A fuzzy approach for the selection of non-traditional sheet metal cutting processes

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ABSTRACT

This work presents a methodology for the selection and comparison of non-traditional sheet metal cutting processes as a new structure of selection by means of an expert system. The model is generated from a knowledge base acquired from diverse experts, and the use of fuzzy logic techniques. With a simple input of the parameters of a piece, the system offers the most appropriate cutting options (based on the requirements of the piece) allowing a non-expert user selecting the most appropriate process with emphasis on a predefined priority: finish, cost or time. The selection process consists of four base algorithms that measure the attributes of each process as a dependent indicator of the other processes, that is, a pre-selection that considers (1) the process capability to cut a material-thickness relation, (2) the speed that can be achieved with this relation, (3) the inherent complexity of the piece to be cut, and (4) the process tolerance. Results of experiments under three different approaches prove that the expert system here presented accurately prioritizes the most convenient cutting processes.

1. Introduction

Cutting processes have been under a constant change due to the increasing necessity of the industry to develop end items with optimal characteristics that make agile their introduction to the market. Sheet metal cutting is part of a group of hundreds of different processes for various applications. Within the sheet metal cutting processes are laser, plasma, oxyfuel and waterjet cutting among others, also known as Non-Traditional Machining (NTM) processes. These processes have continuously extended their field of application being increasingly used with thicker materials, higher cutting speeds and better cutting quality, placing them as an excellent option for cutting sheet metal. Part of the operating parameters for these processes (e.g. cutting speed, required tolerances, thicknesses and materials to be cut) overlap between one process and another in certain ranges. This could be misinterpreted if it is believed that any of the aforementioned processes can be used under the same circumstances. Frequently, the selection of a cutting process is done through a simple decision-making and it is based on the experience or previous knowledge (Manocher, 2008). However, choosing the right cutting process is a key factor for the optimization of the entire production process (Swift & Booker, 2003), it allows faster time to manufacturing and product delivery, reduces high manufacturing costs, material waste and avoids secondary operations for lack of quality.

The use of methodologies for the selection of cutting processes is a viable alternative that must consider certain limitations on the use of matrices (Dargie, Parmeshwar, & Wilson, 1982), families of schemes (Abshy, 2005), diagrams and technical data used progressively to identify the best solution (Dieter, 1997; Halevi & Weill, 1995). Generally the result is a list of feasible processes but there is no way to quantitatively compare them, ie the user must select from the list of processes according to the prior knowledge and experience.

Multi-criteria decision making (MCDM) is a well known branch of decision making, which evaluates a finite set of alternatives on the basis of two or more criteria, choosing the best alternative from the set of candidates, or sorting the alternatives into a preference preorder (Wang & Kwong, 2014). MCDM methods support the subjective evaluation of performance criteria by decision makers (Mardani, Jusoh, & Zavadskas, 2015). In order to set the ranking of alternatives, these models typically determine the attributes, set a quantitative measure according to the relevance of the
attribute, and then assign a score as a result of diverse procedures. Most preferred MCDM models in literature include the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) and the Analytic Hierarch Process (AHP). Hybrid techniques for selecting processes often are composed of a combination of AHP–TOPSIS, and other MCDM methods such as Multicriteria Optimization and Compromise Solution (VIKOR) and Preference Ranking Organization Method for Enrichment Evaluation (PROMETHEE) (Caliskan, Kursuncu, Kurbanoglu, & Guven, 2013; Jahan, Mustapha, Ismail, Sapuan, & Bahraminasab, 2011; Jagadish & Ray, 2014; Liu, Mao, Zhang, & Li, 2013).

