A Novel FMEA approach for ranking Mould Designs in foundries

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ABSTRACT: This paper addresses a novel Failure Mode and Effect Analysis (FMEA) to prioritize the mould design of a specific cast component by evaluating the risks associated with failure modes using a case study data. The data is obtained from a macro foundry industry in India. Traditional FMEA uses Risk priority Number (RPN) to evaluate risk level of a component or process. The RPN index is found by calculating the product of severity (S), occurrence frequency (O) and detection (D) indexes. The various sets of S, O, and D indexes may produce an identical value of RPN. But in foundries, prioritizing the failures through the traditional FMEA produces unmatched results when RPN values are identical during preproduction trials. This research paper explains an alternate FMEA approach named FEAROM (Failure Effects And Resolution Of Modes) to determine matched result in practice for finalizing the mould designs. Modified fuzzy TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) method interdependent with the Analytic Hierarch Process (AHP) is used for validating the results obtained using FEAROM method. The results presented are based on an experimental study carried out for a specific component in a foundry using the sand casting method. It is found that proposed FEAROM model harmonizes nicely in practice and turns out quality castings.

Keywords: Failure mode effect analysis, Risk Priority Number, Failure Effects And Resolution Of Modes, TOPSIS, AHP

1. INTRODUCTION
Currently, the foundries are encountering mammoth pressure to manufacture high quality casting at a high requisite speed. To ensure the essential quality level, the foundries have to put into service a continuous quality enhancement strategy during development stage of cast components. Failure deterrence is an important practice to improve the quality level [Ahmed, 1996; S. Dowlatshahi, 2001; Lu, 2002]. Among the various failure prevention techniques, FMEA has been used popularly in several areas during the past few decades. Traditional FMEA approach is based on three important indexes, viz., severity (S), occurrence (O) and detection (D) with scale levels of 1 to 10 indicated in Table 1.

Table 1. Traditional rating for S, O, D indexes of failures

<table>
<thead>
<tr>
<th>Level</th>
<th>Severity [S]</th>
<th>Occurrence [O]</th>
<th>Ability to detect [D]</th>
</tr>
</thead>
<tbody>
<tr>
<td>10</td>
<td>Safety issue and/or non-compliance with government regulation without warning</td>
<td>Almost every time</td>
<td>Almost no</td>
</tr>
<tr>
<td>9</td>
<td>Safety issue and/or non-compliance with government regulation with warning</td>
<td>1 in 2</td>
<td>Very remote</td>
</tr>
<tr>
<td>8</td>
<td>Operation down for a significant period of time and major financial impact; Loss of primary function</td>
<td>1 in 5</td>
<td>Remote</td>
</tr>
<tr>
<td>7</td>
<td>Serious disruption to operations, defects caught at customer site, requires major rework or scarp; Reduction in primary function</td>
<td>1 in 10</td>
<td>Very low</td>
</tr>
<tr>
<td>6</td>
<td>Major disruption to operations and requires light rework or scarp; Loss of comfort or convenience function</td>
<td>1 in 100</td>
<td>Low</td>
</tr>
<tr>
<td>5</td>
<td>Minor disruption to operations and requires light rework or scarp; Loss of comfort or convenience function</td>
<td>1 in 500</td>
<td>Moderate</td>
</tr>
<tr>
<td>4</td>
<td>Inconvenience to the process and requires minor rework; Returnable appearance and/or noise issue noticed by the most customers</td>
<td>1 in 1,000</td>
<td>Moderately High</td>
</tr>
<tr>
<td>3</td>
<td>Inconvenience to subsequent task and require minor rework; Non-returnable appearance and/or noise issue noticed by customers</td>
<td>1 in 5,000</td>
<td>High</td>
</tr>
<tr>
<td>2</td>
<td>Inconvenience to current task and requires minor rework; Non-returnable appearance and/or noise issue rarely noticed by customers</td>
<td>1 in 50,000</td>
<td>Very high</td>
</tr>
<tr>
<td>1</td>
<td>No discernable effect</td>
<td>Almost impossible</td>
<td>Almost certain</td>
</tr>
</tbody>
</table>

In traditional FMEA the RPN index is calculated as: RPN = S × O × D
In traditional RPN evaluation, the original ordinal scale values of S, O and D is transformed into a new metric cardinal scale value. This cardinal scale defines the RPN does not cover the range [1, 1000] continuously and presents a series of “holes” corresponding to prime numbers present in the range itself. Actually, 88% of the scale is empty with only 120 unique RPNs because some of the RPNs are repeating. For example, RPN 120 appears 24 times from product of S, O and D. Other extremes 1, 123, 1000 appear only once. RPNs are not continuous and heavily distributed at the bottom of the scale from 1 to 1000. This leads to series of problems in RPN interpretation. This causes problems in interpreting the meaning of the differences between different RPNs. For example, the difference between 400 and 500 the same as or less than the difference between 600 and 700 is not interpreted.

