# "If Only My Foundry Knew What it Knows ...": A 7Epsilon Perspective on Root Cause Analysis and Corrective Action Plans for ISO9001:2008

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## Abstract:

The 7Epsilon penalty matrix approach visualizes factor-response in-process data so that variation in process settings (i.e. measurable factors) that are correlated to variation in response can be identified. The method is applicable to any multivariate data analysis project for root cause reasoning to develop new hypotheses, identify and carry out corrective actions for reduction in variation of response. It can be used to analyze in-process data for investment casting process including all of its sub processes like wax pattern making, shell making, melting, casting, heat treatment etc. The paper describes how an investment casting foundry benefitted by implementing the 7steps of the 7Epsilon methodology for continual process improvement as per the requirements of the clause 8 of the ISO9001:2008 standard. Further opportunities have also been identified for process improvement case studies.

Authors have realized that the foundry industry, whether its aerospace or automotive, investment casting or sand casting, needs to address a cultural issue regarding reusing of process knowledge and in-process data in decision making for continual process improvement projects. The role of trade associations as well as a pathway for operator training within 7Epsilon continual process improvement philosophy has been discussed. It is hoped that the panel discussions and the conference environment will provide useful feedback/insights for all stakeholders.

Keywords: Process Control, Defect Analysis, Six Sigma, Continual Process Improvement, Casting Process Optimization

## Introduction: 7Epsilon, Six Sigma and Continual Process Improvement

7Epsilon – a new innovative approach to continual process improvement in foundries refines the Measure, Analyse, Improve and Control stages of Six Sigma as per ISO 9001:2008 requirements (Figure 1). The 7 steps of 7Epsilon are explained in this paper with reference to an example investment casting foundry scenario. These steps are similar to the steps defined by Dr. HMd Roshan[1].
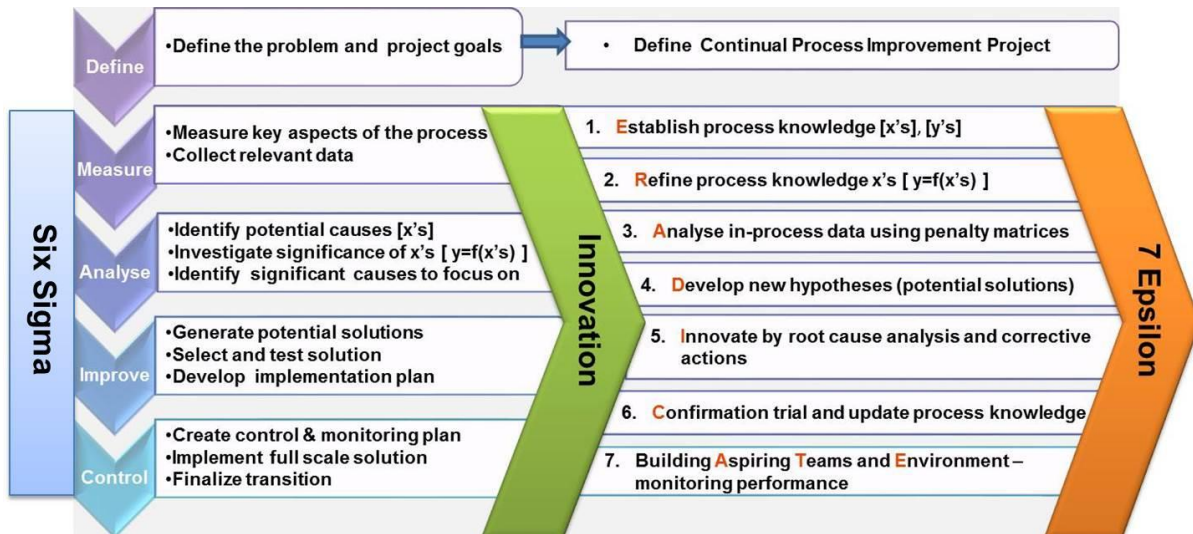
Figure1: Transition from Six Sigma to 7Epsilon for continual process improvement
(www.7epsilon.org)

**Foundry Scenario:** An investment casting foundry explored the investigation of the effect of alloy composition in a Nickel based super alloy known to have variable castability, as Shrinkage defects are common. When physics based simulation techniques are unable to justify the occurrence of Shrinkage defect, the solution could be held within the chemical composition of the alloy. This case study explores the effect composition of the melt has on the Shrinkage found in parts.

This example is part of the one day 7Epsilon training course given by the authors.

A High level process map is drawn to identify and name the core processes in the foundry and list the casting defects that are attributable to the concerned processes[2]. Pareto chart helped in identifying the most commonly occurring 'Shrinkage' defect and the parts that contributed to maximum manufacturing cost. This task is similar to that undertaken in the *Define* stage of Six Sigma to design your goal.

The foundry experts wanted to decide the optimal chemical composition to reduce Shrinkage defect in a Nickel based super alloy. The foundry decided to implement the 7Epsilon approach for continual process improvement. The aim was to develop process control improvements for reduction in process variation that may contribute to the occurrence of shrinkage. The foundry decided to perform root cause analysis using the following 7 steps of 7Epsilon methodology (as explained on www.7epsilon.org website and shown in Figure 1) to **ERADICATE** defects.

