar{\Delta}_j$ are calculated as:

$$\bar{\delta}_{cj} = \frac{1}{n_c \cdot N_j}\left(\sum_{l=1}^{N_j}\delta p_{1l} + \sum_{l=1}^{N_j}\delta p_{2l} + \ldots + \sum_{l=1}^{N_j}\delta p_{il}\right) \tag{5.6}$$

$$\bar{\Delta}_j = \frac{1}{N_j}\sum_{l=1}^{N_j}\delta q_l \tag{5.7}$$

where δp_{il} and δq_l mean the values of δp_i and δq corresponding to the l^{th} beam (from the N_j) passing through the considered set of windows, $i = 1, 2, ... n_c$.

- A linear regression, having the shape:

$$y = a_c \cdot x + b_c \tag{5.8}$$

is fitted to the set of points $\left(\bar{\delta}_{cj}, \bar{\Delta}_j\right)_{j=1,2...k}$, the Root Mean Square Error (RMSE) being also calculated.

The values of criteria evaluating cluster potential are:

$$MP_c = a_c, MC_c = 1 - b_c \text{ şi } MU_c = RMSE \tag{5.9}$$

5.8. Causal links tree

As regards causal models identifying procedure, the maximal cluster represents the starting point, hence defines the first causal model. Every time when a number of clusters are generated by reducing with 1 the dimension of the ones defining the already identified causal models, the new clusters are having values of a selected criterion higher than a pre-established threshold define new causal models of the *q* effect-variable. Their corresponding clusters of variables follows to be further submitted to the couple of algorithms from above. The procedure of identifying new causal models is stopped when any of the smaller clusters generated does not show enough modeling potential.

As already mentioned, the causal models tree is the representation of causal models concerning the same effect-variable. The tree results after identifying the whole set of causal models concerning the addressed effect-variable. The representation shows the value of criterion assessing the modeling potential for each model and suggests the way on which this was obtained in models identifying procedure. It is a graph-type representation (figure *5.6*), drawn according to the following rules:

- The cluster of each causal model is represented as rectangle, inside which its cause-variables are mentioned.
- The maximal cluster represents the starting point. The arrow drawn between two rectangles shows that the second cluster results from the first one by discarding the variable whose symbol is mentioned near the arrow.
- The level (height) of representing a certain cluster shows the values of selected criterion (MP_c, MC_c, MU_c, or a weighted combination of them).

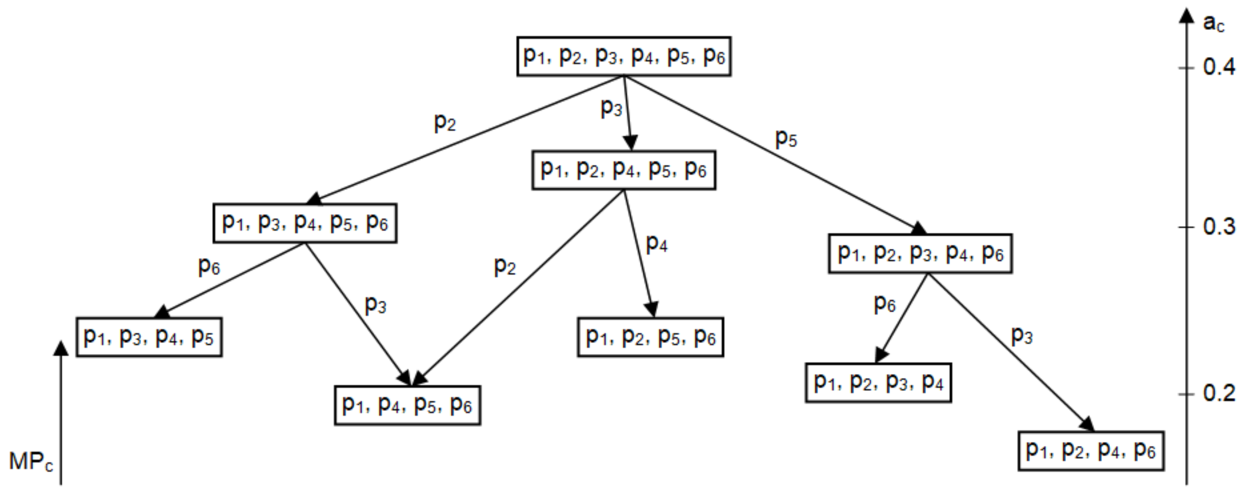


Figure 5.6. The generic causal links tree associated to effect-variable q, drawn after the values of a_c

Chapter 6

Method for comparative assessment of the manufacturing process alternatives

Within this chapter, a method for comparative assessment of the manufacturing process alternatives is developed, that proposes an innovative approach in the analysis of potentially optimal solutions, based on their rankings. The method is designed to assist the selection of the optimal continuation variant for the manufacturing process, at a certain decision level. The comparative assessment means to establish the rankings for two or more alternatives to proceed, according to a certain criterion (e.g. cost, timespan, consumed energy, etc.). The comparative assessment of the potential alternatives is made by reffering them to the cases of already performed manufacturing processes, whose parameters have been registered in the database.

According to the holistic optimization method of the manufacturing process, this is described by a number of cause-variables, respectively effect-variables. The application of the comparative assessment method is done after the causal identification completion, respectively after the adoption of a set of cause-variables describing the effect-variable of interest at the present moment, by applying the method presented in the previous chapter.

6.1. Comparative assessment problem

Problem solution has been developed starting from the following key-ideas:

- The most relevant information about a process can be reached by recording the information concerning its past deployments in the form of an instances database, here including, obviously, both conditions and results.
- There is no need to know the precise value of criterion for two (or more) potential alternatives in order to compare them after this criterion. Instead of this, the comparison is easier to make by finding neighborhoods of already performed cases (with known results) to which each potential alternative belongs.
- The most efficient comparative assessment can be reached by adapting the amount of processed information to required comparison level. Sometimes many potential alternatives can be rejected after relative superficial analysis, while few (often only last two) potential alternatives might ask a more serious effort to decide which the best is.

Problem solution proposed in the thesis consists in replacing the direct comparison of potential alternatives by successive comparisons between each of them and the cases from instances database, on the base of the variables with known values. The result of such comparison is the ranking of the potential alternative, this being found without directly evaluating the value of the criterion on which the comparison is based.

The key-issue of comparative assessment is the definition of the nearness between two cases, which should be assessed starting from the values of cases known descriptors. The form of nearness function should be actually determined by modeling a set of cases from instances database, appropriately chosen. The ranking of a certain potential case results by analyzing the nearness between it and the ones from instances dataset (sorted after the targeted criterion). Potential case neighborhoods can be delimited and iteratively narrowed, until the resulted ranking becomes precise enough to distinguish between it and the other(s) potential cases in competition.

6.2. The algorithm of the comparative assessment method

The algorithm after which the appropriate ranking is assigned to a given alternative is illustrated in figure 6.1.

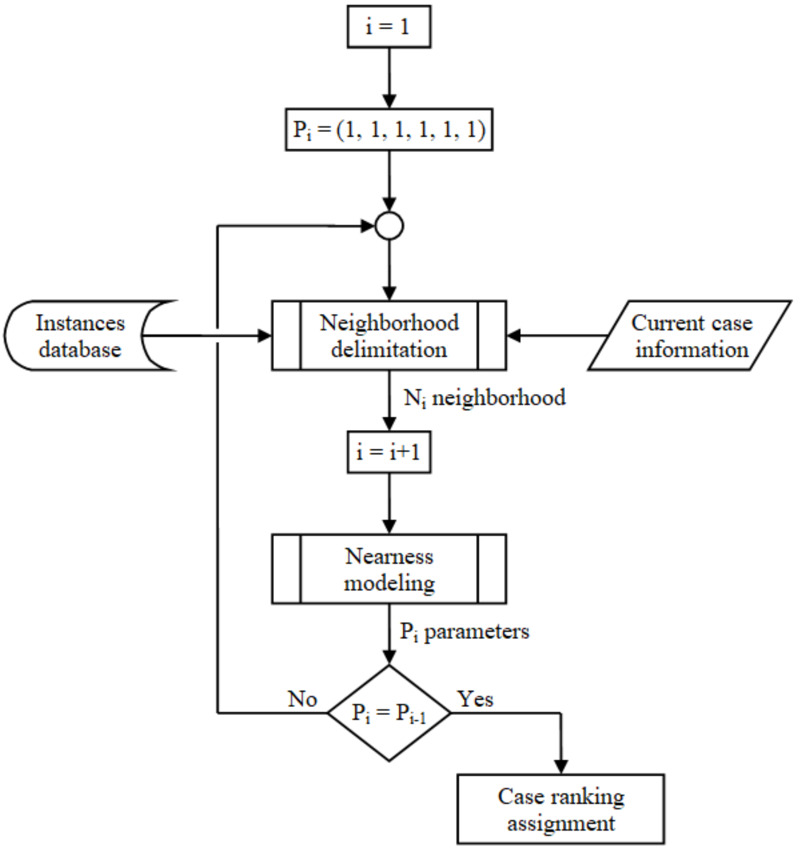


Figure 6.1. Ranking assignment algorithm

The comparative assessment method is based on two procedures: *i)* the procedure for neighborhood delimitation and *ii)* the procedure for nearness modeling.