Another inherent drawback in the RPN analysis is that various sets of S, O and D may produce exactly the same value of RPN. For example, consider two different events having values of (5, 6, 1) and (10, 3, 1) for S, O and D respectively. Both these events will have a total RPN value of 30, but their hidden risk implications may be totally different. This may lead to either waste of resources and time or in some cases a high risk event may go unnoticed.

Furthermore the RPN scale properties lead to a series of problems in the RPN interpretation. For example, if two or more failure modes have the exact RPN, one may face difficulty in selecting which failure mode demands higher priority for corrective action. Also, the assumption is that the three failure mode indexes are all equally important. The relative importance among S, O and D is not taken into consideration. But in real practical applications the relative importance among the factors exists because different experts have different knowledge and judgments. Further, in order to ensure the estimation more precise and more reliable there is a need to handle the subjective or qualitative information associated with the analysis in consistent and logical manner even after suitable weights are assigned to the S, O and D indexes.

Many researchers have proposed modified versions of the FMEA approach to overcome the above difficulties associated with it. One among them is the assessment of RPN prioritization in FMEA using fuzzy logic system (Bowles and Bonnell, 1998; Bowels 2003). Xu et al., (2002) proposed a fuzzy logic base approach for FMEA with fuzzifier and defuzzifier method to address the interdependencies among various failure modes with uncertain and imprecise information. Sharma et al., (2005) proposed a fuzzy logic based approach resolves the limitations of conventional RPN evaluation and also permits the experts to combine S, O and D indexes in a more flexible and realistic manner. Wang et al., (2009) proposed a fuzzy FMEA approaches to overcome the shortcomings of the traditional FMEA by combining fuzzy sets with different techniques. Other fuzzy FMEA approaches have been proposed for the RPN calculation in the literature (Bowles and Pealz 1995; Bragila et al. 2003; Pillay and Wang 2003; Guimaraes and Lapa 2004; Garcia et al. 2005). Vast majority of fuzzy FMEA approaches employs fuzzy- if then rules for prioritization of failure modes. This requires vast amount of expert knowledge and expertise. In particular, different experts may have different knowledge and judgments. When their judgments are inconsistent, it is nearly impossible to combine or reduce rules. In general, most of these techniques are very complex and require a special function definition and technical know-how. In particular, these methods are quite complex to manage and are not always available to the designers. Hence, there is a clear need to develop a straightforward and simple fuzzy logic approach for FMEA which can take advantage of the benefits of fuzzy logic. Moreover, Wong and Lai (2011) indicated in their work that most research is carried out only in Universities and suggested to make more effort to develop real world applications. Also, the authors have attempted traditional FMEA method for finalizing mould designs in foundries and found that it produces unmatched results in real time practice.
These issues motivated the authors to devise a simplified but an effective fuzzy FMEA model named FEAROM (Failure Effects And Resolution Of Modes). The FEAROM methodology is developed based on the investigations of Franceschini and Galetto (2001) and Sellapan and Karuppusami (2009). The new logic synthesis expression for Risk Priority Code (RPC) to change the order of priority among indexes is the basis for our work. The new logics of synthesis expresses changed composition of the operators and tie-ranking rule which is different from the one proposed by Franceschini and Galetto (2001). It is appropriate to apply for finalizing mould designs in foundries during preproduction trials.

The proposed FEAROM model eliminates the drawbacks associated with the traditional FMEA and helps the FMEA team to implement consistent and suitable strategy to find the most favorable mould design in preproduction trials. The approach also enables the possibility of accounting the discriminating importance of the characteristic indexes. FEAROM method is capable of dealing with information expressed on an ordered qualitative scale. An artificial numerical conversion of the scale is not necessary. The proposed FEAROM model is a fuzzy multi-criteria decision-making (MCDM) method. Hence it has been validated using similar MCDM method called modified fuzzy TOPSIS (MFTOPSIS) method is interdependent to the AHP method.

2.0 SOLUTION METHODOLOGY

The proposed FEAROM approach is discussed in detail under this section. Also, the MFTOPSIS method hybrid with AHP used for validating the results of the FEAROM approach is discussed under this section.

2.1 FEAROM METHODOLOGY

Initially, the methodology uses the traditional FMEA to find the rank order of mould designs. The mould design that has the least RPN value is considered most important, next higher RPN value as second important and so on.

The FEAROM model advocates the decision making criteria to prioritize mould designs during the development stage of cast components. This method is suitable when the three index values, viz., S, O and D are considered equally important or different weights are given for each index by team members. The decision making criteria utilizes an ordered qualitative scale for data processing which have ordinal properties only. The proposed FEAROM model considers fuzzy subset to find the rank order of the mould designs in preproduction trials.

The projected FEAROM technique is proficient to deal with the circumstances when,

- The ranking scale for S, O and D is assigned different values by the team members but the indexes have the same maximum importance.
- Two or more mould designs have the same RPN.
- When three S, O, and D indexes are assumed with a different level of importance

The evaluation criteria S, O and D are denoted by K_j (with j = 1, 2, 3) while the alternative mould designs during development stage are denoted by M_i (with i = 1, ..., m). The grade membership of alternatives M_i in K_j indicates the degree to which M_i satisfies the criterion specified.

