Method for Holistic Optimization of the Manufacturing Process

Cezarina Afteni, Gabriel Frumuşanu and Alexandru Epureanu

Abstract—**This paper concerns a new approach of the optimization problem, intending to turn into profit the last evolutions from IT domain. On the base of this approach, both new concept (the holistic optimization), and method ("zoom & pick") for its implementation it in manufacturing process optimization were developed. According to the new concept, the optimization problem gets a new structure, which includes not only the optimal solution finding, but also the optimal formalization of the problem as well as the tooling for assessing the position of potential solutions relative to the optimal one. The method for holistic optimization successively addresses the optimized object at different levels of its description. The main application domain is the manufacturing process from "Make to Order" environment, which is difficult to optimize because of dealing with a wide range of products.**

Index Terms—**Holistic optimization, manufacturing process, comparative assessment, optimality assurance system.**

I. Introduction

The request for optimization is of general interest in almost all fields of nowadays activities and manufacturing makes no exception. As consequence, a tremendous number of researches were already performed, aiming to find approaches and methods for solving a wide range of problems e.g. [1]-[5]. The most encountered formats of conventional optimization problem are mentioned below.

- **The standard optimization**, which means the finding of the global minima or maxima of a function / set of functions on a given set. Given a function $f:\Omega\subset R^n\to R$, the standard extremization problem can be defined as $\min\limits_{x\in\Omega} f(x)$ or $\max\limits_{x\in\Omega} f(x)$, that is finding f^* and x^* (the extreme value of f and its corresponding extremizer). Deterministic, stochastic, heuristic and metaheuristic methods for solving the problem can be noticed [6]-[8].
- **The multi-objective optimization**, which aims to extremize, at the same time, multiple objective functions. For example, in minimization problems this can be defined as $\min\limits_{x\in X}\left[f_1(x), f_2(x)\ldots f_n(x)\right]$, where X is the space of feasible solution-vectors. Multi-objective optimization methods can be grouped into four classes: no preference, a priori, a posteriori and interactive methods [9]-[14]. At the first class, no decision maker is expected to be available, but a neutral compromise solution is identified without preference information, while the other three involve preference information from the decision maker, in different ways.
- **The multilevel optimization** is more complicated and involves more problems, embedded one in another. For example, a bilevel minimization problem can be defined as $\min\limits_{x\in X,y\in Y} F(x,y)$, while $y\in\arg\min\limits_{z\in Y} f(x,z)$, where $F, f: R^{n_x}\times R^{n_y}$, $X\subseteq R^{n_x}$ $Y\subseteq R^{n_y}$. Bilevel optimization problems are hard to solve. One solving method is to reformulate bilevel optimization problems to optimization problems for which robust solution algorithms are available [15]. Evolutionary methods [16], though computationally demanding, could be an alternative tool to offset some of these difficulties and lead to an approximate optimal solution.
- **The multistage (discrete) optimization** generalizes standard optimization by modeling hierarchical decision problems, involving sequential/multi-stage decision processes. The canonical problem to be solved, in minimization case, is:
- $\min\limits_{x,y}\left(\sum\limits_{t=1}^{T} f_t(x_t y_t):(x_{t-1},x_t,y_t)\in X_t,\forall t\right)$, 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 [17] or Benders' technique [18].

The conventional optimization supposes, in general, to find the optimal solution of an imposed optimization problem described in one of the above-presented formats. Despite they were successfully applied in solving many problems, from the manufacturing domain also, there are at least two specificities for which their applicability in manufacturing process optimization is questionable: *i)* the specific structure of the manufacturing process, and *ii)* the specific definition of the optimization problem in its case. Issuing from here, this paper proposes a new concept, namely the holistic optimization, and an original method for manufacturing process optimization according to this concept. Both concept and method complies much better to the above-mentioned specificities.

In what concerns the paper structure, next section states the approach of basic manufacturing concepts, according to our vision. The third section presents the holistic optimization concept. The fourth section describes the proposed method, while the fifth deals with an exercise of method application. Last section is for conclusion.

II. The Approach

Manufacturing comprises the chain of actions through which the product subjected by a certain market request is realized. Five segments can be distinguished in the

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manufacturing chain, namely: ordering preparing, design, planning, programming and processing, (Fig. 1). Inside each segment, ideas, information and materials are processed, this leading to the metamorphosis of manufactured object.