A key role in the application of the method is played by a so-called "nearness function", with which the nearness between two cases is assessment. The form of the nearness function is determined by modeling a set of cases from the case database. In the variant proposed here, the identification of the nearness function is made on the basis of a set of cases from the database, by determining the values of two parameters for each of the n_p cause-variables considered. The selection of such a set from database, meaning a neighborhood of the current case, is made on the basis of the resulting parameters values at the last identification of the nearness function.

In order to facilitate the explanations concerning algorithm functioning, we make the hypothesis that a case is defined by *effect-variable* (the scalar variable T), and by three *cause-variables* (the scalar variables x, y and z). In these conditions the instances database means a recorded set of n lines:

$$\{(x_k, y_k, z_k, T_k) | k = 1\ldots n\}. \tag{6.1}$$

The instances database is here considered as an ordinate set, its lines being sorted after the ascending value of T_k, hence to each line its current number from this list may be associated as ranking. The current case, for which we search the rank, is defined through its cause-variables values x, y and z, while its effect-variable T is unknown. The values of variables recorded in database are separately scaled on columns, hence $x_k, y_k, z_k, T_k \in [0,1], \forall k = 1\ldots n$.

The values of *x*, *y* and *z* are also scaled, together with their corresponding column from database.

6.3. The neighborhood delimitation procedure

From the very beginning, we need to state that by *similar cases* we mean cases having close values of cause-variables, which is expected to have also close values of result-variable. A certain number of similar cases can be grouped around a *pivot-case* (x_v, y_v, z_v, T_v), hence forming a neighborhood of it.

Neighborhood delimitation action targets to find neighborhood profile, defined by the specific combination of *windows* $x_v \pm \delta_x$, $y_v \pm \delta_y$, $z_v \pm \delta_z$, and $T_v \pm \delta_T$ (see figure 6.2), which include all coordinates sets (x_k, y_k, z_k, T_k) of neighborhood cases.

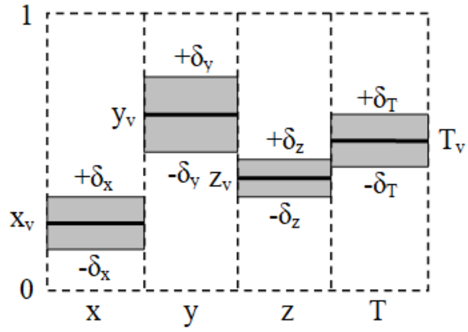


Figure 6.2. Neighborhood profile

The values of δ_x, δ_y and δ_z are considered as interdependent, satisfying the relation:

$$A \cdot \delta_x{}^{\alpha} = B \cdot \delta_y{}^{\beta} = C \cdot \delta_z{}^{\gamma} = \varepsilon \tag{6.2}$$

In relation (6.2), *ε* means the nearness degree of cases from neighborhood, (hereby *ε* = zero corresponds to identical cases), while *α*, *β*, *γ* exponents and *A, B, C* coefficients mean parameters of nearness function *d*. The expression of nearness function, when calculated between current case and database generic case *k* is:

$$d_k = \operatorname{sgn}(x - x_k) \cdot |x - x_k|^{\alpha} \cdot A + \operatorname{sgn}(y - y_k) \cdot |y - y_k|^{\beta} \cdot B + \operatorname{sgn}(z - z_k) \cdot |z - z_k|^{\gamma} \cdot C \tag{6.3}$$

In relation (6.3) *sgn* is the well-known *signum* function [47], [48]. The six parameters can be grouped as coordinates of vector *P* = *P*(*α*, *β*, *γ*, *A*, *B*, *C*), their values resulting by modeling of the considered set of cases.

The target of *Neighborhood delimitation* procedure is to select from *Instances database* the set of cases corresponding to a given profile of neighborhood, resulted for a given value of nearness degree, *ε* and a given pivot-case (x_v, y_v, z_v, T_v). This can be done by calculating, at first, from (6.2), the values of δ_x, δ_y and δ_z:

$$\delta_x = \left(\varepsilon / |A|\right)^{1/\alpha},\ \delta_y = \left(\varepsilon / |B|\right)^{1/\beta},\ \delta_z = \left(\varepsilon / |C|\right)^{1/\gamma} \tag{6.4}$$

followed by extracting from Instances database the cases whose cause-variables satisfy:

$$x_k \in \left[x_v - \delta_x, x_v + \delta_x\right],\ y_k \in \left[y_v - \delta_y, y_v + \delta_y\right],\ z_k \in \left[z_v - \delta_z, z_v + \delta_z\right]. \tag{6.5}$$

The value of *ε* is a parameter of algorithm application, depending on both database dimension and structure, and also on the specific of the comparative assessment problem intended to be solved by case ranking assignment.

At i^{th} iteration of procedure, the selection aiming N_i neighborhood delimitation is made by using the nearness function resulted by replacing in (6.3) the values from current form P_i of parameters vector, as they resulted after nearness modeling on N_{i-1} neighborhood, at previous iteration.

6.4. The nearness modeling procedure

After delimiting the current neighborhood N_i of the current case, the nearness between included cases is modeled in order to find a more precise expression of nearness function, resulted for a new set of its parameters values, $P_i(\alpha, \beta, \gamma, A, B, C)$. In this purpose, at first, the case from N_i that is closest to current case is chosen as pivot. Then, the coordinates differences $\Delta x_j = x_j - x_v$, $\Delta y_j = y_j - y_v$, $\Delta z_j = z_j - z_v$ and $\Delta T_j = T_j - T_v$, are calculated for each of the n_i cases (x_j, y_j, z_j, T_j) from N_i.

Finally, the relation between ΔT, on one side and Δx, Δy and Δz, on the other side, is modeled by *nonlinear multiple regression*, model expression being chosen in connection with nearness function (6.3):

$$\Delta T = b_4 \cdot \operatorname{sgn}\Delta x \cdot \left|\Delta x\right|^{b_1} + b_5 \cdot \operatorname{sgn}\Delta y \cdot \left|\Delta y\right|^{b_2} + b_6 \cdot \operatorname{sgn}\Delta z \cdot \left|\Delta z\right|^{b3} \tag{6.6}$$

The values resulted from modeling for model parameters vector $B = (b_1, b_2, b_3, b_4, b_5, b_6)$ are then transferred to the new form of nearness parameters vector $P_i(\alpha, \beta, \gamma, A, B, C)$, following to be further used for delimitating a new version of current case neighborhood.

Procedures 6.3 and 6.4 are successively run until two consecutive forms of nearness parameters vector P_{i-1} and P_i result identical (see figure 1). At that moment, it may be concluded that the results in applying the rank assignment algorithm are stable.

As consequence, the current case result may be calculated by using the last identified form of (6.6) and current case rank is established after the resulted value of effect-variable T, by inserting it in the *Instances database* at the suitable position.

Chapter 7

Experimental validation

The method for holistic optimization of the manufacturing process is validated through numerical experiments, carried out as several case studies, both for causal identification method and for comparative assessment method. The application of structural identification method was also exemplified in a case study.

In the first study, the application of the structural identification method in bearing manufacturing case is presented. In other three case studies, the causal identification method and the comparative assessment method were validated and evaluated, in integrated manner. In this purpose, three databases were used:

- An artificial instances database, in a turning operation case – in this case, the objective function considered was the cost;
- A database extracted from the industrial environment, in a bearing ring turning – in this case, the objective function considered was the timespan;
- A database extracted from the industrial environment, in a roller bearing manufacturing case – in this case, the objectiv function considered was the cost.

7.2. Causal identification and comparative assessment for the cost estimation of a turning operation – artificial instances database

The case study presented here was developed to validate and evaluate correlate the causal identification method (chapter 5) and the comparative assessment method (chapter 6) in the cylindrical part turning, on an artificial instances database.

▪ *Causal identification*

In order to apply the method for causal identification in the cylindrical part turning, the steps presented in chapter 5 were followed.

P1. Process identification

The following set of eleven cause-variable was considered as having potential of a turning operations: the turned part length *L* and diameter *D*, the required level of part accuracy *A*, the machinability of part material *M*, the rigidity *R*; the cutting speed *v*, the feed *s*; the cutting depth *t*, the main cutting force *F*, the power absorbed by lathe *P*, the removed chips volume, *V*. Three other parameters were chosen as effect-variables the machining cost *C*, the machining timespan *TS* and the consumed energy *E*.

Some remarks are made regarding these variables:

- The first five (*L*, *D*, *A*, *M* and *R*) are purely exogenous (independent). The next six variables (*v*, *s*, *t*, *F*, *P* and *V*) are depending on the first five, while the last three (*C*, *TS* and *E*), are depending on all previous eleven.
- Most of the variables have clear physical meaning, so they can be expressed directly through their values. The exceptions (*A*, *M* and *R*) shall be expressed by conventional dimensionless values, from 1 to 10, assigned after synthesizing some features.

