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"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 famous quotes of a former Chairman, president and CEO of Texas Instruments and Chairman of HP "if only we knew what we know" are very much applicable to the foundry industry. Despite the fact that many advances have been made in the field of foundry technologies relating to simulation software, moulding machines, binder formulation and alloy development, poor quality still remains a major issue that affects many foundries not only in terms of lost revenues but also contributing to negative environmental impacts. On an annual casting production of 95 million tonnes, assuming that on average 5% defective castings are produced with a production cost of 1.2€ per kg for ferrous alloys, the foundry industry is losing 5.7 billion €, producing landfill waste well in excess of two million tonnes and releasing just under two million tonnes of CO_2 emissions. Foundries have vast proportion of knowledge that is waiting to be tapped, documented, shared and reused in order to realise the saving potential of 5.7 billion € per year. This ambitious goal can only be achieved by developing effective knowledge management strategies to create, retain and re-use foundry and product specific process knowledge whilst supporting a smart and sustainable growth strategy. This is the focus of 7Epsilon (7ε), an innovative methodology led by Swansea University along with a consortium of European universities and research organisations. At the core of 7ε capabilities is casting process optimisation which is defined as a methodology of using existing casting process knowledge to discover new process knowledge by studying patterns in data [1].

According to the 7ε terminology, casting process knowledge is actionable information in the form of a list of measurable factors and their optimal ranges to achieve a desired business goal [1,2]. In this paper a penalty matrix approach is described for discovering main effects and interactions among process factors and responses by analysing data collected during a stable casting process. Through a practical cases study it is shown how this technique can be used as an effective tool in the root cause analysis of nonconforming products in the implementation of ISO9001:2008 requirements for continual improvement. In addition some practical aspects concerning the development of a knowledge management repository to store and retrieve foundry process knowledge are discussed. A template to document and structure foundry and product specific process knowledge is proposed so that knowledge can be stored and retrieved more efficiently by process engineers and managers with the final aim to improve process operations and reduce defects rates, taking a significant step towards achieving zero defect manufacturing.

Keywords: Continual Process Improvement, Zero Defect Manufacturing, Quality, Process Knowledge, Data Analysis, Casting Optimisation, Six Sigma, 8D, 7Epsilon, 7ε, FMEA.

INTRODUCTION

Metal casting process is a complex manufacturing process with several sub-processes such as patternmaking, molding, coremaking, melting and pouring, heat treatment, welding and finishing. It is also energy intensive process. On average foundries lose a minimum of 5% of their revenue in scrap (rejected castings) and rework. On an annual casting production of 95 million tonnes, with a production cost of 1.2€ per kg for ferrous alloys, the foundry industry is losing 5.7 billion €[1]. This indicates that there is a scope for improvement in metal casting process and its sub-processes. ISO 9000 quality management standards have gone evolution ever since their inception in 1987 and presently have ISO 9001:2008. This quality management system standard focuses on 'Process Approach' and 'Continual Improvement' and these are highly relevant to the foundries to be profitable.

In the foundry context, process knowledge is described as actionable information, in terms of the optimal tolerance limits and target values for continuous factors and optimal levels for discrete factors, in order to achieve desired process response(s)[1]. Reducing rejection rates from 5% to 2-3% and then further to 0% requires understanding of product specific process knowledge that also happens to be foundry specific. The metal casting process is considered as a complex process not only because it has several sub-processes but, for most sub-processes, it is difficult to assign variability in process responses to the tolerance limits or levels of one or more measurable factors. Each foundry has its own product specific local optimum for various measurable factors and it is normally not possible to reproduce the same process variability in two foundries – even if the foundries are owned by the same management. This makes foundry managers wonder whether manufacturing zero defect castings is an 'art' or 'science'. If it was just 'art' then experienced foundry operators would have developed the skill of manufacturing zero defect castings without the need of continuous professional development, access to technical peer reviewed literature and any formal qualifications. If it was just 'science' then foundry engineers would have solved the zero defect rejection problem by answering 'exam style questions' correctly. One of the challenges that the foundry industry is facing is the capture, storage and reuse of both skills; the 'art' and the 'science', in order to continually improve the process. The next generation of foundry engineers are growing up in the Google and Wikipedia age who rely on internet for instantaneous access to structured knowledge and may not have the privilege of receiving formal foundry training during their undergraduate degree training. Most of the foundry departments across many prestigious Universities have lost their identities over the last 15-20 years. In order to remain sustainable and avoid the risk of rediscovering the wheel, the foundry trade associations, suppliers and foundry experts also need to embrace a cultural change in the way knowledge is disseminated.

Foundries have vast proportion of knowledge that is waiting to be tapped, documented, shared and reused in order to realize the saving potential of 5.7 billion € per year. This indicates that foundries do not have the technology and/or the culture to produce castings without incurring these costs that could affect their profitability. We have a serious problem of 'Technology Gap' in our foundry industry. The gap in technology lies in the lack of process knowledge in foundries and lack of adequate personnel trained in process control.

Process knowledge can be obtained by developing a sound understanding of the relationship between process factors and responses for a specific casting. Process engineers can learn product specific process characteristic by re-using past experiences and analysing patterns in data. In order to discover improvement opportunities engineers need to be able to analyse sometimes weak patterns in noisy data. At the same time, it is critical that past knowledge is made available at the right time to verify hypothesis and support decision making. In modern foundries, knowledge is stored in the form of electronic documents or databases but it is often underutilised due to the fact that knowledge is scattered in heterogeneous systems and difficult to be retrieved. Usually there is not a single entry point to access process knowledge so a lot of effort is spent in knowledge retrieval.

The 7Epsilon (7ε) (www.7epsilon.org) approach is designed to address this gap. The 7ε term was coined by Dr. Patricia Caballero at Tecnalia in Spain and the 7 steps of 7ε to ERADICATE defects were introduced by Dr. Rajesh Ransing at Swansea University, UK who is also leading the initiative along with a consortium of European research institutions and trade associations. The approach is similar to Six Sigma initiatives in that it has the usual 'Define, Measure, Analyse, Improve and Control' steps. However, it focuses on foundry and product specific continual process improvement and knowledge discovery by analyzing in-process data and recommends a knowledge repository concept to reuse the knowledge in order to stimulate a culture of innovation. In other words, it also helps foundry CEO's and chairpersons to share the famous quotes of a former Chairman, president and CEO of Texas Instruments and Chairman of HP "if only we knew what we know …".

Between July 2013 and October 2013, Drs Rajesh and Meghana Ransing, have personally trained over 150 foundry engineers from UK, Spain, Poland, Sweden and India on the 7ε approach. An on-demand internet based course, given by Dr Roshan, is also available from the American Foundrymen Society. Almost all engineers have said that they would recommend the course to their colleagues. The feedback comments are available on the 7ε website (www.7epsilon.org). A need was identified for a prescriptive template that any process engineer can use for the root cause analysis and developing a corrective action plan for ISO9001:2008. It was decided to formalize the 7ε template for continuous process improvement studies and present it in this paper as a 'use case'.