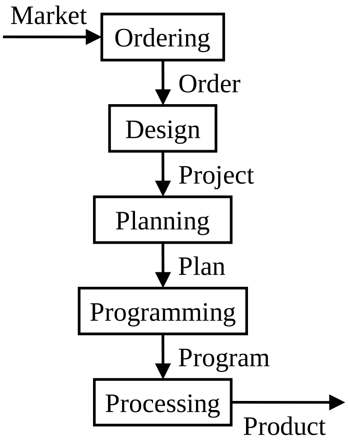

Fig. 1. The manufacturing chain.

The manufacturing system is an ensemble of facilities and assets, selected such as they are appropriate for supporting the manufacturing chain.

The operating of manufacturing system in order to obtain the requested products means manufacturing process. The process that the manufacturing system has performed up to the current moment means the manufacturing activity.

The constitutive items of the manufacturing activity are the manufacturing jobs. Such a job is defined as the accomplishment of a given manufacturing task, according to a given procedure and using a given component of the system.

The accomplishment of a job can be described through the values of some variables, which are of two types: independent (description-variables), and dependent (effect-variables). A set of particular values for the description- and effect-variables for a given job is obtained by monitoring and means an instance.

The manufacturing process is defined as the current flow of jobs accomplished by the manufacturing system. According to our approach, the optimization means to ensure the manufacturing process optimality in each moment. This can be done by optimizing the flow of decisions through which the manufacturing process ongoing is controlled. During this control, the optimization desiderate should be considered as reference, while the decision means the control variable. In concrete terms, the process optimization has to be supported by an optimality assurance system, embedded in the currently existing quality assurance system.

III. Holistic Optimization Concept

In our vision, the "holistic optimization" defining is that:

- *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.

We have developed the holistic optimization concept in direct connection to the requirements of manufacturing process optimization. Because the conventional optimization concept is well known, it is much easier to describe the holistic optimization by referring it to conventional optimization (see Table I).

TABLE I: The Key Features Describing Holistic vs. Conventional Optimization

Issue	Conventional optimization	Holistic optimization
Optimization area	Life-cycle segment of the object submitted to optimization	Entire life-cycle of the object submitted to optimization
Optimization goal	The best solution for a given request of optimization	The best formulation, best assessment, and best solution for a given request of optimization
Optimization action	Occasional action of optimum finding	Continuous activity of optimality assurance
Optimization space	The R^n Euclidian space, formed by *n* real variables	The V^m causal space, formed by *m* causal variables and the dependence relations between them
Optimization variables	Independent	Dependent
	Numerical	Logical
Optimization request format	Already formalized problem	Goals following to be subsequently formalized
Optimization problem format	Standard *or* Multi-objective *or* Multilevel *or* Multistage	Standard *and/or* Multi-objective *and/or* Multilevel *and/or* Multistage
Optimized object modeling	Analytical	Causal
Optimized object evaluation	Absolute	Comparative

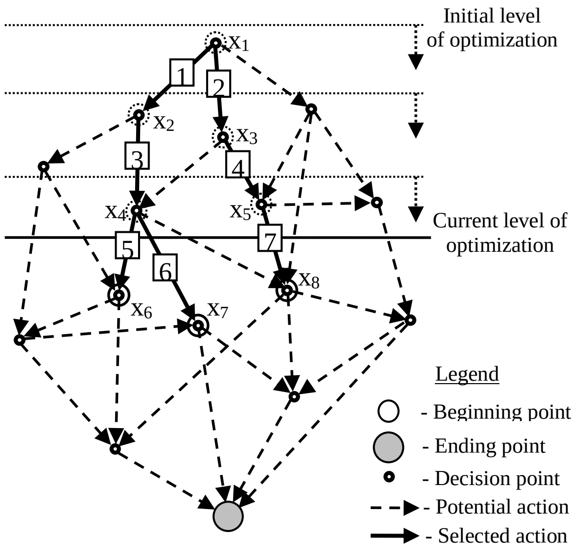

Fig. 2. Causal space of the optimized object.

Unlike the conventional optimization, acting in a Euclidian space, the holistic optimization is performed inside a so-called causal space (Fig. 2). The causality variables are decisions concerning both optimized object and optimization problem. These variables are interdependent, because the decision at a given moment depends on the previous decisions and determines the following decisions. The value of such a variable is an action to be accomplished.

The conventional optimization is performed on a fixed optimization area, namely the area comprised between the beginning and the end of a unique problem, according to a fixed problem format (be it standard, multi-objective or other), which, once established, does not change until the optimal solution finding. Unlike this, 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. This means, in fact, to generate new optimization problems, to which new optimization areas are assigned by setting new beginning points (though, the ending points remain the same). The criteria for object evaluation may also change, as well as the problem format (e.g. from standard to multi-objective). Thus, in Fig. 2, according to the current level of optimization, after completing the actions ongoing when this level is reached (namely the actions 5, 6 and 7) the decision points x_6, x_7 and x_8 become beginning points for new optimization problems.