The relations describing the real turning process express *v*, *s*, *t*, *F*, *P* and *V* depending on *L*, *D*, *A*, *M* and *R*, as follows:

$$t = \frac{5.1 \cdot R - 0.1 \cdot A}{10} \text{ [mm]}, \tag{7.1}$$

$$s = \frac{4.4 - 0.4 \cdot A}{10} \text{ [mm/rot]}, \tag{7.2}$$

$$v = \frac{C_v}{s^{0.3} \cdot t^{0.2} \cdot T^m}\left(\frac{10}{M} \cdot x_v + \frac{R}{10} \cdot y_v\right) \text{ [m/min]}, \tag{7.3}$$

$$F = C_F \cdot s^{0.8} \cdot t\left(x_F + \frac{M}{10} \cdot y_F\right) \text{ [daN]}, \tag{7.4}$$

$$P = \frac{F \cdot v}{6000} \cdot \frac{1}{\eta} \text{ [kW]}, \tag{7.5}$$

$$V = \frac{\pi \cdot D \cdot L \cdot t}{10^3} \text{ [cm}^3\text{]}. \tag{7.6}$$

In relations (7.3) and (7.4) C_v, x_v and y_v, respective C_F, x_F and y_F means constants to which the values are given. In relation (7.6), part dimensions *L* and *D* are expressed in millimeters.

The relations for calculating *C*, *TS* and *E* depending on *v*, *s*, *t*, *F*, *P* and *V* are:

$$C = \frac{V}{v \cdot s \cdot t}\left[\left(1 + k + \frac{\tau_{sr}}{T}\right)c_\tau + \frac{\tau_{sr} \cdot c_\tau + c_s}{T} + \frac{P \cdot c_e}{60}\right] \text{ [Euro]}, \tag{7.7}$$

$$TS = \frac{V}{v \cdot s \cdot t}\left(1 + k + \frac{\tau_{sr}}{T}\right) \text{ [min]}, \tag{7.8}$$

$$E = \frac{P \cdot V}{v \cdot s \cdot t} \cdot \frac{1}{60} \text{ [kWh]}. \tag{7.9}$$

In relations from above, *k* means the ratio between the auxiliary time and the machining time, τ_{sr} - the time for worn tool changing [min], *T* – tool durability [min], c_τ - the wage specific cost [Euro/min], c_s - the tool expenditure between two consecutive tool changes [Euro], c_e - the energy price [Euro/kWh].

P2. Data concatening

The instances database is obtained by data concatenating regarding the manufacturing process considered. This is an artificial database, obtained as follows:

- The intervals [30, 300] and [20, 200], în millimeters, have been adopted for *L* and *D*, respectively. The conventional values of *A*, *M* and *R* are comprised in [1, 10] interval. Relative uniform divisions of these five intervals, composed by *n* = 150 points each, were adopted.
- The order of points from each of the five divisions has been separately randomized, with the help of Microsoft Excel facilities, thus resulting the first five columns of the instances database with 150 lines.
- The values of *v*, *s*, *t*, *F*, *P* and *V* have been calculated with formula (7.1) - (7.6) for each set of *L*, *D*, *A*, *M* and *R values,* located on the same line in the database.
- The values of *C*, *TS* and *E* have been calculated with formula (7.7) - (7.9), on the base of the values previously found for *v*, *s*, *t*, *F*, *P* and *V*.
- The values in each of the 14 columns, generated as shown above, were scaled separately in the range [0, 1], using a dedicated MatLab application.

The resulted artificial instances database has been stored as Microsoft Excel file.

P3. Instances comparing

The beams database has been obtained with the help of a MatLab application written in this purpose, by comparisons between the 150 instances from database, as explained in chapter 5, sub-chapter 5.5. Hereby, $N = C_{150}^{2} = 11175$ lines (beams) compose the beams database, which has also been stored as Microsoft Excel file.

P4. Variables assessing

At first, the reference threshold has been set to $h_{ref} = h_7 = 0.2097$, hence $h_{k\text{-}1} = h_6 = 0.2621$.

P4.1. Dimensionality reduction

According to the algorithm presented in sub-chapter 5.6.1, at Step 1, windows having *H = 0* and $h = h_{ref}$ were considered for the beams components corresponding to ten of the eleven cause variables, while for the eleventh the image dimension Δ_i was measured (*i* = 1, 2, 11, successively). The values obtained for Δ_i, by using a dedicated MatLab application, are shown in table 7.1. As it can be noticed, $\Delta_{min} = 0.2036$, corresponds to variables *A* and *s*, hence one of them (e.g. *s*) may be discarded. At Step 2, the action from previous step is repeated for the remaining ten cause-variables and another one is discarded, namely *t*, and so on. After Step 5, $\Delta_{min} = 0.3600 > h_6$, so the seven cause-variables remaining until here can be considered relative independent and the maximal cluster is [*L*, *D*, *A*, *M*, *R*, *v*, *F*].

Table 7.1. Images dimensions Δ_i and Δ_{min} values

Cause-variable	Successive steps of dimensionality reduction				
	Step 1	Step 2	Step 3	Step 4	Step 5
L	0.9333	0.9333	0.9333	0.9333	0.9333
D	0.7889	0.7889	0.7889	0.7889	0.9056
A	0.2036	0.8409	0.8409	0.8409	0.8409
M	0.7611	0.7611	0.7611	0.7611	0.7611
R	0.2078	0.2078	0.3278	0.3278	0.3600
v	0.4084	0.4084	0.4084	0.4084	0.4084
s	0.2036	-	-	-	-
t	0.2043	0.2043	-	-	-
F	0.3842	0.3842	0.3851	0.3851	0.3851
P	0.2050	0.2050	0.2050	-	-
V	0.2385	0.2385	0.2385	0.2385	-

One can notice that the actually independent cause-variables (the first five from table 7.1) retrieve themselves all in the maximal cluster, which confirms what we knew from the very beginning (when the artificial instances database has been built) and proves the reliability of the proposed method. Another important remark is that only 7/11 cause-variables remained for modeling the effect-variables, which means a significant ease of the modeling problem.

P4.2. Assessing the variables modeling potential

The criteria for assessing the modeling potential have been determined for each cause-variable of the maximal cluster, according to the algorithm above presented in sub-chapter 5.6.2, 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 7.2.

Table 7.2. The values of a, b, and RMSE

	L	D	A	M	R	v	F
a	0.2644	0.1895	0.0222	0.1273	0.0561	0.0650	0.0575
b	0.0269	0.0358	0.0475	0.0378	0.0486	0.0476	0.0437
RMSE	0.0021	0.0031	0.0010	0.3427	0.0029	0.0001	0.0002

P5. Causal models identification

P5.1. Generating smaller clusters

In order to draw the causal link tree, it must be started from the maximal cluster and established, first of all, from which derived clusters the tree will be formed. In connection to this, the cause-variables which must be kept must be chosen when the smaller clusters are successively generated. The criterion underlying this choice must be one of the three attributes of modeling potential (MP, MC, MU).

In the considered case study, the cause-variables were selected according to *MC* criterion (hence, after values of *b*). More specific, the variables with lowest *MC* (highest values of b) are suitable to be discarded. The cause-variables selections and the resulted clusters are presented in table 7.3-a, 7.3-b and 7.3-c.

Table 7.3-a. Generation of 6-variables clusters

Variables	L	D	A	M	R	v	F
b	0.0269	0.0358	0.0475	0.0378	0.0486	0.0476	0.0437
Resulted clusters		[L, D, M, R, v, F]		[L, D, A, M, v, F]		[L, D, A, M, R, F]	

Table 7.3-b. Generation of 5-variables clusters

Variables	L	D	M	R	v	F
b	0.0289	0.0352	0.0415	0.0557	0.0492	0.0332
Resulted clusters			[L, D, M, v, F]		[L, D, M, R, F]	
Variables	L	D	A	M	v	F
b	0.0244	0.0313	0.0519	0.0474	0.0532	0.0601
Resulted clusters			[L, D, A, M, F]		[L, D, A, M, v]	
Variables	L	D	A	M	R	F
b	0.0278	0.0375	0.0486	0.0427	0.0493	0.0444
Resulted clusters			[L, D, M, R, F]		[L, D, A, M, F]	

Table 7.3-c. Generation of 4-variables clusters

Variables	L	D	M	v	F
b	0.0276	0.0303	0.0456	0.0619	0.0487
Resulted clusters		[L, D, M, F]		[L, D, M, v]	
Variables	L	D	M	R	F
b	0.0278	0.0375	0.0474	0.0557	0.0601
Resulted clusters		[L, D, M, F]		[L, D, M, R]	
Variables	L	D	A	M	F
b	0.0284	0.0291	0.0446	0.0507	0.0604
Resulted clusters		[L, D, A, F]		[L, D, A, M]	
Variables	L	D	A	M	v
b	0.0358	0.0411	0.0522	0.0554	0.0649
Resulted clusters		[L, D, A, v]		[L, D, A, M]	

In all three tables from above, the variables having the highest value of *b* have been marked with red. It should be noticed that because of discarding the same variables in different successions, some clusters were obtained twice in the same structure. Hereby, the causal tree will include 1 + 3 + 4 + 6 = 14 clusters.