PROCESS APPROACH

Any activity, or set of activities, that uses resources to transform inputs to outputs are considered as a 'Process' according to ISO 9001:2008. In order to be profitable, organizations need to initially identify all the relevant processes and their interrelationships. The output of one process will be input into the next process. The systematic identification and management of the processes employed within a foundry and the interactions between such processes is considered as the "PROCESS APPROACH". An example of process in foundries is shown in Fig. 1.
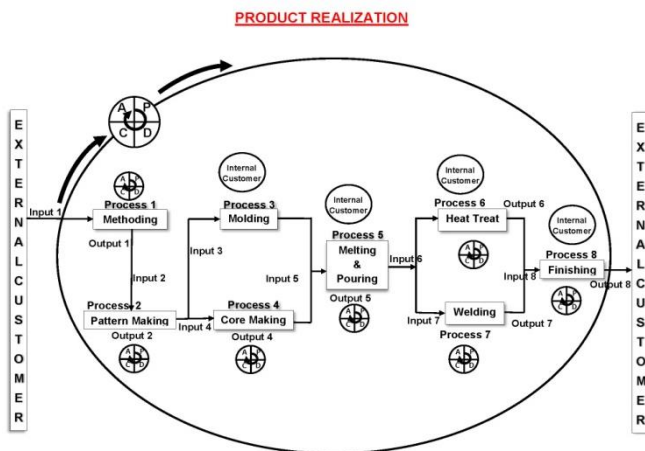
Fig. 1 – The systematic identification of processes in the foundry industry is shown in a Product Realization diagram.

The sub-processes that are potential candidates for continuous process improvements studies in individual foundries will be specific to the foundries and need not be the same in all foundries. The first step to become profitable is to identify the sub-processes specific to the foundry.

PROCESS EFFECTIVENESS

ISO 9001:2008 emphasizes the importance of process effectiveness. Performance metrics for each of the sub-processes need to be identified and monitored. There needs to be an evidence of continual improvement in the performance metrics of the processes in the foundry. This indicates that ISO 9001:2008 is not only a Quality Management System, but also a Business Management System to improve the bottom line of foundries. Process effectiveness is related to process optimization. Process optimization is the identification and control of input process parameters (Factors) to achieve the desired output (Response) in any process.

Optimizing foundry processes is not a trivial task because both the factor response relationships and the optimal conditions are process and part specific.
Even for the same foundry a set of parameters can produce acceptable casting for one part but not for another[2]. Available literature can often help process engineers in achieving process improvement objectives, but in most cases trends leant from the literature are too generic to drive process optimisation. Improvement can usually be achieved by performing small adjustments to the process, ultimately leading to significant savings in terms of cost reduction and waste minimisation.

THE 7ε METHODOLOGY

The 7ε methodology adds an innovation layer over Six Sigma's DMAIC processes. It is a novel approach to process improvement that focuses on knowledge retention and reuse as well as knowledge discovery in order to stimulate a culture of innovation. Although the methodology has been developed in the context of the foundry industry can be applied to other fields. 7ε introduces 7 Steps to **ERADICATE** Defects:

Knowledge Retention and Reuse
1. **E**stablish process knowledge
2. **R**efine process knowledge by compiling explanations for factor-response relationships.

Knowledge Discovery
3. **A**nalyse In-process data using penalty matrix approach.
4. **D**evelop hypotheses for new product specific process knowledge.
5. **I**nnovate using rootcause analysis and conducting confirmation trials.

Culture of Innovation
6. **C**orrective actions and update process knowledge.
7. Build **A**spiring **T**eams and **E**nvironments by monitoring performance.

7ε recognises the importance of discovering product specific process knowledge to find optimal ranges of process factors to achieve well defined business goals. It differs from other process improvements methodologies like Six Sigma because it focuses on analyzing in-process data, introduces a knowledge refinement step and repository concept which support root cause analysis and decision making. Knowledge retention is also promoted through the knowledge repository. The 7ε repository plays an essential role to ensure knowledge is retained and readily accessed. An overview of the 7ε methodology is provided in Fig. 2.
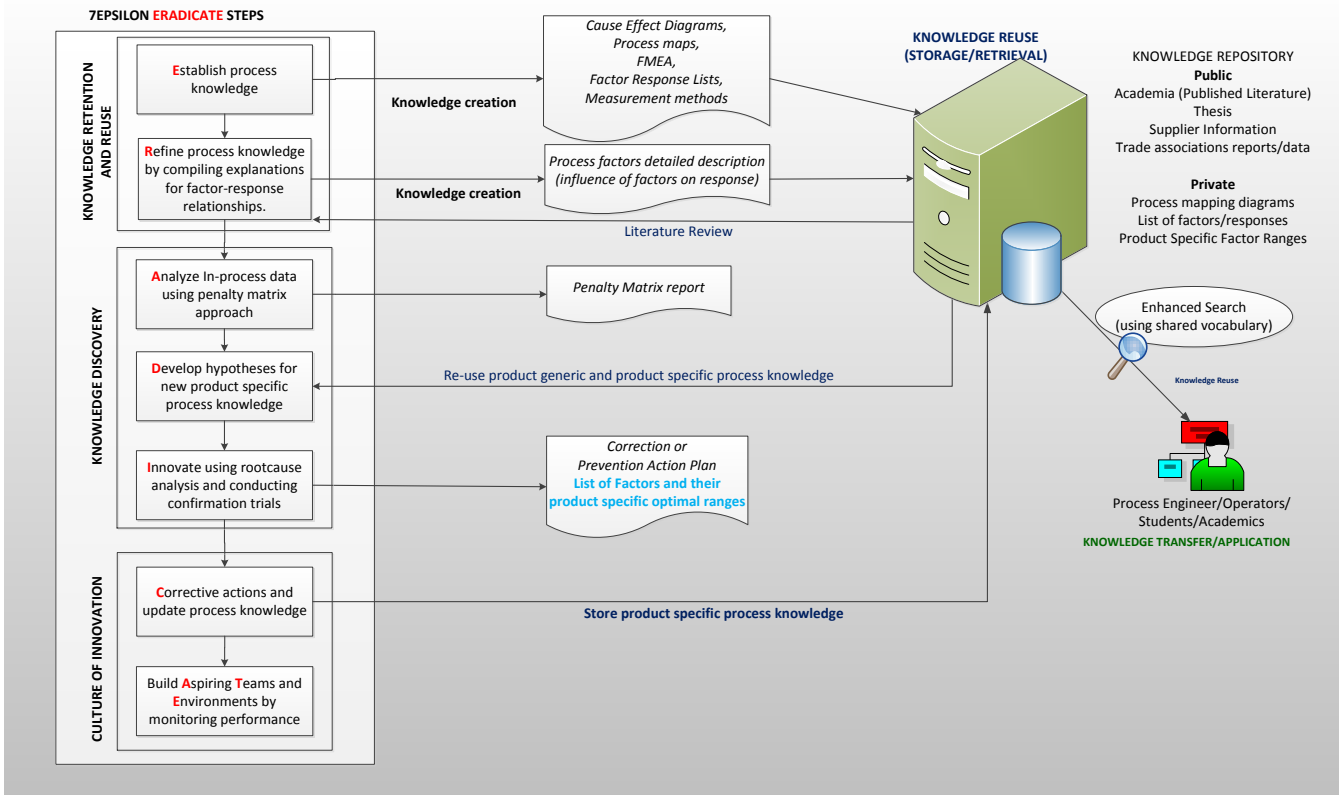
Fig. 2 - The 7ε methodology includes seven steps to achieve process improvement objectives required by ISO9001 standard. Central to the methodology is a knowledge repository concept to facilitate knowledge re-use.

