

National University of Science and Technology "POLITEHNICA" Bucharest University Center of Pitesti Faculty of Mechanics and Technology SCIENTIFIC BULLETIN AUTOMOTIVE series year XXX, no. 34



RISKS PRIORITIZATION IN THE INJECTION MOLDING PROCESS USING FMEA METHOD COMPARATED WITH TOPSIS METHOD

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Article history

Received	05.07.2024
Accepted	15.10.2024

DOI <u>https://doi.org/10.26825/bup.ar.2024.005</u>

Abstract: In the automotive industry, the injection molding process is frequently used as a result of the massive market penetration of plastic products. 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 to evaluate and rank the failure modes that could occur in the plastic injection 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 of 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 needed, at the end of the paper comparing the results obtained by the two methods. This paper can also serve as a guide to prevent failures of injection molded parts.

Keywords: Risk prioritization, FMEA method, TOPSIS method, molding plastic materials process

INTRODUCTION

It can be said that today, there is no branch of technology that does not benefit, in a certain way, from the discoveries and research of the last century that led to the obtaining of plastic materials.

Initially, they entered the technique replacing the classic materials (metal, wood, ceramic...). Gradually, however, they established themselves and came out of the stage of replacement material. They asserted themselves, due to their special properties, as new materials, usable in conditions where classic materials could not cope. Plastic materials have equaled the mechanical resistance of metals but are much lighter and more resistant to atmospheric and chemical agents. The duration of the production cycle to obtain a part is much shorter and the technological process less complicated than in the case of metals or other materials.

However, there are a number of issues to be considered and a number of risks involved in the processing process. Methods have been developed that, through a rigorous analysis, prevent the occurrence of these problems and eliminate the possible causes that would lead to their occurrence.

PRESENTATION OF THE FMEA METHOD

One of the most important quality management inductive analysis techniques is Failure Mode and Effects Analysis (FMEA). FMEA is an engineering method used to define, identify and eliminate potential failures, problems and errors from a system before they reach the customer [1].

The purpose of this paper is the Process FMEA analysis. PFMEA is used to analyze the already developed or existing processes. PFMEA focuses on potential failure modes associated with both the process safety/effectiveness/efficiency and the functions of a product caused by the process problems. Applying FMEA to a process means following a series of successive steps: analysis of the process, list of identified potential failures, evaluation of their frequency, severity and detection technique, global evaluation of problem, and apply of the corrective and preventive actions that could eliminate or reduce the chance of potential failures [2].

In quantification of the risk PFMEA uses indicator (RPN), defined as the product of the severity (S), occurrence (O), and detection (D) of the failure. Traditional PFMEA uses five scales and scores of 1–10, to measure the probability of occurrence, severity and the probability of not detection. Even through the traditional RPN model is simple and has been well accepted for safety analysis, it suffers from several weaknesses. In [3, 4] it is pointed out that the same RPN score can be obtained from a number of different score combinations of severity, occurrence, and detect.

Although the same RPN is obtained, their hidden risk implications may be totally different. In [5] is suggested to give the occurrence factor the most weight in the RPN calculation because it affects the likelihood of a fault reaching the customer.

PRESENTATION OF THE TOPSIS METHOD

The TOPSIS is one of the multi-criteria decision-making methods which was introduced by Yoon and Hwang [6]. 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. defined the selection of sustainable energy using a standard TOPSIS method in uncertain situations [7].

An assumption of TOPSIS is that the criteria are monotonically increasing or decreasing. Normalisation is usually required as the parameters or criteria are often of incongruous dimensions in multi-criteria problems [8, 9]. 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 [10]. It is a method of compensatory aggregation that compares a set of alternatives, normalising 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 $(x_{ij})_{m \times n}$.

