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Towards Sustainability of Manufacturing Processes by Multiobjective Optimization: A Case Study on a Submerged Arc Welding Process

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ABSTRACT Optimization on the basis of sustainability brings important benefits to manufacturing process as sustainable productions constitute a crucial aspect in modern manufacturing. This paper presents a new formalized framework for optimizing the sustainability of manufacturing processes. Unlike previous approaches, the proposed technique combines a methodology for selecting the sustainability indicators and a multi-objective optimization for improving the three sustainability pillars (economy, environment and society). While selecting the significant sustainability indicators in the considered manufacturing process relies on the ABC judgment method, the Saaty's method enables weighting the chosen indicators in order to combine them into suitable economic, environmental and social sustainability indexes. Other technological aspects, usually taken as objectives in previous works, are considered constraints in the proposed approach. The optimization is performed by using nature inspired heuristics, which return the set of non-dominated solutions (also known as Pareto front), from which the most convenient alternative is chosen by the decision maker, depending on the specific conditions of the process. For illustrating the usage of the proposed framework, it is applied to the optimization of a submerged arc welding process. Compared with currently used welding parameters, the computed optimal solution outperforms the economic and environmental sustainability while keeps equal the social impact. The results show not only the effectiveness of the proposed approach, but also its flexibility by giving a set of possible solutions which can be chosen depending on how are ranked the sustainability pillars.

INDEX TERMS Manufacturing systems, optimized production technology, Pareto optimization, sustainability.

NOMENCLATURE

$\mathcal{A}$	Set of predefined environmental indicators
a_i	i-th predefined environmental indicator
B	Joint width [mm]
$\mathcal{B}$	Set of predefined economic indicators
b_i	i-th predefined economic indicator
$\mathcal{C}$	Set of predefined social indicators
c_i	i-th predefined social indicator
D	Vessel diameter [mm]
E	Electric power [kW.h]
G_{F}	Wasted flux [g]

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G_S	Generated slag [g]
G_W	Wasted wire [g]
$\mathbf{g}$	Set of inequality constraints
g_i	i-th inequality constraint
$\mathbf{h}$	Set of equality constraints
h_i	i-th equality constraint
I	Welding current [A]
L	Joint length [mm]
P	Joint penetration [mm]
R	Joint reinforcement height [mm]
S	Welding speed [m/h]
U	Welding voltage [V]
U	Set of weights of the environmental indicators
u_i	Weight of the i-th environmental indicator
V	Set of weights of the economic indicators
v_i	Weight of the i-th economic indicator
W	Set of weights of the social indicators
w_i	Weight of the i-th social indicator
$\mathcal{X}$	Subset of manufacturing process parameters
$\mathbf{x}$	Vector of manufacturing process parameters
x_i	i-th manufacturing process parameter
Y_A	Environmental sustainability index
Y_B	Economic sustainability index
Y_Γ	Social sustainability index
Z_E	Electric power cost [$]
Z_F	Flux cost [$]
Z_L	Labor cost [$]
Z_W	Wire cost [$]
A	Set of environmental indicators
α_i	i-th environmental indicator
α_i^0	Reference value of the i-th environmental indicator
$\hat{\alpha}_i$	Normalized value of the i-th environmental indicator
B	Set of economic indicators
β_i	i-th economic indicator
β_i^0	Reference value of the i-th economic indicator
$\hat{\beta}_i$	Normalized value of the i-th economic indicator
Γ	Set of social indicators
γ_i	i-th social indicator
γ_i^0	Reference value of the i-th social indicator
$\hat{\gamma}_i$	Normalized value of the i-th social indicator
ε_{CO_2}	Carbon dioxide emission [g]
ζ_E	Unit electric power cost [$/kW.h]
ζ_F	Unit flux cost [$/kg]
ζ_L	Unit labor cost [$/h]
ζ_W	Unit wire cost [$/kg]
τ	Total production time [min]
$\cos\phi$	Phase factor

I. INTRODUCTION

Nowadays, the digital transformation of the manufacturing industry is paving the way to face new challenges but also partially solved problems [1]–[3]. One strategic goal in current researches on industrial production is reducing the impact caused by manufacturing processes. The so-called Triple Bottom Line (TBL) [4] aims to consider the three main aspects (usually also known as pillars or dimensions) of the sustainability: environment, economy and society [5]. The final goal should be a fully sustainable process, which accomplishes all the dimensions. In spite of some criticism, such as difficulties in measurement (specially in social issues), lack of holistic point of view, and shortcomings as compliance mechanics [6], TBL allows enterprises redefine value to not only focus on the end product or service but also to include the systemic cost of delivering goods [7], and remains being a useful approach, which is widely applied for evaluating manufacturing processes sustainability [8].

TABLE 1. Main sustainability indicators used as optimization objectives.

Dimension	Indicator	Reference
Environmental	Energy consumption	[12]–[21]
	Carbon emission	[16]–[18], [20]–[22]
	Material and/or tool waste	[19], [21], [23]
Economic	Cost	[17], [21], [22]
	Productivity	[12]–[14], [20]–[22], [24]
	Quality	[12]–[15], [19], [21], [23]–[26]
Social	Health and safety	[18]
	Labor and workforce training	[21]

For designing actual sustainable manufacturing processes, evaluating the environmental, economic and/or social impacts is not enough. These impacts must be minimized through selecting the optimal process parameters and setup [9]. Table 1 shows the sustainability indicators used as manufacturing optimization objectives, from a review. A significant amount of these researches, used either a single objective optimization or several objectives combined into a unique target by using some kind of aggregation (which is known as *a priori* approach [10]). These methods, which actually transform a multi-objective optimization problem into a single-objective one, have shown some drawbacks, including the subjectivity in the supplied preference information and the inability for finding solutions in non-convex regions [11].

On the contrary, the *a posteriori* approach, firstly, brings the set of non-dominated solutions (which are optimal in the wide sense that no other solution in the considered search space, can improve one of the objectives without worsening, at least, another one), which is known as the Pareto front and, after that, allows choosing the most convenient alternative from these solutions [27]. Pareto-based techniques have become the most suitable choice for solving multi-objective optimization problems [28] and has been widely applied for practical manufacturing cases [29]. Furthermore, due to the complex nature of multi-objective optimization [30] the so-called gradient-free heuristics, which are stochastic techniques, usually inspired in natural processes or systems, have become the most popular choices for obtaining the Pareto fronts [31].

