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Risk Prioritization in the Laser Cutting Process Using the FMEA Method Compared to the TOPSIS Method

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Abstract
In the car manufacturing industry, the laser cutting process is frequently used. For this reason, establishing risks and preventing them is a permanent concern of quality management and more. To prioritize these risks, a series of models and methods established by research in the field are applied. Two case studies are presented in the paper, in order to evaluate and rank the failure modes that could occur in the laser cutting process. In the first, the classic FMEA method is used, and in the second the TOPSIS method. Failure mode and effect analysis (FMEA) is one of the well-known quality management techniques that is used for continuous improvement in product or process design. The approach proposed by the method is simple, but there are some limitations in obtaining a good estimate of failure rates. Thus, a new risk assessment system based on the TOPSIS theory is necessary, at the end of the paper comparing the results obtained by the two methods. This work can also serve as a failure prevention guide those who perform the laser cutting operation.

Keywords
risk prioritization, FMEA method, TOPSIS method, laser cutting process

1. Introduction

The struggle to gain new markets and maintain position in an existing market forces companies to produce goods or services at the best value for money. In this context, the implementation of production processes with high productivity and efficiency is of particular importance. Within the existing production processes, obtaining a high quality of the manufactured products, as well as the reduction of scraps, requires the early establishment of potential associated risks and their prioritization so that appropriate measures can be taken in a timely manner.

In the automotive industry, the laser cutting process occupies a special place, along with welding, machining, etc.

2. Description of the FMEA Method

One of the most important preventive methods is Failure Mode and Effects Analysis (FMEA). FMEA is a systematic method of identifying and preventing product and process problems before they occur. FMEAs are focused on preventing defects, enhancing safety, and increasing customer satisfaction. [1, 2]. The traditional FMEA determines the risk priority of each failure modes using the risk priority numbers (RPN), which can be obtained as a product of three risk factors namely Severity (S), Occurrence (O) and Detection (D). The RPN value for each failure mode is ranked to find out the failures with higher risks [3].

Unfortunately, the crisp RPN method shows some important weaknesses when FMEA is applied in the real-world cases. Therefore, a number of approaches have been suggested in the literature to enhance the FMEA methodology, such as technique for ordering preference by similarity to ideal solution (TOPSIS) [4], analytic hierarchy process (AHP) [5], grey theory [6], data envelopment analysis (DEA) [7], decision making trial and evaluation laboratory (DEMATEL) [8], evidential reasoning approach [9] and so forth, like Genetic Algorithms (GA). GA can be used to search for solutions difficult to obtain by other conventional methods, in different areas. They can be run on computer or can be accelerated on parallel hardware structures [10]. Furthermore, it is usually difficult and inaccurate to give a direct and correct numerical evaluation of the risk factors, such as occurrence (O), severity (S), and detection (D), in FMEA [4]. Much information in FMEA can be expressed in a linguistic way such as likely, important or very high and so on [11].

3. Description of the TOPSIS Method

The TOPSIS is one of the multi-criteria decision-making methods which was introduced by Yoon and Hwang [12]. The shortest distance is called the positive ideal solution, and the farthest distance is called the negative ideal solution. The comparative proximity of positive and negative ideal solutions is calculated using the Euclidean distance. Afsordegan et al. [13] defined the selection of sustainable energy using a standard TOPSIS method in uncertain situations.

An assumption of TOPSIS is that the criteria are monotonically increasing or decreasing. Normalization is usually required as the parameters or criteria are often of incongruous dimensions in multi-criteria problems [14, 15]. Compensatory methods such as TOPSIS allow trade-offs between criteria, where a poor result in one criterion can be negated by a good result in another criterion. This provides a more realistic form of modelling than non-compensatory methods, which include or exclude alternative solutions based on hard cut-offs [16]. It is a method of compensatory aggregation that compares a set of alternatives, normalizing scores for each criterion and calculating the geometric distance between each alternative and the ideal alternative, which is the best score in each criterion.

Step 1

Create an evaluation matrix consisting of m alternatives and n criteria, with the intersection of each alternative and criteria given as x_{ij}, we therefore have a matrix $\left(x_{ij}\right)_{m\times n}$.