CASE STUDY

Professional organizations related to foundries all over the world can contribute by communicating the importance of continual improvement of foundry sub-processes and promote the dissemination of information relating to these processes. This would in turn assist foundries to be more profitable than they are today and hopefully the foundries will contribute to the less utilization of energy than what it is today. The following paragraphs will illustrate a case study on how to achieve continual improvement in one of the sub-processes namely melting in a low alloy steel foundry. For continual improvement, one needs to identify one product at a time and improve the process specific to the product. A process is considered to be 'EFFECTIVE' if there is no scrap or rework attributable to the sub-process.

It is necessary to have the skills of identifying all the responses and factors for the process, collect and analyze the data and take appropriate actions for continual improvement. The analysis should be able to provide actionable information, so the necessary actions can be taken. This will also satisfy the requirement of AS 9100 that requires Process Validation. Process validation is carried out by determining the process capability of identified responses and the factors relevant to the process. In general, the customer specifications will have the requirements on product such as they need to meet the dimensional tolerances, freedom from casting defects both internal and external. It is the responsibility of the foundries to determine the specifications for process parameters to achieve the product specifications. In this case study a step by step procedure to discover PRODUCT SPECIFIC PROCESS KNOWLEDGE'[1, 2] is provided.

PROBLEM STATEMENT

A low alloy steel foundry has a product specification that has the requirement of carrying out a fracture test on the test block and having 0% of fractured surface area with conchoidal nature. The chemistry of the product is considered to play a significant role in the incidence of conchoidal fracture. The product material specification is described in Table 1. Although the chemistry of the heats for the products was within the material specification, the fracture tests were failing in conchoidal fracture[3]. This is also referred as rock candy fracture or intergranular fracture. A simple scatter plot of the percentage of conchoidal fractured surface out of the unit fractured surface (1 in x 1 in) for each observation shows variability of values across the process (Fig. 3).

Table 1 - Product Specifications

Element	Concentration
C	0.20-0.25
Mn	0.90-1.0
Si	0.40-0.60
S	0.015 max
P	0.015 max
Ni	1.70-1.90
Cr	0.90-1.2
Mo	0.40-0.50
Cu	0.30 max
Al	0.06 max
Ti	0.025 max
Zr	0.025 max
Ca	0.006 max

The foundry decided to perform root cause analysis following the 7ε methodology. A step by step description of the methodology will be described in the next sections.
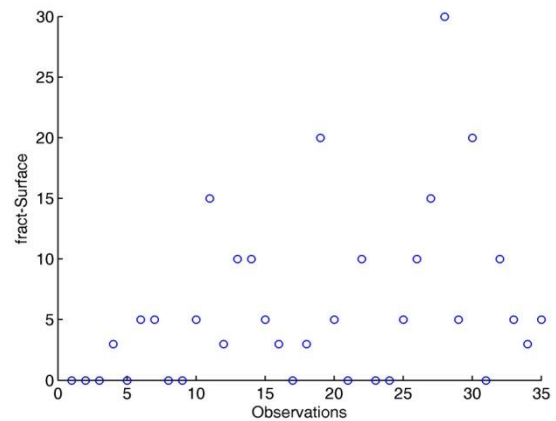
Fig. 3 - The scatter plot of %Conchoidal Fractured Surface shows variation of responses in different batches.

STEP1 – ESTABLISH PROCESS KNOWLEDGE

The first step of the 7ε methodology is a preliminary phase where engineers acquire knowledge about the process, its factors and responses as well as causal relationships. This phase is similar to the "Define" step of Six Sigma projects. A team of people is formed and the team starts to gather process knowledge which is then externalised and codified using pictorial diagrams such as Process Maps, SIPOC Diagrams and Cause and Effect Diagrams. This phase enables to capture team member knowledge and is considered crucial to the success of process improvement activities[4].

An example of Process Map for Melting and Pouring process is shown in Fig. 4.
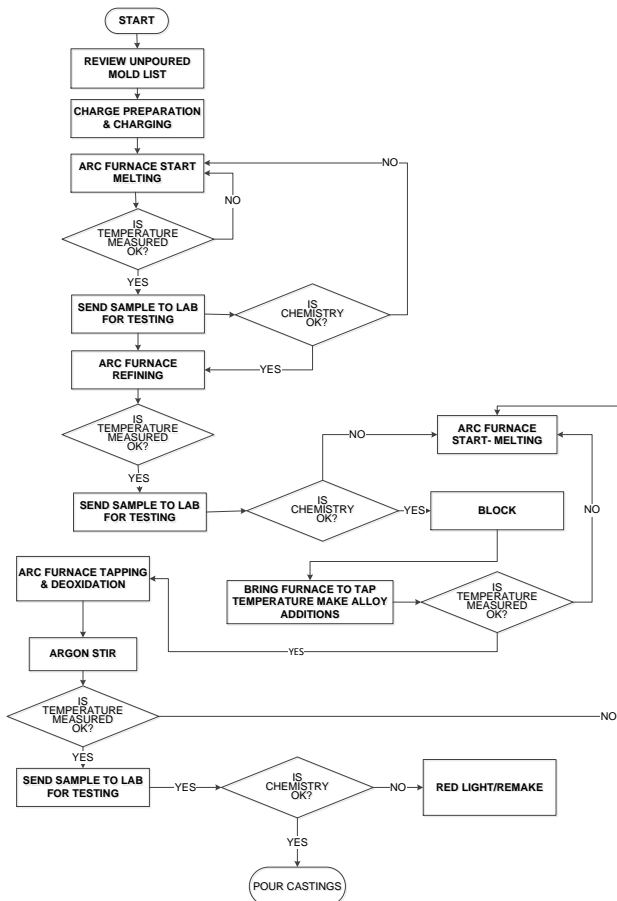
Fig. 4 – The Process Map for Melting and Pouring is a flowchart that indentifies all the process steps.

SIPOC (suppliers, inputs, process, outputs, customers) diagrams are also used to identify all the relevant elements of process improvement including suppliers, customers, input and output of the process. An example of SIPOC diagram is given in Fig. 5.

Finally causal relationships between process inputs and outputs are also visualised by using Cause and Effect diagrams as shown in Fig. 6.

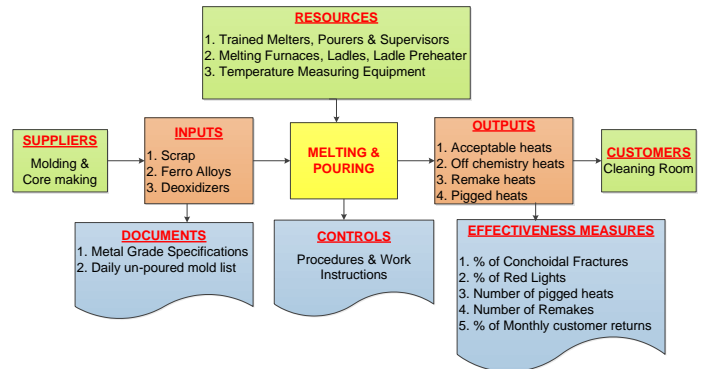**Fig. 5 – The SIPOC Diagram for Melting and Pouring is an high level description of the all the process components. Effectiveness measures are also identified.**
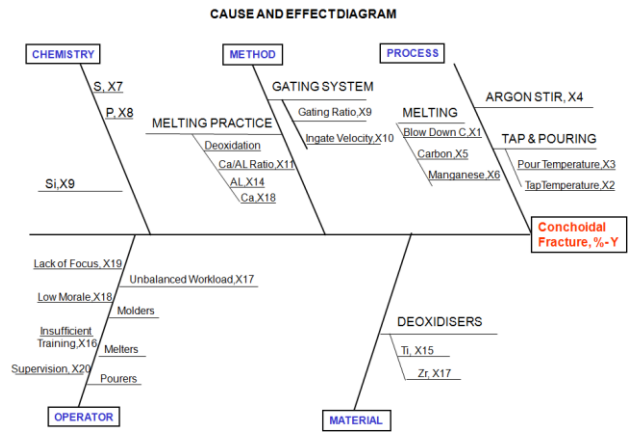
Fig. 6 – A Cause and Effect Diagram shows causal relationship between process inputs and outputs. It is often used in root cause analysis.