Step 2

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

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{k=1}^{n} x_{kj}^2}}, i=1,2,\dots m \text{ and } j=1,2,\dots n$$
(1)

Step 3

Calculate the weighted normalised decision matrix

$$t_{ij} = r_{ij} \times w_i$$
, $i = 1, 2, ..., m$ and $j = 1, 2, ..., n$, (2)

where,

$$w_j = \frac{W_j}{\sum_{k=1}^n W_k}, j = 1, 2, \dots n$$
(3)

so that $\sum_{i=1}^{n} w_i = 1$ and W_j is the original weight given to the indicator v_j , j = 1, 2, ..., n. Step 4

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

$$A_{w} = \{(max (t_{ij} | i=1,2,...,n) | j \in J_{-}), (min (t_{ij} | i=1,2,...,n) | j \in J_{+})\} \approx \{t_{wj}, j=1,2,...,n\},$$
(4)

$$A_{b} = \{(\min(t_{ij} \mid i=1,2,...,n) \mid j \in J_{-}), (\max(t_{ij} \mid i=1,2,...,n) \mid j \in J_{+})\} \approx \{t_{bj}, j=1,2,...,n\},$$
(5) where,

 $J_{+} = \{j=1,2,...,n \mid j\}$ associated with the criteria having a positive impact, and $J_{-} = \{j=1,2,...,n \mid j\}$ associated with the criteria having a negative impact. **Step 5**

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

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

(6)

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

$$d_{ib} = \sqrt{\sum_{j=1}^{n} (t_{ij} - t_{bj})^2}, \ i = l, 2, \dots m$$
(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

$$s_{iw} = d_{iw} / (d_{iw} + d_{ib}), \ 0 \le s_{iw} \le l, \ i = l, 2, ..., m$$
(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, ..., m).

CASE STUDY FOR MOLDING PLASTIC MATERIALS PROCESS. ESTABLISHING THE CRITICAL FAILURE VARIANT

Classical FMEA application

In the first part of the study a classical application of Design FMEA has been realized for molding plastic materials process. The injection molding process consists in bringing the mixture based on thermoplastic polymers into a plastic state, followed by its introduction under pressure into a relatively cold mold until it turns into a solid state. Thermoplastic materials such as polyethylene, polypropylene, polyvinyl chloride, polyamide, ABS, etc. are currently processed.

Through this processing process, various products with complex shapes and desired properties can be obtained economically.

In this technological manufacturing process (fig.1), molds with one nest or many nests can be used, which contributes to increasing the productivity of the injection machine. The injection process is a cyclic phenomenon, each cycle includes several operations. In order to make an injected part in optimal conditions of quality and efficiency, in addition to a high-performance injection machine and a suitable mold, a good choice of the thermoplastic material is also necessary, which takes into account its behavior in the processing conditions, as well as the conditions imposed by the injected parts.



Figure 1. The injection molding machine [11]

The evaluation of the failure modes is carried out by scoring the respective risk factors of occurrence, severity, and detection. For this purpose, usually 10-level scales are being used. The failure modes 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 (96 and 108). Also, for C_2 and C_8 the same value is obtained for RPN (60). Some of the data can be seen in Table 1 [12].

Potential failure mod	Potential effect of failure	Potential cause of failure	S	0	D	RPN
Incomplete part	FM1.Reject Customer	C1. Temperature of mould too low	5	3	6	90
	deeply dissatisfied	C2.Temperature of cylinder too low	5	2	6	60
		C3. Pressure of cylinder too low	4	4	6	96
		C4.Insufficient quantity of material injected -incorrect adjustment	3	6	4	72
Burss	FM3 Reject Customer deeply	C8. Clamping force too low - failure in the hydraulic system	3	5	4	60
	dissatisfied	C9. Clamping force too low – incorrect adjustment	4	3	7	84
		C10. Clamping plan damaged /used	4	3	9	108
Blister	FM4. Reject Customer deeply dissatisfied	C11. Temperature of mould too high	5	2	8	80

Table 1. Conventional FMEA for Injection molding process

TOPSIS application

> Step 1:

The selection criteria considered are the risk factors:

C₁: severity (S);

C₂: occurrence (O);

C₃: detection (D).

Decision variants V_i are the eight (C_1 , C_2 , ... C_{11}) potential faults that can occur on the injection molding 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: $W_1 = 0.5$; $W_2 = 0.3$; $W_3 = 0.2$.