P5.2. Assessing the modeling potential of a cluster

The characteristics of the modeling capacity must be evaluated for each cluster, by finding, using *Curve fitting tool* from MatLab, the values for a_c, b_c and *RMSE*, by applying the specific procedure defined in 5.7.2. These values are presented in Table 7.4.

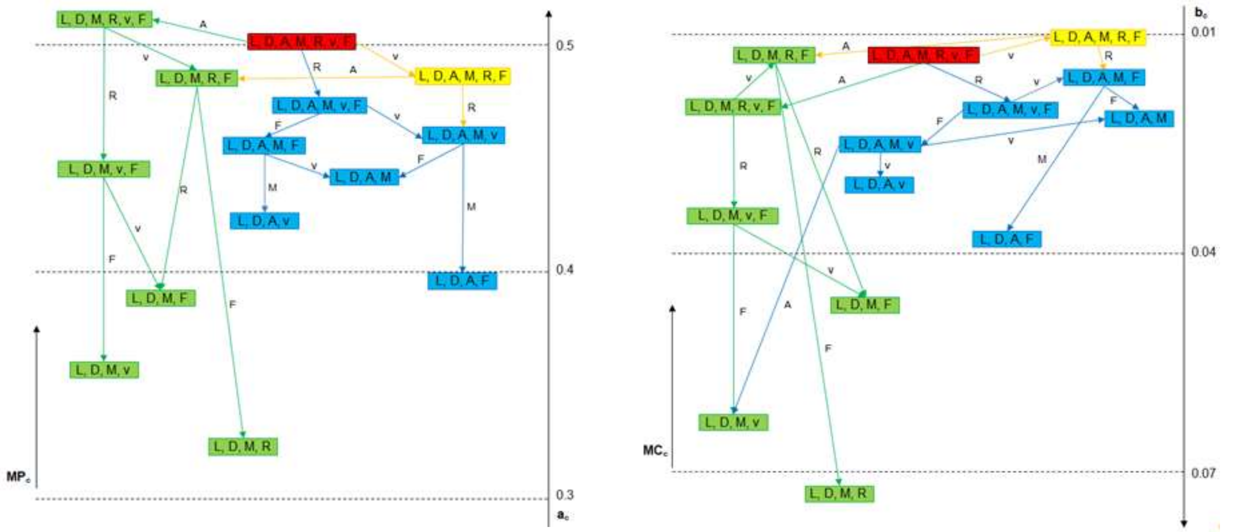
Table 7.4. The values of a_c, b_c and RMSE

Clusters variables	a_c	b_c	RMSE
[L, D, A, M, R, v, F]	0.5051	0.0163	0.0040
[L, D, M, R, v, F]	0.5110	0.0217	0.0086
[L, D, A, M, v, F]	0.4800	0.0227	0.0032
[L, D, A, M, R, F]	0.4923	0.0116	0.0032
[L, D, M, v, F]	0.4510	0.0382	0.0046
[L, D, M, R, F]	0.4954	0.0166	0.0076
[L, D, A, M, F]	0.4657	0.0180	0.0031
[L, D, A, M, v]	0.4769	0.0235	0.0035
[L, D, M, v]	0.3654	0.0641	0.0045
[L, D, M, F]	0.3879	0.0472	0.0011
[L, D, M, R]	0.3114	0.0730	0.0054
[L, D, A, F]	0.3818	0.0453	0.0033
[L, D, A, M]	0.4522	0.0197	0.0031
[L, D, A, v]	0.4275	0.0398	0.0026

P6. Causal links tree

The position of each cluster is determined in the causal links tree on height direction (as already mentioned) according to the value of one of its MP_c, MC_c sau MU_c modeling characteristics (therefore, in relation to the a_c, b_c and *RMSE values*). The causal link trees drawn by the values of a_c and b_c are shown in figure 7.1 (a) și (b).

After examining the two causal links tree in figure 7.1, it can be seen that the hierarchy of sets is identical or similar in both variants. Under normal modeling accuracy, it is not relevant which of the two causal link trees is drawn and used to choose the cause-variables to be used for effect-variable modeling.



(a) (b)

Figure 7.1. The causal models tree drawn after criterions a_c (a) şi b_c (b)

It is very important to notice that the causal trees *correspond to what we knew from the very beginning*: the models including the five independent cause-variables are showing better potential. *As it also would be expected*, the models with more cause-variables are proving, in general, better potential than the ones with fewer cause-variables. Finally yet importantly, the model [*L, D, A, M*] still has a reasonable potential, hence a significant reduction of the model dimension (4 instead of 7) by applying the presented method, under the conditions of a good modeling potential.

- ***Feasibility assessment***

The feasibility of the method, synthesized in graphical form through the causal link tree in figure 7.1, was tested by finding and evaluating the NN models of the effect-variable built on the basis of the 14 clusters of cause-variables that make up each tree. The tool for modeling with the neural networks NN-tool from MatLab eats used for this purpose. The quality of the resulting models was evaluated as well as the concordance between it and the cause-variable position in the causal links tree.

The NN-models having two layers (the hidden layer with 10 neurons) were built on the base of the artificial instances database with 150 lines presented at 7.2 (104 lines were used for training the network, 23 for validation and 23 for testing the model). The NN-model performance was evaluated through the values of the correlation coefficient between output and target values (*R-coefficient*, see figure 7.2) and through the error histogram (figure 7.3).

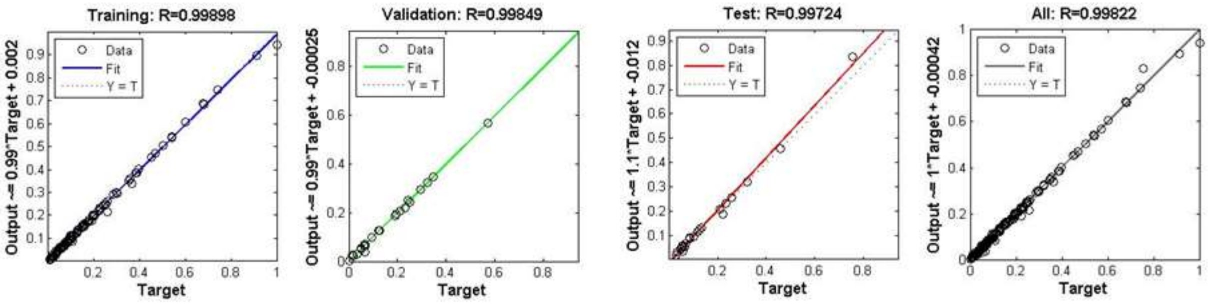
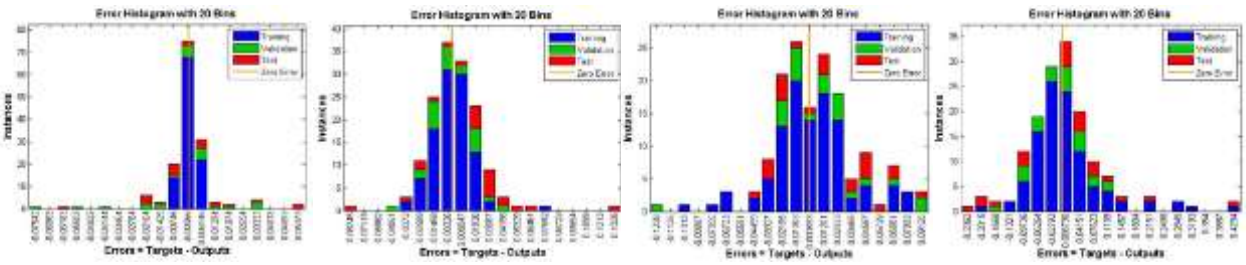


Figure 7.2. The value of R coefficient corresponding to the maximum cluster



(a) (b) (c) (d)

Figure 7.3. Examples of error histograms (a) cluster [L, D, A, M, R, v, F], (b) cluster [L, D, M, R, F], (c) cluster [L, D, A, M] and (d) cluster[L, D, M, R]

Table 7.5. The R-coefficients values

Crt. no.	Cluster variables	R-Coefficient			
		Training	Validation	Test	All
1	[L, D, A, M, R, v, F]	0.9990	0.9985	0.9972	0.9982
2	[L, D, M, R, v, F]	0.9973	0.9857	0.9874	0.9872
3	[L, D, A, M, v, F]	0.9990	0.9897	0.9910	0.9953
4	[L, D, A, M, R, F]	0.9999	0.9980	0.9885	0.9962
5	[L, D, M, v, F]	0.9938	0.9338	0.9477	0.9751
6	[L, D, M, R, F]	0.9992	0.9787	0.9808	0.9917
7	[L, D, A, M, F]	0.9992	0.9938	0.9878	0.9944
8	[L, D, A, M, v]	0.9829	0.9339	0.9181	0.9697
9	[L, D, M, v]	0.9393	0.7560	0.9202	0.9124
10	[L, D, M, F]	0.9311	0.8369	0.9277	0.9164
11	[L, D, M, R]	0.8879	0.8058	0.7182	0.8389
12	[L, D, A, F]	0.9443	0.8997	0.8315	0.9176
13	[L, D, A, M]	0.9500	0.9531	0.8456	0.9374
14	[L, D, A, v]	0.9997	0.9932	0.9926	0.9977

In order to enable the comparison between causal models modeling potential and corresponding NN-models performance, at first the values of a_c, 1-b_c (table 7.4) and R (All, table 7.5) were scaled to interval [0, 1]. Then, the three clusters of values were represented versus the current number of the model (table 7.5), by joining each cluster of resulted points into a poly-line (figure 7.4).