The TOPSIS method evaluates multiple alternatives against the selected criteria assuring the nearest distance from the positive ideal solution and farthest from the negative ideal solution. Design, Engineering and Manufacturing Systems issue is a broad area in the TOPSIS publications (Behzadzian, Oraghara, Yazdani, & Ignatiu, 2012). The AHP, consists of three main operations, including hierarchy construction, priority analysis, and consistency verification (Ho, 2008), and is based on the experience and knowledge of decision makers. In combination with other methodologies, TOPSIS has been used for the selection of manufacturing technologies (Tansel, 2012), in particular for the selection of NTM processes based on hybridized methods of TOPSIS and AHP (Choudhury et al., 2013; Das & Chakraborty, 2011). For addressing the problems that are marked by different conflicting interests, several Fuzzy Multiple Criteria Decision-Making (FMCDM) methods have been proposed. FMCDM approaches improve the quality of decisions by creating the development more efficient, rational and explicit (Mardani et al., 2015). FMCDM methods have addressed machine tool selection (Aya & zdemir, 2011; Önüt, Soner Kara, & Efendigil, 2008; Samvedi, Jain, & Chan, 2012). NTM process selection (Roy, Ray, & Pradhan, 2014), and other process engineering decision-making problems that involve multiple options and criteria (Tan, Aviso, Huelgas, & Promentilla, 2014).

A major limitation of MCDM tools is that they do not retain and reuse knowledge, and managers are unable to make effective use of knowledge and experience of previously completed projects to help with the prioritization of future cases (Tan, Lim, Platts, & Koay, 2006). In order to solve complex problems, in the last three decades knowledge-based systems (KBS) have been playing an important role in new decision support tools by emulating the reasoning processes of human experts. KBS are composed of two main components: a knowledge base (facts and rules about the expertise domain) and an inference engine (reasoning).

Besides being used in various decision making problems, KBS have also been implemented for process selection. In Sanchez and Nagi (2001) a review of agile manufacturing systems including KBS is presented. A “Machining Expert” was developed in Chakraborti, Mitra, and Bhattacharyya (2007) for handling non-traditional machining data. Parameters of processes were conglomerated and presented in a normalized fashion. The normalization of the available data was dealt with management information system and presented in the form of a software. Edison, Jehadeesam, and Raajenthiren (2008) developed a web-based knowledge base system for identifying the most appropriate NTM process. Input parameter requirements such as material type, shape applications, process economy and some of the process capabilities are introduced to the system. The selection is made by restricting the choice of certain NTM processes based on linguistic variables such as “good,” “fair” and “poor”. The development of an expert system for abrasive water jet machining (AWJM) process is presented in Vundavilli, Parappagoudar, Kodali, and Benguluri (2012). The system was developed by using fuzzy logic (FL) and a knowledge base. Three approaches were considered to predict the depth of cut in AWJM. The first approach deals with the construction of Mamdani-based fuzzy logic system. In approach 2, the data base and rule base of the FL-system are optimized, whereas in the third approach, the total FL-system is evolved automatically.

Most of the proposed KBS and MCDM methods are knowledge-intensive and require input parameters that may exceed the capabilities of non-expert users. Due to the complexity of the methods for the selection process, either by means of a MCDM, KBS or by prior knowledge on each process, there exists the need of an user-friendly tool that can emulate the behavior that an expert would have when selecting a non-traditional cutting process (eliminating the subjective judgments and keeping the experience and knowledge), a tool capable of identifying the attributes and get the most appropriate combination of attributes in conjunction with the actual requirements of the machining application.

A possible solution for designing complex systems, in which it is required to incorporate the experience of an expert or the related concepts appear uncertain, is the use of soft computing techniques such as fuzzy systems. An important advantage of fuzzy systems is their ability for handling vague information. The flexibility provided by fuzzy set theory for knowledge representation makes fuzzy rule-based systems very attractive when compared with traditional rule-based systems (Montseny & Sobrevilla, 2001).

In order to facilitate the decision-making of non-traditional sheet metal cutting processes, in this work we present an expert system based on fuzzy logic techniques. The model is generated from a knowledge base acquired from diverse experts. With a simple input of the parameters of a piece, the system offers the most appropriate cutting options allowing a non-expert user selecting the most appropriate process (quantitatively accurate) with emphasis on a predefined priority: finish, cost or time. The results of different experiments show that the presented system for the selection and comparison of sheet metal cutting processes, meets the requirements for its use in the selection of non-traditional cutting processes.

This work is divided into five sections. First, Section 2 presents an overview of the model. Then, Section 3, describes the base algorithms that extract and measure the attributes of each process. Section 4 presents the selection process mainly focusing on time, finish and cost. Finally results and conclusions are shown in Sections 5 and 6 respectively.