The FEAROM model suggests a two step procedure:

Step 1: Calculate Risk Priority Code (RPC)

\[
RPC (M_i) = \frac{\text{Max}_j \{\text{Min}(I(K_j), g_j(M_i))\}}{	ext{Min}_j \{\text{Min}(I(K_j), g_j(M_i))\}}
\] (2)

where

- RPC (M_i) is the Risk Priority Code for the moulds design M_i
- I(K_j) is the importance associated with each criterion K_j = L_k
- L_k is the jth level of the scale (refer Table 3)
- K_j(M_i) = L_q (refer Table 2)

From equation (2) it is evident that the Max operation selects the largest of its arguments. If all the arguments are low, they do not affect the Max operation. Consider a criterion that has more importance, it will get an importance rating of L_k that is high on the scale. When we take Min of the importance criteria with evaluation K_j (M_i) we still get a low score. Thus, it is clear that high-importance criterion have little effect on the overall score (based on Franceschini and Galetto, 2001, p 8).

The formulation suggested in the equation (2) satisfies the properties of Pareto optimality. The term \[\text{Min} \{\text{Min}(I(K_j), g_j(M_i))\}\] indicates that ‘if the criterion is important, then it has a low score’. The mould design with the most dangerous failure mode is the one with the highest RPC value.

Step 2: Calculate Critical Failure Mode (CFM)

The CFM equation given below is used for determining the least RPC value. The mould design with the lowest RPC value is chosen as per FEAROM method.

\[
\text{CFM} (M_i^*) = \text{Min}_{M_i \in A} \bigg\{\text{RPC} (M_i)\bigg\}
\] (3)

where

- A is the set of failure modes of mould designs
- RPC (M_i) is defined on a new 10 point ordinal scale

If two or more mould designs have the same critical failure mode, then the following equation is used for breaking the tie:

\[
T (M_i) = N (M_i)
\] (4)

Where,
N (M_i) is the number of elements in the row corresponding to M_i for which L_ij < CFM (M^)

Let L_ij denote the levels of S, O and D respectively corresponding to the mould designs M_i where i = 1, 2, 3... m and j = 1, 2, 3. Take 1 ≤ L_ij ≤ 10 for all i, j. L_ij precisely takes the levels {1, 2, ..., 10} in some order as shown in Table 2.

Table 2. General form (L_ij) of moulds design indexes and RPN

<table>
<thead>
<tr>
<th>Moulds design</th>
<th>S</th>
<th>O</th>
<th>D</th>
<th>RPN</th>
</tr>
</thead>
<tbody>
<tr>
<td>M_1</td>
<td>L_{11}</td>
<td>L_{12}</td>
<td>L_{13}</td>
<td>R_1</td>
</tr>
<tr>
<td>M_2</td>
<td>L_{21}</td>
<td>L_{22}</td>
<td>L_{23}</td>
<td>R_2</td>
</tr>
<tr>
<td>.</td>
<td>.</td>
<td>.</td>
<td>.</td>
<td>.</td>
</tr>
<tr>
<td>.</td>
<td>.</td>
<td>.</td>
<td>.</td>
<td>.</td>
</tr>
<tr>
<td>M_m</td>
<td>L_{m1}</td>
<td>L_{m2}</td>
<td>L_{m3}</td>
<td>R_m</td>
</tr>
</tbody>
</table>

The importance rating and correspondence map for S, O and D, is mentioned in Table 3. These values are used in FEAROM model to rate the relative importance of S, O and D.

Table 3. Correspondence map and Relative importance rating of S, O and D [Franceschini and Galetto, 2001]

<table>
<thead>
<tr>
<th>Level (L)</th>
<th>S Index</th>
<th>O Index</th>
<th>D Index</th>
<th>I(S,O,D)</th>
</tr>
</thead>
<tbody>
<tr>
<td>L_1</td>
<td>No</td>
<td>Almost never</td>
<td>Almost certain</td>
<td>No</td>
</tr>
<tr>
<td>L_2</td>
<td>Very slight</td>
<td>Remote</td>
<td>Very high</td>
<td>Very low</td>
</tr>
<tr>
<td>L_3</td>
<td>Slight</td>
<td>Very slight</td>
<td>High</td>
<td>Low</td>
</tr>
<tr>
<td>L_4</td>
<td>Minor</td>
<td>Slight</td>
<td>Moderate high</td>
<td>Minor</td>
</tr>
<tr>
<td>L_5</td>
<td>Moderate</td>
<td>Low</td>
<td>Medium</td>
<td>Moderate</td>
</tr>
<tr>
<td>L_6</td>
<td>Significant</td>
<td>Medium</td>
<td>Low</td>
<td>Significant</td>
</tr>
<tr>
<td>L_7</td>
<td>Major</td>
<td>Moderately high</td>
<td>Slight</td>
<td>Major</td>
</tr>
<tr>
<td>L_8</td>
<td>Extreme</td>
<td>High</td>
<td>Very slight</td>
<td>High</td>
</tr>
<tr>
<td>L_9</td>
<td>Serious</td>
<td>Very high</td>
<td>Remote</td>
<td>Very high</td>
</tr>
<tr>
<td>L_10</td>
<td>Hazardous</td>
<td>Almost certain</td>
<td>Almost impossible</td>
<td>Absolute</td>
</tr>
</tbody>
</table>