Although some works [32]–[37] have reported the *a posteriori* multi-objective optimization of sustainability of manufacturing processes, based on existing studies, only two [21], [38] includes the three pillars of the sustainability as objectives. Nevertheless, none of these papers have presented a systematic approach which combines the evaluation of sustainability by following the principles of the TBL and the optimization of this sustainability by using the TBL dimensions as targets.

Among the different manufacturing processes, automatic or robotic welding is widely used in industry. A brief analysis of reported optimization approaches for these processes in the last years is summarized in Table 2.

Two main facts arise from this summary. In the first place, multi-objective optimization through metaheuristic algorithms is the most used strategy in recent reports on welding processes optimization. As a second fact, no studies have been found which simultaneously optimizes a automatic welding process by considering the TBL concepts and, also using the technical requirements as constraints.

It can be noted that optimization, on the before-mentioned works, has been mostly targeted to technical or economical goals, such as dilution, mechanical properties, bead geometry, weight of the deposited metal, or heat affected zone size. Nevertheless, some works were based on sustainability points of view. Consequently, a SAW process can be a suitable choice for validating any sustainability-based optimization methodology.

This study aims to formalize a methodology for optimizing the sustainability of manufacturing processes, by following an *a posteriori* approach, which use the three dimensions of the TBL as optimization objective. Important components of the proposed technique are not only the optimization and decision-making processes themselves, but also the identification of the significant indicators, which allow to characterize the sustainability from the environmental, economic and social points of view and to model the relationships between these indicators and the process parameters that are used as decision variables in the optimization. A case study, on a submerged arc welding process, is also presented in order to exemplify and validate the methodology.

TABLE 2. Summarized review on automatic or robotic-based welding optimization.

Reference	Objective functions	Decision variables	Optimization method
[39]	Hardness	Voltage, current, feed, and speed	Taguchi
[40]	Width of bead, and height of bead	Voltage, current, and speed	Response surface methodology
[25]	Bead width, reinforcement, and penetration	Voltage, feed, speed, nozzle to plate distance, flux condition and plate thickness	Genetic algorithm JAYA algorithm and desirability approach
[24]	UTS, hardness, deposition rate, reinforcement height, bead width	Current, voltage, speed and heat input	Taguchi-desirability function
[41]	Welding strength, Weld deposition rate	Current, speed, root gap and electrode angle	Response surface and genetic algorithm
[42]	UTS and Hardness	Voltage, feed, speed and nozzle to plate distance	Taguchi
[43]	Bead height	Voltage, current, speed, nozzle to plate distance	Genetic algorithm
[44]	Dilution, reinforcement and reinforcement/bead width ratio	Voltage, feed and nozzle to plate distance	ANOVA
[45]	Bead width, weld reinforcement, weld penetration, tensile strength and weld hardness	Current, voltage, speed and feed	Jaya, QO-Jaya, genetic algorithm, particle swarm optimization, imperialist competitive algorithm
[46]	UTS and hardness	Current, voltage, speed	Taguchi-fuzzy inference system
[47]	Productivity and cost	Welding path	Genetic algorithm, particle swarm optimization
[48]	Joint dimensions and dilution	Voltage, speed, wire feed rate, contact distance	Generalized reduced gradient
[49]	Cost	Torch angle	Modified article swarm optimization
[50]	Joint geometry	Current, speed, and gas flow	Ratio analysis method
[51]	Pose of welding torch	Welding trajectory	Offline programming
[52]	Total tracking error	Welding path	Genetic algorithm
[53]	Strength	Rotational speed, welding speed, tilt angle, and pin profile	Henry Gas Solubility Optimization

II. SUSTAINABILITY INDICATORS FOR MANUFACTURING PROCESSES

The optimization of the sustainability in manufacturing processes is based on quantification their negative impacts [21]. Quantification of these impacts is commonly carried out by using a set of indicators, which can be defined as "the operational representation of an attribute of a given system, by a quantitative or qualitative variable, including its value, related to a reference value" [54]. A variable selected as indicator should fulfill some requirements such as measurable, relevant, understandable, usable, data accessible, timely manner and long-term oriented [55]. Reliability of sensor data is another key issue to be considered [56]. Furthermore key performance indicators (KPI) should have some critical characteristics such as properly derived from appropriate strategy, clearly defined with an explicit purpose, relevant and easy to maintain, simple to understand and use, provide fast and accurate feedback, link operations to strategic goals,

TABLE 3. Summary of key performance indicators sets.

Reference	Dimensions	Indicators count	Comments
[55]	Environmental, Economic, Social, Technological Advancement and Performance Management	212	National Institute of Standards and Technology (NIST). Designed for manufacturing processes. Higher number of indicators than other approaches.
[59]	Environmental, Economic, Social, Technological Advancement and Performance Management	36	Sustainable Manufacturing Indicator Repository (SMIR). Designed for manufacturing processes.
[60]	Environmental, Economic and Social	20	Key performance indicators of Factory sustainability. Easy to be applied.
[61]	Environmental, Economic and Social	155	ISO standard for a wide context.
[62]	Environmental, Economic and Social	8	Ford Co. Specifically directed to automobile manufacturing and services.
[63]	Environmental protection, Economic growth, Social well-being and Performance management	40	Singapore. Designed for manufacturing industry.
[21]	Environmental, Economic and Social	35	Applied to a turning process.
[64]	Environmental, Economic and Social	26	Applied to three study cases.
[65]	Environmental, Economic and Social	13	For cement industry in Indonesia.
[66]	Environmental, Economic and Social	43	Directed to manufacturing environment.

and stimulate continuous improvement [57]. In the upcoming years, the hybridization of optimization methods and machine learning will enable new progress in this field [58].

Selecting the proper set of indicators is far from being a simple task. Table 3 summarizes several approaches proposed in the recent decade.

Considering its advantages (such as simplicity and adaptability to different manufacturing processes), in the present work, the indicator set proposed by [66] is adopted as a starting point (see Fig. 1). These indicators can be formally defined as:

$$\mathcal{A} = \{a_i \in \mathbb{R}, i = 1, \ldots, 20\}; \quad (1a)$$

$$\mathcal{B} = \{b_i \in \mathbb{R}, i = 1, \ldots, 9\}; \quad (1b)$$

$$\mathcal{C} = \{c_i \in \mathbb{R}, i = 1, \ldots, 14\}; \quad (1c)$$

where $\mathcal{A}$, $\mathcal{B}$, and $\mathcal{C}$ are the sets of base indicators for the environmental, economic and social dimensions, and a_i, b_i, and c_i are the corresponding individual indicators. It is important to remark that this set of indicators is a starting point, where those which are convenient for the analyzed manufacturing process are chosen from, by using the ABC judgment method, as it is explained in the next section.