Step 1: **E**stablish process knowledge [x's], [y's]

Step 2: **R**efine process knowledge [y = f(x's)]

Step 3: **A**nalyse in-process data using penalty matrices

Step 4: **D**evelop hypotheses (potential solutions) for new product specific process knowledge

Step 5: **I**nnovate using rootcause analysis and conducting confirmation trials

Step 6: **C**orrective actions and update process knowledge
Step 7:  Build **A**spiring **T**eams and **E**nvironments by monitoring performance

**Step 1:  Establish process knowledge [x's], [y's]**
A team of process experts is formed to capture team member's knowledge about the process, its factors and responses as well as causal relationships codified using pictorial diagrams such as Process Maps, SIPOC Diagrams, Cause and Effect Diagrams. Experts identified 15 chemical components of the melt for the analysis which may have an effect on Shrinkage. The parameters are listed in Table 1.

| Carbon | C | Cobalt | Co | Iron | Fe | Tantalum | Ta | Tungsten | W | Al + Ti |
|--------|---|--------|-----|------|-----|----------|-----|----------|---|---------|
| Aluminium | Al | Chromium | Cr | Molybdenum | Mo | Titanium | Ti | Nitrogen | N | Ta/Ti |
| Boron | B | Copper | Cu | Niobium | Nb | Zirconium | Zr | Oxygen | $O_2$ | |

Table 1 – Analysis Parameters

**Step 2:  Refine process knowledge [y = f(x's)] by compiling explanations for factor response relationships**
7ε methodology introduces the "knowledge refinement" step as an extension to traditional process improvement approaches. The importance of this step lies in understanding the relationship between process responses Y and process parameters X and how the variability in factors (X's) affects responses (Y). Foundries usually rely on "process experts" but unavailability of experts may give rise to issues. Process knowledge acquired by foundries needs to be systematically collected, recorded and made available to users at fingertips for future references. "Knowledge retention and reuse" is highly imperative for the success of 7Epsilon project as per the ISO 9001:2008 clause 8 requirement.

1. During this step, process engineers systematically research about process factors and responses to find out
   a. how factors are related to responses and how they can be measured;
   b. importance of factors in relation to responses
2. The outcome of this phase is a written description of process factors' characteristics with respect to one or more responses.

An example of Shrinkage response and Niobium is given below. Process engineers and foundry managers are expected to create a similar list for all measurable factors and responses. The current target value and the tolerance limit for all chemical compositions for a given cast components must also be specified (e.g. Nb: 0.75% ± 0.15). The authors define this value and the tolerance limit as part of the foundry and product specific process knowledge[3]. Relevant technical literature is scanned to study inter-relationships between factors and responses and notes are made. For example, in this case the peer reviewed literature suggested an increased Niobium and Aluminum tends to reduce inter-dendritic shrinkage porosity[4].

**Step 3: A̲nalyse in-process data using penalty matrices**

Typically, in-process data are routinely being collected as part of ISO9001:2008 implementation. Data capturing tools and sensors regularly collect process parameter data whereas response data on defective or rework castings are collected at casting inspection and machining stages. Data is stored automatically in databases and manually using spreadsheets, charts etc. "Knowledge Reuse" facilitates knowledge discovery which is at the heart of the 7Epsilon approach. The fragmented data stored in different systems needs to be retrieved and reused for analysis to gain new insights into the process.

In this foundry scenario, data on 60 batches were collected. The production data for 60 batches with 15 process parameters from Table 1 and %Shrinkage rate was recorded. Each row in the Figure below presents a batch. Process data for parameters in Table 1 is linked to the number of defective castings via batch number, date and shift. Although the range of each component was maintained within the specifications of the alloy, there was room for adjustments to be made. The objective of this study was to find out if the occurrence of Shrinkage defects can be minimized by altering any of the chemical components to their top, middle or bottom range specified for this alloy.