2.3 Validation using Modified Fuzzy TOPSIS (MFTOPSIS) Method hybrid with AHP Method

The familiar fuzzy TOPSIS method has been modified to suit the selection of an appropriate mould design in foundries. The outcome of MFTOPSIS method is used to verify and validate FEAROM model. Hwang and Yoon (1981) were the first to develop the TOPSIS method for solving multiple criteria decision making problem. It is based on the concept that the chosen alternative should have the shortest distance from the positive ideal solution and the farthest from the negative ideal solution. Lai et al. (1994) used the TOPSIS method for solving a multi-criteria water quality management problem. Mohammed et al. (2012) used a new technique named Information Entropy Weighting (IEW) combined with TOPSIS method to rank the consulting firm. Ali Akbar Farhangi et al., (2012) proposed a model to design the quality of Employee-Organization Relationships (EORs) based AHP method. Reza Kiani mavi et al., (2012) proposed a study to identify and prioritize the Effective Factors in Material Requirement Planning implementation using Fuzzy AHP method. Ali Dadar Moghadam et al., (2012) used the TOPSIS method is interdependent to the AHP method in ranking the training methods that are used for sustainable agriculture. Suitably, the present paper considers the importance weight for each criterion in TOPSIS method is integrated to the AHP method.

Analytic Hierarchy Process (AHP)

The AHP is used to provide weight criteria of decision factors to MFTOPSIS method. Thomas L. Saaty (1980) was the first to develop the AHP for decision making where objective is to select the best alternative. It is based on the concept that the inconsistencies in making subjective judgments are sorted out. AHP is a multi criteria decision-making method that can be used in both subjective and objective evaluation criteria. AHP allows the systematic consideration and evaluation of multiple decision criteria. The analytical hierarchy process involves pairwise comparisons of the decision elements. The use of AHP in solving a decision problem involves the following five steps [Francis and White, 1984]:

Step 1: Setup the decision hierarchy by breaking down the decision problem into a hierarchy of interrelated decision elements.

Step 2: Collect input data by pairwise comparison of decision elements.

Step 3: Use the eigenvalue method to estimate the relative weights of decision elements.

Step 4: Check for consistency using the consistency ratio (CR) is ((μ - 1)/ (n - 1))/ACI. μ is the largest positive eigen value. ACI is the average consistency index of randomly generated weights. According to Saaty, the values for ACI depended on the order (n) of the matrix and are as follows (first row is the order of the matrix; second row is the ACI value).

<table>
<thead>
<tr>
<th>n</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0</td>
<td>0.58</td>
<td>0.90</td>
<td>1.12</td>
<td>1.24</td>
<td>1.32</td>
<td>1.41</td>
<td>1.45</td>
<td>1.4</td>
<td>1.4</td>
</tr>
</tbody>
</table>

As a working rule of AHP, a CR value of 10% or less is acceptable.

The relative importance (weights) of the categories and criteria in the model for pairwise comparisons is established as follows:

\[ W = (L_n - L_i) + 1 \]  \hspace{1cm} (5)

where W = Weight or relative importance
L_n and L_i are any two criteria.
The relative importance is W when $L_n > L_i$ and it is $1/W$ when $L_n < L_i$.

Each comparison in pair is made to evaluate the importance of one factor over another relative to the criteria to be evaluated at that point. In typical analytic hierarchy studies a nine-point scale is used as explained in Table 4.

**Table 4. The Nine-point scale used by the AHP**

<table>
<thead>
<tr>
<th>Intensity of importance</th>
<th>Definition explanation</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 Equal importance</td>
<td>Two activities contribute equally to the objective</td>
</tr>
<tr>
<td>3 Weak importance of one</td>
<td>Experience and judgment over the other slightly favor one activity over the other</td>
</tr>
<tr>
<td>5 Essential or strong</td>
<td>Experience and judgment over the other strongly favor one activity over the other</td>
</tr>
<tr>
<td>7 Demonstrated importance</td>
<td>An activity is strongly favored and its dominance is demonstrated in practice</td>
</tr>
<tr>
<td>9 Absolute importance</td>
<td>The evidence favoring one activity over another is of the highest possible order</td>
</tr>
<tr>
<td>2, 4, 6, 8 Intermediate values</td>
<td>When compromise is between two adjacent needed judgments</td>
</tr>
</tbody>
</table>

Following steps are considered in MFTOPSIS method (based on Pragati Jain, 2011). A set of $m$ alternatives and $n$ attributes are considered.

**Step 1:** Construct normalized decision matrix: $Y = (y_{ij})_{m \times n}$ matrix.

Normalize scores or data are as follows: $v_{ij} = \frac{y_{ij}}{\sum_{j=1}^{n} y_{ij}}$

for $i = 1, 2, 3, \ldots, m$; $j = 1, 2, 3, \ldots, n$

**Step 2:** The weighted normalized decision matrix is constructed by assuming a set of weights for each attribute $w_j$ for $j = 1, 2, 3, \ldots, n$, such that, each $w_j \in (0, 1)$ and $\sum_{j=1}^{n} w_j = 1$ or simply it can be said that each $w_j$ is a normalized fuzzy number.