III. OPTIMIZATION METHODOLOGY DESCRIPTION

The proposed methodology is based on six steps, which are described in the following paragraphs.

A. FIRST STEP: PROCESS CHARACTERIZATION

The first step starts with the identification of studied manufacturing process parameters, $\mathbf{x} = \{x_1, x_2, \ldots x_m\} \in \mathcal{X} \subset \mathbb{R}^m$, which are those variables that can be freely selected (although fulfilling some constraints) and determine the process performance. For example, in a turning process, the parameters are the cutting speed, feed and depth of cut, while in a heat treatment, temperature, time and cooling media should be chosen.

After selecting the parameters, the process inventory is established, by identifying the corresponding inputs and outputs. Inputs include raw materials, tools, energy and labor, among others. Outputs, on the other hand, comprise not only the goods obtained of modified in the process, but also other outcomes such as residuals and emissions.

B. SECOND STEP: SUSTAINABILITY INDICATORS SELECTION AND WEIGHTING

After defining the process inventory, the significant indicators are chosen for each sustainability dimension, by using the ABC judgment method [67]. Three aspects of each indicator are evaluated: (i) relevance, (ii) data availability, and (iii) strategy alignment. One of three possible levels (A = high, B = medium, and C = low) is assigned to each aspect. With the obtained evaluations, an order and is obtained for each indicator. Only the indicators with orders I (AAA) and II (AAB, ABA and AAB) are selected. This procedure is carried out on the basis of a consensus by a group of experts.

An indicator can be also neglected if it is not affected by the process parameters (i.e., if it is a constant value). Consequently, it can be stated:

$$\mathrm{A} = \{\alpha_1, \alpha_2, \ldots, \alpha_n\} \subseteq \mathcal{A}; \quad (2a)$$

$$\mathrm{B} = \{\beta_1, \beta_2, \ldots, \beta_p\} \subseteq \mathcal{B}; \quad (2b)$$

$$\Gamma = \{\gamma_1, \gamma_2, \ldots, \gamma_q\} \subseteq \mathcal{C}; \quad (2c)$$

where A, B and Γ, are the sets of significant indicators, in the environmental, economic, and social dimensions (which are subsets of the proposed indicator sets, $\mathcal{A}$, $\mathcal{B}$ and $\mathcal{C}$), and α_i, β_i, and γ_i are the corresponding significant indicators.

Additionally, the experts weigh up all the selected indicators, through the Saaty analytic hierarchy process [68]. The weights are given such that the total sum, for a dimension,

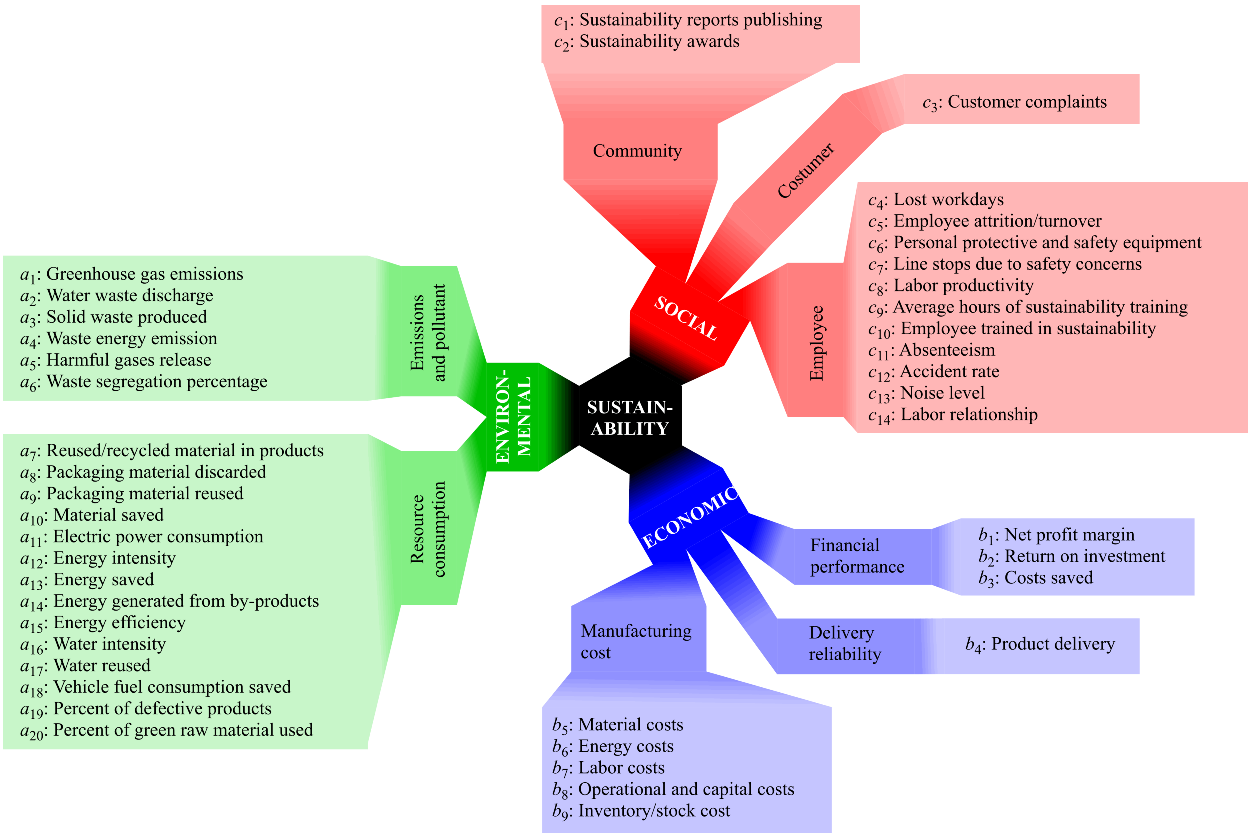


FIGURE 1. Selected sustainability key performance indicators.

be equal to one:

$$\mathrm{U} = \{u_1, u_2, \ldots, u_n\} : \sum_{i=1}^{n} u_i = 1; \tag{3a}$$

$$\mathrm{V} = \{v_1, v_2, \ldots, v_p\} : \sum_{i=1}^{p} v_i = 1; \tag{3b}$$

$$\mathrm{W} = \{w_1, w_2, \ldots, w_q\} : \sum_{i=1}^{q} w_i = 1; \tag{3c}$$

where u_i, v_i, and w_i are the weights given for environmental, economic, and social indicators, and U, V, and W, are corresponding sets.

