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A fundamental study on qualitatively viable sustainable welding process maps

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ABSTRACT

Welding is a ubiquitous process within manufacturing that also results in some negative environmental impacts due to emissions and inefficient utilization of energy and materials. The conventional approach of obtaining shop-floor applicable welding conditions considering maximum penetration, minimum weld width, minimum dilution, etc. are difficult to simultaneously achieve or if accidently achieved are not necessarily be sustainable and practically applicable. The article proposes an approach for developing welding process maps in sustainability framework. A two-stage approach is presented wherein a number of near-optimal solutions based on realistic quality aspects are acquired through meta-heuristic optimization and Fuzzy classifier is used to assess multiple solutions on the basis of their sustainability. The approach is demonstrated for an actual thick weld considering weld specifications as objectives of optimization and electrical power and material utilization as sustainability aspects in classification. The results show that qualitatively viable sustainable process maps for complex engineering systems can be obtained as a first measure before changes in machine, material or processes are considered. A diligent use of modelling, optimization, and classification in sequence have potential to address the quality and sustainability conflict for a wide variety of products obtained from a process.

1. Introduction

Development of a process map for welding processes is a challenging task because of their complex multi-input multi-output (MIMO) attribute. The welding operations consume a good amount of energy and material. A very few investigations are carried out on evaluation of welding processes' sustainability. The welding processes are additive in nature and consumes a good amount of energy and material. Therefore, reduction in energy, material, and emission associated with a welded product seek more attention among '6 R's of sustainability' – reduce, reuse, repair, recycle, rethink, and refuse. Some of the recent investigations aimed at reducing environmental foot prints due to welding include studies on welding fume [1], energy efficiency of hot-wire laser welding [2], electromagnetic force field [3], welding spatter [4], metal evaporation [5], flux consumption in submerged arc welding [6], etc. There are very few computational investigations on the sustainability of welding operations. Vimal et al. [7] presented a case study on sustainable shielded metal arc welding process through modelling, assessment and deployment strategies. Sproesser et al. [8] investigated life cycle assessment of thick metal plate welds. Wilson et al. [9] presented energy and environmental impact analysis laser direct deposition in remanufacturing of turbine blades. Drakopoulos et al. [10] assessed environmental impact of ship hull repair.

A critical analysis of the aforementioned investigations indicates that welding process parameters obtained in sustainability framework are perhaps non-existing in current literature. Conventionally, operating parameters obtained through welding process optimization are reported using different criteria like weld bead geometry, weld sequence, distortion mechanical properties, etc. Among these criteria, weld bead geometry is most popular criteria that is investigated in the last few years [11]. The load-bearing capacity of a weld has direct relation with weld features like bead width, penetration, reinforcement, etc. Theoretically, a weld bead must have maximum penetration, minimum weld width, minimum dilution, and minimum reinforcement. However, in practical conditions, it is very difficult to satisfy all these criteria, as they are interrelated and conflicting as well. A strict attention to one may result deviation in others. Therefore, the forgoing optimization studies based on 'Theoretical criteria' are referred as a compromise [12] as objectives rarely all simultaneously satisfy, thus, are more unlikely to sustain or reproduce.

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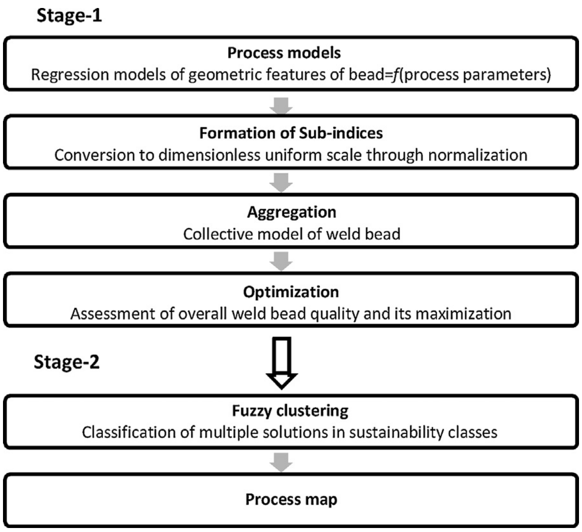

Fig. 1. Scheme of sustainable process map development.