Then, each column of the normalized decision matrix is multiplied by its associated weight. An element of the new matrix is: $v_{ij} = w_j \cdot r_{ij}$

**Step 3:** The ideal and negative ideal solutions are determined.

Ideal solution: $A^* = \{v_i^*, \ldots, v_n^*\}$, where $v_j^* = \max_{\{j \in J; j \neq i\}} (v_j)$

Negative ideal solution: $A^- = \{v_i, \ldots, v_n\}$, where $v^- = \min_{\{j \in J; j \neq i\}} (v_j)$

Let $J$ be the set of benefit attributes or criteria (more is better) and $J'$ be the set of negative attributes or criteria (less is better).

**Step 4:** The separation measures for each alternative are calculated.

The separation from the ideal solution is:

$$S_i^* = \sqrt{\sum_{j=1}^{n} (v_j^* - v_{ij})^2}$$

$i = 1, \ldots, m$

Similarly, the separation from the negative ideal alternative is:

$$S_i = \sqrt{\sum_{j=1}^{n} (v_j - v_{ij})^2}$$

$i = 1, \ldots, m$

**Step 5:** The relative closeness to the ideal solution $C_i^*$ is determined:

$$C_i^* = \frac{S_i}{S_i^*}$$

$0 < C_i^* < 1$

The alternative to $C_i^*$ closest to 0 is selected.

3. **APPLICATION OF FEAROM THROUGH AN EXPERIMENTAL CASE STUDY**

The study was carried out in the steel sand casting foundry called SHREE HARIE STEEL & ALLOYS located at Coimbatore city of India. The Bearing Housing, which is being manufactured using CO$_2$ sand casting, is considered in this work. The Bearing Housing is made using ASTM A 352 WCB grade steel. The aim of this work is to predict and finalize the appropriate mould design in order to produce qualitatively superior castings. Three alternative mould designs ($M_1$, $M_2$ and $M_3$) of bearing housing are considered by the industry during the preproduction trials as shown in Figures 1-3. The pattern for the Bearing Housing is shown in Figure 4. The sample of inspection-ready settled castings, which was made using one of the moulds discussed above, is shown in Figure 5.
As mentioned earlier, the objective of this work is to determine the best of the three mould designs. A brainstorming session is conducted with the FMEA team members of the industry to determine the S, O and D values for each design. The FMEA team is also accounted the past experiences on the similar products. The values shown in Table 5 are supervised data of the FMEA team members. The average values of the failure indexes for each mould design is considered as shown in Table 6. These values are used for selecting the best mould design using a modified novel FMEA approach named FEAROM method.

3.1 Ranking using Traditional FMEA and FEAROM method

In traditional FMEA, it is appropriate to consider least RPN value first, next higher RPN value second and so on for prioritizing the mould designs during the development stage. Hence, the traditional FMEA ranking order is 3, 1 and 1 for M1, M2 and M3 respectively [refer column six in Table 6].

It is evident that the mould designs M2 and M3 are equally ranked and this leads to difficulty in selecting the preferable mould design using traditional FMEA method. This problem can be overcome using FEAROM method, as discussed below, for two cases.

**Case (a):** The same maximum importance (L10) is assumed for all characteristic indexes (S, O and D). This is similar to traditional FMEA. The importance rating is shown below.

\[
I(S) = L_{10}; \quad I(O) = L_{10}; \quad I(D) = L_{10}
\]

**Step 1:** The aggregated RPC index for the three mould designs M1, M2 and M3 is calculated using equation (2) [refer column seven in Table 6]:

\[
\text{RPC} (M_1) = \max [\min (L_{10}, L_9), \min (L_{10}, L_5), \min (L_{10}, L_3)]
\]

\[
\text{RPC} (M_2) = \max [L_9, L_5, L_3] = L_9
\]

\[
\text{RPC} (M_3) = \max [L_6, L_3, L_6] = L_6
\]

**Step 2:** The calculation of Critical Failure Mode (CFM) is done using equation 3:

\[
\text{CMF} (M^*) = \min \{L_9, L_9, L_6\} = L_6 = \text{RPC} (M_3)
\]

Based on the CFM analysis, the most preferable mould design is M3. But still a tie exists between the other two mould designs. This tie could be overcome by using the tie ranking rule mentioned in equation 4.

**Tie ranking rule for M1 and M2 is:**

\[
T (M_1) = N (M_1) \quad \text{where} \quad N (M_i) = \text{the number of times} \quad L_{ij} < L_6
\]

Therefore, \( T (M_1) = 2; \quad T (M_2) = 1 \)

Since \( T (M_2) < T (M_1) \), M2 is the preferable mould design than M1.