C. THIRD STEP: MODELING OF INDICATORS AND CONSTRAINTS

In order to carry out the optimization process, the models relating the process parameters (as independent variables) and the sustainability indicators must be obtained. These models have a functional form:

$$\alpha_i = \alpha_i(\mathbf{x}), \quad i = 1, 2, \ldots, n; \tag{4a}$$

$$\beta_i = \beta_i(\mathbf{x}), \quad i = 1, 2, \ldots, p; \tag{4b}$$

$$\gamma_i = \gamma_i(\mathbf{x}), \quad i = 1, 2, \ldots, q; \tag{4c}$$

which can be obtained either by analytical modeling or by using some empirical relationship, depending on the nature of the considered process. Some of the most frequently used modeling techniques include linear and nonlinear regression models, artificial neural networks, and fuzzy and neurofuzzy inferences systems. Other tools, such as digital twins [69], [70] and cyber-physical systems [71], can be used.

For making compatible the dimensions of the indicators, they are normalized by using the equations:

$$\hat{\alpha}_i(\mathbf{x}) = \frac{\alpha_i(\mathbf{x})}{\alpha_i^0}, \quad i = 1, 2, \ldots, n; \tag{5a}$$

$$\hat{\beta}_i(\mathbf{x}) = \frac{\beta_i(\mathbf{x})}{\beta_i^0}, \quad i = 1, 2, \ldots, p; \tag{5b}$$

$$\hat{\gamma}_i(\mathbf{x}) = \frac{\gamma_i(\mathbf{x})}{\gamma_i^0}, \quad i = 1, 2, \ldots, q; \tag{5c}$$

where $\hat{\alpha}_i$, $\hat{\beta}_i$, and $\hat{\gamma}_i$, are the normalized environmental, economic, and social indicators, and α_i^0, β_i^0, and γ_i^0 are the reference values for each indicator, which correspond to the mean values of the independent variables.

Additionally, constraints that are based on technical or legal considerations, and which are also functions of the selected parameters, are established for the process, either in form of inequality:

$$\mathbf{g} = \{g_i(\mathbf{x}) \leq 0, i = 1, 2, \ldots, s\}; \tag{6}$$

or in form of equality:

$$\mathbf{h} = \{h_i(\mathbf{x}) = 0, i = 1, 2, \ldots, t\}. \tag{7}$$

D. FOURTH STEP: OPTIMIZATION

The optimization step aims to select the process parameters for minimizing the impact of the three sustainability dimensions, given by:

$$Y_{\mathrm{A}}(\mathbf{x}) = \sum_{i=1}^{n} u_i \hat{\alpha}_i(\mathbf{x}); \tag{8a}$$

$$Y_{\mathrm{B}}(\mathbf{x}) = \sum_{i=1}^{p} v_i \hat{\beta}_i(\mathbf{x}); \tag{8b}$$

$$Y_{\Gamma}(\mathbf{x}) = \sum_{i=1}^{q} w_i \hat{\gamma}_i(\mathbf{x}). \tag{8c}$$

where Y_{A}, Y_{B}, and Y_{Γ} are the environmental, economic, and social impact indexes.

The three considered objectives use to be conflicting (i.e., improving one of them causes the worsening in another one). Therefore, the multi-objective optimization is carried out through the *a posteriori* approach, where the different targets are not combines into a single one (which actually transform the problem in a single-objective optimization), but they are simultaneously optimized, for obtained the so-called Pareto front. As there is an agreement in the literature [72]–[74] on the convenience of using gradient-free nature-inspired heuristics for solving *a posteriori* multi-objective optimization problems, one of them should be selected for doing this task in the proposed methodology. Some studies have compared several heuristics for solving some practical problems [75], [76]. The heuristic performance evaluation was done by using the hypervolume, which takes into account not only how close is the obtained Pareto front to the actual one (convergence) but also how uniform is the distribution of the obtained non-dominated solutions (diversity) [77]. However, as the so-called No Free Lunch theorems state that there is no an algorithm that outperforms all the other ones for any class of problems [78]. Consequently, no theoretical foundation can be used for choosing the most proper heuristic for any particular problem and, therefore, it is strongly recommended to perform the optimization by using several heuristics and to compare the outcomes for choosing the most convenient alternative.

E. FIFTH STEP: DECISION-MAKING

As the Pareto front is almost always composed by multiple points, the solution that will be actually used must be selected from them. In order to make this decision, the relative importance of each sustainability dimension must be evaluated. For example (see Fig. 2 if the environmental issues play a key role, in the considered process, the point A is the most convenient. On the contrary, if economic impact must be prioritized, point B offers the most convenient solution. Finally, point C represents the best choice from the social point of view. All the other points are trade-off solutions, which can be selected depending on the specific workshop conditions.

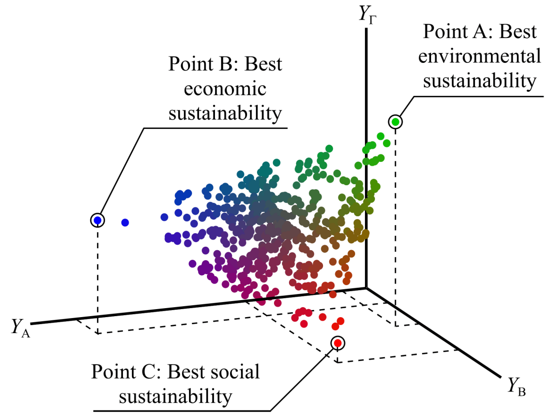


FIGURE 2. Pareto front example.

Although choosing the most convenient solution from the Pareto front involves some subjectivity, as it deals with optimal solutions, it outperforms any *a priori* approach, where the preference information is supplied before carrying out the optimization process, which may provide an inconvenient dominated solution.

F. SIXTH STEP: VALIDATION

An important final step is the validation of the chosen solution through some practical experimentation. This issue plays a key role in the proposed methodology, because the inherent errors of fitted models may have cumulative effect on the performance of the selected solution. The comparison between the predicted and the observed values of the solution must be compared by using the proper statistical tests.