2. Selection model overview

During the final stages of design, the geometry of the piece is essentially fixed, and the material has been specifically selected, so the problem is mainly the cutting process to be used. When a new task is considered, the designer begins to question about related factors to the task he wants to answer. For example: What processes can cut a 10 mm thick steel sheet? or How fast can these sheets be cut? The first question leads to the need of information about the capability of thickness and material that the processes can cut. The second one will require more information about parameters that influence the cutting speed of the possible processes. In the context of task-based selection, this information is called attributes. This term refers broadly to the process, material and design characteristics that in some way must be combined to provide necessary information to evaluate whether the requirements can be met (Shercliff & Lovatt, 2001).

The proposed system combines the attributes of the process, the material and design to meet a particular criterion (priority), producing a set of selection results. There are essentially two alternative ways in which these selection results can be used, either for detection, where the choices are discarded if they cannot meet the requirements of the piece, or for ranking, where a quantitative measure allows ranking the cutting options. From simple input requirements of a piece: material, thickness and geometry (angles and perforations), the system offers a list of the most suitable
processes, based on the finish priority $F$, cost $C$, time $T$ or process (which evaluates the priorities $F$, $C$ and $T$ for each process). Each process $i$ has a $F_i$, $C_i$ and $T_i$ value in the $[0, 1]$ interval, being the one closest to 1 the most appropriate process. If a process does not meet the requirements of the piece, the system does not eliminate it, but it is assigned a value of 0 in $F_i$, $C_i$ and $T_i$ instead.

3. Base algorithms for measuring attributes

Before choosing a cutting process based on predetermined criteria, either cost, finish, time or the process itself, it is necessary to measure the attributes of each process, that is, a pre-selection that considers the following: (1) the process capability to cut a material-thickness relation, (2) the speed that can be achieved with this relation, (3) the inherent complexity of the piece to be cut, and (4) the process tolerance.

Base algorithms allow this pre-selection, assigning a capability, speed, complexity and tolerance value to each process, according to the piece characteristics. Each base algorithm will give as a result a value in the $[0, 1]$ interval as a dependent indicator of the other processes. The following sections describe each base algorithm.

3.1. Capability algorithm

The piece thickness often requires or restricts the use of a particular process. For example if a 2 mm thick iron sheet needs to be cut, oxifuel cutting would not be acceptable if a minimum quality cut is needed, since the heat input that this process transfers to the sheet produces significant deformations, creates mechanical stress and therefore the loss of uniformity. This piece would be perfectly cut with laser or plasma, but how ideal the laser (plasma) would be? The capability algorithm is designed to be an initial filter of process elimination. Considering that not all processes can cut all materials and not all processes can cut all thicknesses, the algorithm shows the capability that a process $i$ has to cut a material $m$ with a thickness $t$. For most machine tools the materials and thicknesses that these can cut are previously defined by specification charts from the manufacturers or experts in their use, in which the process capability is fixed by means of a $m-t$ relation. On this premise, it is possible to define a fuzzy set representing the $m-t$ relation for each process.

A fuzzy set $A$ is defined as a linking or matching membership function for the elements of a domain or universe of discourse $U$ with elements in the $[0, 1]$ interval ($A: X \in [0, 1]$), the closer $A(u)$ is to 1 the higher would be the membership of object $u$ to set $A$. Membership functions indicate the degree that each given known universe element belongs to this set. For example, if there is a piece of a material $m$ with a thickness $t$, each cutting process will have a membership degree to the capability fuzzy set $P_m$. The closer $P_m(t)$ is to 1, the greater the cutting capability.

In the capability algorithm, a trapezoidal membership function is assigned to each $i$th $1, 2, 3, \ldots, n$ cutting process (Fig. 1), defining the four parameters $a$, $b$, $c$ and $d$ of the trapezium as follows:

$$
\mu_{\text{Trapezoidal}}(a, b, c, d) = \left\{ \begin{array}{ll}
\frac{a-x}{a-b} & \text{if } a < x < b \\
1 & \text{if } b \leq x \leq c \\
\frac{d-x}{d-c} & \text{if } c < x < d \\
0 & \text{otherwise}
\end{array} \right.
$$

The boundaries between sets may overlap, that is, given a piece with a $m-t$ relation, it is possible that one or more processes are capable of cutting the work piece with the same, lower or higher capability one process from another. The main advantage of using fuzzy sets will be the removal of a membership threshold (e.g. a specific value to be achieved or exceeded, for the process in question can be labeled as “capable”). If the thickness threshold of a process is 20 mm, all pieces measuring 20 mm or more can not be cut with this process. Under this criterion, a piece measuring 100 mm shall also be withheld to another measuring 21 mm, since both have earned the label “incapable”. However, with fuzzy sets the transitions are smoother, allowing to reproduce the reality more faithfully.