Figure 7.4. Comparison between causal models potential and NN

After examining the diagrams from figure 7.4, we can draw the following conclusions:

- The profile of the three poly-lines is similar in what concerns the general look and the most of the trends between successive points.
- The three poly-lines have common points (8-th and 11-th) or very close ones (1-st, 6-th, 10-th and 12-th).
- There is an obvious grouping of the points in domains (e.g. between 0.8 and 1, or below 0.6) showing either both good, or both low modeling capacity and model performance.

This entitles us to consider positive the result of method feasibility validation. The differences appearing in the cases of some clusters might be explained by the difference between the dimensions of the application domains: for the proposed method the dataset has 11175 beams, while for finding the *NN*-models, there were only 150 instances.

▪ ***Comparative assessment***

1. Case ranking assignment

We supposed a current case (L_1 = 0.85, D_1 = 0.3, A_1 = 0.6, M_1 = 1), needing to be ranked relative to the instances database from above. At first, the pivot (L_{v1} = 0.840741, D_{v1} = 0.327778, A_{v1} = 0.58287, M_{v1} = 1, C_{v1} = 0.250209), has been chosen from instances database, the algorithm for case ranking assignment has been iteratively run. The modeling by nonlinear multiple regression has been performed in MatLab (*Optimization tools* package). The algorithm stabilizes rapidly, after only eight iterations –the nine iteration gives same results as the previous one. As consequence, relation (6.6) can be used (in the form resulted after last modeling by multiple nonlinearr regression) for calculating $\Delta C_1 = C_1 - C_{v1}$. The obtained value is ΔC_1 = -0.00367, hereby C_1 = 0.24653 and considered case ranking is R_1 = 117.

2. Comparative assessment

Let us consider two different current cases: first id the one addressed in previous section, while second is (L_2 = 0.65, D_2 = 0.55, A_2 = 0.4, M_2 = 0.3). One has to choose from the two cases the one having the smallest value of effect-variable.

The algorithm for case ranking assignment is applied once again, for second potential case, to which the pivot (L_{v2} = 0.65185, D_{v2} = 544444, A_{v2} = 414905, M_{v2} = 0.25888, C_{v2} = 0.12446) is associated from the same instances database. This time, the algorithm stabilizes after only six iterations and delivers the following results: A = 6.4576, B = 0.57096, C = 0.33746, D = α = 3.644, β = 1.563, γ = 0.89287, with *RMSE* = 0.071. In the same manner as above, we find ΔC_2 = 0.004455, C_2 = 0.12892 and case ranking is R_2 = 84. In conditions of the addressed problem, we have $R_2 < R_1$ hence second case must be taken.

7.3. Causal identification and comparative assessment for timespan estimation when turning bearing rings – database extracted from the industrial environment –

The case study presented here was developed to validate and evaluate correlate the causal identification method (chapter 5) and the comparative assessment method (chapter 6) in the manufacturing process for turning roller bearings rings, on a database extracted from the industrial environment.

▪ *Causal identification*

In order to apply the method for causal identification in the manufacturing process for turning bearings rings, the steps presented in chapter 5 were followed.

P1. Process identification

To identify the process, a database containing information about turning several types of bearings was used. For these, the following set of ten cause-variables, was considered as having potential of a turning process: the ring exterior and interior diameters D_e and D_i, the ring width *L*, the cutting speed *v*, feed *s*, and depth *t*, the volume of removed material *V*, the maximum cutting force *F* and power *P* and the complexity index I_c (In connection with the ring profile). The timespan *TS* was selected as effect-variable.

P2. Data concatening

The database has 155 instances, some of them being presented, for example, in tables 7.6-a and 7.6-b, before and after scaling respectively.

Table 7.6-a. Real instances database (actual values, excerpt)

Instance crt. no.	D_e [mm]	D_i [mm]	L [mm]	v [m/min]	f [mm/rot]	t [mm]	V [mm^3]	F [N]	P [kW]	I_c [-]	TS [min]
1	89	69.4	31.2	259.6	0.35	0.82	48.39	970.8	5.50	3.7	3.59
2	125	108.6	31.2	261.8	0.17	0.76	40.33	523.5	3.37	2.5	3.79
3	170	139.9	39.2	277	0.30	0.19	144.0	205.5	1.88	7.7	2.52
4	215	181.8	47.2	300	0.32	0.17	217.4	188.1	1.87	2.2	3.84
5	190	157.4	36.2	286.5	0.34	0.11	167.7	127.4	1.50	4.2	2.79
. . .	. . . .										

Tabelul 7.6-b. Real instances database (scaled values, excerpt)

Instance crt. no.	D_e	D_i	L	v	f	t	V	F	P	I_c	TS
1	0.222	0.235	0.320	0.274	0.861	0.470	0.110	0.493	0.431	0.310	0.306
2	0.368	0.407	0.320	0.291	0.361	0.433	0.091	0.252	0.220	0.169	0.322
3	0.551	0.545	0.432	0.416	0.733	0.084	0.332	0.080	0.073	0.757	0.214
4	0.735	0.729	0.543	0.605	0.777	0.070	0.503	0.070	0.073	0.136	0.327
5	0.633	0.621	0.390	0.494	0.833	0.033	0.387	0.038	0.036	0.361	0.237
. . .	. . . .										

P3. Instances comparing

This time, the beams database generated with the same MatLab application has $N = C_{155}^{2} = 11935$ beams.

P4. Variables assessing

P4.1. Dimensionality reduction

The procedure has been applied in the same conditions as in the case of the artificial instances database: $h_{ref} = h_7 = 0.2097$, $h_{k-1} = h_6 = 0.2621$. The results are presented in table 7.7.

Table 7.7. Images dimensions Δ_i and Δ_{min}

Cause-variable	Successive steps of dimensionality reduction			
	Step 1	Step 2	Step 3	Step 4
D_e	0.2445	0.2445	-	-
D_i	0.2353	0.2626	0.5183	0.5183
L	0.7234	0.7234	0.7234	0.7234
v	0.6407	0.6407	0.6407	0.6407
f	0.7322	0.7322	0.7322	0.9155
t	0.5643	0.5643	0.5643	0.8818
V	0.6152	0.6152	0.7088	0.7088
F	0.2288	0.3099	0.25305	-
P	0.2225	-	-	-
I_c	0.9491	0.9491	0.9491	0.9491

Three cause-variables (D_e, *F* and *P*) were founded as dependent on the others and discarded. The remaining seven cause-variables lead to the maximal cluster: [D_i, *L*, *v*, *f*, *t*, *V*, I_c].

P4.2. Assessing the modeling potential of variables

The three criteria for assessing the modeling potential have been evaluated for each cause-variable of the maximal cluster, by calculating the values of *a*, *b*, and *RMSE*, relative to *TS* as effect-variable. The results are presented in table 7.8.

Table 7.8. The values of the a, b and RMSE

	D_i	L	v	f	t	V	I_c
a	0.1272	0.2241	0.05765	0.0041	0.02191	0.3234	0.01558
b	0.04458	0.03765	0.04864	0.05269	0.04961	0.03479	0.05466
RMSE	0.00116	0.00058	0.00176	0.00112	0.00185	0.00171	0.00269

P5. Causal models identification

P5.1. Generating smaller cluster

The *MC* (assessed through the values of *b*) was adopted as criterion for selecting the cause-variable to be discarded when generating smaller clusters. Three clusters with 6 cause-variables each has been generated from the maximal cluster in the first stage. Then, two clusters with 5 cause-variable resulted from each of these three, in the second stage. Finally, two clusters of 4 cause-variable 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 4-variables clusters. Variables selection and resulted clusters are presented in tables 7.9-a, 7.9-b and 7.9-c.