IV. CASE STUDY ON A SUBMERGED ARC WELDING PROCESS

A. PROCESS CHARACTERIZATION

The considered process is the submerged arc welding process of the equatorial joint of pressured vessel for liquefied petroleum gas. The identified process parameters are the current, $x_1 \equiv I$, voltage, $x_2 \equiv U$, and welding speed, $x_3 \equiv S$, which are defined, by considering the technical characteristics of the machine and following the literature recommendations [79], into the following intervals:

$$200\,\mathrm{A} \leq I \leq 300\,\mathrm{A}; \tag{9a}$$

$$20\,\mathrm{V} \leq U \leq 30\,\mathrm{V}; \tag{9b}$$

$$41\,\mathrm{m/h} \leq S \leq 85\,\mathrm{m/h}. \tag{9c}$$

Furthermore, the considered process inputs (see Fig. 3) includes the parts to be welded, the electrode wire, the flux, the electric power and the labor used in the process. On the other hand, outputs comprises the welded parts (including the corresponding joint), slag, fumes, heat and noise.

B. SUSTAINABILITY INDICATORS SELECTION AND WEIGHTING

For selecting and weighing up the sustainability KPI's, eleven experts were chosen. Seven of them came from the industry

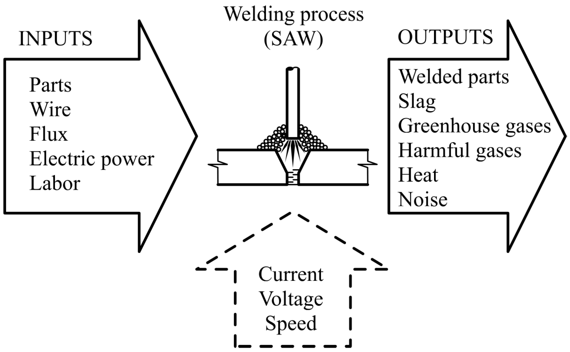


FIGURE 3. Input and output inventory of the SAW process.

TABLE 4. Outcomes of the ABC judgment method for the SAW process.

Key performance index	Relevance	Data availability	Strategy alignment	Order
a_1: Greenhouse gases emission	A	A	A	I
a_3: Solid waste produced	A	A	A	I
a_4: Waste energy emission	C	A	C	VI
a_5: Harmful gasses emission	A	C	A	III
a_{10}: Material saved	A	A	A	I
a_{11}: Electric power	A	A	A	I
b_5: Material cost	A	A	A	I
b_6: Energy cost	A	A	A	I
b_7: Labor cost	A	A	A	I
c_8: Labor productivity	A	A	A	I
c_{13}: Noise level	B	C	A	V

and five from the academia. Nine of they were mechanical engineers while two, industrial engineers. Four had the degree of Ph.D., one of M.Sc., and the other were B.Sc. They had an average of 29.6 years of experience (in a range from 10 to 57).

As a first action, the process inventory and proposed KPI's were analyzed together. By consensus, indicators that were not represented in the inventory were eliminated. For determining the most influential of the remaining indicators, the ABC judgment method was applied. Table 4 shows the evaluation given by the experts to the three considered aspects of each KPI (i.e., relevance, data availability, and strategy alignment). From these evaluations, the order is determined for each KPI. Finally, only KPI's belonging to order I are considered in the optimization.

The first selected environmental KPI (greenhouse gases), was centered on carbon dioxide emissions, ε_{CO_2}, corresponding to the consumed electric power, because the fume amount generated by the SAW process can be neglected [80]. Therefore, the first environmental indicator can be formalized as:

$$\alpha_1 = \varepsilon_{CO_2}(\mathbf{x}). \tag{10}$$

TABLE 5. Outcomes of the Saaty analytic hierarchy process.

	α_1	α_2	α_3	α_4	α_5	Weights
α_1	1.0000	0.3333	3.0000	3.0000	1.0000	0.2308
α_2	3.0000	1.0000	5.0000	5.0000	3.0000	0.3846
α_3	0.3333	0.2000	1.0000	1.0000	0.3333	0.0769
α_4	0.3333	0.2000	1.0000	1.0000	0.3333	0.0769
α_5	1.0000	0.3333	3.0000	3.0000	1.0000	0.2308

The second selected environmental KPI (solid waste) comprise the generated slag amount, G_S, which can be formalized by the expression:

$$\alpha_2 = G_S(\mathbf{x}). \tag{11}$$

The third selected environmental KPI (material saved), was divided into two different indicators, in order to quantify the waste of wire, G_W, and flux, G_F:

$$\alpha_3 = G_W(\mathbf{x}); \tag{12a}$$
$$\alpha_4 = G_F(\mathbf{x}). \tag{12b}$$

The last environmental KPI (electric power), can be centered on the electric power used in the welding process, E:

$$\alpha_5 = E(\mathbf{x}). \tag{13}$$

On the other hand, the three selected economic KPI's (material, labor, and energy costs) were consolidated into a single indicator:

$$\beta_1 = Z_w(\mathbf{x}) + Z_f(\mathbf{x}) + Z_e(\mathbf{x}) + Z_l(\mathbf{x}); \tag{14}$$

where Z_W is the wire cost, Z_F is the flux cost, Z_E is the electric power cost, and Z_L is the labor cost.

Finally, the selected social KPI is important for employees because, in the first place, a higher productivity allows to obtain a better remuneration as additional payments and, in a second place, increases the subjective satisfaction of the workers for their labor. Labor productivity can be expressed as units per man-hour. In this work, the selected metric was the unit total time, τ, for the considered process:

$$\gamma_1 = \tau(\mathbf{x}). \tag{15}$$

The inverse of this metric is just the number of operations which are carried out in a unit time, therefore, minimizing this metric causes a maximization of the labor productivity.

After defining the indicators, the Saaty analytic hierarchy process was used for weighing the environmental indicators (as the economic and social pillars are described by a single indicator, there is no need to weigh up). Table 5 shows the judgments given, by consensus, by the experts, to the relationships between the indicators. It also show the weights computed from these judgments, with a consistency ratio of 0.0124, which is lower than 0.1 and, therefore, the set of judgments is reliable.

TABLE 6. Mean values of the measured variables in the experimental study.