Table 1 shows the values of parameters $a$, $b$, $c$ and $d$ for various processes and materials. For example, if an 80 mm thick aluminum piece needs to be cut, it can be observed in Table 1, that laser cutting is not able to cut the piece, since the maximum thickness the process can cut is 12 mm, plasma may cut it with difficulty since 80 mm is its maximum thickness. The most appropriate would be waterjet cutting because 80 mm is far from 140 mm, thickness in which this process begins to lose its cutting capability. Oxifuel cutting can not cut aluminum, due to this parameters $a$, $b$, $c$ and $d$ are set to zero. In summary, the capability algorithm returns $P_m(t) \in [0, 1]$ as the capability that a process $i$ has to cut a material $m$ with a thickness $t$, and is denoted by the following pseudo-code:

```
Begin Capability (input variables: m, t)
  Retrieve parameters a, b, c and d for all processes of material m
  Evaluate membership degree P_m(t) for each process i
Return P_m(t) for each process i
End
```

3.2. Speed algorithm

Cutting speed is a value related to the material to be machined and its thickness. An important factor that can influence in the production volume and the cutting quality is the cutting speed. A very low speed will cause loss of time; a very high speed may result in
loss of quality. The speed algorithm allows evaluating the process cutting speed in terms of the other processes for a given \( m - t \) relation. The reason is very simple, it cannot be said that the cutting speed of a process is fast or slow if it is not compared to the speed of other processes when cutting the same piece. It is necessary to normalize the speeds to do this comparison, that is, converting the data to a new definition interval as:

\[
y = \frac{(y_{\text{max}} - y_{\text{min}}) \cdot (x - x_{\text{min}})}{(x_{\text{max}} - x_{\text{min}}) + y_{\text{min}}}
\]

(2)

where: \( y \) is the result of normalization, \([y_{\text{min}}, y_{\text{max}}]\) is the normalization interval, \( x \) is the vector to be normalized, and \( x_{\text{min}} \) and \( x_{\text{max}} \) are the maximum and minimum values of \( x \). For the comparison, the normalization interval is \([0, 1]\) where 0 is the minimum speed and 1 the maximum, therefore \( x_{\text{min}} \) and \( x_{\text{max}} \) will be 0 and 1 in all cases. This way the normalization for interval \([0, 1]\) is:

\[
y = \frac{x}{x_{\text{max}}}
\]

(3)

The speed algorithm is denoted by the following pseudo-code:

**Algorithm** Speed (input variables: \( m, t \))

- Retrieve for each \( i \) the speeds \( s_{mi}(t) \)
- Normalize the speeds \( s_{mi}(t) \)
- Return \( s_{mi}(t) \) for each process \( i \)

EndAlgorithm

The speed algorithm returns \( s_{mi}(t) \in [0, 1] \) as a result of normalizing the cutting speed of a process \( i \) according to the cutting speed of the other processes for a \( m - t \) relation. The cutting speed is obtained from tables developed by metal working experts and the use of different tools. The data thickness is obtained in the same way. Nowadays most of the manufacturers have various cutting speed tables (in \( \text{mm} / \text{min} \) or \( \text{in} / \text{min} \)) already defined and published, where the material thickness and other characteristics are associated with the cutting speed. Some examples can be found in: Hypertherm (2007), KMT Waterjet Systems Inc. (2014), Powell and Kaplan (2004).

In order to retrieve the \( s_{mi}(t) \) for each process, it is necessary to define for each material all speeds within a defined thickness interval (for example from 0 to 200 mm) with increments of 1 mm. The speed values are taken from the manufacturers tables. An example of mild steel cutting speeds with different processes is shown in Table 2.