In conventional optimization, the evaluation of the effect-variables is absolute. Unlike this, in holistic optimization the effect-variables evaluation is comparative.

IV. The "Zoom and Pick" Method for Holistic Optimization of the Manufacturing Process

Let us consider a manufacturing process aiming to deliver a certain product. The process main specificities, to which the conventional optimization fails to answer in satisfactory manner, are:

- 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.
- The jobs performed during the process have different natures. At the same time, their exigencies are diverse (e.g. the existence of bottleneck points or of unused available resources).
- The description-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.
- The causal relations either between the description-variables or between the description-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.

The holistic optimization concept and the here introduced method have been developed as optimization tools intended for the manufacturing process, hence they are answering much better to the specificities from above. The method is applied on three stages, namely the past activity "zoom & pick", the assessment tooling "zoom & pick", and the current process "zoom & pick".

A. Past Activity "Zoom and Pick"

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 analyzed 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.

B. Assessment Tooling "Zoom and Pick"

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.

C. Current Process "Zoom and Pick"

Let us consider an activity with five potential zoom levels (A, B, C, D and E), Fig. 3. The job(s) comprised between two consecutive zoom levels will be referred as way. The ways are represented by thick arrows and denoted by letters according to their starting level (e.g. the ways from B to C level are B1, B2, etc.). Because the manufactured object may retrieve itself in different forms to a certain level, due to arriving here on different ways, each such a form must be separately represented. Obviously, the ways issuing from different forms of the object belonging to the same level are also different. Despite in practice they can exist several ways for bringing the object from a level to the next one, for simplicity we considered maximum two ways for this.

A path results between any state of the object, from any level, and a process ending point. The process-accomplishing path is the path between process beginning and any of process ending points. For defining a path, at a given level a single way can be selected, after passing by a decision point. It should be noticed that for actually accomplishing the process, it is enough to follow a single path only. The ensemble of all potential paths that can be used for obtaining the product forms the product graph (Fig. 3).

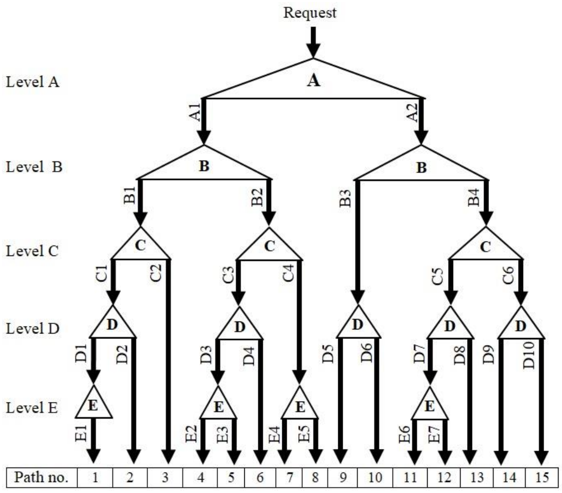

Fig. 3. Generic product graph.

The transition between two successive levels by a given way supposes that either the entire object or components resulted by its decomposition are submitted to different basic jobs issued from the accomplishment of a certain typical job. A component from a certain level may further decompose in subcomponents (further referred, generically, also as components) at the next level(s). In other situations, more components may join in a single ensemble.

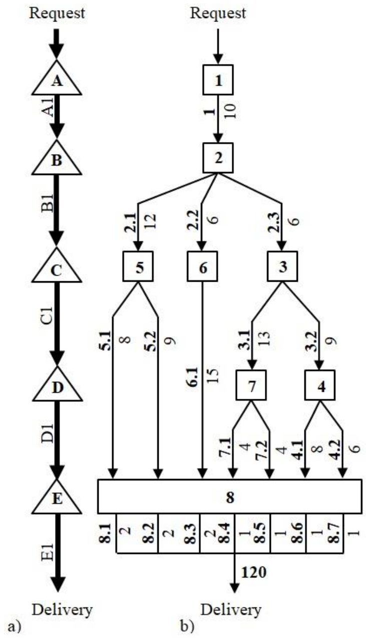

Fig. 4. The jobs chains for a hypothetical process-accomplishing path.