Table 7.9-a. Generation of 6-variables clusters

Variables	D_i	L	v	f	t	V	I_c
b	0.0445	0.0376	0.04864	0.05269	0.04961	0.03479	0.05466
Resulted clusters		[D_i, L, v, t, V, I_c]		[D_i, L, v, f, V, I_c]		[D_i, L, v, f, t, V]	

Table 7.9-b. Generation of 5-variables clusters

Variables	D_i	L	v	t	V	I_c
b	0.05314	0.03771	0.0521	0.0541	0.03757	0.05427
Resulted clusters		[D_i, L, v, V, I_c]		[D_i, L, v, t, V]		
Variables	D_i	L	v	f	V	I_c
b	0.04535	0.04114	0.05046	0.05362	0.02285	0.0541
Resulted clusters		*[D_i, L, v, V, I_c]*		[D_i, L, v, f, V]		
Variables	D_i	L	v	f	t	V
b	0.05295	0.04771	0.05579	0.06024	0.05769	0.04001
Resulted clusters		*[D_i, L, v, t, V]*		*[D_i, L, v, f, V]*		

Table 7.9-c. Generation of 4-variables clusters

Variables	D_i	L	v	V	I_c
b	0.05281	0.04195	0.05341	0.03541	0.05556
Resulted clusters	[D_i, L, V, I_c]			[D_i, L, v, V]	
Variables	D_i	L	v	t	V
b	0.05777	0.05241	0.05879	0.06036	0.0438
Resulted clusters	[D_i, L, t, V]			*[D_i, L, v, V]*	
Variables	D_i	L	v	f	V
b	0.05826	0.05323	0.06101	0.0638	0.03906
Resulted clusters	[D_i, L, f, V]			*[D_i, L, v, V]*	

Finally, they resulted only 3 (instead of 6) distinct clusters with 5 variables and 4 (instead of 6) clusters with 4 variables. Hereby the causal tree will be formed from 1 + 3 + 3 + 4 = 11 clusters.

P5.2. Assessing the modeling potential cluster

The criteria for assessing the modeling potential of remained clusters were evaluated through the values of a_c, b_c and *RMSE*, presented in table 7.10.

Table 7.10. The values of a_c, b_c and RMSE

Cause-variables from cluster	a_c	b_c	RMSE
[D_i, L, v, f, t, V, I_c]	0.4058	0.0261	0.0034
[D_i, L, v, t, V, I_c]	0.4013	0.0266	0.0030
[D_i, L, v, f, V, I_c]	0.4263	0.0240	0.0030
[D_i, L, v, f, t, V]	0.4178	0.0287	0.0041
[D_i, L, v, V, I_c]	0.4167	0.0263	0.0028
[D_i, L, v, t, V]	0.4064	0.0314	0.0048
[D_i, L, v, f, V]	0.4253	0.0310	0.0044
[D_i, L, V, I_c]	0.3722	0.0344	0.0023
[D_i, L, v, V]	0.4339	0.0314	0.0047
[D_i, L, t, V]	0.3774	0.0365	0.0365
[D_i, L, f, V]	0.3919	0.0372	0.0039

- ***Comparative assessment***

1. Case ranking assignment

We supposed a current case (D_{i1} = 0.3, L_1 = 0.7, v_1 = 0.5, V_1 = 0.45), needing to be ranked relative to the instances database from above. At first, the pivot (D_{iv1} = 0.27903, L_{v1} = 0.69646, v_{v1} = 0.48360, V_{v1} = 0.47986, TS_{v1} = 0.42490), has been chosen from instances database. Then, the algorithm for case ranking assignment has been iteratively run. The algorithm stabilizes rapidly, after only three iterations – the four iterations give same results as the previous one. As consequence, relation (6.6) can be used (in the form resulted after last modeling) for calculating $\Delta TS_1 = TS_1 - TS_{v1}$. The obtained value is ΔTS_1 = 0.00391, hereby TS_1 = 0.42881 and considered case ranking is R_1 = 145.

2. Comparative assessment

Let us consider two different current cases: first is the one addressed in previous section, while second is (D_{i2} = 0.6, L_2 = 0.3, v_2 = 0.75, V_2 = 0.25). One has to choose from the two cases the one having the smallest value of effect-variable.

The algorithm for case ranking assignment is applied once again, for second potential case, to which the pivot (D_{iv2} = 0.59238, L_{v2} = 0.27930, v_{v2} = 0.73795, V_{v2} = 0.25873, TS_{v2} = 0.23477) is associated from the same instances database. This time, the algorithm stabilizes after only six iterations. In the same manner as above, we find ΔTS_2 = 0.00147, TS_2 = 0.23330 and case ranking is R_2 = 100. In conditions of the addressed problem, we have $R_2 < R_1$ hence second case must be taken.

Chapter 8

Final conclusions & original contributions

The research activity included in the doctoral thesis entitled "Holistic optimization of manufacturing process" was carried out during three years, in the Manufacturing Engineering Department, of the Faculty of Engineering, from "Dunarea de Jos" University of Galati, approaching a current and very captivating topic: the development of a new concept regarding the manufacturing process optimization – *the holistic optimization*, as well as the development of some original methods that allow the implementation of this concept in practice.

Within this chapter, the original contributions of the author of the thesis are highlighted, the final conclusions of the doctoral thesis are presented and future prospects for validation and development of the research results presented in the thesis are identified.

Original contributions

The following original contributions can be identified within the doctoral thesis:

- Following the study of technical literature, scientific papers and doctoral thesis in this field, the documentation of the current state regarding the approaches concerning the optimization of the manufacturing performance has been realized.
  - The bibliography analysis was developed in the following directions:
    - ✓ The optimization problem type (e.g. unicriterial and multicriterial).
    - ✓ The objective function (e.g. the productivity, the manufacturing cost, the manufactured surface roughness, the cutting force magnitude, the energy consumption, etc.).
    - ✓ The solutioning methods (e.g. GA, ANN, PSO, ACO, LF, Combinatorial techniques, etc.).
- According to the existing research, some shortcomings in dealing with the problem of optimizing the manufacturing process are highlighted, a reconsideration of the concept of optimization is proposed, the research directions are defined and the research objectives are enounced.
- The holistic optimization concept was developed in direct connection to the requirements of manufacturing process optimization, the key features describing the optimization were identified by referring it to conventional optimization.
- According to the holistic optimization concept, an original method for optimizing the manufacturing process is proposed.
- The development of a method for manufacturing process structural identification, that allows the structuring of its activities, at all levels involved (order acceptance, production planning, product design, processes planning and product processing), by elaborating the tree of specific activities, has been accomplished. The relations between the manufacturing process stages and the afferent information circuit are revealed and the identification of the manufacturing process variants, at the level of each manufacturing activity, is performed.

- The development of an innovative method for manufacturing process causal identification, that allows multiple forms to be provided for one and same causal relationship has been realized. The method is designed aiming to be applied in the case of holistic optimization of the manufacturing process, before the comparative assessment of the results of the activities that can be selected at the level of a decision point in the manufacturing process graph. The method allows the identification of the most appropriate set of cause-variables, on the basis of which a effect-variable can be evaluated, depending on the specific conditions of a particular manufacturing process. The method purpose is to elaborate *the tree of causal links*.
- The development of an original method for comparative assessment of the manufacturing process alternatives, that proposes an innovative approach in the analysis of potentially optimal solutions, based on their rankings, has been carried out. The method is designed to assist the selection of the optimal continuation variant for the manufacturing process, at a certain decision level. The application of the comparative assessment method is done after the causal identification completion, respectively after the adoption of a set of cause-variables describing the effect-variable of interest at the current moment.
- The method for structural identification in bearing manufacturing has been sampled in a case study. The aim was to draw the manufacturing graph, including the structuring of its activities, at all involved levels (order acceptance, production planning, product design, processes planning and product processing). There were also identified the manufacturing process alternatives, at the level of each manufacturing activity stage.
- The validation of both the methods for causal identification and comparative assessment, through numerical experiments, has been carried out by three case studies, using different types of database:
  - an artificial instances database, in a turning operation case, having as objective function the cost *C*;
  - a database extracted from the industrial environment, in a bearing ring turning case, having as objective function the timespan *TS*;
  - a database extracted from the industrial environment, cu date reale, in a roller bearing manufacturing case, having as objective function the cost *C*.

Final conclusions

At thesis end, a number of general conclusions can be summarized as follows:

1. After a systematic analysis on the formulating and solving the optimization problems in general, and those related to the manufacturing process in particular, as reflected in the research publiched so far, a number of shortcomings can be highlighted:
   - The optimization domain does not cover the entire life-cycle of optimization object. When this object is the manufacturing process, the life-cycle is comprised between product ordering (by the client) and product delivering (to the client).
   - The purpose of optimization, is defined unilaterally/narrowly, reffering only to the best sollution solution for the optimization problem, according to a predefined criterion/set of criteria.
   - The conventional optimization is not sufficiently adapted to the specific requirements of manufacturing processes, because: *i)* although the process must be optimized in its wholeness, but often this is not feasible from the beginning; successive decisions should be taken during the process, while the decision from a given level cannot be taken before establishing the job from previous level; *ii)* the jobs performed during the manufacturing

taken during the process, while the decision from a given level cannot be taken before establishing the job from previous level; *ii)* the jobs performed during the manufacturing process have different natures, at the same time, their exigencies are diverse; *iii)* the effect-variables of a certain job, which should be used for evaluating a given effect from the process end, are not precisely known; *iv)* the causal relations either between the cause-variables or between the cause-variables and the effect-variables are not a priori known.