In practical situations at shop-floor, weld bead geometry criteria arise from the product specifications. A qualified welding process specification (WPS) provides ranges of different geometric features of a weld bead essential for desired performance. The weld bead features should be simultaneously controlled within their respective range. These ranges, henceforth designated as 'practical criteria', can be used as objectives in multi-criteria optimization. These criteria are wider than the theoretical criteria and many near-optical solutions can be obtained, however a unique global optimum is most unlikely to be determined. In such scenario the process optimization exercise may lead to a process map that is practiced in some of the welding processes like resistance spot welding [13]. With development and proven applicability of soft-computational techniques such as neural network [14] and fuzzy algorithm [15] in welding, the multiple solutions can be precisely obtained and further processed. The multiplicity offers the possibility of screening those solutions that qualify sustainability norms and can lead to sustainable process maps, as offered in this investigation.

This primary objective of this investigation is to present a holistic approach of obtaining shop-floor applicable sustainable welding process map. In specific, the investigation also aims to demonstrate the proposed approach through a case study on twin wire welding wherein theoretical (conventional and unsustainable) method of obtaining workable process parameters is compared with the proposed one. A two-step methodology is proposed wherein quality responses (i.e. attributes of weld geometry) are first optimized and then feasible solutions are classified as per sustainability aspects like power demand, material deposition rate, etc. Next section of the article gives algorithm of the proposed approach. Followed to it is a case study on twin wire welding and subsequently results of the investigation are presented and discussed.

2. Algorithm for sustainable process map

The approach for sustainable process map development is a two stage process based on hybridization of multi-criteria optimization with fuzzy classification. The algorithm is depicted in Fig. 1. Though the flow chart shows welding as a candidate process, the algorithm is equally applicable to various manufacturing process. In the first stage, process models of different features of weld geometry are developed and a weld bead model is obtained using 'aggregation index technique' that is subsequently optimized through meta-heuristic technique. The optimization yields multiple near-optimal solutions. In the second stage multiple near-optimal solutions are classified on the basis of sustainability aspects and clusters or classes of sustainability are identified using fuzzy clustering that leads to a process map. A sustainability class represents combination of process conditions that can produce a similar quality of individual sustainability aspects, e.g. if three aspects of sustainability S_1, S_2 and S_3 and are graded as maximum, minimum, and moderate and represented as *max*, *min*, and *mod*, respectively, a total twenty-seven sustainability classes can be made., e.g. [$max(S_1)$, $min(S_2)$, $max(S_3)$], [$min(S_1)$, $mod(S_2)$, $max(S_3)$], [$min(S_1)$, $min(S_2)$, $max(S_3)$], [$max(S_1)$, $min(S_2)$, $min(S_3)$] etc. However, the sustainability aspects in practical situations may attain any value between maximum and minimum, thus multiple near-optimal solutions are classified in predefined number of classes or clusters using Fuzzy C-mean method (FCM) as explained in later part.

2.1. Problem description

Let a system be multi-input multi-output (MIMO) type that comprises of m quality responses (i.e., outputs). There are n input variables (x) that affect the quality responses. Let the number of samples (observations) is p. The j^{th} response ($1 \le j \le m$) can be defined as follows:

$$y_j = f_j(x_i) \quad i = 1, \ldots, n \ \ and \ j = 1, \ldots, m \tag{1}$$

The MIMO system is converted into a multi-input single-output (MISO) systems through aggregation function [16], as follows:

$$g = \left(1 - m + \sum_{j=1}^{m} (s_j)^{-\frac{1}{\beta}}\right)^{-\beta} \tag{2}$$

where s is non-dimensionalized and normalized (between 0 and 1) quality response termed as sub-index. 'β' is a positive constant. Furthermore, it is known that $\beta \approx 0.4$ prevents the limitations shown by conventional methods of aggregation such as weighted–sum or geometrical means [17]. The sub-indices are computed from the process response (i.e. output) expressed as a function of input variables. Therefore, the aggregation function becomes a non-linear function of input variables. The sub-index value of 0 represents goodness of the output (e.g., for a response output desired to be lower-the-better type the minimum and maximum response will yield sub-index as 1 and 0, respectively). The actual industrial processes operate over a sufficiently wide range of such input variables that can yield desired output. Thus, multiple optimum solutions can be obtained. These outputs, though qualitatively acceptable as per the product specifications, may differ in their level of sustainability. The problem under consideration encompasses a method to understand the level sustainability of qualitatively viable optimal solutions.

2.2. Process models

The process models $y_j = f_j(x_i)$ are developed using 'best subset selection regression' method as shown in Fig. 2.

The algorithm first identifies the predictor (first order and second order terms input variables and their interactions) producing the largest coefficient of determination (R^2) that is defined as follows:

$$R^2 = \frac{SS_{Model}}{SS_{Total}} \tag{3}$$

where SS_{Model} and SS_{Total} are the sum of squares of predicated and actual responses, respectively [18]. In subsequent iterations, predictors are increased one by one and each stage the best combi-