| LB | c | c | c | c | c | d | c | c | c | c | c | c | c |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Shrink Scrap | Carbon | Aluminium | Boron | Cobalt | Chromium | Copper | Iron | Molybden | Niobium | Tantalum | Titanium | Tungsten | Zirconium |
| 0.12 | 0.101 | 3.23 | 0.009 | 7.857 | 15.2 | <0.02 % | 0.086 | 1.663 | 0.846 | 1.587 | 3.23 | 2.556 | 0.037 |
| 0 | 0.093 | 3.145 | 0.009 | 7.971 | 15.295 | <0.02 % | 0.086 | 1.644 | 0.798 | 1.558 | 3.211 | 2.594 | 0.05 |
| 0.15 | 0.107 | 3.249 | 0.009 | 7.781 | 15.248 | <0.02 % | 0.152 | 1.691 | 0.893 | 1.653 | 3.278 | 2.423 | 0.031 |
| 0 | 0.103 | 3.249 | 0.008 | 8.028 | 15.096 | <0.02 % | 0.105 | 1.653 | 0.865 | 1.568 | 3.211 | 2.489 | 0.035 |
| 0 | 0.105 | 3.183 | 0.008 | 7.781 | 15.001 | <0.02 % | 0.124 | 1.682 | 0.808 | 1.52 | 3.107 | 2.423 | 0.032 |
| 0 | 0.107 | 3.107 | 0.008 | 7.8 | 15.295 | <0.02 % | 0.19 | 1.663 | 0.808 | 1.615 | 3.145 | 2.442 | 0.022 |
| 0 | 0.109 | 3.145 | 0.01 | 7.866 | 15.267 | <0.02 % | 0.095 | 1.691 | 0.77 | 1.653 | 3.192 | 2.451 | 0.024 |
| 0 | 0.112 | 3.287 | 0.009 | 7.743 | 15.305 | <0.02 % | 0.19 | 1.663 | 0.817 | 1.672 | 3.211 | 2.461 | 0.023 |
| 0.02 | 0.106 | 3.145 | 0.009 | 7.838 | 15.352 | <0.02 % | 0.095 | 1.644 | 0.808 | 1.596 | 3.164 | 2.461 | 0.023 |
| 0 | 0.106 | 3.249 | 0.008 | 7.809 | 15.276 | 0.0002 | 0.095 | 1.634 | 0.817 | 1.558 | 3.173 | 2.48 | 0.024 |
| 0 | 0.108 | 3.097 | 0.008 | 7.781 | 15.286 | <0.02 % | 0.095 | 1.653 | 0.836 | 1.625 | 3.202 | 2.432 | 0.023 |
| 0 | 0.108 | 3.183 | 0.008 | 7.828 | 15.286 | <0.02 % | 0.095 | 1.634 | 0.798 | 1.577 | 3.145 | 2.48 | 0.026 |
| 0 | 0.106 | 3.24 | 0.008 | 7.857 | 15.02 | <0.02 % | 0.143 | 1.663 | 0.865 | 1.615 | 3.173 | 2.518 | 0.03 |
| 0 | 0.108 | 3.268 | 0.009 | 7.895 | 15.267 | <0.02 % | 0.171 | 1.672 | 0.865 | 1.568 | 3.211 | 2.47 | 0.03 |

Figure 2 – Batch wise production data for Shrinkage and Chemistry for a Nickel based alloy.

The 7Epsilon Penalty Matrix approach was adopted to perform root cause analysis and discover product specific optimal and avoid process settings. The Penalty Matrix algorithm[3], uses a simple but novel idea of associating penalty values to responses and displaying data using bubble diagram and penalty matrices.

Zero penalty value is assigned to the best performing observations and 100 penalty value to the worst performing observations. Intermediate values are linearly scaled between zero and 100. A transformation of response values into 0 to 100 penalty values forms the basis of analysis.

In addition to domain knowledge the following heuristic rules may also be used in determining upper and lower thresholds.

- penalizing the worst 10-15% (or more) observations or at least 5-10 bad points (whichever is higher) while giving a penalty value 0 to the best 30-40% (or more) or 10-20 good points (whichever is higher);
- plot the scatter of responses values in ascending (or descending) order and find by visual inspection two points where the curvature of the plot changes.

Figure 3 shows the scatter plot of %Shrinkage defects per batch showing variation of response in ascending order in different batches. The green and red line divides the data into regions of penalty values. In this example, 0 penalty is applied to desired response (i.e. batches with up to 0% Shrinkage rate) and 100 penalty to unacceptable response (i.e. batches with above 3% Shrinkage rate) and values are linearly scaled from 1 to 99 for the remaining batches. These threshold values are chosen to create a meaningful variation in response values.

Response penalty values are then transferred to process parameter data values to identify process settings that are correlated to desired, undesired and intermediate response values. Optimal and avoid regions of process settings are displayed in bubble diagrams. Figure 4 (a) and (b) respectively show the scatter and bubble diagrams for an average Zirconium value measured during the production of the response batch.
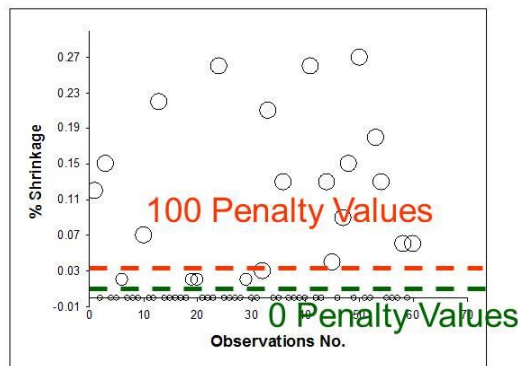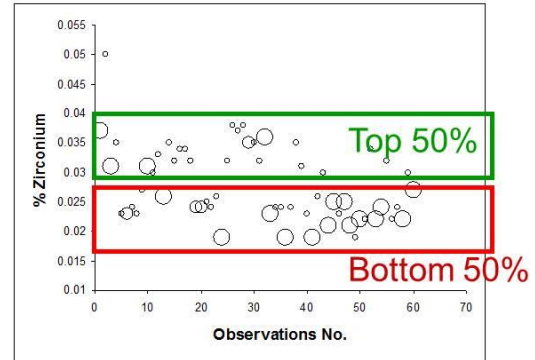