Step 2

The matrix $\left(x_{ij}\right)_{m\times n}$ is then normalized to form the matrix R=$\left(r_{ij}\right)_{m\times n}$, using the normalisation method

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{k=1}^{n} x_{kj}^2}}, \quad i = 1,2,\ldots m \quad \text{and} \quad j = 1,2,\ldots n \tag{1}$$

Step 3

Calculate the weighted normalized decision matrix

$$t_{ij} = r_{ij} \times w_j, \quad i = 1,2,\ldots m \quad \text{and} \quad j = 1,2,\ldots n, \tag{2}$$

where

$$w_j = \frac{W_j}{\sum_{k=1}^{n} W_k}, \quad j = 1,2,\ldots n \tag{3}$$

so that $\sum_{i=1}^{n} w_i$=1 and W_j is the importance coefficient for each criterion.

Step 4

Determine the worst alternative (A_w) and the best alternative (A_b):

$$A_w = \{(\max(t_{ij} \mid i=1,2,\ldots,n) \mid j \in J_-), (\min(t_{ij} \mid i=1,2,\ldots,n) \mid j \in J_+)\} \approx \{t_{wj}, j=1,2,\ldots,n\}, \tag{4}$$

$$A_b = \{(\min(t_{ij} \mid i=1,2,\ldots,n) \mid j \in J_-), (\max(t_{ij} \mid i=1,2,\ldots,n) \mid j \in J_+)\} \approx \{t_{bj}, j=1,2,\ldots,n\}, \tag{5}$$

where

J_+ = {j=1,2,…,n | j} associated with the criteria having a positive impact, and

J_- = {j=1,2,…,n | j} associated with the criteria having a negative impact.

Step 5

Calculate the distance between the target alternative i and the worst condition A_w

$$d_{iw} = \sqrt{\sum_{j=1}^{n}\left(t_{ij} - t_{wj}\right)^2}, \quad i = 1,2,\ldots m \tag{6}$$

and the distance between the target alternative i and the best condition A_b

$$d_{ib} = \sqrt{\sum_{j=1}^{n}\left(t_{ij} - t_{bj}\right)^2}, \quad i = 1,2,\ldots m \tag{7}$$

where d_{iw} and d_{ib} are distances from the target alternative *i* to the worst and best condition, respectively.

Step 6

Calculate the similarity to the worst condition

$$S_{iw} = d_{iw} / (d_{iw}+ d_{ib}), \quad 0 \leq S_{iw} \leq 1, \quad i = 1,2,\ldots m \quad (8)$$

$S_{iw} = 1$, if and only if the alternative solution hast the best condition, and
$S_{iw} = 0$, if and only if the alternative solution hast the worst condition.

Step 7

Rank the alternatives according to $s_{iw}(i =1,2,\ldots m)$.

4. Establishing the Critical Failure Variant. Case Study for Laser Cutting Process

4.1. Laser cutting process

Laser cutting is mainly a thermal process in which a focused laser beam is used to melt material in a localized area. A co-axial gas jet is used to eject the molten material and create a kerf. A continuous cut is produced by moving the laser beam or work-piece under CNC control.

Laser cutting is a thermal based non-contact process capable of cutting complex contour on materials with high degree of precision and accuracy. It involves process of heating, melting and evaporation of material in a small well defined area and capable of cutting almost all materials. Ranganathan & Viswanathan [17] stated that the demand for laser cutting process is increasing in the production industries like aerospace, automobile, ship building and nuclear industries because of the ability of laser to cut materials with attractive processing speed, high productivity and ability to cut materials with complex shapes.

Madić et al. [18] stated that laser cutting is a thermal, non-contact and highly automated process well suited for various manufacturing industries to produce components in large numbers with high dimensional accuracy and surface finish. They also stated that high power density beam when focused in a spot melts and evaporates material in a fraction of second and the evaporated molten material is removed by a coaxial jet of assist gas from the affected zone as shown in Figures 1 and 2.