- The possible existence of a high number of jobs needed for obtaining the product involves a too large number of variables to be managed – the dimensionality of the optimization problem to be solved is too large for the existing computational resources.

2. The shortcomings above mentioned can be eliminated by reconsidering of the concept of optimization and elaborating the methodological support necessary for implementation of holistic optimization in practice.
3. Starting from the classical techniques related to optimization (the multistage optimization, the predictive analysis, and the combinatorial optimization), from which holistic optimization takes its specific elements, the holistic optimization concept in direct connection to the requirements of manufacturing process optimization was developed. The key features that describe the holistic optimization was identified by referring it to conventional optimization.
4. An original method for optimizing the manufacturing process was developed. The most important actions, based on which the current activity is evaluated are: *i)* the structural identification, *ii)* the causal identification, and *iii)* the comparative assessment.
5. The method for structural identification of the manufacturing process allows the structuring of its activities, at all involved levels (order acceptance, production planning, product design, processes planning and product processing), by *i)* elaborating the tree of specific activities, the relations between the manufacturing process stages and the afferent informational curcuit are realed, *ii)* identifying of the manufacturing process alternatives, at the level of each manufacturing activity, *iii)* selecting the best alternatives at each level of the manufacturing activity, according to different optimization criteria (such as, for example, cost, timespan, energy consumption, other critical consumption or combinations thereof). By applying the structural identification method, integrated with the holistic optimization method, the number of potential activities to be evaluated can be significantly reduced.
6. The method for causal identification of the manufacturing process allows to provide multiple sets of variables with potential for application in the manufacturing process modeling, to describe the same effect-variable, from which the user can choose the most appropriate solutions for solving a comparative assessment problem. Thus, it is possible to select the most influential, easy to measure and as few as possible variables, so that the resulting model has the lowest complexity, according to the required level of estimation accuracy. The tree representation of multiple causal links is intuitive and allows to users an easy orientation on the modeling potentials of the different sets of cause-variables. The use of the proposed causal identification method allows a significant reduction in the dimensionality of the addressed problem, which has a favorable impact on the subsequent elaboration of the model needed to perform the comparative assessment.
7. The method for comparative assessment of the manufacturing process alternatives proposes an innovative approach in the analysis of potentially optimal solutions, when choosing between two or more process alternatives, based on their rankings, according to a certain criterion (cost, timespan, energy consumed). This ranking facilitates the selection of the optimal continuation variant for the manufacturing process, at a certain decision level, by replacing the direct comparison of the potential alternatives with successive comparisons between each of them and the cases recorded in the database.

8. The method for holistic optimization of the manufacturing process is validated through numerical experiments, carried out as case studies: *i)* exemplifying the application of structural identification method and its integration in the case of a holistic optimization process in bearing manufacturing case, *ii)* causal identification and comparative assessment for the cost estimation of a turning operation (with the help of an artificial instances database), *iii)* causal identification and comparative assessment for timespan estimation for bearing ring turning (with the help a database extracted from the industrial environment), and *iv)* causal identification and comparative assessment for the cost of roller bearing manufacturing (with the help a database extracted from the industrial environment).
9. The exemplification regarding the application of the structural identification method, within a holistic optimization process in bearing manufacturing case, allowed the successive evaluation and selection of the optimal activities from different levels of the manufacturing process, thus obtaining the optimal manufacturing path for taking over an order for the bearing manufacture.
10. The second case study validates the applied causal identification method, integrated with the comparative assessemnt method. Thus, by causal identification, the number of cause-variables needed to evaluate the cost of turning operation can be reduced substantially: instead of the eleven variables used to generate the database, a maximum cluster of seven cause-variables was identified (the turned part lenght and diameter, the required level of part accuracy, the part material machinability and rigidity, the cutting speed and the main cutting force); even clusters of four cause-variables have been identified that model the cost well enough (e.g. the turned part lenght and diameter, the required level of part accuracy and the part material machinability). It has also been shown that the methods work satisfactorily even in the case of a database with substantially smaller number of cases. The comparative assessment method works very efficiently, the results provided being stabilized after a small number of iterations (4 ...8). Moreover, by analyzing these results one can highlight the situations in which the case-cariables chosen for the comparative assessment were not correctly selected.
11. The third case study validates once again the proposed methods; by causal identification, the number of cause variables needed to evaluate the timespan of a bearing ring turning is reduced substantially: instead of the ten variables, a maximum cluster of six cause-variables (the ring interior diameter and width, the cutting speed and the maximum cutting force, the volume of removed material and the complexity index); even clusters of four cause-variables have been identified that model the cost well enough (e.g. the ring interior diameter and width, the cutting speed and the volume of removed material). The comparative assessment method works very well, the results are true, after a small number of iterations of the algorithm (3).
12. In the fourth study, verisimilar results were also obtained, which validate the proposed methods. 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 (the bearing interior diameter and width, the bearing weight, the dynamic capacity, the limit speed under greasing conditions and the limit speed under oil conditions) even clusters of three cause-variables have been identified that model the cost well enough (e.g. the bearing weight, dynamic capacity and the limit speed under oiling conditions). Comparative assessment cost provides plausible results, after a very small number of iterations (2).

Future research perspectives

Starting from the results of research presented in the thesis, some future directions for their valorization and for further research can be outlined:

1. Analysis of the possibilities to apply the holistic optimization method at all stages of the manufacturing process.

2. Validation of the feasibility of the optimization method when applied to other manufacturing processes than cutting (forming, welding, plastic injection etc.).

3. Development, based on the methods of structural identification, causal identification and comparative assessment, of an integrated software product of "Decision Support System" type.

List of scientific papers elaborated during the doctoral program

ISI indexed papers:

1. G. Frumușanu, **C. Afteni** & A. Epureanu, ***„Causal identification of the manufacturing system",*** *Journal of Manufacturing Science and Engineering* – in submission (paper MANU-19-1677).

ISI indexed conference volumes:

1. **C. Afteni**, G. Frumuşanu & A. Epureanu**,** ***"Instance-based comparative assessment with application in manufacturing"*****,** IOP Conf. Ser. Mater. Sci. Eng., vol. 400, art. no. 042001, pp. 0-8, 2018. DOI: 10.1088/1757-899X/400/4/042001.

2. G. Frumuşanu, **C. Afteni**, N. Badea, & A. Epureanu, ***„Energy-efficiency based classification of the manufacturing workstation",*** IOP Conf. Ser. Mater. Sci. Eng., vol 227, art. no. 012047, pp. 0-9, 2017. DOI: 10.1088/1757-899X/227/1/012047.

BDI indexed papers:

1. **C. Afteni**, G. Frumuşanu & A. Epureanu**,** ***„Method for Holistic Optimization of the Manufacturing Process",*** International Journal of Modeling and Optimization, vol. 9, art. no. 5, pp. 139-144, 2019. DOI: 10.7763/IJMO.2019.V9.721.

2. **C. Afteni** & G. Frumuşanu, ***„Comparative assessment by neural networks modeling"***, Annals of University „Dunarea de Jos" of Galati, Fascicle V, Technologies in machine building, pp. 35-40, 2018, (http://www.cmrs.ugal.ro/TMB/2018/L05_Anale2018-Afteni_1.pdf).

3. **C. Afteni** & G. Frumuşanu, ***„A Review on Optimization of Manufacturing Process Performance",*** International Journal of Modeling and Optimization, vol. 7, art. no. 3, pp. 139-144, 2017. DOI: 10.7763/IJMO.2017.V7.573.

4. G. Frumuşanu, N. Badea, **C. Afteni** & A. Epureanu, ***„Method for energy-efficient planning of the industrial processes”,*** MATEC Web Conf., vol. 112, art. no. 09003, pp. 1-8, 2017. DOI: 10.1051/matecconf/201711209003.

5. M. Afteni, I. Terecoasa, **C. Afteni** & V. Păunoiu, **“*Study on hard turning process versus grinding in bearing components process flow”,*** International Conference on Advanced Manufacturing Engineering and Technologies, pp. 95-111, 2017. DOI:10.1007/978-3-319-56430-2_8.

6. M. Afteni, I. Terecoasa, V. Păunoiu, G. Frumuşanu & **C. Afteni**, ***„Study on lead time improvement for production of bearing components”****,* Annals of University „Dunarea de Jos” of Galati, Fascicle V, Technologies in machine building, pp. 41-46, 2016, (http://www.cmrs.ugal.ro/TMB/2016/L_06_MA.pdf).

References (selective)

[1] C. Afteni și G. Frumuşanu, „A Review on Optimization of Manufacturing Process Performance”, *Int. J. Model. Optim.*, vol. 7, nr. 3, pp. 139-144, 2017.

[2] Lucian Tudose; Dumitru Pop, „Proiectare optimală cu Algoritmi Genetici”, în *Editura Mediamira*, Cluj-Napoca, 2002, pp. 5-336.

[3] P. C. Priarone, „Quality-conscious optimization of energy consumption in a grinding process applying sustainability indicators”, *Int. J. Adv. Manuf. Technol.*, vol. 86, nr. 5-8, pp. 2107-2117, 2016.