Response Bubble Diagram

Figure 3 - The scatter plot of Shrinkage shows variation of response in different batches with the chosen penalty function
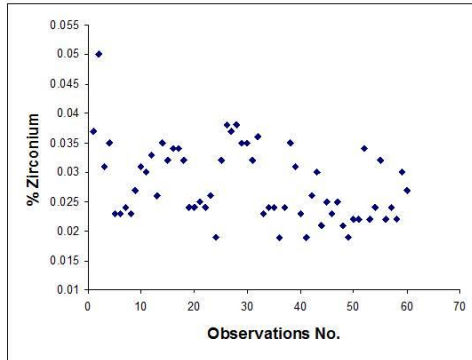
Main Effects Scatter Diagram

Main Effects Bubble Diagram

Figure 4 - Scatter (a) and bubble (b) diagrams for Zirconium

In the bubble diagram (Figure 4(b)), the radius of the circle represents the corresponding Shrinkage penalty value. From a visual inspection of the bubble diagram it can be found that values of Zirconium above the median (or 0.03 and above) are desirable since they are associated with low penalty values. A limitation of bubble diagrams is that, in the presence of overlapping observations, it might be difficult to find optimal regions. In this case the same data can be visualised using penalty matrices.



**Zirconium**

| | Q1 | Q2 | | Q3 | Q4 |
|---|---|---|---|---|---|
| Minimum | | | Median | | Maximum |
| 0.019 | 0.023 | 0.026 | 0.032 | | 0.05 |

Q4: Optimal; Range: Top 25%, {>=0.032 & <=0.05}; Strength: 3.5; No. of Interactions: 0
Q3 & Q4: Optimal; Range: Top 50%, [>0.026 & <=0.05]; Strength: 2.8; No. of Interactions: 1 ; Max. Interaction Strength: 3.2
Q1 & Q2: Avoid; Range: Bottom 50%, [>=0.019 & <=0.026]; Strength: 2.8; No. of Interactions: 3 ; Max. Interaction Strength: 3.4

| Penalty | Q1 | Q2 | Q3 | Q4 |
|---|---|---|---|---|
| 80-100 | 9 | 4 | 3 | 2 |
| 60-80 | 1 | 2 | | 1 |
| 40-60 | | | | |
| 20-40 | | | | |
| 0-20 | 7 | 9 | 5 | 17 |

Main Effects Penalty Matrix

Figure 5 – Penalty matrix for Zirconium and Shrinkage is shown in the picture.

In penalty matrices rows correspond to five penalty bins (0-20, 20-40, 40-60, 60-80, 80-100) and columns correspond to factor quartile ranges (Q1-bottom 25%, Q1+Q2 –bottom 50%, Q4-top 25%, Q3+Q4-top 50%, Q2+Q3-middle 50% quartile range of factor). Using penalty matrices it possible to find optimal and avoid ranges based on quartiles. An example of penalty matrix of Shrinkage for Zirconium is shown in Fig. 5. A study of this Figure shows that Quartiles Q3+Q4 or Top 50% range has twenty two (i.e. seventeen plus five) data points with a penalty value of 0-20, one data point with a penalty value of 40-60 and five (i.e. three plus two) data points with a penalty value of 80-100. Top 50%

range of Zirconium corresponds to an optimal range since it has a higher proportion of response values with low penalties.

This method can be further extended to analyse interactions between any two factors. An interactions bubble diagram and penalty matrix between Zirconium and Boron is shown in Figures 6(a) and (b) respectively.



Zirconium
F1: Zirconium, Range:Top 50%,[>0.026 & <=0.05]; Strength: 2.8
F2: Boron, Range:Bottom 50%,[>=0.007 & <0.009]; Strength: 2.0
**Strength of Optimal Interaction: 3.2**

| Penalty | F1:F2 | F1:~F2 | ~F1:F2 | ~F1:~F2 |
|---------|-------|--------|--------|---------|
| 80-100  | 1     | 4      | 5      | 8       |
| 60-80   | 1     | 0      | 0      | 3       |
| 40-60   | 0     | 0      | 0      | 0       |
| 20-40   | 0     | 0      | 0      | 0       |
| 0-20    | 15    | 7      | 5      | 11      |

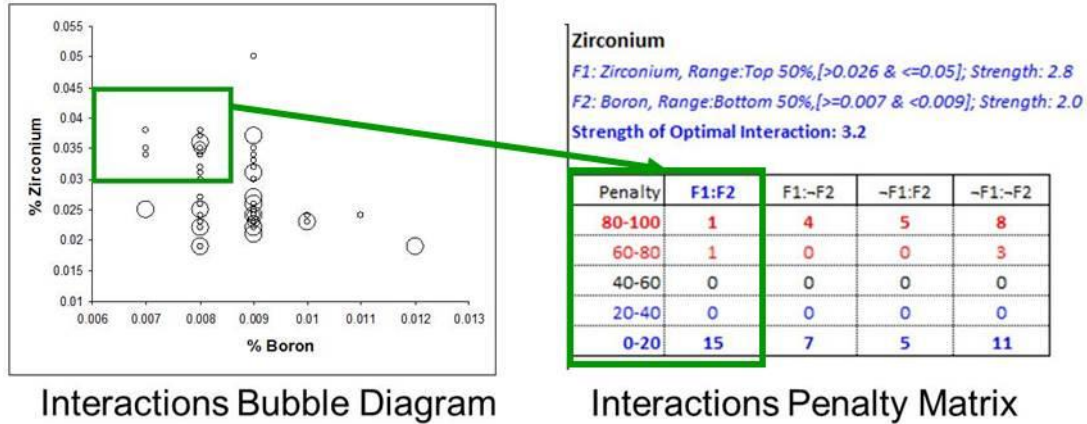Interactions Bubble Diagram      Interactions Penalty Matrix

FiFigure 6 - Bubble diagram and penalty matrix can be used to find out optimal and avoid ranges due to interactions of two factors. Top 50% of (F1) and Bottom 50% of (F2) is considered optimal.