STEP 2 – REFINE PROCESS KNOWLEDGE BY COMPILING EXPLANATIONS FOR FACTOR-RESPONSE RELATIONSHIPS

Process knowledge is obtained by knowing that process responses Y are functions of process factors X. An understanding of the type of functional relationship and how the variability of factors affects responses is an essential prerequisite to develop a sound process approach. Generic knowledge about input/outputs relationships can come from experience after observing the process over the time or by referring to findings from published literature. However the knowledge acquired by foundries in not systematically collected and made available for future references. Foundries often rely on "process experts" but issues may arise when "experts" are not available.

The 7ε methodology extends traditional process improvement approaches since it introduces a "knowledge refinement" step. During this phase process engineers systematically research about process factors and responses to find out:

- how factors are related to responses and how they can be measured;
- Importance of factors in relation to responses.

Knowledge acquisition at this stage is supported and facilitated by means of a knowledge repository which indexes and stores process knowledge created by academia or during past process improvement activities. The outcome of this phase is a written description of process factors' characteristics with respect to one or more responses.

As part of this case study on conchoidal fracture the following descriptions were created.

X1: Carbon Drop: In the basic melting practice of steel, charge carbon is so adjusted that during the Oxygen blow there is a minimum carbon drop of 30 points. During the Oxygen blow the extra carbon is oxidized and the resulting CO bubbles essentially remove N and H from the melt.

X2: Tap temperature: Higher tap temperatures have been found to result in the retention of harmful gases in the liquid metal.

X3: Pouring Temperature: Higher pouring temperature than the optimum also have been found to be undesirable in the production of sound castings.

X4: Argon Stirring: Argon stirring is found be very useful in removing the harmful gases N and H through the bubbling action and also maintain uniformity in temperature in the ladle.

X5: %C: Higher C than the optimum is found to have undesirable effect in increasing the propensity of defects resulting from quenching.

X6:%Mn[6]: Optimum range of Mn is necessary to minimize the harmful effects of S in the melt and to produce sound castings.

X7: %S: S in the melt plays a significant role in the incidence of brittle fracture in steel castings[5, 6]. Although 0.015% is the upper limit in the specification, lower percentages can cause brittle fractures. It is essential to determine the optimum range of S to minimize incidence of brittle fracture such as Conchoidal Fracture

X8: %P: P in the melt plays a significant role in the incidence of brittle fracture in steel castings[5, 6]. Although 0.015% is the upper limit in the specification, lower percentages can cause brittle fractures. It is essential to determine the optimum range of P to minimize incidence of brittle fracture such as Conchoidal Fracture

X9: %Si: Si steel mainly influences the castability and it has less significant role compared to S, P and Mn.

X10:%Ni: Ni plays a significant role in the properties of steel castings, specifically in impact properties, enhancing significantly to higher properties. Generally higher Ni steel castings are preferred in applications requiring higher Charpy values at low temperatures of -40F. However, these higher percentages of Ni in low alloy steels have disadvantages making the steel as a long-freezing range alloy with tendency towards micro-porosity and the resulting poor properties. Also, care needs to be taken during heat treatment to prevent the formation of retained austenite.

X11: %Cr: Cr provides hardness and hardenability to steel castings. However, care needs to be exercised in controlling the range of this element, as this can adversely affect the impact properties.

X12: %Mo: Mo is very desirable element in steel castings, as it increases the hardenability, enables to have higher tempering temperatures without adversely affecting the hardness, resulting in desirable impact properties.

X13: %Cu: Cu is an undesirable element in low alloy steel castings, and it is desirable to control the range of this element.

X14: %Al: Al in steel castings comes from the deoxidizer. In low strength steel castings, Al can be tolerated up to 0.08%, however higher strength steel castings need to have lower percentages to prevent brittle fractures resulting from Aluminum Nitride[7]. A minimum percentage of Al of about 0.02% is necessary to prevent the propensity for pinholes in steel castings.

X15:%Ti: Ti in steel castings is added as a deoxidizer to enable having low percentages of Al thus preventing the formation of Aluminum Nitride. Titanium is a more powerful deoxidizer compared to Aluminum and will tie up Nitrogen more effectively. However percentage of Ti should be carefully controlled to prevent the formation of excessive titanium carbonitrides. Titanium[8] also acts as a grain refiner in steel castings.

X16: Mn/S Ratio: Mn/S ratio is helpful to control the propensity of steels for cracking tendency. Although individual elements Mn and S need control, this ratio needs to be high to reduce the tendency for brittle fracture.

X17: %Zr: Similar to Ti, Zirconium[9] will stabilize the nitrogen and helps to reduce the formation of brittle fracture due to Aluminum Nitride.

X18: %Ca: the purpose of calcium treatment in steels after aluminum deoxidation is to modify the composition of alumina inclusions and form low melting point calcium

aluminates that float at a faster rate and produce cleaner liquid steel[10].

X19:Ca/Al Ratio: Calcium is added to molten steel to modify the morphology of inclusions formed due to aluminum deoxidation. The relative percentages of Ca and Al are essential to the formation of clean steel and Ca/Al ratio determines the optimum ratio to provide clean steel with minimal tendency for brittle fracture.

A factor-response table is also created. The table contains a list of factors and measurement methods as shown in Fig. 7.

Factor (X)	Method of Measure	Units	Continuous/ Discrete	Frequency of Data	Response (Y)
Carbon drop (X1)	Melt/Pour Log	Number	Continuous	Every heat	%Conchoidal (Y1)
Tap Temperature (X2)	Melt/Pour Log	Deg F	Continuous	Every heat	%Conchoidal (Y1)
Pouring Temperature (X3)	Melt/Pour Log	Deg F	Continuous	Every heat	%Conchoidal (Y1)
Argon Stir Time (X4)	Melt/Pour Log	Deg F	Continuous	Every heat	%Conchoidal (Y1)
% Carbon (X5)	Melt Sheet	%	Continuous	Every heat	%Conchoidal (Y1)
% Mn (X6)	Melt Sheet	%	Continuous	Every heat	%Conchoidal (Y1)
% Sulfur (X7)	Melt Sheet	%	Continuous	Every heat	%Conchoidal (Y1)
% Phosphorus (X8)	Melt Sheet	%	Continuous	Every heat	%Conchoidal (Y1)
% Silicon (X9)	Melt Sheet	%	Continuous	Every heat	%Conchoidal (Y1)
% Nickel (X10)	Melt Sheet	%	Continuous	Every heat	%Conchoidal (Y1)
% Chromium (X11)	Melt Sheet	%	Continuous	Every heat	%Conchoidal (Y1)
% Molybdenum (X12)	Melt Sheet	%	Continuous	Every heat	%Conchoidal (Y1)
% Copper (X13)	Melt Sheet	%	Continuous	Every heat	%Conchoidal (Y1)
% Aluminum (X14)	Melt Sheet	%	Continuous	Every heat	%Conchoidal (Y1)
% Titanium(X15)	Melt Sheet	%	Continuous	Every heat	%Conchoidal (Y1)
Mn/S Ratio (X16)	Melt Sheet	%	Continuous	Every heat	%Conchoidal (Y1)
% Zirconium (X17)	Melt Sheet	%	Continuous	Every heat	%Conchoidal (Y1)
% Calcium (X18)	Melt Sheet	%	Continuous	Every heat	%Conchoidal (Y1)
Ca/Al Ratio (X19)	Melt Sheet	%	Continuous	Every heat	%Conchoidal (Y1)

Fig. 7 - The Factor-response table for Melting and Pouring shows the list of relevant factor and their measurement methods.