	C_1 (S)	C ₂ (O)	C_3 (D)		C_1 (S)	C ₂ (O)	<i>C</i> ₃ (D)
$V_1(C_1)$	5	3	6	$V_{5}(C_{8})$	3	5	4
$V_2(C_2)$	5	2	6	V ₆ (C ₉)	4	3	7
$V_3(C_3)$	4	4	6	$V_{7}(C_{10})$	4	3	9
$V_4(C_4)$	3	6	4	$V_{8}(C_{11})$	5	2	8

 Table 2. The consequences of the variants for each criterion

Step 2: Determination of the normalized matrix

In this stage, the consequences of the variants for each criterion are calculated using the normalisation method and the relation 1.

The results are presented in the normalized matrix, Table 3.

Table	3.	Norma	lized	matr	ix	(\mathbf{R}))

	C_1	C_2	C_3		C_1	C_2	C_3		
V_1	0,421	0,283	0,328	V_5	0,337	0,472	0,219		
V_2	0,421	0,189	0,328	V_6	0,253	0,283	0,383		
V_3	0,337	0,378	0,328	V_7	0,253	0,283	0,492		
V_4	0,337	0,567	0,219	V_8	0,421	0,189	0,438		

Step 3: Determination the weighted normalised decision matrix The relation (2) is used for the calculation, and the results are listed in Table 4.

	Tuble 1. Weighted hormanised decision matrix (1)							
	C_1	C_2	C_3		C_1	C_2	C_3	
V_1	0,210	0,085	0,066	V_5	0,126	0,142	0,044	
V_2	0,210	0,057	0,066	V_6	0,126	0,085	0,077	
V_3	0,168	0,113	0,066	V_7	0,168	0,085	0,098	
V_4	0,168	0,170	0,044	V_8	0,210	0,057	0,088	

Table 4. Weighted normalised decision matrix (T)

 Step 4: Determine the worst alternative (A_w) and the best alternative (A_b) Relation 4 and 5 are used and it results: A_w= (0,210; 0,170; 0,044)

 $A_b = (0,126; 0,057; 0,098)$

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_{I}	V_2	V_3	V_4	V_5	V_6	V_7	V_8
$d_{\rm w}$	0,088	0,115	0,074	0,042	0,089	0,124	0,109	0,121
d _b	0,094	0,090	0,077	0,132	0,101	0,035	0,050	0,085

Table 5. Distance for worst condition Aw and for best condition At

> Step 6: Calculate the similarity to the worst condition, using the relation 8. The results are presented in the table 6.

	Table 0. Similarity to the worst condition							
	V_{I}	V_2	V_3	V_4	V_5	V_6	V_7	V_8
S_{w}	0,482	0,562	0,491	0,241	0,468	0,779	0,684	0,589

Table 6. Similarity to the worst condition

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_6 , V_7 , followed by V_8 , V_2 and V_3 .



Figure 2. A graphic of the obtained results

CONCLUSIONS

Table 7. Comparative analysis of the results							
Rank	Order of priority by RPN	Order of priority by S_w					
1	$V_7(C_{10})$	$V_{6}(C_{9})$					
2	$V_{3}(C_{3});$	$V_7(C_{10})$					
3	$V_{1}(C_{1})$	$V_{8}(C_{11})$					
4	$V_{6}(C_{9})$	$V_{2}(C_{2})$					
5	$V_{8}(C_{11})$	$V_{3}(C_{3})$					
		RankOrder of priority by RPN1 V_7 (C10)2 V_3 (C3);3 V_1 (C1)4 V_6 (C9)					

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

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_7 , clamping plan damaged /used, what it can produce unacceptable piece for customer. Another, equally important problem is given by the V6 variety, respectively clamping force too low– incorrect adjustment.

- ✓ Thus, the TOPSIS method confirms, to a large extent, the results obtained by applying the FMEA method in the prioritization of risks in the plastic injection process.
- ✓ In order to obtain even more conclusive results, it is necessary to apply other methods. This constitutes a future research direction.

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