**Step 4 - Develop hypotheses (potential solutions) for new product specific process knowledge**
In the presence of large number of factors, when the calculation of penalty matrices for main effects (i.e. single factor) and interactions becomes quite cumbersome, commercial software like p-matrix data visualizer (www.7epsilon.org) have ability to rank important penalty matrices from hundreds or thousands of possible combinations.
- p-matrix reports are analysed and main effects and interactions among process parameter settings and their correlation with response variation is studied.
- Hypotheses on causation are established by using the knowledge developed in the 'Refine process knowledge step' and correlations discovered in the 'Analyse in-process data using penalty matrices step'.

Using p-matrix, the following factors that have a significant effect on Shrinkage have been selected. The following hypotheses (Table 2) were generated and put on the agenda for discussion during the next 7Epsilon Quality Control Meeting.

| Respon | Res | Lo | Highe | Factor name | Level | Optimal/Avoid | Strength | No. of Interactions | Max. Int | Min. Value | Max. Value | Level with Values |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Shrink | LB | 0 | 0.03 | Niobium | Middle 50% | Optimal | 6 | 0 | | 0.656 | 0.893 | {>0.77 & <0.827} |
| Shrink | LB | 0 | 0.03 | Carbon | Middle 50% | Optimal | 3.5 | 0 | | 0.086 | 0.113 | {>0.095 & <0.106} |
| Shrink | LB | 0 | 0.03 | Carbon | Top 50% | Optimal | 3.3 | 0 | | 0.086 | 0.113 | [>0.103 & <=0.113] |
| Shrink | LB | 0 | 0.03 | Iron | Top 50% | Optimal | 3.4 | 0 | | 0.057 | 0.2 | [>0.114 & <=0.2] |
| Shrink | LB | 0 | 0.03 | Aluminium | Top 25% | Optimal | 3.6 | 0 | | 3.059 | 3.306 | {>=3.24 & <=3.306} |
| Shrink | LB | 0 | 0.03 | Zirconium | Top 50% | Optimal | 2.8 | 1 | 3.2 | 0.019 | 0.05 | [>0.026 & <=0.05] |
| Shrink | LB | 0 | 0.03 | Boron | Bottom 50% | Optimal | 2 | 5 | 3.3 | 0.007 | 0.012 | [>=0.007 & <0.009] |
| Shrink | LB | 0 | 0.03 | Aluminium + Titanium | Bottom 25% | Avoid | 3 | 0 | | 6.204 | 6.527 | {>=6.204 & <=6.299} |
| Shrink | LB | 0 | 0.03 | Cobalt | Top 50% | Avoid | 2.2 | 6 | 3.4 | 7.714 | 8.028 | [>7.847 & <=8.028] |
| Shrink | LB | 0 | 0.03 | Nitrogen | Bottom 50% | Avoid | 2 | 1 | 3 | 11.4 | 38.95 | [>=11.4 & <=23.75] |

Table 2 – Optimal and Avoid parameter ranges that can have an effect of reducing the Shrinkage defect.

| Respon | Res | Lo | Highe | Factor name | Level | Optimal/Avoid | Strength | No. of Interactions | Max. Int | Min. Value | Max. Value | Level with Values |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Shrink | LB | 0 | 0.03 | Aluminium + Titanium | Top 75% | Optimal | 2.5 | 1 | 3.1 | 6.204 | 6.527 | [>6.299 & <=6.527] |
| Shrink | LB | 0 | 0.03 | Cobalt | Bottom 50% | Optimal | 2.2 | 4 | 3.3 | 7.714 | 8.028 | {>=7.714 & <=7.847} |
| Shrink | LB | 0 | 0.03 | Nitrogen | Top 50% | Optimal | 2 | 1 | 2.9 | 11.4 | 38.95 | [>23.75 & <=38.95] |

Table 3 – Avoid settings from Table 2 converted into their complementary optimal settings to reduce Shrinkage defect.

## Step 5 - Innovate using rootcause analysis and conduct confirmation trials

Innovation occurs when new root causes that are supported by trends in the literature are found and product specific process knowledge is discovered.
- A decision is taken to collect more in-process data, plan one or more design of experiments or conduct confirmation trials in order to propose new tolerance limits.
- Foundries can determine the optimum ranges for all the process variables [X's] and design corrective actions plan and implement to validate the hypotheses and create new product specific process knowledge.
- It must also be remembered that correlation does not mean causation. However, during the innovation stage, care must be taken not to suppress new ideas from team members. Like in any brain storming session, every idea must be welcomed. The ideas are then critically assessed with reference to the domain knowledge and wisdom with an open mind on the possibility of creating new knowledge.