I (A)	U (V)	S (m/h)	G_W (g)	G_F (g)	G_S (g)	B (mm)	P (mm)	R (mm)
200	20	63	49	112	73	6.34	1.38	0.78
300	20	63	59	137	80	7.73	1.93	0.63
200	30	63	63	147	82	8.21	2.57	0.88
300	30	63	75	162	100	9.84	2.95	0.80
200	25	41	70	148	91	9.12	2.14	1.08
300	25	41	81	196	102	10.58	2.65	0.87
200	25	85	43	101	66	5.62	1.66	0.67
300	25	85	59	140	78	7.75	2.39	0.46
250	20	41	65	150	91	8.58	1.71	0.93
250	30	41	79	189	107	10.31	2.87	1.04
250	20	85	43	98	67	5.61	1.42	0.56
250	30	85	61	137	87	7.90	2.54	0.67
250	25	63	61	142	82	7.96	2.18	0.87
250	25	63	58	133	80	7.61	2.12	0.83
250	25	63	63	138	87	8.21	2.17	0.83

C. MODELING OF INDICATORS AND CONSTRAINTS

Sensoring systems and experimental procedures are still a bottleneck for efficient modeling approaches [81]. In order to obtain the models relating the chosen indicators and the process parameters, an experimental study was carried out. All the values were referred to the length of the welded joint, L, which is computed from the vessel diameter, $D = 310\,\text{mm}$, through the geometric relationship:

$$L = \pi D = 974\,\text{mm}. \tag{16}$$

Experiments were designed by using a Box-Behnken design. For each experimental point, the waste of wire, G_W, and flux, G_F, the generation of slag, G_S, and the dimensions of the joint cross-section (i.e., the joint width, B, penetration, P, and reinforcement height, R) were measured. Three replicates were obtained for each experimental point.

For the experimental study (see Fig. 4), a KAIYUAN flux welding machine was used (1). The welded material was JIS 3116 sheet with 2.2 mm thickness (2). 2 mm-diameter EM12K (3) wire and PV60-3 flux were used in the welding process. The distance from the wire to the sheet was fixed at 16 mm. During the experiments the variation of current, voltage and speed were monitored. For measuring the welding speed, a PCE-151 tachometer (7) was used. Flux and wire waste were determined by the differential weighing method. To determine the amount of slag generated, a collector (8) was placed at the lower part of the machine, so that, after welding, the slag is removed by blows and then weighed. All the weights were carried out in a SF-400D weighing scale, with an accuracy of 0.01 g. For obtaining the parameters of the weld bead, a ZEISS Axio Observer Z1M optical microscope, with a magnification of 50X, was used. Outcomes are shown in Table 6.

By using the obtained experimental data, empirical models were fitted by using linear regressions, giving the following expressions:

$$G_W = 23.6 + 0.126I + 1.54U - 0.504S; \tag{17a}$$

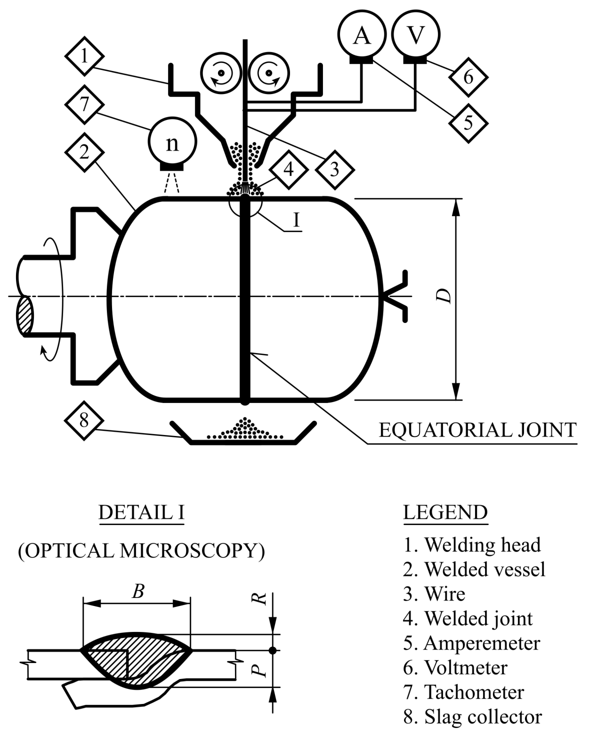


FIGURE 4. Welding experimental setup.

$$G_F = 49.6 + 0.319I + 3.46U - 1.17S; \tag{17b}$$

$$G_S = 46.5 + 0.120I + 1.67U - 0.527S; \tag{17c}$$

$$B = 3.14 + 16.5 \cdot 10^{-3}I + 0.200U - 66.5 \cdot 10^{-3}S; \tag{17d}$$

$$P = -1.49 + 5.42 \cdot 10^{-3}I + 0.112U - 7.771 \cdot 10^{-3}S; \tag{17e}$$

$$R = 1.46 - 1.66 \cdot 10^{-3}I + 12.2 \cdot 10^{-3}U - 8.84 \cdot 10^{-3}S. \tag{17f}$$

In all these models, the determination coefficient, R^2, was higher than 0.69, meaning than the models as fitted explain more than the 69% of the variability in the corresponding dependent variable. In all the cases, as the probability associated to the F-test is lower than 0.01, there is a statistically significant relationship between dependent and independent variables, at the 99% confidence level. Furthermore, as the probability associated to the t-test is lower than 0.05, all the dependent variables appearing in the models are significant at the 95% confidence level. In all the models, no trend can be identified in the residual-plots.

By using analytical relationships, combined with the previously obtained models, some other expressions were obtained. Hence, the wasted electric power, E, can be computed by the expression:

$$E = \frac{\sqrt{3}LIU\cos\phi}{1000S}; \tag{18}$$

where $\cos\phi = 0.9$ is the phase factor, which was calculated using a two-channel oscilloscope to compute the apparent