Subsequently a Cause and Effect matrix is used to quantify and rank the importance of factors with respect to a given response. For instance the Cause and Effect Matrix in Fig. 8 shows all the five performance metrics indicated in the SIPOC diagram (Fig. 5), as Y1 toY5. The scores given in the row titled "Importance Score" indicate the relative importance of each of the Ys to the process performance. Conchoidal fractures can lead to the scrapping of the castings and the monthly returns from customers are not acceptable and as such these are given a score of nine. % Red lights are given a score of only four, as this involves the correction of the heat to bring the heat into specification limits to become a green light heat. Number of remakes and pigged heats are given a score of six as these costs will be high, but as not critical as conchoidal fractures and customer returns. For each of these Ys, Xs are given appropriate scores based their association. These scores are subjective based on domain expertise. Only a data collection on each of the Xs and

the corresponding Ys will be able to identify the Xs that are indeed associated with the corresponding Ys.

Output Variables (Y's):	% 0f Conchoidal fractures (Y1)	% Red Lights (Y2)	Number of Pigged heats (Y3)	Number of Remakes (Y4)	% of Monthly Customer Returns (Y5)	Weighted Score
Importance Score (1-10):	9	4	6	5	9	
Input/Process Variables (X's)						
			Association Scores (X's to Y's)			
Carbon Drop (X1)	8	1	1	1	8	159
Tap Temperature, F (X2)	7	1	1	1	7	141
Pouring Temperature (X3)	7	1	1	1	7	141
Argon Stir Time (X4)	7	1	1	1	7	141
% Carbon (X5)	8	8	3	3	8	209
% Manganese (X6)	7	8	3	3	7	191
% Sulfur (X7)	9	8	8	8	9	282
% Phosphorus (X8)	9	8	8	8	9	282
% Silicon (X9)	4	6	3	3	4	129
% Nickel (X10)	6	7	7	7	6	213
% Chromium (X11)	7	7	7	7	7	231
% Molybdenum (X12)	6	5	5	5	6	228
% Copper (X13)	7	8	8	8	7	246
% Aluminum (X14)	8	6	4	4	8	212
% Titanium (X15)	8	7	4	4	8	216
Mn/S ratio(X16)	8	7	4	4	8	216
% Zirconium (X17)	8	7	4	4	8	216
% Calcium (X18)	8	8	4	4	8	220
Ca/Al Ratio (X19)	8	8	4	4	8	220

Output variables are on a scale of 1 to 10 : 1: Least important and 10: Most important to customer
Association Multiplier: 0: No association; 1: Weak; 3: Moderate; 9: Strong

Fig. 8 - The Cause and Effect Matrix shown in this picture quantifies the rank and importance of factors with respect to a number of process responses.

As will be shown later in this papers a Penalty Matrix approach is capable of identifying the Xs that are indeed related to the Ys. Also, it is not sufficient to identify the mere name of the factor, it is essential to determine the range of the factor that minimizes the harmful effects of Ys.

STEP 3 – **A**NALYZE IN-PROCESS DATA USING PENALTY MATRIX APPROACH

After process engineers have gained an understanding of important factors that might affect process responses data retrieval strategies can be devised. Typically in a foundry data are routinely being collected as part of ISO9001:2008 implementation. Otherwise new data collection strategies need to be implemented. Information about measurement methods discovered during the previous phase can assist engineers in the implementation of data collection strategies.

In the case study data on 35 different heats were collected as shown in Appendix A. The data matrix contains 19 factors and one response, namely percentage of Conchoidal Fractured Surface (or Conchoidal Fracture). The input data file is formatted in Microsoft Excel format with the values for each batch or heat being stored in the corresponding row and columns representing responses and factors.

A Penalty Matrix approach is adopted to perform root cause analysis [1] and discover product specific process knowledge. The Penalty Matrix algorithm[1, 11] discovers product specific optimal and avoid ranges by visualizing patterns in data. It uses a simple but novel idea of associating penalty values to responses and displaying data using bubble diagram and penalty matrices. Penalty values are calculated by performing a transformation of response values that assigns a zero penalty value to the best performing observations and 100 penalty value to the worst performing observations. Intermediate values are linearly scaled between zero and 100. Lower and upper thresholds to determine best and worst performing observations are chosen by the analyst based on experience and previous domain knowledge. In addition to domain knowledge some heuristic rules can be also used to determining upper and lower thresholds such as:

- penalizing the worst 10-15% observations or at least 5-10 bad points (whichever is higher) while giving a penalty value 0 to the best 30-40% 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.

In this case study the second rule is used (examination of the curvature of scatter plot), leading to a lower threshold value for the conchoidal fracture of 0% and upper threshold value of 10%. Any value between 0% and 10% is linearly scaled to give a corresponding penalty value between 0 and 100. The scatter plot of responses with corresponding threshold values is shown in Fig. 9.
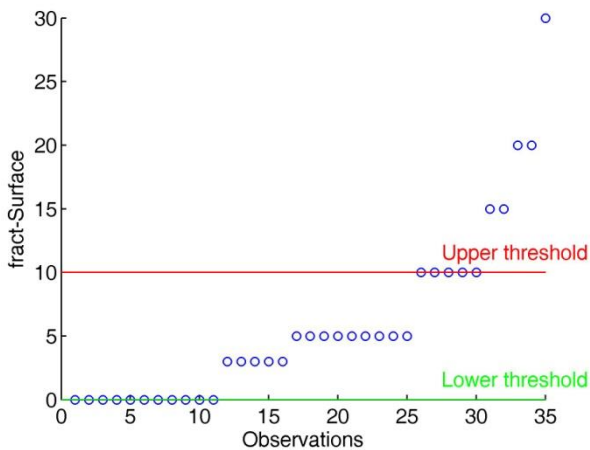
Fig. 9- The scatter plot of responses shows the upper and lower thresholds for penalty values.

Penalty values can be displayed in bubble diagrams to help process engineers to identify regions of desired, undesired and intermediate response values. Fig. 10 shows scatter and bubble diagrams for %Ti.