Intermediate speeds are obtained by interpolating the values using the linear interpolation equation:

\[
s_x = s_1 + \left( t_x - t_1 \right) \frac{s_2 - s_1}{t_2 - t_1}
\]

(4)

where \( s_x \) is the intermediate speed to be found for a given thickness \( t_x \). \( s_1 \) and \( s_2 \) are the known speeds before and after \( s_x \) for thicknesses \( t_1 \) and \( t_2 \) respectively.

### 3.3. Complexity algorithm

The geometry and complexity of a piece are intrinsically related to the optimal selection of cutting processes and parameters. For example, the cutting requirements for pieces with multiple edges, very acute or very sharp tips will not be equal to those with flanges or simple geometries to cut, since the requirements for the latter are minimal. An essential step in the selection process is to define the complexity of the piece. This algorithm defines the complexity of the piece based on the number of angles and perforations. An interview to 20 metal sheet cutting experts was performed. Basic multiple choice questions were presented in order to outline the main factors that define the complexity of a piece. Even when a small group agreed that the material has a prime role, the results showed that the complexity is essentially defined by the piece geometry, specifically the number of angles \( a \) and the number of perforations \( p \).

In order to define the complexity according to \( a \) and \( p \), it is necessary to separately define the complexity in terms of \( a \), then in terms of \( p \) and finally weighting these values. The complexity can be linguistically labeled as “Simple”, “Medium” or “Complex”; to do this, six fuzzy membership functions were defined representing the complexity of the piece in terms of \( a \) and \( p \); \( \mu_{aS}, \mu_{aM}, \mu_{aC} \) and \( \mu_{pS}, \mu_{pM}, \mu_{pC} \) are the membership functions for the sets that define a piece as “Simple”, “Medium” or “Complex” based on the number of angles. In the same way \( \mu_{C} \) and \( \mu_{pC} \) are the membership functions that represent the complexity based on the number of perforations. This way, the complexity is defined from the aggregation of \( \mu_{aS}, \mu_{aM} \) and \( \mu_{aC} \) functions, as:

\[
\chi = \mu_{aS}(W_a) + \mu_{aM}(W_a) + \mu_{aC}(W_a)
\]

(5)

where \( \chi \) could be \( S \), \( M \) or \( C \); \( W_a \) and \( W_p \) are the weights for \( \mu_{aS}, \mu_{aM} \) and \( \mu_{aC} \) respectively. Heuristically the best results were obtained with the combination of \( W_a = 0.4 \) and \( W_p = 0.6 \), because any perforation involves a higher complexity than those without perforations. The complexity membership functions are trapezoidal, \( a \), \( b \), \( c \) and \( d \) values were defined according to the study results (Table 3).

The total complexity of the piece as a quantitative value between 0 and 1 (not only as a linguistic variable) can be defined as follows: if the piece was defined as “Simple” (\( S > M \) and \( S > C \)) then the total complexity \( c_t \) is given by \( c_t = \frac{1}{2} S \). If the piece is found to be “Medium” or “Complex”, the total complexity is defined by \( c_t = \frac{1}{2} + (\frac{1}{2} M) \) and \( c_t = \frac{1}{2} + (\frac{1}{2} C) \) respectively. In summary, the complexity is evaluated by the following algorithm:

**Algorithm** Complexity (input: \( a, p \))

- Evaluate \( \mu_{aS}, \mu_{aM}, \mu_{aC}, \mu_{pS}, \mu_{pM}, \mu_{pC} \)
- Calculate complexity \( S, M \) and \( C \)
- Find the max between \( S, M \) and \( C \)
  - If \( \text{max} = S \)
    - \( c_t = \frac{1}{2} S \)
  - If \( \text{max} = M \)
    - \( c_t = \frac{1}{2} + (\frac{1}{2} M) \)
  - Else
    - \( c_t = \frac{1}{2} + (\frac{1}{2} C) \)
- Return \( c_t \)