The Fig. 4-a presents a hypothetic process-accomplishing path, extracted from the product graph shown in Fig. 3. In Fig. 4-b, all the jobs needed in order to obtain the product by following this path are presented. The jobs concerning the entire object are denoted by simple numbers (e.g. 1), while the ones concerning its components include the ”.” separator (e.g. 2.1, 2.2 ..., where the numbers before and after the dot refer to job and to component, respectively). An arrow symbolizes each job, the effect issued by it being specified under the corresponding arrow. A determined set of jobs (hence arrows), starting from process beginning point, corresponds to each component, no matter of component level. This set means the jobs chain of the considered component.

The accomplishment of each job is characterized by a resulting effect (be it cost, timespan, consumed energy etc.). The cumulated effect of all jobs corresponding to the ways composing a path (when all jobs effects are of the same type) means the process effect corresponding to this path. More types of effect can be measured for the same path, by values of the corresponding effect-variables.

The problem addressed in this paper can be formulated now as the selection, from product graph, of the optimal process-accomplishing path, according to a flexible criterion / set of criteria.

As it can be easily observed, the product graph may be very complex. Frequently, the structure of jobs needing to be performed in order to cover the process-accomplishing path is also complicated. Moreover, the evaluation of path effect by decomposing the typical jobs in basic nominal jobs, finding the effect for each of them and, finally, cumulating these effects is also a difficult task. For these reasons, the application of the combinatorial optimization method is not feasible for solving the problem, neither the application of other methods selecting the optimal path on the base of path effects direct evaluation.

The proposed optimization method avoids the mentioned difficulties. According to the method, current process “zoom & 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 B).
- 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 B).
- 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.

In what concerns the choice of the most suitable arguments (job description-variables), this can be done by instance-based causal identification of the manufacturing system [19], while the comparative assessment between two or more typical jobs can be realized after the values of their effect-variables, according to the method presented in [20].

V. Illustrative Exercise

We further present an exercise in order to facilitate the understanding of both concept and method, above proposed. Let us consider the case of a manufacturing system for mechanical products, whose manager intends, at a given moment, to optimize the manufacturing process in holistic manner. The targeted optimization accuracy is set at 10%.

Hypothetical results of the past activity “zoom & pick” stage are sampled in Table II, while the ones of the assessment tooling “zoom & pick” stage – in Table III. It should be noticed that there, the potential sets of arguments (causal models) corresponding to a given function R*k* are denoted by (S*k*.1, S*k*.2, ... S*k*.n).

According to current process “zoom & pick”, the loop of actions includes the following (Table 4):

- The first zoom level, A, is order acceptance.
- Three potential typical jobs are picked, namely A1, A2 and A4 from Table 2.
- For assessment tooling, the following actions are performed (see Table 3): zoom to level P and pick the goal P1 is picked, and corresponding to it, zoom to level Q and pick the assessment criterion Q1. Then zoom to level R and pick function R1 and, finally, zoom to level S and pick the causal model S1.2.
- The picked jobs A1, A2 and A4 are comparatively assessed.
- The jobs A1 and A4 are discarded because their evaluated results are significantly weaker.
- The job A2 is picked as optimal solution (having 35% optimization uncertainty, denoted by *Delta*, in Table 4), so the order for reduction gears is the accepted one.

Because the uncertainty of optimization at first level is higher than the targeted accuracy level, the loop of actions from above must be successively retaken, as it follows:

- At the second zoom level, B, corresponding to assembly design, three potential jobs are picked: B1, B2 and B3. Passing to 4.2 stage, P2, Q3, R2 and S2.1 are picked for assessment tooling. Finally, after performing C stage, B2 typical job (namely to produce a worm reduction gear) is picked as optimal, with 30% uncertainty.

- At the third zoom level (C, subassembly design), three subassemblies are identified as the most significant. Because there are available singular potential jobs for each of them, these jobs are automatically picked as optimal. After reevaluation, the level of uncertainty for worm subassembly reaches the level of 10% previously set for optimization accuracy, hence, in its case, the optimization is stopped, while for the other two subassemblies, it continues.

- At the fourth zoom level (D, part design), three parts are considered as having the higher optimization potential: the case itself (from case subassembly), the wheel shaft and the worm wheel (both from worm wheel subassembly). Two potential typical jobs, D1 and D2 are identified for case manufacturing, while singular ones are available for other parts. After the comparative assessment, D1 is picked as optimal (with 17% uncertainty). As consequence, the optimization is continued for the case and for the worm wheel, while for the wheel shaft it is stopped (only 8% uncertainty).

- At the fifth zoom level (E, process planning), there are available two alternatives of process plan for the case (among which E2 is picked as optimal) and a single one, E3, for the worm wheel.