(a)

(b)
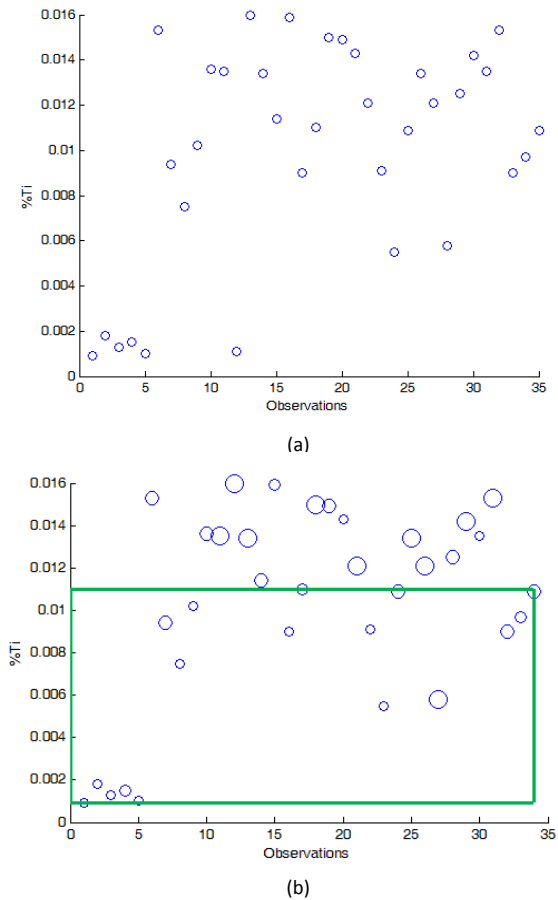
Fig. 10 - Scatter (a) and bubble (b) diagrams for %Ti are shown in the picture.

In the bubble diagram (Fig. 10 (b)) the radius of the circle represents the corresponding Conchoidal Facture penalty value. The penalty values combined with Importance Scores described in Fig. 8 can help in estimating cost saving opportunities. From a visual inspection of the bubble diagram it can be found that values of %Ti below the median (0.011) 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.

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 to Q4). Using penalty matrices it possible to find optimal and avoid ranges based on quartiles. An example of penalty matrix of Conchoidal Fracture for %Ti is shown in Fig. 11.

	Q1	Q2		Q3		Q4
Minimum			**Median**			**Maximum**
0.0009	0.0075	0.011		0.0135		0.016

Q1 & Q2: Optimal; Range: Bottom 50%, [>=0.0009 & <=0.011];
Q1: Optimal; Range: Bottom 25%, {>=0.0009 & <=0.0075};
Q3 & Q4: Avoid; Range: Top 50%, [>0.011 & <=0.016];

| Penalty	Q1	Q2	Q3	Q4
80-100	1		4	5
60-80				
40-60		4	2	3
20-40	2	2		1
0-20	6	3		2

Fig. 11 – The Penalty Matrix of Conchoidal Fracture for %Ti helps in identifying regions of desired and undesired response. It can be seen that Bottom 50% of %Ti (Q1 and Q2) is an optimal range since it has a high proportion of low penalty values.

A study of this figure shows that nine data points lie in Bottom 50% range (quartiles Q1 and Q2) with a penalty value of 0-20, four data points lie in Bottom 50% with a penalty value of 20-40 and one data point lies in Bottom 50% with a penalty value of 80-100. Bottom 50% range of %Ti corresponds to an optimal range since it has a higher proportion of response values with low penalties.

This method can be further extended to analyze interactions between any two factors. Fig. 12 shows respectively the bubble diagram and penalty matrix of interactions between %Carbon Drop and Ca/Al ratio. In the example, process conditions when Ca/Al ratio is in the Bottom 50% range (F1) and Carbon Drop in the Top 50% range (F2) are considered optimal due to higher number of good batches (0-20 penalty values) compared to bad ones.

STEP 4 - DEVELOP HYPOTHESES FOR NEW PRODUCT SPECIFIC PROCESS KNOWLEDGE

The results of the analysis conducted with the Penalty Matrix approach are used during Quality Improvement meetings to develop new hypothesis on possible root causes of defects. This step is crucial for the implementation of the 7ε methodology. Although it may be perceived very similar to other process improvement approaches, 7ε recommends that hypothesis formulation does not happen only as a result of data driven analysis.
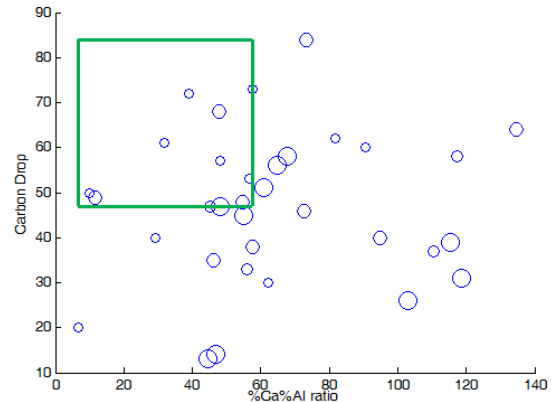
F1: %Ca/%Al ratiox1000, Range:Bottom 50%,[>=6.667 & <=57.5]; Strength: 1.5
F2: Carbon Drop, Range:Top 50%,[>47 & <=84]; Strength: 1.9
Strength of Optimal Interaction: 2.9

Penalty	F1:F2	F1:¬F2	¬F1:F2	¬F1:¬F2
80-100	0	4	3	3
60-80	0	0	0	0
40-60	3	1	2	3
20-40	0	2	1	2
0-20	6	2	2	1

Fig. 12 - Bubble diagram and penalty matrix can be used to find out optimal and avoid ranges due to interactions of two factors. Bottom50% of Ca/Al ratio (F1) and Top 50% of Carbon Drop (F2) is considered optimal.

Firstly correlations and patterns found using the Penalty Matrix approach needs to be prioritised. The calculation of penalty matrices for main effects (i.e. single factor) and interactions can become quite cumbersome in the presence of large number of factors. In the case study, the P-Matrix software (http://www.p-matrix.com) has been used to calculate penalty matrices. In addition the software provides strength values to prioritize optimal/avoid ranges. Another possible way of ranking strength is using Principal Component Analysis[1].

Following the study five factors have been identified as those that have a significant effect on the process response, namely the incidence of Conchoidal Fracture. These are: %Ti, %S, Mn/S Ratio, %Ca/%Al ratio and Carbon Drop. Also the following optimal ranges were found:

- %Ti: 0.0009 to 0.011
- %S: 0.007 to 0.009
- Mn/S Ratio: 104 to 134
- %Ca/%Al ratiox1000: 6.67 to 57.5
- Carbon Drop: 47 to 84

In addition, one avoid range was found:
- %Ti: 0.011 to 0.016

The optimal and avoid ranges are compared with trends found during the "knowledge refinement" phase (step 2) accessed via the knowledge repository. Causation is then inferred if the results of the analysis are supported by the knowledge base, otherwise it is suggested that correlations should be dropped. For example, the ranges for Carbon Drop, %P and %Ca/%Al ratio x1000 for the in-process data used in this case study are such that the individual correlations of each factor with Conchoidal Fracture are very weak however, the interactions of Carbon Drop and %P as well as Carbon Drop and %Ca/%Al ratio x1000 (Fig. 12) are relatively strong. The current literature, as well as the domain knowledge, does not support any relationship between Carbon Drop and %P that can jointly influence the occurrence of Conchoidal Fracture. As a result, this relationship is ignored. However, this is not true for the Carbon Drop and %Ca/%Al ratio relationship. A minimum Carbon Drop of 30 points (preferably 50 points) is necessary to remove Nitrogen and Hydrogen from the melt. Conchoidal Fracture occurs due to the formation of Aluminium Nitride. Hence, it was decided to maintain higher Carbon Drop as suggested by the penalty matrix analysis.