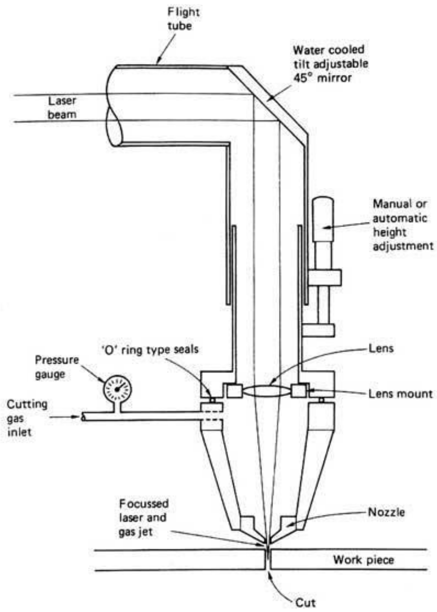

Fig. 1. Diagram of a laser cutter [19]

Fig. 2. Lasser cutting process [20]

Laser cutting process has always been a major research area for getting the exceptionally good quality of cut like reduced surface roughness, kerfs width and heat affected zone (HAZ). The quality of cut solely depends on the setting of process parameters like cutting speed, focal point, laser power, assist gas pressure etc.

4.2. Classical FMEA application

In the first part of the study a classical application of Process FMEA has been realized for laser cutting process. Laser cutting is a precise method of cutting a design from a given material using a CAD file to guide it. For this process the FMEA team identified 15 failures modes with different potential causes [21]. Risk Priority Numbers (RPNs) of the failure modes are calculated. The evaluation of the failure modes is carried out by scoring the respective risk factors of occurrence, severity, and not detection. For this purpose, usually 10-level scales are being used. The failure mode with higher RPNs are assumed to be more important and will be given higher priorities for correction. It is presented the failure with highest RPN values (72, 75, 80, 84, 96 and 120). Some of the data can be seen in Table 1. Not all 15 items are given in this table.

Table 1. Conventional FMEA for laser cutting process

Failure mode	**Failure effect (s)**	**Cause (s)**	**S**	**O**	**D**	**RPN**
FM1. The cutting part remained welded to the part	Unable to assemble to chain customer	C1. State of sheet surface unsuitable (oxidized carbon coated, ...)	7	4	2	56
	Unable to assemble to chain customer	C2. Set up of machine incorrect	7	2	2	28
FM2. Tolerance on hole diameter not respected/ taper too much	Unable to assemble to chain customer	C3. Set up of machine incorrect	7	2	3	42
FM3. Geometry of cutting non-compliant (nonconforming outline, contour discontinuity, ...)	Unable to assemble to chain customer	C4. Displacement of the sheet during fast movements between cuts	8	1	4	32
FM4. Slot / crater / “flash” at the start of cutting	Unacceptable part for the customer	C5. State of sheet surface unsuitable	8	3	3	**72**
		C6. Slip of the part before the end of the cutting	8	4	3	**96**
		C7. The cutting part previously is slipping during the movement of the machine and pass under the beam	8	3	4	**96**
		C8. Set up of machine (by operator) is incorrect	8	5	2	**80**
FM5. Significant deformation of the part after cutting	Rejection of the part (the part had to be reworked)	C9. Piece with grand length cut in a sheet, which releases stresses after cutting	5	3	5	**75**
		C10. Square format sheet loaded in the wrong direction with respect to nesting (rolling direction)	5	1	10	50
FM6. Bad aspect of the cutting edge (burrs, scratches, ...)	Unacceptable piece for the customer	C11. Machine settings incorrect	8	3	5	**120**
		C12. Bad alignment of mirrors	7	4	1	28
		C13. Head touch a part already cut	7	4	3	**84**
		C14. Loss of beam power	7	3	1	21

FM7. Missing of a cutting	Unable to assemble on the chain customer	C15. File stored in the machine different from the original file	7	1	4	28
FM8. Thickness below to the tolerances	Endangering persons	C.16. Reference sheet is supplied nonconforming	8	2	3	48
FM10. Lack of marking	Identification impossible by client	C.18. Machine settings (by the operator) incorrect	4	2	3	24
FM11. Position of the marking on the part nonconforming	Client not satisfied	C.19. Incorrect programming	4	2	2	16
FM13. Size marking nonconforming (character height)	Non –readable marking	C.22 Incorrect machine settings (by the operator)	4	3	2	20
	Identification impossible by client	C.23 Loss of beam power	3	2	3	18
FM14. The material (sheet) is bitten	Unacceptable piece for the customer	C.24 The sheet rested long time in stock and / or she took moisture	8	2	5	**80**

4.3. Classical TOPSIS application

Step 1: The selection criteria considered are the risk factors:

C_1: severity (S);

C_2: occurrence (O);

C_3: detection (D).