Hence the rank order of mould designs is M3, M2 and M1 respectively (refer column eight in Table 6)

**Case (b):** In the selection of mould design, i.e., in the present context, it is essential to define different levels of importance for the three indexes S, O and D. This is because disagreed values are assigned by the FMEA team members for each index. Therefore, traditional FMEA approach based on RPN cannot be applied for mould design selection.

The FMEA team members of the industry decided to assign different levels of importance for the indexes S, O and D as given below. Generally, severity (S) is given the highest rating followed by occurrence (O). Detection (D) is given least rating. This is due to the practical implications / constraints prevalent for the particular process in the industry.

\[
I(S) = L_{10}; \quad I(O) = L_8; \quad I(D) = L_6
\]
By applying equation (2) to (4), the results obtained are shown in columns (9) and (10) in Table 6.

Table 5. Failure Mode and Effects Analysis Worksheet

<table>
<thead>
<tr>
<th>FMEA Team:</th>
<th>Production manager, Moulds engineers, Quality engineer</th>
</tr>
</thead>
<tbody>
<tr>
<td>Team Leader:</td>
<td>Quality assurance manager</td>
</tr>
<tr>
<td>Component:</td>
<td>Bearing Housing (A sand casting component)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Moulds design brief details</th>
<th>Potential Failure Mode</th>
<th>Potential Effect(s) of Failure</th>
<th>Severity</th>
<th>Potential Cause(s)/Mechanism(s) of Failure</th>
<th>Occurrence</th>
<th>Detection method</th>
<th>Detection</th>
<th>RPN</th>
</tr>
</thead>
<tbody>
<tr>
<td>METHOD 1 (M1)</td>
<td>Runner: 35 x 25 Ingate: 30 x 20 Chills: 22 Nos No. of cores = 3 Riser: 90 x 150 – 2 Nos 75 x 150 – 3 Nos 50 x 150 – 1 No 100 x 150 – 1 No Yield: 46% (3 pieces)</td>
<td>Shrinkage is in section</td>
<td>Rejected at manufacturing plant</td>
<td>10</td>
<td>Improper directional solidification due to inadequate risers feeding</td>
<td>6</td>
<td>Radiography/ultrasonic testing</td>
<td>4</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>9</td>
<td>5</td>
<td>3</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>8</td>
<td>4</td>
<td>2</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Average</td>
<td>9</td>
<td>5</td>
<td>3</td>
<td>135</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

| METHOD 2 (M2) | Runner: 35 x 25 Ingate: 30 x 20 Chills: 22 Nos No. of cores = 3 Riser: 90 x 150 – 2 Nos 75 x 150 – 3 Nos 50 x 150 – 1 No 38 x 100 – 1 No Yield: 49.5% (3 pieces) | Shrinkage is in section | Rejected at manufacturing plant | 9 | Inadequate riser feeding | 3 | Radiography/Ultrasound testing | 7 | |
| | | | | 8 | 2 | 6 | | |
| | | | | 10 | 1 | 5 | | |
| Average | 9 | 2 | 6 | 108 |

| METHOD 3 (M3) | Runner: 35 x 25 Ingate: 30 x 20 Chills: 22 Nos No. of cores = 3 Riser: 90 x 150 – 2 Nos 75 x 150 – 3 Nos 50 x 150 – 1 No 38 x 100 – 1 No Put up riser introduced Yield: 47.5% (3 pieces) | Shrinkage is found in flange | Rejected at manufacturing plant | 7 | Adequate riser is not present at flange portion | 4 | Radiography/Magnetic particle inspection | 8 | |
| | | | | 5 | 3 | 6 | | |
| | | | | 6 | 2 | 4 | | |
| Average | 6 | 3 | 6 | 108 |

Table 6. Calculation of RPN and RPC indexes for the moulds designs

<table>
<thead>
<tr>
<th>Mould Designs (Yield)</th>
<th>Mean values of S</th>
<th>Mean values of O</th>
<th>Mean values of D</th>
<th>RPN</th>
<th>FMEA Rank order</th>
<th>FEAROM Case (a)</th>
<th>FEAROM Case (b)</th>
<th>Note: I(S), I(O), I(D) are the importance associated with each index</th>
</tr>
</thead>
<tbody>
<tr>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
<td>(5)</td>
<td>(6)</td>
<td>(7)</td>
<td>(8)</td>
<td>(9)</td>
</tr>
<tr>
<td>M1</td>
<td>9</td>
<td>5</td>
<td>3</td>
<td>135</td>
<td>3</td>
<td>L_9</td>
<td>L_9</td>
<td>L_9</td>
</tr>
<tr>
<td>M2</td>
<td>9</td>
<td>2</td>
<td>6</td>
<td>108</td>
<td>1</td>
<td>L_9</td>
<td>L_9</td>
<td>L_9</td>
</tr>
<tr>
<td>M3</td>
<td>6</td>
<td>3</td>
<td>6</td>
<td>108</td>
<td>1</td>
<td>L_9</td>
<td>L_9</td>
<td>L_9</td>
</tr>
</tbody>
</table>

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3.2 Validation using MFTOPSIS Method hybrid with AHP Method

The mould design cases solved using FEAROM method is also attempted using the MFTOPSIS method integrating with AHP Method.