- At the sixth zoom level (F, operation programming), there are identified two alternatives for worm wheel machining F2 and F3, and a single one for case machining. After picking F2 as optimal, the entire optimization process is stopped, because in all cases the reevaluated uncertainty level drops under 10%. Hereby the last potential zoom level (G, phase accomplishing) is ignored and the manufacturing process optimization is considered as accomplished.

TABLE II: PAST ACTIVITY ZOOM & PICK

Zoom level	Optimization object	Typical jobs
A	Order	A1 – Clutch; A2 – Reduction gear; A3 – Door closing mechanism; A4 – Brake
B	Assembly	B1 – Planetary reduction gear; B2 – Worm reduction gear; B3 – Cycloidal reduction gear
C	Subassembly	C1 – Case subassembly; C2 – Worm wheel subassembly; C3 – Worm subassembly
D	Part	D1 – Cast case; D2 – Welded case; D2 – Wheel shaft; D4 – Worm wheel
E	Plan	E1 – Case plan I, E2 – Case plan II, E3 – Worm wheel plan
F	Operation	F1 – Milling; F2 – Hobbing; F3 – Turning
G	Phase	-

TABLE III: ASSESSMENT TOOLING “ZOOM AND PICK”

Zoom level	Optimization object	Typical features
P	Goal	P1- Efficiency; P2 - Productivity; P3 - Ecologicity; P4 - Quality; P5 - Throughout; P6 - Assets using degree
Q	Criterion	Q1 - Cost/product; Q2 - Cost/quantity; Q3 - Timespan; Q4 - Time/quantity; Q5 - Profit/product; Q6 - Profit rate; Q7 - Energy/product; Q8 - Energy class; Q9 - Quality class
R	Function	R1 - Cost [Euro/dm^3]; R2 - Time [min/ dm^3]; R3 - Energy [KWh/ dm^3]
S	Arguments	(S1.1, S1.2, S1.3); (S2.1, S2.2); … according to job causal model

TABLE IV: CURRENT PROCESS “ZOOM AND PICK”

Problem formalizing by			Assessment tooling by				Solution finding by		
“*zoom*”	“*pick*”		“*zoom*”				“*zoom & pick*”		
			P	Q	R	S			
			“*pick*”						
Levels	Variables	Values	Goals	Criteria	Functions	Arguments	Results	Delta	Go to
A	x_A	A1, A2, A4	P1	Q1	R1	S1.2	A2	35%	B-level
B	x_B	B1, B2, B3	P2	Q3	R2	S2.1	B2	30%	C-level
C	x_{C1}	C1	P1	Q2	R1	S1.2	C1	22%	D-level
	x_{C2}	C2	P1	Q2	R1	S1.1	C2	20%	D-level
	x_{C3}	C3	P1	Q2	R1	S1.3	C3	10%	Stop
D	x_{D1}	D1, D2	P3	Q7	R3	S3.1	D1	17%	E-level
	x_{D2}	D3	P2	Q4	R2	S2.1	D3	8%	Stop
	x_{D3}	D4	P2	Q4	R2	S2.2	D4	15%	E-level
E	x_{E1}	E1, E2	P1	Q1	R1	S1.1	E2	11%	F-level
	x_{E2}	E3	P1	Q1	R1	S1.2	E3	12%	F-level
F	x_{F1}	F1	P1	Q2	R1	S1.2	F1	9%	Stop
	x_{F2}	F2, F3	P2	Q3	R2	S2.1	F2	7%	Stop
G	x_G	-	-	-	-	-	-	-	-

VI. Conclusion

Frequent, the conventional optimization fails to give satisfactory results in the case of the manufacturing process due to its specificities, such as the need for optimization in its wholeness, (often this being not feasible from the beginning), or the different natures of the jobs performed during the process (their exigencies being also diverse).

The challenge faced by this paper has been to deliver a concept and an optimization method more adequate to manufacturing process optimization. The result consists in the development of the holistic optimization concept together with the "zoom & pick" method for performing this type of optimization.

The defining elements of the holistic optimization are the coverage of entire life-cycle of the manufacturing process, the completeness in addressing the optimization aspects, and the providing of the permanent optimization of decisions flow through which the process ongoing is controlled.

The proposed optimization method works in three successive stages, namely two preparatory stages, dedicated to the analysis of the past activity performed by the manufacturing system and to the identification of potential assessment tooling, and one operational stage for actually optimizing the current process, by comparative assessment.

Both the here introduced concept and method may ground, at conceptual level, the development of a system for optimality assurance in manufacturing, included in the currently existing system for quality assurance. In this manner, the manufacturing process optimization might become a current activity, while the optimization benefits could be more completely fructified than in the case of the conventional approach case.

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