EndAlgorithm
3.4. Tolerance algorithm

The cutting tolerance is highly associated to the geometry of the piece; a proper cutting tolerance will bring certain benefits: among others, more uniform holes and cleaner cuts, flatter parts with less deformations, higher precision, and not only affects the quality of the pieces but also the life of the tools. The tolerance algorithm, depending on the piece complexity, specifies the tolerance of a process in terms of the tolerance of the other processes. Considering that each cutting process is defined with a minimum tolerance \( t_{\text{min}} \) and a maximum tolerance \( t_{\text{max}} \), this algorithm evaluates for each process \( i \) the tolerance-complexity relation. First normalizes the tolerance between the different processes and then evaluates the tolerance-complexity relation. Columns 2 and 3 of Table 4 show \( t_{\text{min}} \) and \( t_{\text{max}} \) tolerances of four processes and in columns 4 and 5 their corresponding normalized tolerances \( n_{t_{\text{min}}} \) and \( n_{t_{\text{max}}} \).

Once having \( n_{t_{\text{min}}} \) and \( n_{t_{\text{max}}} \), the tolerance-complexity relation \( X_1 \) of a process \( i \) is now given by:

\[
X_1 = 1 - \left( \left[ (n_{t_{\text{max}}} - n_{t_{\text{min}}}) \times c_i \right] + n_{t_{\text{min}}} \right)
\]

(6)

In summary, the tolerance algorithm is defined with the following pseudo-code:

```
Algorithm Tolerance (input variables: \( c_i \))
Retrieve tolerances \( t_{\text{min}} \) and \( t_{\text{max}} \)
Normalize obtaining \( n_{t_{\text{min}}} \) and \( n_{t_{\text{max}}} \)
Evaluate
\[
X_i = 1 - \left( \left[ (n_{t_{\text{max}}} - n_{t_{\text{min}}}) \times c_i \right] + n_{t_{\text{min}}} \right)
\]
Return \( X_i \)
EndAlgorithm
```

4. A predefined priority for process selection

In the initial stages of this research interviews were conducted to various experts in the area of non-traditional cutting processes. They all agreed that for the selection it is necessary to consider a predefined priority: finish, time or cost. This section details the selection based on a predefined priority by combining the base algorithms for measuring attributes.

4.1. Priority: time

There are many scenarios in which the delivery time of one or several pieces is crucial, even if it means the sacrifice of the finish or cost. For example, may be the case when it is necessary to replace a piece that has failed and is more likely to produce it than to wait a couple of weeks to get the piece replacement (e.g. from another country). The cutting time is inseparably related to the cutting speed, and the cutting speed is related to the material and its thickness. The selection with time as a priority is given by the following equation:

\[
T_i = S_m(t)(W_s) + P_m(t)(W_p)
\]

(7)

where \( W_s \) and \( W_p \) are the weights for the speed and capacity attributes respectively. Heuristically best results are obtained when the weight combination is distributed in \( W_s = 0.6 \) and \( W_p = 0.4 \) because there may be two or more processes with the same \( m - t \) cutting capacity, but these processes will have different cutting speeds which will make the difference in the cutting time.

4.2. Priority: finish

The finish is given by the requirements of the piece (material, thickness and complexity) and the attributes of the process (the cutting capability based on \( m - t \) and the cutting tolerances). This priority will indicate if a process will provide better \( (F_i - 1) \) or less \( (F_i - 0) \) cutting quality based on its tolerance and capability:

\[
F_i = X_i \times P_m(t)
\]

(8)

4.3. Priority: cost

Under a user–client relationship, the cost is reduced to a simple comparison between the cutting time and the operating costs per hour \( H_c \). For example the operating costs per hour based on consumables, abrasive, electricity, water, gas, and spares are: Plasma $44.65, Oxifuel $33.80 (Hypertherm, 2014), Waterjet $23.47 (Wardjet, 2014). This priority is given by:

\[
C_i = \begin{cases} 
1; & T_i = 1 \\
1 - [(1 - T_i) \times H_c]; & 0 > T_i > 1 
\end{cases}
\]

(9)