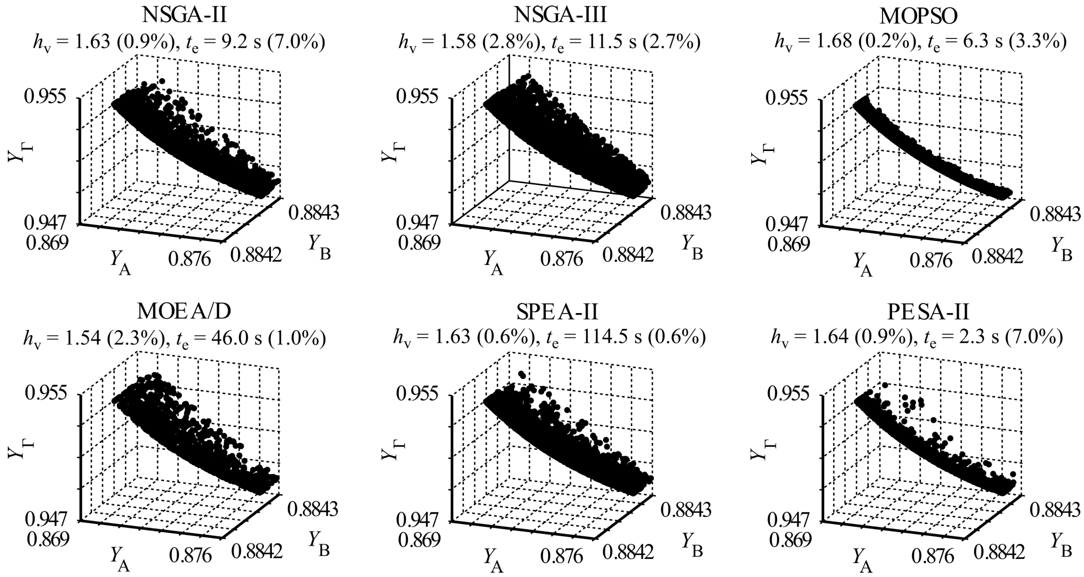


FIGURE 5. **Comparison of the outcomes from the selected heuristics.**

power and true power. From this value, the corresponding generated carbon dioxide, ε_{CO_2}, can be determined by using the factor given by the electric utility that supplies the power to the factory [82]:

$$\varepsilon_{CO_2} = 0.8753\,\frac{\text{kg}}{\text{kW.h}}\,E. \tag{19}$$

The total time used in the operation, τ, can be computed by summing technological time, τ_T, and auxiliary time, τ_A:

$$\tau = \tau_T + \tau_A; \tag{20}$$

where technological time is defined by:

$$\tau_T = \frac{60L}{S}; \tag{21}$$

and the auxiliary time, for this specific welding process was set to $\tau_A = 3.68$ min.

On the other hand, the process costs (labor cost, Z_L; wire cost, Z_W; flux cost, Z_F; and energy cost, Z_E) can be determined as follows:

$$Z_L = \zeta_L \tau; \tag{22a}$$
$$Z_W = \zeta_W G_W; \tag{22b}$$
$$Z_F = \zeta_F G_F; \tag{22c}$$
$$Z_E = \zeta_E E; \tag{22d}$$

where $\zeta_L = 5.81$ \$/h is the unit labor cost, $\zeta_W = 2.65$ \$/kg is the unit wire cost, $\zeta_F = 6.21$ \$/h is the unit flux cost, and $\zeta_E = 0.12$ \$/kW.h is the unit electric power cost. All the units costs were supplied by the accounting unit of the company which produce the vessels.

All KPI's (computed by equations 10... 15)) are, then, normalized by using the values corresponding to the mean level of the independent variables (i.e., $I = 250$ A, $U = 25$ V, and $S = 63$ m/h):

$$\hat{\alpha}_1 = \alpha_1/0.1134; \tag{23a}$$
$$\hat{\alpha}_2 = \alpha_2/85.05; \tag{23b}$$
$$\hat{\alpha}_3 = \alpha_3/0.1506; \tag{23c}$$
$$\hat{\alpha}_4 = \alpha_4/61.85; \tag{23d}$$
$$\hat{\alpha}_5 = \alpha_5/142.14; \tag{23e}$$
$$\hat{\beta}_1 = \beta_1/1.5118; \tag{23f}$$
$$\hat{\gamma}_1 = \gamma_1/4.6175. \tag{23g}$$

Finally, the sustainability indexes are computed by the corresponding weighted sums:

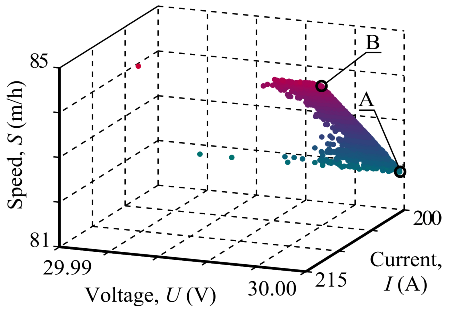
$$Y_A(\mathbf{x}) = 0.2308\hat{\alpha}_1 + 0.3846\hat{\alpha}_2 + 0.0769\hat{\alpha}_3 + 0.0769\hat{\alpha}_4 + 0.2308\hat{\alpha}_5; \tag{24a}$$
$$Y_B(\mathbf{x}) = \hat{\beta}_1; \tag{24b}$$
$$Y_\Gamma(\mathbf{x}) = \hat{\gamma}_1. \tag{24c}$$

For completing the definition of the optimization problem, the constraints, related to the welded joint dimensions are formalized by the following relationships:

$$7.0\,\text{mm} \le B \le 9.0\,\text{mm}; \tag{25a}$$
$$P \ge 2.2\,\text{mm}; \tag{25b}$$
$$0.5\,\text{mm} \le R \le 1.5\,\text{mm}; \tag{25c}$$

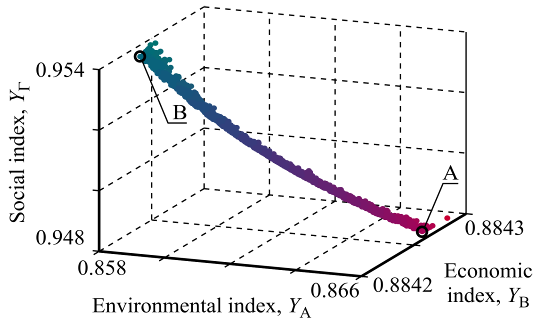
which can be rewritten, in a normalized form, as:

$$g_1(\mathbf{x}) = \frac{7.0}{B} - 1 \le 0; \tag{26a}$$
$$g_2(\mathbf{x}) = \frac{B}{9.0} - 1 \le 0; \tag{26b}$$
$$g_3(\mathbf{x}) = \frac{2.2}{P} - 1 \le 0; \tag{26c}$$



b) Pareto set

FIGURE 6. Obtained Pareto set.



a) Pareto front

FIGURE 7. Obtained Pareto front.

$$g_4(\mathbf{x}) = \frac{0.5}{R} - 1 \leq 0; \tag{26d}$$

$$g_5(\mathbf{x}) = \frac{R}{1.5} - 1 \leq 0. \tag{26e}$$

D. OPTIMIZATION

The optimization process was carried out by using six different heuristics: nondominated sorting genetic algorithm II (NSGA-II) [83] and III [84], Multi-Objective Evolutionary Algorithm based on Decomposition (MOEA/D) [85], Multi-Objective Particle Swarm Optimization (MOPSO) [86], Strength Pareto Evolutionary Algorithm (SPEA-II) [87], and Pareto Archived Evolutionary Strategy (PESA-II) [88]. All the optimizations were executed with population sizes of 1000 solutions and stopped after 10^5 evaluations of the objective function. For comparing the performance of the six heuristics, 30 replicates were carried out and the mean value and variation coefficient were computed for the hypervolume (because it can measure both the convergence and diversity of the Pareto fronts [77]) and execution time of the each one. Fig. 5 shows the results. As can be seen, MOPSO returned the higher convergence in the obtained Pareto fronts (the lower variation in the corresponding hypervolume) with a low execution time. Consequently, MOPSO outcomes were selected for the considered problem.