Decision variants V_i are the 21 potential faults (C_1-C_{16}, C_{18}, C_{19}, C_{22}-C_{24}) that can occur on the laser cutting process.

The consequences of the variants depending on the established criteria are presented in Table 2 and are the scores given by the specialists for calculating the RPN (Table 1). To determine the coefficients of importance W_j, a team of three specialists was formed: the process manager, the quality manager, the operator. They awarded, for each consequence, a grade from 0-1 so: W_1= 0.5, W_2= 0.3, and W_3= 0.2.

Table 2. The consequences of the variants for each criterion

	C_1(S)	C_2(O)	C_3(D)
V_1 (C_1)	7	4	2
V_2 (C_2)	7	2	2
V_3 (C_3)	7	2	3
V_4 (C_4)	8	1	4
V_5 (C_5)	8	3	3
V_6 (C_6)	8	4	3
V_7 (C_7)	8	3	4
V_8 (C_8)	8	5	2
V_9 (C_9)	5	3	5
V_{10} (C_{10})	5	1	10
V_{11} (C_{11})	8	3	5
V_{12} (C_{12})	7	4	1
V_{13} (C_{13})	7	4	3
V_{14} (C_{14})	7	3	1
V_{15} (C_{15})	7	1	4
V_{16} (C_{16})	8	2	3
V_{17} (C_{18})	4	2	3
V_{18} (C_{19})	4	2	2
V_{19} (C_{22})	4	3	2
V_{20} (C_{23})	3	2	3
V_{21}(C_{24})	8	2	5

Step 2: Determination of the normalized matrix

In this stage, the consequences of the variants for each criterion are calculated using the normalization method and the relation (1). The results are presented in the normalized matrix, Table 3.

Table 3. Normalized matrix (R)

	C_1	C_2	C_3
V_1	0.226	0.322	0.135
V_2	0.226	0.161	0.135
V_3	0.226	0.161	0.203
V_4	0.258	0.081	0.271
V_5	0.258	0.242	0.203
V_6	0.258	0.322	0.203
V_7	0.258	0.242	0.271
V_8	0.258	0.403	0.135
V_9	0.161	0.242	0.338
V_{10}	0.161	0.081	0.667
V_{11}	0.258	0.242	0.338

	C_1	C_2	C_3
V_{12}	0.226	0.322	0.068
V_{13}	0.226	0.322	0.203
V_{14}	0.226	0.242	0.068
V_{15}	0.226	0.081	0.271
V_{16}	0.258	0.161	0.203
V_{17}	0.129	0.161	0.203
V_{18}	0.129	0.161	0.135
V_{19}	0.129	0.242	0.135
V_{20}	0.097	0.161	0.203
V_{21}	0.258	0.161	0.338

Step 3: Determination the weighted normalized decision matrix

The relation (2) is used for the calculation, and the results are listed in Table 4.

Table 4. Weighted normalized decision matrix (T)

	C_1	C_2	C_3
V_1	0.113	0.097	0.027
V_2	0.113	0.048	0.027
V_3	0.113	0.048	0.041
V_4	0.129	0.024	0.054
V_5	0.129	0.073	0.041
V_6	0.129	0.097	0.041
V_7	0.129	0.073	0.054
V_8	0.129	0.121	0.027
V_9	0.081	0.073	0.068
V_{10}	0.081	0.024	0.135
V_{11}	0.129	0.073	0.068

	C_1	C_2	C_3
V_{12}	0.113	0.097	0.014
V_{13}	0.113	0.097	0.041
V_{14}	0.113	0.073	0.014
V_{15}	0.113	0.024	0.054
V_{16}	0.129	0.048	0.041
V_{17}	0.065	0.048	0.041
V_{18}	0.065	0.048	0.027
V_{19}	0.065	0.073	0.027
V_{20}	0.049	0.048	0.041
V_{21}	0.129	0.048	0.068

Step 4: Determine the worst alternative (A_w) and the best alternative (A_b)

Relations (4) and (5) are used and it results:

A_w= (0.129; 0.121; 0.014)

A_b = (0.049; 0.024; 0.135)

Step 5: Calculate the distance between the target alternative *i* and the worst condition A_w, using relation (6) and the distance between the target alternative *i* and the best condition A_b, using relation (7). The results are presented in the Table 5.