Table 4

<table>
<thead>
<tr>
<th>Process</th>
<th>( t_{\text{min}} )</th>
<th>( t_{\text{max}} )</th>
<th>( m_{t_{\text{min}}} )</th>
<th>( m_{t_{\text{max}}} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Waterjet</td>
<td>0.0254</td>
<td>0.127</td>
<td>0.0254/3.175 = 0.08</td>
<td>0.127/3.175 = 0.04</td>
</tr>
<tr>
<td>Laser</td>
<td>0.0762</td>
<td>0.3809</td>
<td>0.0762/3.175 = 0.024</td>
<td>0.3809/3.175 = 0.1199</td>
</tr>
<tr>
<td>Plasma</td>
<td>0.254</td>
<td>0.3809</td>
<td>0.254/3.175 = 0.08</td>
<td>0.3809/3.175 = 0.1199</td>
</tr>
<tr>
<td>Oxifuel</td>
<td>1.5875</td>
<td>3.175</td>
<td>1.5875/3.175 = 0.5</td>
<td>3.175/3.175 = 1</td>
</tr>
</tbody>
</table>

Table 5

<table>
<thead>
<tr>
<th>Piece Mat</th>
<th>( t_{\text{min}} )</th>
<th>( t_{\text{max}} )</th>
<th>( Q )</th>
<th>Time min</th>
<th>Exp</th>
<th>System</th>
</tr>
</thead>
<tbody>
<tr>
<td>SS</td>
<td>15</td>
<td>High</td>
<td>6:31</td>
<td>WJ</td>
<td>WJ 0.97</td>
<td>P1 0.89</td>
</tr>
<tr>
<td>MS 51</td>
<td>3:10</td>
<td>P1</td>
<td>P1</td>
<td>0.63</td>
<td>Ox 0.98</td>
<td></td>
</tr>
<tr>
<td>Al 30</td>
<td>47:15</td>
<td>WJ</td>
<td>WJ 0.91</td>
<td>Ox 0.98</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Al 2</td>
<td>0.23</td>
<td>Ls</td>
<td>Ls 0.93</td>
<td>P1 0.91</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Steel 60</td>
<td>77:00</td>
<td>WJ</td>
<td>WJ 0.91</td>
<td>P1 0.70</td>
<td></td>
<td></td>
</tr>
<tr>
<td>SS 2</td>
<td>0.43</td>
<td>PI</td>
<td>PI</td>
<td>0.91</td>
<td>Ox 0.98</td>
<td></td>
</tr>
<tr>
<td>Al 6</td>
<td>3:16</td>
<td>WJ</td>
<td>WJ 0.91</td>
<td>Ls 0.96</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Al 12</td>
<td>1:35</td>
<td>Ls</td>
<td>Ls 0.97</td>
<td>Ls 0.97</td>
<td></td>
<td></td>
</tr>
<tr>
<td>MS 100</td>
<td>3:15</td>
<td>Ox</td>
<td>Ox 0.97</td>
<td>P1 0.91</td>
<td></td>
<td></td>
</tr>
<tr>
<td>MS 19</td>
<td>2:05</td>
<td>Ls</td>
<td>Ls 0.97</td>
<td>WJ 0.99</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 4 Maximum and minimum tolerances for diverse processes (tolerances in mm).
where $H_i$ must be normalized using Eq. (3). In cases where more than one $T_i = 1$ exists, the system prioritizes the process with lower $H_i$.

4.4. Priority: process

Once given the requirements of the piece, this priority will release a value in $T_i$, $F_i$, and $C_i$ for each process, including specific information as basic components, principles of operation, cutting speeds, general considerations, advantages and disadvantages, among others.

5. Experiments and results

The software “Metal Cutting Process Selector V1.1©” or MCPS was developed to evaluate the performance and accuracy of the proposed system. The aim was to show that the selection made by diverse experts and by the system is quantitatively comparable, demonstrating the potential of this system as a basic tool for decision making in the selection of non-traditional cutting processes. Pieces of aluminum, steel, titanium and stainless steel were used, for they are the most common materials in cutting applications. The pieces were selected from real examples, pieces that have been previously analyzed by experts and manufactured with a non-traditional cutting process: laser, plasma, oxifuel or waterjet cutting.

Each of the pieces has a quality and cutting time, diverse dimensions and degrees of complexity, thicknesses ranging from 2 to 100 mm in some cases. The experiments were carried out considering three different approaches discussed below.