The report generated in step 4 is discussed in the 7Epsilon Quality Control meeting. The Confirmation trial was approved with the optimal chemical component ranges based on the following five criteria.
1. Component settings with high main effect strength (> 3),
2. Settings with low main effect strength (<3) but with one or more strong interactions (with interaction strength =>3) are chosen for the trial.
3. Settings with strong avoid main effect strength (>3) converted to their complimentary optimal ranges.
4. Settings with low avoid main effect strength (<3) but with one or more strong avoid interactions (with interaction strength =>3) converted to their complimentary optimal ranges.
5. Optimal or avoid setting with high number of interactions ( 4, 5 or higher number)

The strengths are calculated with commercial p-matrix data visualizer software and high strength values suggest that the corresponding penalty matrix is important. These potential trends need to be checked with the domain knowledge in the literature and as identified in the Step 2: Refine Process Knowledge. Update the knowledge recorded in Step 2 if necessary.

**Step 6 – <u>C</u>orrective actions and update process knowledge**
- New knowledge obtained in the previous step is stored in tabular form and consists of a list of parameters with their new specifications. It must be noted that the new specification ranges are specific for a given part and process.
- The new knowledge acquired contributes to devise preventive and corrective action plans to achieve reduction of Sand Inclusions defects as required by ISO 9001:2008 standard.
- This knowledge is reused alongside the process knowledge compiled in the 'Refine process knowledge' step.

**Step 7 - Build <u>A</u>spiring <u>T</u>eams and <u>E</u>nvironments by monitoring performance**
- Once the new process specifications have been implemented, foundries must continually monitor the responses of defects so that continual improvement on the processes can be made to meet the requirement of ISO 9001:2008.
- The foundry specific 7Epsilon process knowledge repository can also be used to train operators and process engineers.

Using the 7Epsilon analysis the foundry was able to quickly identify complex relationships and lower the number of defective castings produced.

**<u>Further Examples of Foundry Scenarios</u>**

Between July 2013 and October 2013, Drs Rajesh and Meghana Ransing, 7ε coordinators and course instructors, have personally trained over 150 foundry engineers in UK, EU and India on the 7ε approach. ICME - UK, Swerea Swecast - Sweden, Foundry Research Institute - Poland and Tecnalia - Spain hosted the 7Epsilon courses in their countries. Experts from leading steel, aerospace and automobile foundries, foundry, technology and quality specialists; consultants, academia, and environmental specialists were among the participants.

Discussions revolved around applicability of the method and mainly comparisons with statistics. The direct assistance and time allowed for exercises and an open dialogue was particularly liked. Participants believed that data visualization using penalty matrices will allow foundry men to design corrective actions within short time. In-process data sent in advance helped foundry men to learn the course content through their own example. Participants appreciated that 7Epsilon method puts light on new hypotheses for corrective actions. The essence of the course was reflected in the group discussion sessions during the latter part of the day. The interactions amongst participants lead to intriguing foundry

scenarios for 7Epsilon implementation which were presented with thought provoking conclusions.  The general observations made by the participants on this approach are also enclosed in this paper. Participants' feedback is available on www.7espilon.org.

Few foundry scenarios relevant to investment casting foundries that were identified during brainstorming sessions in the course are compiled and presented in this paper along with the observations about the penalty matrix analysis for the benefit of the wider foundry community.

## <u>Opportunities for continual process improvements (Foundry Scenarios):</u>
The penalty matrix data visualizer software can be used for investigation of reasons of occurrence of defects in castings, to discover opportunities for further strengthening material properties, energy saving, reduction in rework and finishing costs. For investment casting process including its sub-processes, data on discrete parameters such as operators, shift, furnace to continuous factors like pouring time, pouring temperature, chemical compositions, wax and shell room parameters etc. can be analyzed.

For continual improvement, identify one product at a time or a family of products which share similar process settings and improve the process specific to the product. A typical process improvement project has 1 to 2 process responses (defect, material property), 20 to 30 factors or process parameters (continuous or discrete) and as low as 30-50 observations for responses and factors. Observations should include both good data i.e. when desired response was achieved, as well as bad data i.e. when desired response was NOT achieved. Good or approximate traceability among process parameter readings and castings is desirable to ensure meaningful results of analysis.

## Responses, process parameters and traceability
Traceability relates to the sampling frequency of responses and process parameters and the linkage between the two.  Responses include % rejection values per batch, porosity score or rework time per component, defects like inclusions, cracks, shrinkage and porosity etc; material properties such as UTS, YS, %EL, machinability index etc. Response values are recorded every 30 minutes, or per batch, per heat, per shift, per day or per component. The date and time of manufacture is also normally recorded.

Factors or process parameters may be associated with a number of sub-processes e.g. mould/shell making process, core making process, melting process, casting process, heat treatment and machining process. We have continuous factors (e.g. pouring time, pouring temperature, chemical compositions, humidity values, % carbon values etc.) and discrete factors (e.g. operator name, furnace type, oven, shift etc.).

Frequency of capturing data for factors can be different to that of responses. Response value can either be associated with only one value of factor(s) or multiple values of factor(s).
- E.g. % rejections due to shell crack are recorded per batch and can either be associated with

- a corresponding single value for 'humidity' recorded per batch referred to as 'equal sampling rate' OR
- multiple values say 5-6 values of 'humidity' recorded per batch referred to as 'higher sampling rate'.