Table 5. Distance for worst condition A_w and for best condition A_b

	V_1	V_2	V_3	V_4	V_5	V_6	V_7	V_8	V_9	V_{10}
d_w	0.032	0.076	0.079	0.105	0.055	0.036	0.062	0.013	0.087	0.162
d_b	0.145	0.128	0.116	0.114	0.133	0.143	0.124	0.166	0.089	0.032

V_{11}	V_{12}	V_{12}	V_{14}	V_{15}	V_{16}	V_{17}	V_{18}	V_{19}	V_{20}	V_{21}
0.072	0.029	0.039	0.051	0.106	0.078	0.101	0.098	0.081	0.112	0.091
0.115	0.155	0.135	0.145	0.103	0.126	0.098	0.112	0.120	0.097	0.107

Step 6: Calculate the similarity to the worst condition, using the relation (8). The results are presented in the Table 6.

Table 6. Similarity to the worst condition

	V_1	V_2	V_3	V_4	V_5	V_6	V_7	V_8	V_9	V_{10}
S_w	0.179	0.372	0.406	**0.479**	0.293	0.201	0.335	0.073	**0.494**	**0.835**

V_{11}	V_{12}	V_{13}	V_{14}	V_{15}	V_{16}	V_{17}	V_{18}	V_{19}	V_{20}	V_{21}
0.835	0.157	0.226	0.258	**0.507**	0.382	0.506	0.467	0.404	**0.535**	**0.459**

Step 7: Establishing the order of priority

It will be done in the descending order of the values obtained for the coefficient S_w. A graphic representation of the obtained results is in Figure 3. The highest values were obtained for variants V_{10}, V_{11}, followed by V_{20}, V_{15}, V_9, V_4 and V_{21}.

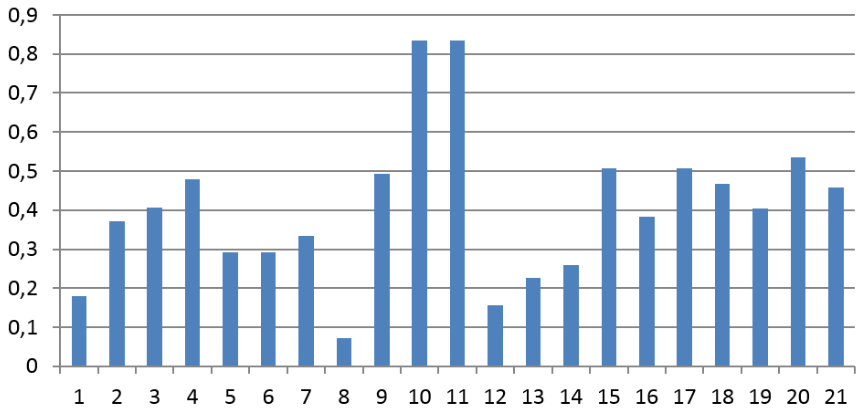

Fig. 3. A graphic of the obtained results

5. Conclusions

A comparative analysis of the obtained results (Table 7) leads us to the following conclusions:

- ✓ Both when applying the FMEA method, through the RPN calculation, and through the application of the TOPSIS method, through the S_w calculation, the variant with the highest priority order is V_{11}, machine settings incorrect, what it can produce unacceptable piece for customer. This presents the greatest risks in the laser cutting process;
- ✓ V_9 and V_{21} are also found in both approach methods on important places in the ranking;
- ✓ In order to obtain even more conclusive results, it is necessary to apply other methods. This constitutes a future research direction.

Table 7. Comparative analysis of the results

Rank	Order of priority by RPN	Order of priority by S_w
1	V_{11} (C_{11})	V_{10} (C_{10}); V_{11} (C_{11})
2	V_6 (C_6); V_7 (C_7)	V_{20} (C_{23})
3	V_{13} (C_{13})	V_{15} (C_{15})
4	V_8 (C_8); V_{21} (C_{24})	V_9 (C_9)
5	V_9 (C_9)	V_4 (C_4)
6	V_5 (C_5)	V_{21} (C_{24})

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