5.1. Expert vs system: finished parts

Manufactured metal parts were chosen according to the experience and knowledge of various experts (see Table 5), the purpose is to confirm that the system selects as the expert the most appropriate cutting process. The user inputs the parameters and a priority for the design (Fig. 2 top). The result is displayed both numerically and graphically, the selected priority is shown in the top (Fig. 2 bottom).

Experiments on pieces 1, 3–5, and 7 were conducted under the priority of finish (the required quality was high), in all cases the results indicate that both, the system and the expert chose the same cutting process; waterjet or plasma cutting.

In the results of piece 2, the system (as the expert) indicates that the best option is plasma cutting ($T_{pl} = 1$) under the priority of time (the required quality was medium) and oxifuel as a second option ($T_{pl} = 0.63$).

Contrary to the choice made by the expert, the results of piece 6 indicate that laser cutting ($T_{la} = 1$) provides a better solution for this particular piece under the priority of time (the required quality was low); while the plasma cutting is also a good choice ($T_{pl} = 0.7$). Laser cutting provides the advantage of using less energy and being more precise than plasma when cutting thinner section metals, is generally more precise and accurate than plasma cutting whilst also being faster and providing better quality cuts on thinner metals up to 10 mm thickness (Farley LaserLab, 2014). This was evidenced in the results of piece 8 (aluminum 12 mm thick) the piece was cut with laser, however as it can be seen in the figure the cutting quality is very low. The system indicates that the best option is plasma cutting ($T_{pl} = 1$ and $C_{pl} = 0.38$) under the priority of time and cost, then waterjet cutting ($T_{wj} = 0.51$ and $C_{wj} = 0.32$), and laser as last option ($T_{la} = 0.18$ and $C_{la} = 0.00$). Laser is less suitable for cutting aluminum as this is a reflective metal and causes potentially harmful back reflection on the machine.

Table 6

<table>
<thead>
<tr>
<th>Piece</th>
<th>Material</th>
<th>Thickness</th>
<th>Angles</th>
<th>Perforations</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Mild steel</td>
<td>12 mm</td>
<td>6</td>
<td>2</td>
</tr>
<tr>
<td>2</td>
<td>Mild steel</td>
<td>25 mm</td>
<td>6</td>
<td>2</td>
</tr>
<tr>
<td>3</td>
<td>Mild steel</td>
<td>16 mm</td>
<td>4</td>
<td>7</td>
</tr>
</tbody>
</table>
The Metal Cutting Process Selector is an instrument that eases the decision making for selecting non-traditional cutting processes, it reduces human error by providing accurate quantitative results. Although in this work only four cutting processes were considered, future research will focus on expanding the range of NTM processes and the use of various platforms such as web-based and mobile applications. The MCPS system could also consider the selection history as part of the selection process when similar input parameters are identified.

6. Conclusions

A key factor for the optimization of the entire production process is the selection of the ideal NTM process, because it allows faster time to manufacturing and product delivery, reduces costs, material waste and avoids secondary operations for lack of quality. Selecting an optimal NTM process is a difficult task due to the presence of numerous criteria and sub-criteria that reduce the alternative processes. The Metal Cutting Process Selector is an instrument that eases the decision making for selecting non-traditional cutting processes, it reduces human error by providing accurate quantitative results.

The main contribution of MCPS compared to other expert systems is that the system requires a minimum amount of input parameters and that these requirements allow a non-expert user in NTM processes to use the system. According to the information provided by the user (the requirements of the piece), the system orderly offers the most appropriate cutting options with emphasis on a predefined criterion: finish, cost or time. Several experiments were conducted using pieces from real examples that were previously analyzed by experts and manufactured with a non-traditional cutting process.

The three different approaches: expert vs system on finished parts, process vs process, and experts vs system for cutting options, proved that the MSCP system, using diverse techniques including fuzzy logic, is able to accurately prioritize the most convenient cutting processes; in 92% of the analyzed cases the system coincided with the first option of the expert, and those which did not coincide, the selection provided by the system was supported according to the requirements and the given priority. Furthermore, the MCPS can also be used as an educational tool to train inexperienced or novice designers.

Although in this work only four cutting processes were considered, future research will focus on expanding the range of NTM processes and the use of various platforms such as web-based and mobile applications. The MCPS system could also consider the selection history as part of the selection process when similar input parameters are identified.

References