E. DECISION-MAKING

After an overview of the graphical representation of the Pareto set (Fig. 6) it stands out the fact that all the values correspond to voltages, $U \approx 30\,\text{V}$, while the current and speed move into the intervals I = (200 to 215) A and S = (81 to 85) m/h.

In the Pareto front (see Fig. 7), two remarkable points can be identified (denotes as A, and B). The corresponding values of the decision variables are listed in Table 7. As can be seen, differences on impact indexes between points A and B are negligible (less than 1%). By considering the social sustainability (based on productivity), which represents a key aspect in employees salary (with the consequent satisfaction), point A is preferred for the analyzed specific conditions.

TABLE 7. Optimal solutions.

Parameter	Point A	Point B	Industry
I (A)	213	200	300
U (V)	30	30	30
S (m/h)	85	81.8	85
B (mm)	7.00	7.00	8.44
P (mm)	2.37	2.32	2.84
R (mm)	0.72	0.77	0.58
G_W (g)	53.8	53.8	64.8
G_F (g)	121.9	121.5	149.6
G_S (g)	77.4	77.5	87.8
E (kW.h)	0.1141	0.1114	0.1607
ε_{CO_2} (g)	99.9	97.5	140.7
τ (min)	4.38	4.40	4.38
Z ($)	1.34	1.34	1.54
α_1	0.8899	0.8595	1.2407
α_2	0.9096	0.9111	1.0324
α_3	0.7578	0.7394	1.0674
α_4	0.8698	0.8694	1.0470
α_5	0.8576	0.8547	1.0528
β_1	0.8845	0.8843	1.0214
γ_1	0.9480	0.9534	0.9480
Y_A	0.8763	0.8698	1.0890
Y_B	0.8845	0.8843	1.0214
Y_Γ	0.9480	0.9534	0.9480

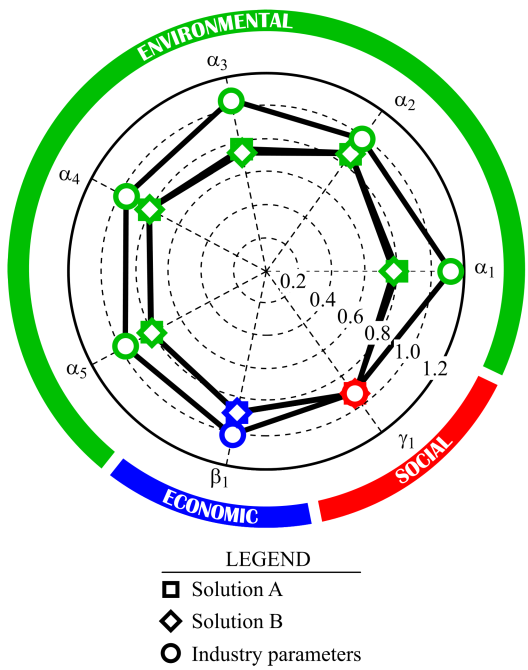


FIGURE 8. Comparison between optimized and currently used welding parameters.

In order to evaluate the outcomes of the optimization, they were compared with the welding parameters currently used by the industry ($I = 300$ A, $U = 30$ V, and $S = 85$ m/h). Fig. 8 shows the comparison. As can be seen, the optimized solutions improves all the environmental and economic indicators in a range between 10% and 30%, without worsening the social sustainability.

V. CONCLUDING REMARKS

The main conclusion from this work points to the suitability of the proposed approach for improving the sustainability of manufacturing processes. The formalized optimization methodology targets to the three pillars of sustainability, as considered in the Triple Bottom Line: i.e., environment, economy and society. The methodology includes not only a proposed set of sustainability indicators, but also the tool for selecting and weighting them. The optimization is carried out by using an *a posteriori* approach, which allows, firstly, obtaining a set of non-dominated solutions (also known as Pareto front) and, then, selecting from them the most convenient choice, depending on the specific industrial conditions. These features allow to apply this technique under practical industrial conditions and, on the other hand, increase the accuracy in the results and the flexibility in the decision-making processes.

The executed case study showed the application of the proposed methodology to a submerged arc welding process. The outcomes highlighted the novelty of the proposed approach and its advantages over other previous studies. In the first place, this method allowed to perform the optimization by taking into account the main sustainability issues, but also considering the main technical aspects of the process. Moreover, on the contrary with regard to other approaches, it includes a set of steps that can be applied, from scratch to any manufacturing process, given the proper data is available for fitting the corresponding model. Finally, the Pareto-based optimization gives a set of optimal solutions, which represents different combinations of the goals. This approach allows a better informed decision-making, because the other way (i.e., the *a priori* approach) requires the ranking of the objectives without knowing the actual relationships between them. It can be also remarked that the optimized solution significantly overcomes the parameters currently used by the industry.

Two main shortcomings can be noted in the proposed methodology. The first one is the need of choosing the parameters in the used optimization approach. These parameters may heavily affect the optimization outcomes. Although this is a common drawback of all the heuristics, more effort should be done for obtaining practical guidance on how to select these values, at least, for the most typical manufacturing processes optimization. The second shortcoming is related with the decision making process which now relies completely on the human decision-maker skills and experience. One way to address this challenge is by expert-based systems and deep learning.

Furthermore, future works will be directed to apply the proposed methodology to other manufacturing processes in order to validate the used tools and techniques. The convenience of the proposed set of indicators should be also analyzed and, if necessary, modified and enhanced. The integration in an Industry 4.0 environment or in a pilot line will be another research and technical aspect to be explored in further work.

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