Identification of a unique identifier that is common to both factors as well as responses holds the key to linking factor-response data. Unique identifiers can be heat no, batch id, shift, date and time etc. Unique identifier can also be created to link response data to factor data. E.g. Rejection rate is recorded after every 2 hours. Pouring temperature, chemistry are recorded every 10 minutes. Using date and time every value of rejection will be linked to 12 corresponding values of pouring temperature, chemistry and sand parameters. The analysis will need 30 values of rejection and corresponding 30*12=360 values of process parameters linked using date+time+batch id as our unique identifier.

The best way to begin a 7Epsilon project is to start analyzing your existing data to realize immediate cost saving opportunities.

**Further examples of Investment Casting Foundry Scenarios**
1. **Cracks**
   - Investigation of reasons for Cracks in parts
   - Data on Chemistry, Heat and Pre-heat temperatures
   - Recorded cracks in part as 0 (desired) or 1 (undesired)
   - Collected observations for 126 batches
   - Sampling rate of response is same as sampling rate of process parameter data
   - P-matrix found strong Main Effects

2. **Inclusions**
   - Investigation of reasons for occurrence of Inclusions in Casting part
   - Recorded %casting defect for 100 batches during a month.
   - Recorded shell room parameters
     Face coat viscosity and density, Back up viscosity and density, humidity of shell room, drying times in stages 2 to 5, operator names at each stage, weight of shell, weight loss after baking, dewax temperature, dewax cycle time.
   - Batch wise Process parameter data on parts and no. of trees per hanger, size and orientation of parts, operators,
   - Collection of data before and after process changes such as slurry changed, boiler clave cleaned etc.
   - Lots of missing data
   - P-matrix enables to reinforce traceability in in-process data by linking casting scrap with casting process data, shell scrap and shell room data via date and time of casting batch. It found optimal ranges of viscosity, humidity, temperature and drying time between coats

3. **Slag**
   - Investigation of reasons for occurrence of Slag
   - No. of Rejected castings with Slag
   - Collected 50 observations of in-process data
   - Process parameters with one observation for every heat - Die no, no of shells, batch no, melt no, chemistry, shell preheating temp, furnace temp, etc.
   - Two parameters with higher sampling rate than the response are follows
        a. Pouring temp - 4 values for every heat
        b. Pouring time / shell - 10 values for every heat
   - P-matrix found Longer pouring time and lower pouring temp ranges to be optimal.
   - Melt no. can be further investigated by analysing chemical composition of every melt.

4. **Shell Scrap**
   - Investigate reasons for occurrence of Shell Scrap
   - Recorded %shell scrap for 120 batches
   - Following shell room data is collected
        o Weekly data on slurry, silica, total solids, polymers, binder viscosity,
        o Daily data for 6 weeks on Density, Viscosity for $1^{st}$ prime, $2^{nd}$ prime and backup coats.
   - Daily readings of Humidity and Temperature recorded every 20 seconds.
   - P-matrix enabled to reinforce traceability in in-process data by linking process data with scrap results using date and time of shell batch.

5. **Oxides defect**
   - Recorded number of defective castings in 200 batches
   - Batch wise process data on pouring date, master heat, furnace and ceramic core supplier
   - P-matrix discovered a heat number having an avoid correlation with the oxide defect.
   - Heat number can be further investigated by analysing chemical composition of every heat.

**In addition to foundry scenarios, participants made the following observations:**
- **Correlation does not mean Causation –** p-matrix discovers correlations and correlations do not always lead to causation. **Domain knowledge is necessary to interpret correlations.**
- p-matrix discovers correlations within the input data. It does not have additional knowledge about your process.
- If p-matrix does not discover any correlation between factors and responses in a study, then it can be concluded that current tolerance limits are perhaps robust and it is necessary to include data on additional parameters and rerun analysis to discover new correlations.

- Some of its findings discover possible existence of hidden causes which require further investigation. E.g. If a correlation is discovered between ladle numbers 1-4 and lower defect rate then the possibility of a hidden factor such as pouring temperatures can be investigated further.
- Its findings **are pointers for discussion** to make a decision and it doesn't mean that you need to implement all of them.
- The tool generates new hypotheses for possible inclusion in a corrective action plan in order to design a confirmation trial.
- The tool is meant **to be used by decision makers.**
- It's ease of use and interpretation provides you an easy way to get access to those patterns without spending a lot of time.
- If you get even one or two pointers using a p-matrix study, it's a study well worth. Even if you knew the patterns, p-matrix results will still increase your confidence in communicating the information to process engineers or supervisors.
- **Within process specifications** – The method finds correlations between process parameter settings (within specifications) and response variation. It cannot and does not recommend extrapolating the results outside current specifications.
- **Our objective is to get process engineers to use in-process data for everyday analysis**.
- p-matrix assigns a correlation strength between 1 and 10 (1 = important to know, 10 = exceptionally strong. The patterns are statistically significant for p-matrix correlation strength values above 3.5 or 4.
- The strength of doing a p-matrix analysis is that it reinforces traceability in your process data, and develops a scheme to retrieve your data and undertake analysis.