STEP 5 - INNOVATE USING ROOT CAUSE ANALYSIS AND CONDUCTING CONFIRMATION TRIALS

Innovation is generated when new root causes that are supported by trends in the literature are found. Based on the results of previous phase, foundries are expected to determine the optimum ranges for all the process variables (Xs) and carry out confirmation trials to validate the hypothesis. In this case study only one Y, namely % Conchoidal fracture response or defect has been selected as a representative case study. Foundries are expected to identify all the potential defects related to the parts they manufacture and determine the product specific process parameters that give sound castings.

STEP 6 – CORRECTIVE ACTIONS AND UPDATE PROCESS KNOWLEDGE

Upon successful completion of Confirmation Trials, the new knowledge obtained in the previous steps can be then be stored in tabular form and consists of a list of values with their new specifications. It must be noted that the new specification ranges are specific for a given part and

process. The product specific process knowledge discovered as part of this case study is summarized in Table 2.

The new knowledge acquired contributes to devise preventive and corrective action plans to achieve reduction of Conchoidal Fracture defects as required by ISO9001:2008 standard. Following a successful trial plan FMEA (Failure Mode Effect Analysis) tables are also updated to include the new specification ranges in the recommended action field. The updated FMEA table is shown in Fig. 13.

In addition operators need to be trained on the new process specifications. The 7ε methodology also requires updating the knowledge base so that the new specification ranges can be stored and indexed for future use in the 7ε repository.

STEP 7 – BUILD ASPIRING TEAMS AND ENVIRONMENTS BY MONITORING PERFORMANCE

Once the new process specifications have been implemented, foundries must continually monitor the responses of defects so that continually improvement on the processes can be made to meet the requirements of ISO 9001:2008.

Table 2 - Product specific process knowledge

Sub-Process	Process Variable (CTQ)	Specification Range	Frequency of data collection
Melting and Pouring	Carbon Drop (X1)	47-84	Every Heat
Melting and Pouring	% Sulfur (X7)	0.007-0.009	Every Heat
Melting and Pouring	%Titanium (X15)	0.0009-0.011	Every Heat
Melting and Pouring	Mn/S Ratio (X16)	104-134	Every Heat
Melting and Pouring	%Ca/%Al Ratiox1000 (X19)	6.67-57.5	Every Heat

Process / Requirements	Potential Failure Mode	Potential Effect(s) of Failure	SEV	Class	Potential Cause(s) Mechanism(s) of Failure	Occur	Current Process Controls	Detect	RPN	Recommended Action(s)
Melting - Chemistry	Incorrect Carbon Drop points during Oxygen Blow (X1)	% Conchoidal fracture(Y1)	6	FF	Melter Error - Improper Training of Melters in the Oxygen blow	6	Periodic Auditing by Supervisor	8	288	Optimal range 47-84
Melting - Chemistry	Incorrect percentage of S (X7)	% Conchoidal fracture(Y1)	8	FF	Melter Error - Inadequate Training of Melter in Basic Slag practice	8	Periodic Auditing by Supervisor	8	512	Optimal range 0.007-0.009
Melting - Chemistry	Incorrect percentage of Ti (X15)	% Conchoidal fracture(Y1)	7	FF	Melter Error - Inadequate Training of Melter in Deoxidation Practice	8	Periodic Auditing by Supervisor	8	448	Optimal range 0.0009 to 0.011
Melting - Chemistry	Incorrect Ratio of Mn/S (X16)	% Conchoidal fracture(Y1)	7	FF	Melter Error - Inadequate Training of Melter in melting practice	7	Periodic Auditing by Supervisor	6	294	Optimal range 104-134
Melting - Chemistry	Incorrect Ratio of Ca/Al (X19)	% Conchoidal fracture(Y1)	7	FF	Melter Error - Inadequate Training of Melter in Deoxidation Practice	8	Periodic Auditing by Supervisor	8	448	Optimal range 6.67-57.5

Fig. 13- Failure Mode Effect Analysis (FMEA) is updated after the discovery of product specific process knowledge.
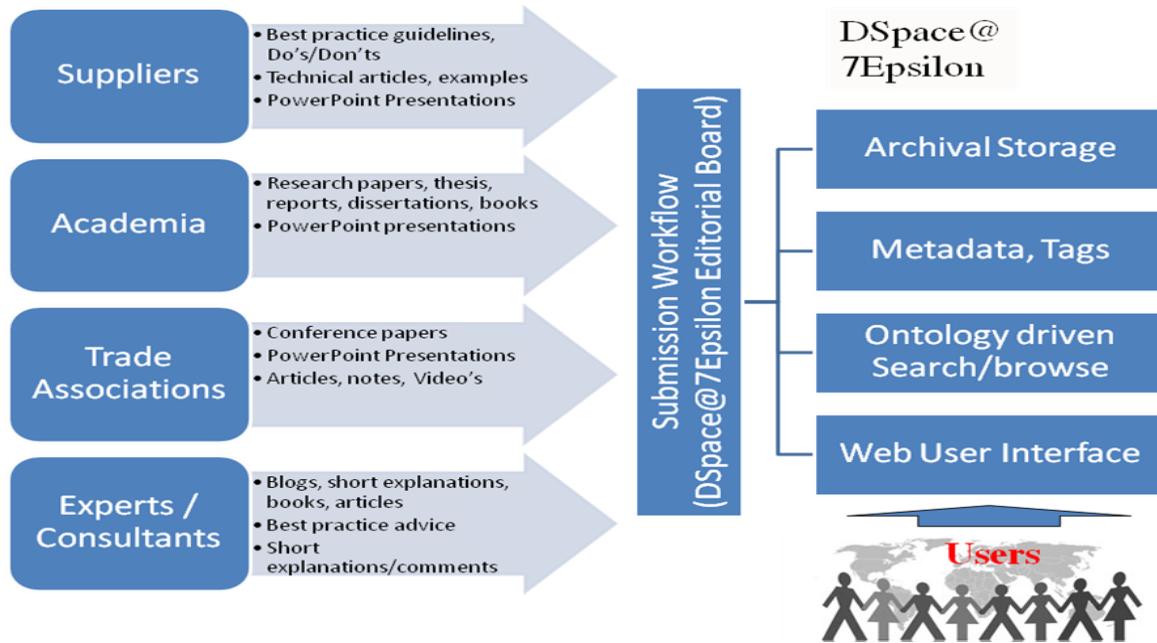
KNOWLEDGE REPOSITORY

The 7ε methodology introduces the concept of a knowledge repository to store and index foundry process knowledge. Typically during process improvement activities process engineers need to access proprietary foundry knowledge as well as knowledge from a variety of sources, including trade associations, academia or suppliers. This knowledge is usually scattered throughout the organisation or over the World Wide Web and knowledge retrieval can become a cumbersome task due to the lack of efficient retrieval methods.

The 7ε repository provides a single entry point to access and re-use foundry knowledge. It also links product specific process knowledge discovered with data driven methodologies to generic foundry knowledge acquired by academia and trade associations. In order to demonstrate the knowledge repository concept a prototype system has been build. Although a detailed description of the technologies used for building the knowledge repository prototype system is outside the scope of this paper, a brief overview is given below.

The 7ε repository has been developed by using DSpace, a web based open source software package to store and manage a wide range of digital content, including word processing files, pictures, videos and data files.