Case (a): As applied for FEAROM approach, maximum importance (L_n) is assumed for all the three characteristics indexes. The three mould designs M_1, M_2 and M_3 are considered as alternatives and the indexes S, O, and D are the attributes. The relative weights are calculated as follows using AHP method:

AHP method:
Relative weight between S and O, S and D and O and D is:
(L_n − L_i) + 1 = (10 − 10) + 1 = 1

Step 1: Pairwise comparison matrix

(S, O, D)
S: 1 1/3 1
O: 1 1 1/3
D: 1 1 1

Step 2: Formation of normalized matrix

<table>
<thead>
<tr>
<th>Attributes</th>
<th>S</th>
<th>O</th>
<th>D</th>
</tr>
</thead>
<tbody>
<tr>
<td>S</td>
<td>1/3</td>
<td>1/3</td>
<td>1/3</td>
</tr>
<tr>
<td>O</td>
<td>1/3</td>
<td>1/3</td>
<td>1/3</td>
</tr>
<tr>
<td>D</td>
<td>1/3</td>
<td>1/3</td>
<td>1/3</td>
</tr>
</tbody>
</table>

Step 3: The weights of various criteria are as follows:
Severity (S) = 0.33
Occurrence (O) = 0.33
Detection (D) = 0.33
⇒ W = {S, O, D} = {0.33, 0.33, 0.33}

Step 4: Check for consistency

The consistency ratio (CR) is

0.006

Because CR value is less than 10%, the present matrix is consistent.

MFTOPSIS Method:
Weight of each attributes, W = {0.33, 0.33, 0.33}

<table>
<thead>
<tr>
<th>Attributes</th>
<th>S</th>
<th>O</th>
<th>D</th>
</tr>
</thead>
<tbody>
<tr>
<td>M_1</td>
<td>9</td>
<td>5</td>
<td>3</td>
</tr>
<tr>
<td>M_2</td>
<td>9</td>
<td>2</td>
<td>6</td>
</tr>
<tr>
<td>M_3</td>
<td>6</td>
<td>3</td>
<td>6</td>
</tr>
</tbody>
</table>

Step 1: Calculate (∑y_i^2)^1/2 for each column and divide each column by that to get r_i^2 values (refer Table 8).

Table 8. r_i^2 = y_i / (∑y_i^2)^1/2

<table>
<thead>
<tr>
<th>Attributes</th>
<th>S</th>
<th>O</th>
<th>D</th>
</tr>
</thead>
<tbody>
<tr>
<td>M_1</td>
<td>0.64</td>
<td>0.81</td>
<td>0.33</td>
</tr>
<tr>
<td>M_2</td>
<td>0.64</td>
<td>0.32</td>
<td>0.67</td>
</tr>
<tr>
<td>M_3</td>
<td>0.43</td>
<td>0.49</td>
<td>0.67</td>
</tr>
</tbody>
</table>

Step 2: Multiply each column by w_i to get

v_i = w_ij r_ij (refer Table 9)

Table 9. v_i = w_ij r_ij

<table>
<thead>
<tr>
<th>Attributes</th>
<th>S</th>
<th>O</th>
<th>D</th>
</tr>
</thead>
<tbody>
<tr>
<td>M_1</td>
<td>0.2112</td>
<td>0.2673</td>
<td>0.1089</td>
</tr>
<tr>
<td>M_2</td>
<td>0.1056</td>
<td>0.2211</td>
<td></td>
</tr>
<tr>
<td>M_3</td>
<td>0.1617</td>
<td>0.2211</td>
<td></td>
</tr>
</tbody>
</table>

Step 3 (i): The ideal solution A^* is determined by selecting the minimum value from column D and maximum values from columns S and O (from Table 9).

Thus A^* = {0.2112, 0.2673, 0.1089}

Step 3 (ii): The ideal solution A’ is identified by choosing the maximum value from column D and minimum values from columns S and O (from Table 9).

Thus A’ = {0.1419, 0.1056, 0.2211}

Step 4(i): The separation S_i^* is determined for each row from ideal solution A^* = {0.2112, 0.2673, 0.1089} (refer column two of Table 10)

Step 4(ii): Similarly, separation S_i’ is determined for each row from ideal solution A’ = {0.1419, 0.1056, 0.2211} for each row (refer column three in Table 10)

Step 5: The relative closeness to the ideal solution (C_i^*) is calculated using the equation

C_i^* = (S_i^* + S_i’)^1/2 (refer column four of Table 10)

The value of C_i^* for Mould Design M_3 is 0.25. This is the closest value to 0. Therefore, Mould design M_3 is the best alternative.

Case (b): The indexes S, O and D having importance of 10, 8, and 6 respectively are considered in consistent with FEAROM case (b). The set of relative weight (W) is computed using AHP method. The result obtained is as follows.

W = {S, O, D} = {0.633, 0.261, 0.106}

The MFTOPSIS method discussed above is applied for this case also. The results obtained for this case is shown in Table 11. Again, for the weights allotted by the FMEA design team, the alternative M_3 is chosen as the C_i^* value 0.21 is the one closest to 0.