[4] L. Feng, L. Mears, C. Beaufort, și J. Schulte, „Energy, economy, and environment analysis and optimization on manufacturing plant energy supply system”, *Energy Convers. Manag.*, vol. 117, pp. 454-465, 2016.

[5] W. W. and K. Hamacher, „A Stochastic tunneling approach for global minimization”, *Phys. Rev. Lett.*, vol. 82, pp. 3003-3007, 1999.

[6] L. Miguel și R. Nikolaos, „Derivative-free optimization: a review of algorithms and comparison of sofware implementations”, *J. Glob. Optim.*, vol. 56, pp. 1247-1293, 2013.

[7] „https://en.wikipedia.org/wiki/Pareto_efficiency”. .

[8] L. N. Vin, „Fundamente ale optimizării multi-obiectiv a sistemelor complexe de calcul”, *Bul. AGIR*, nr. 4, pp. 77-84, 2016.

[9] T. E. and S. V. Utyuzhnikov, „Directed Search Domain: A Method for Even Generation of Pareto Frontier in Multiobjective Optimization”, *J. Eng. Optim.*, vol. 43, pp. 1-18, 2011.

[10] T. Jagtap și H. Mandave, „Experimental Investigation and Optimization of Cutting Parameters on Surface Roughness and Material Removal Rate in Turning of Nylon 6 Polymer”, vol. 4, nr. 3, pp. 236-246, 2016.

[11] S. A. et al. Mansouri, „Green scheduling of a two-machine flowshop: Trade-off between makespan and energy consumption”, *Eur. J. Oper. Res.*, vol. 248, nr. 3, pp. 772-788, 2016.

[12] K. P. B. et Al., „Bilevel optimization and machine learning”, *Lect. Notes Comput. Sci.*, vol. 5050, pp. 25-47, 2008.

[13] H. I. Calvete, C. Galé, și J. A. Iranzo, „An efficient evolutionary algorithm for the ring star problem”, *Eur. J. Oper. Res.*, vol. 231, nr. 1, pp. 22-33, 2013.

[14] M. T. S. Ahmed și N. Sahinidis, „A finite branch-and-bound algorithm for two-stage stochastic”, *Math. Program.*, vol. 100, pp. 355-377, 2004.

[15] J. F. Benders, „Partitioning procedures for solving mixed-variables programming problems”, *Numer. Math.*, vol. 4, pp. 238–252, 1962.

[16] J. et al. Yan, „A multi-level optimization approach for energy-efficient flexible flow shop scheduling”, *J. Clean. Prod.*, vol. 137, pp. 1543-1552, 2016.

[17] F. et al. Kübler, „Resource efficiency optimization of manufacturing processes using evolutionary computation: A turning case”, *Procedia CIRP*, vol. 29, pp. 822-827, 2015.

[18] D. Tang și M. Dai, „Energy-efficient approach to minimizing the energy consumption in an extended job-shop scheduling problem”, *Chinese J. Mech. Eng.*, vol. 28, nr. 5, pp. 1048-1055, 2015.

[19] Y. Liu, H. Dong, N. Lohse, și S. Petrovic, „A multi-objective genetic algorithm for optimisation of energy consumption and shop floor production performance”, vol. 179, pp. 259-272, 2016.

[20] X. Li, K. Xing, Y. Wu, X. Wang, și J. Luo, „Total Energy Consumption Optimization via Genetic Algorithm in Flexible Manufacturing Systems”, *Comput. Ind. Eng.*, vol. 104, pp. 188-200, 2016.

[21] D. et al. Sreeramulu, „Integration of Process Planning and Scheduling of a Manufacturing Systems using Petri nets and Genetic Algorithm”, *Indian J. Sci. Technol.*, vol. 9, nr. 41, 2016.

[22] L. et al. Zhang, „Production scheduling oriented to energy consumption optimization for process industry based on self-adaptive DE algorithm”, *Int. J. Control Autom.*, vol. 8, nr. 2, pp. 31-42, 2015.

[23] C. Natarajan, S. Muthu, și P. Karuppuswamy, „Investigation of cutting parameters of

surface roughness for a non-ferrous material using artificial neural network in CNC turning”, *J. Mech. Eng. Res.*, vol. 3, nr. 1, pp. 1-14, 2011.
[24] R. Pugazhenthi și M. Anthony Xavior, „A genetic algorithm applied heuristic to minimize the Makespan in a flow shop”, *Procedia Eng.*, vol. 97, pp. 1735-1744, 2014.
[25] S. Wang, X. Lu, X. X. Li, și W. D. Li, „A systematic approach of process planning and scheduling optimization for sustainable machining”, *J. Clean. Prod.*, vol. 87, nr. C, pp. 914-929, 2015.
[26] N. Yusup, A. M. Zain, și S. Z. M. Hashim, „Evolutionary techniques in optimizing machining parameters: Review and recent applications (2007-2011)”, *Expert Syst. Appl.*, vol. 39, nr. 10, pp. 9909-9927, 2012.
[27] G. Zhang, M. Liu, J. Li, W. Ming, X. Shao, și Y. Huang, „Multi-objective optimization for surface grinding process using a hybrid particle swarm optimization algorithm”, *Int. J. Adv. Manuf. Technol.*, vol. 71, nr. 9-12, pp. 1861-1872, 2014.
[28] K. T. Fang și B. M. T. Lin, „Parallel-machine scheduling to minimize tardiness penalty and power cost”, *Comput. Ind. Eng.*, vol. 64, nr. 1, pp. 224-234, 2013.
[29] M. Petrović, N. Vuković, M. Mitić, și Z. Miljković, „Integration of process planning and scheduling using chaotic particle swarm optimization algorithm”, *Expert Syst. Appl.*, vol. 64, pp. 569-588, 2016.
[30] M. Chandrasekaran, M. Muralidhar, C. M. Krishna, și U. S. Dixit, „Application of soft computing techniques in machining performance prediction and optimization: A literature review”, *Int. J. Adv. Manuf. Technol.*, vol. 46, nr. 5-8, pp. 445-464, 2010.
[31] Z. H. Jia, C. Wang, și J. Y. T. Leung, „An ACO algorithm for makespan minimization in parallel batch machines with non-identical job sizes and incompatible job families”, *Appl. Soft Comput. J.*, vol. 38, pp. 395-404, 2016.
[32] P. S. Srinivas, V. R. Raju, și C. S. P. Rao, „Optimization of Process Planning and Scheduling using ACO and PSO Algorithms”, vol. 2, nr. 10, pp. 343-354, 2012.
[33] C. W. Leung, T. N. Wong, K. L. Mak, și R. Y. K. Fung, „Integrated process planning and scheduling by an agent-based ant colony optimization”, *Comput. Ind. Eng.*, vol. 59, nr. 1, pp. 166-180, 2010.
[34] V. B. Pansare, M. V Kavade, și S. D. Sangali, „Optimization of cutting parameters in multipass turning operation using ant colony algorithm”, nr. 4, pp. 955-960, 2012.
[35] A. Iqbal, H. C. Zhang, L. L. Kong, și G. Hussain, „A rule-based system for trade-off among energy consumption, tool life, and productivity in machining process”, *J. Intell. Manuf.*, vol. 26, nr. 6, pp. 1217-1232, 2015.
[36] A. Seker, S. Erol, și R. Botsali, „A neuro-fuzzy model for a new hybrid integrated Process Planning and Scheduling system”, *Expert Syst. Appl.*, vol. 40, nr. 13, pp. 5341-5351, 2013.
[37] G.-S. Liu, Y. Zhou, și H.-D. Yang, „Minimizing energy consumption and tardiness penalty for fuzzy flow shop scheduling with state-dependent setup time”, *J. Clean. Prod.*, vol. 147, pp. 470-484, mar. 2017.
[38] A. S. William J. Cook, William H. Cunningham, William R. Pulleyblank, „Combinatorial Optimization”, *Comput. Handbook, Third Ed. Comput. Sci. Softw. Eng.*, pp. 1-346, 2014.
[39] „Https://en.wikipedia.org/wiki/Predictive_analytics#cite_note-17”.
[40] „http://www.asecib.ase.ro/virginia/cursCO3/capitolul2.pdf”.
[41] „https://en.wikipedia.org/wiki/Decision_support_system”.
[42] „https://en.wikipedia.org/wiki/Instance-based_learning”.
[43] M. Bagge, *Process planning for precision manufacturing: An approach based on methodological studies*. 2014.
[44] P. Denno, C. Dickerson, și J. A. Harding, „Dynamic production system identification for smart manufacturing systems”, *J. Manuf. Syst.*, nr. March, pp. 1-11, 2018.
[45] R. Corne, C. Nath, M. El Mansori, și T. Kurfess, „Study of spindle power data with neural network for predicting real-time tool wear/breakage during inconel drilling”, *J. Manuf. Syst.*, vol. 43, pp. 287-295, 2017.
[46] „https://en.wikipedia.org/wiki/Feature_selection”.
[47] „http://mathworld.wolfram.com/Sign.html”.
[48] „https://en.wikipedia.org/wiki/Sign_function”.