**7Epsilon thoughts for Panel Discussion on the Role of Trade Associations in advancing the industry:**

It is a very positive and welcome sign that AFS, EICF, FEF and ICI have come together on an open panel discussion on this topic, and as part of the 7Epsilon initiative, the authors would like to become active members of this activity.

Casting buyers are increasingly demanding customer rejects on 'parts per million scales' rather than 'the traditional percentage rejection rate'. It is not rocket science to say that foundries need to respond by focusing on 'zero defect manufacturing' rather than 'zero escape manufacturing.'

Authors have realized that the major obstacle in establishing a zero defect manufacturing environment is 'the current foundry culture' rather than 'the current foundry technology'. It is surprising to note that even today the best investment casting foundries struggle in retrieving most relevant in-process data for process improvement case studies. It is unbelievable but it is true. Traceability exists in principle, but in reality, the most relevant in-process data is still 'not few computer clicks away!' Process engineers need to spend hours and hours (sometimes weeks) to link defect data corresponding to 'batches of

shells' or 'casting melts' in a given time period with associated process variables. It is understandable that sampling rates for shell batches or casting melts and process parameters are different. However, this is not a technical problem. **It is a cultural issue that is endemic in the foundry world.** This is not sustainable in a zero defect manufacturing environment and this issue must be addressed. Trade associations have an important role to play in this area.

Most foundries complain that they don't have resources to retrieve or collect in-process data and engage in 7Epsilon projects. Foundry managers complain that graduates are no longer trained in foundry specialization and worse, are less likely to choose manufacturing cast metals as a career route. There is an opportunity for trade associations to make a difference by playing a 'match making' role. On an annual basis, trade associations can ask their member foundries to provide a list of process improvement projects that require a 'pair hands' as an additional resource. Local universities will be pleased to work with trade associations to place their engineering students for their summer projects, gap year projects (for 'year in industry' courses) or final year projects. Trade associations can also plan 7Epsilon or other specialize courses to run synchronized with this program to help students globally and create a 'win-win' situation for all involved. In UK, a pilot study is being planned with the help of Institute of Cast Metal Engineers (ICME) and Cast Metal Federation (CMF). Nothing stops us to make this program global for the benefit of the foundry industry.

Casting buyers, OEM's and suppliers can join hands with trade associations and sponsor an open competition by inviting best continual process improvement case study presentations and reward/recognize process engineers and foundry managers.

Trade associations also need to encourage knowledge sharing by indexing abstracts, highlights of the paper and titles of their own conference papers on Google. Foundry members need to put pressure on trade associations to make conference papers open source and freely available after 3 years. Foundry process engineers should be able to access papers on demand, 24*7. Trade associations need to help bring foundry industry to the 'Google Age'. This will increase citations, impact factors, quality and minimize the need of reusing the same paper, but perhaps worded differently, across various trade association conference platforms.

Maintaining the current cultural status quo is not an option if we want to realise a zero defect manufacturing dream.

## **Operator Training: The 7Epsilon way**

Next generation of engineers are growing in an environment with 'apps', 'social media' 'smart phones' and 'easily accessible knowledge that is continually reused and updated'. Foundries need to embrace this change. Foundries create wealth of 'foundry specific and product specific process knowledge during each process improvement study. This information is normally available as pdf files, scanned files of hand written text/diagrams,

photos, excel data files, word files, audio files etc. There needs to be an easy way of archiving and indexing with heterogeneous data/information/knowledge on a continual basis so that it can be reused within the foundry and becomes part of the operator training program. FMEA diagrams needs to be modified to include tolerance limits on process parameters and reasons whenever they are changed. Data and Knowledge reuse helps operators to visualize the process and understand why and how factors [X's] influence defects [Y's] by identifying importance of tolerance limits e.g. correlating variability in process parameters with defects and understanding its impact on the bottom-line.

Compiling a library of foundry specific process improvement case studies linked with expert knowledge available within the foundry and outside will help operators to continually improve their process knowledge.

DSpace@7Epsilon4Foundries is a knowledge repository prototype that is currently under development and is expected to become available for foundry use by the end of this year.

**<u>Conclusions:</u>**

The main objective of quality control is to hold process variation to a desired level.

A variety of techniques and software solutions are used by foundries today to minimize scrap rate. Physics based simulation techniques are used for studying the influence of design parameters on casting defects. Best practise principles are adopted and regularly reviewed to stabilize the process. In-process data, on number of measurable factors (e.g. pouring time, pouring temperature, chemical compositions, sand parameters etc.) and responses (shrinkage, inclusions, hardness, tensile strength etc.) is also collected and measured.

In spite of the adoption of technological advancements there is still undesirable variability in one or more process responses. It is understood that the measurable factors in foundry processes are not always easy to maintain within their foundry specific established tolerance limits. However, it is also not always clear that the proposed tolerance limit is indeed an optimal and robust limit. It is likely that the process variation may have a predictable pattern and regions within the minimum and maximum data points have correlations with the desired and undesired response values.

A 7Epsilon paradigm has been described as a way for continual process improvement. The focus of 7Epsilon projects is on data and knowledge reuse in order to reduce defects and undesired process outcome. Some of the cultural barriers that have become obstacles in the pursuit of establishing a zero defect manufacturing environment are discussed and the need for all stakeholders (casting buyers, trade associations, suppliers, foundries, universities and students) to come together is highlighted.

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