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4. RESULTS AND DISCUSSIONS

As discussed in the previous sections, a modified FMEA approach termed FEAROM is applied for selecting the best mould design out of three alternatives. The detailed data related to the Bearing Housing sand casting given in Table 5 is used for identifying the best mould design. The best mould design is selected using FEAROM method based on the calculated RPC values (shown in Table 6). Two different cases are solved using FEAROM method. One is considering equal importance for all the three indexes (S, O and D) and the other is considering different importance ratings for S, O and D. The former case alone can be solved using the traditional FMEA approach. Traditional FMEA cannot be applied for the later case. But the proposed FEAROM methodology can solve both the cases.

FEAROM selects the mould design M₃ in both the cases.

Analysis of the data in Table 6 reveals that the mould design M₃ is ranked as first in both case (a) and case (b) using FEAROM model. But the mould design M₂ and M₁ are ranked as first using traditional FMEA method (refer Table 6). This leads to difficulty in selecting the best mould design.

To validate the decision obtained using FEAROM method, MFTOPSIS method is also applied to the same data set shown in Table 6. It is evident from Tables 10 and 11 that MFTOPSIS method also selects mould design M₃ for both the cases. Therefore, the outcome of the FEAROM method matches with the results of the proven TOPSIS method. Table 12 depicts the mould design selected using the three methods, viz., traditional FMEA, FEAROM and MFTOPSIS method.

<table>
<thead>
<tr>
<th>Alternatives</th>
<th>Sᵢ⁺ = ∑(vᵢ⁻vⱼ)² (1)</th>
<th>Sᵢ⁻ = ∑(vᵢ⁻vⱼ)² (2)</th>
<th>Cᵢ⁺* = Sᵢ⁺/(Sᵢ⁺ + Sᵢ⁻) (3)</th>
<th>Cᵢ⁻* = Sᵢ⁻/(Sᵢ⁺ + Sᵢ⁻) (4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>M₁</td>
<td>0</td>
<td>0.209</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>M₂</td>
<td>0.197</td>
<td>0.069</td>
<td>0.26</td>
<td>0.26</td>
</tr>
<tr>
<td>M₃</td>
<td>0.169</td>
<td>0.056</td>
<td>0.25</td>
<td>0.25</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Alternatives</th>
<th>Sᵢ⁺ = ∑(vᵢ⁻vⱼ)² (1)</th>
<th>Sᵢ⁻ = ∑(vᵢ⁻vⱼ)² (2)</th>
<th>Cᵢ⁺* = Sᵢ⁺/(Sᵢ⁺ + Sᵢ⁻) (3)</th>
<th>Cᵢ⁻* = Sᵢ⁻/(Sᵢ⁺ + Sᵢ⁻) (4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>M₁</td>
<td>0</td>
<td>0.188</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>M₂</td>
<td>0.132</td>
<td>0.133</td>
<td>0.5</td>
<td>0.5</td>
</tr>
<tr>
<td>M₃</td>
<td>0.161</td>
<td>0.044</td>
<td>0.21</td>
<td>0.21</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Mould designs</th>
<th>Traditional FMEA</th>
<th>FEAROM method</th>
<th>MFTOPSIS method</th>
</tr>
</thead>
<tbody>
<tr>
<td>M₁</td>
<td>3</td>
<td>3</td>
<td>3</td>
</tr>
<tr>
<td>M₂</td>
<td>2</td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>M₃</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
</tbody>
</table>

Based on the analysis, mould design M₃ is selected by the design team. Therefore, the potential failures in the mould design M₃ needs to be eliminated before final approval. The FMEA design team recommended a put-up riser in addition to other risers in the pattern to eliminate the problem of shrinkage.

The mould design M₃ is implemented and the preproduction trial of the Bearing Housing is cast using the altered pattern. The post trial-production analysis is carried out and the castings obtained using M₃ is found to match the acceptable standards of the customer. Hence the same was adopted by the industry for their batch production.

5. CONCLUSION

This research paper has demonstrated and substantiated the application of the novel method named FEAROM to prioritize the mould design for a Bearing Housing. Two cases were solved for the considered data set. The first case equally rates the indexes S, O and D. Whereas the second case rates index S higher than index O. Index O in-turn is rated higher than index D. Traditional FMEA does not solve the second case. Also, in case of a tie in RPN, traditional FMEA could not select the best method. The proposed FEAROM method is able to overcome the above mentioned difficulties. Based on the outcome of FEAROM method mould design M₃ was selected. MFTOPSIS method was also applied to the same data set to verify the FEAROM outcome. MFTOPSIS method also indicated that mould design M₃ is better for both the cases. Thus
validation of FEAROM model was made. The preproduction trials were carried out using the proposed mould design M1 and the quality of the obtained castings was found to be good. Therefore, FEAROM method can be used for finalizing the mould design for similar sand casting components in future orders during their preproduction trials. The method is also easy to apply and can be used for making multi-criteria decision quickly.

References

2/22/2013