DSpace is widely used by academia and it can perform searches using metadata or full text search. Metadata are description of items which are stored by the system and help to retrieve digital artefacts more efficiently. Secure access to the repository is provided using login credentials. Submission of papers or other documents to the repository is performed following a submission workflow which involves approval given by the 7ε Editorial Board before the digital item is made available to registered users. In addition to indexing of generic knowledge, the repository can be customised to securely store foundry specific knowledge which will then only be accessed within each foundry environment.
New knowledge discovered through 7ε case studies can also be stored and made available for future projects.

In order to improve search precision DSpace standard search capabilities have been enhanced by using the Controlled Vocabulary software adds-on that allows specifying metadata from a fixed taxonomy [12]. In information technologies, taxonomies are hierachical calssifications of terms to describe concepts in a specific domain. They are typically used to enable effient retrieval and sharing of knowledge. As part of the 7ε repository a Foundry Taxonomy is being developed to enhance the retrieval of foundry knowledge. An overview of DSpace capabilities in provided in Fig. 14.

Fig. 14 – Generic foundry process knowledge from heterogeneous sources is indexed in the 7ε repository. Search capabilities are enhanced through the use of ontologies. Digital items are submitted following the submission workflow.

CONCLUSION

A novel methodology, called 7ε, to support the implementation of ISO9001:2008 continual process improvement requirements is described in this paper. The 7ε methodology addresses the "Technology Gap" in the foundry industry due to the lack of process knowledge. A concept of product specific process knowledge is introduced in this paper and this is defined as actionable information which consists of a list of factors and their optimal ranges to achieve well defined business objectives. Compared to Six Sigma's DMAIC process, 7ε adds an innovation layer by introducing a knowledge repository concept to re-use generic and product specific process knowledge created by foundries, academia, trade associations and suppliers.

By means of an industrial case study it is demonstrated how the systematic implementation of the7ε steps to ERADICATE defects leads to improvements in managing foundry sub-processes and reducing existing level of losses due to scrap and rework. Innovation is achieved when the product specific process knowledge discovered using a Penalty Matrix approach is supported by trends in the literature and confirmed during confirmation trials.

Although the case study focuses only on reducing Conchoidal Fracture of a typical low alloy steel casting during Melting and Pouring process, it is expected that the format will be used by foundries across their sub-processes to identify and reduce all types of defects. This paper provides a template for foundries to effectively implement the 7ε methodology not only to achieve compliance to ISO: 9001:2008 but also to assist foundries in becoming more profitable and less energy intensive organizations.

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APPENDIX A

Data on 35 different heats analyzed during Step3.

Obs No	Y1 fract-Surface,%	X1 Carbon Drop	X2 Tap Temperature, F	X3 Pouring Temperature, F	X4 Argon stir, mts	X5 %C	X6 %Mn	X7 %S	X8 %P	X9 %Si	X10 %Ni	X11 %Cr	X12 %Mo	X13 %Cu	X14 %Al	X15 %Ti	X16 Mn/S Ratio	X17 %Zr	X18 %Ca	X19 %Ca/%Al ratiox1000
1	0	57	3039	2840	8	0.21	1.00	0.008	0.013	0.42	1.70	1.04	0.40	0.160	0.03	0.0009	125	0.0096	0.0012	48
2	0	62	2965	2830	3	0.21	1.07	0.008	0.011	0.54	1.61	1.17	0.42	0.170	0.03	0.0018	134	0.0166	0.0027	82
3	0	73	2971	2850	8	0.21	0.96	0.01	0.012	0.54	1.68	1.11	0.42	0.149	0.04	0.0013	96	0.0224	0.0023	58
4	3	33	2980	2850	4	0.2	0.94	0.007	0.1	0.51	1.76	1.05	0.45	0.147	0.04	0.0015	134	0.0201	0.0024	56
5	0	60	2955	2820	2	0.24	1.12	0.01	0.013	0.4	1.72	1.09	0.43	0.153	0.03	0.0010	112	0.0129	0.0029	91
6	5	84	2905	2836	2	0.19	1	0.01	0.01	0.48	1.71	1.04	0.4	0.135	0.04	0.0153	100	0.0029	0.0030	73
7	5	35	3007	2846	4	0.2	0.96	0.009	0.1	0.43	1.69	1.07	0.42	0.133	0.01	0.0094	107	0.0021	0.0006	46
8	0	50	2988	2858	4	0.2	1.06	0.011	0.013	0.5	1.63	1.12	0.4	0.182	0.02	0.0075	96	0.0017	0.0002	10
9	0	61	2960	2850	4	0.19	0.9	0.009	0.01	0.37	1.64	1.02	0.41	0.146	0.02	0.0102	100	0.0025	0.0007	32
10	5	64	2950	2852	4	0.18	0.97	0.1	0.009	0.48	1.63	1.06	0.41	0.179	0.03	0.0136	10	0.0037	0.0035	135
11	15	31	2948	2850	4	0.2	1.07	0.011	0.014	0.4	1.63	1.14	0.4	0.173	0.03	0.0135	97	0.0029	0.0038	119
12	3	42	2983	2860	8	0.2	0.95	0.013	0.015	0.41	1.67	1.05	0.41	0.150	0.04	0.0011	73	0.0125	0.0125	357
13	10	51	2915	2840	3	0.23	1.07	0.01	0.013	0.38	1.65	1.11	0.4	0.139	0.03	0.0160	107	0.0027	0.0017	61
14	10	56	2942	2850	6	0.21	1.1	0.011	0.015	0.39	1.67	1.17	0.41	0.145	0.04	0.0134	100	0.0044	0.0024	65
15	5	48	2957	2860	2	0.23	0.97	0.01	0.014	0.42	1.63	1.09	0.41	0.117	0.03	0.0114	97	0.0030	0.0018	55
16	3	58	2990	2860	12	0.19	0.99	0.009	0.014	0.43	1.73	1.09	0.4	0.120	0.05	0.0159	110	0.0042	0.0054	117
17	0	20	2943	2818	4	0.24	0.95	0.008	0.011	0.6	1.64	1	0.41	0.136	0.03	0.0090	119	0.0029	0.0002	7
18	3	47	2966	2850	3	0.21	1.02	0.01	0.009	0.5	1.65	1.08	0.41	0.124	0.03	0.0110	102	0.0029	0.0014	45
19	20	45	2938	2850	4	0.21	1.01	0.013	0.013	0.5	1.63	1.08	0.41	0.119	0.05	0.0150	78	0.0036	0.0027	55
20	5	68	2994	2850	4	0.18	0.95	0.012	0.014	0.47	1.65	1.06	0.41	0.106	0.05	0.0149	79	0.0041	0.0022	48
21	0	53	2892	2832	2	0.21	0.95	0.011	0.011	0.52	1.63	0.98	0.42	0.140	0.05	0.0143	86	0.0046	0.0026	57
22	10	14	2978	2855	4	0.23	0.99	0.012	0.011	0.48	1.62	1.08	0.44	0.153	0.03	0.0121	83	0.0050	0.0015	47
23	0	72	2959	2832	4	0.19	0.97	0.009	0.009	0.35	1.64	0.97	0.43	0.171	0.04	0.0091	108	0.0022	0.0016	39
24	0	40	3019	2850	4	0.19	1.05	0.011	0.012	0.4	1.63	1.11	0.41	0.135	0.02	0.0055	95	0.0030	0.0007	29
25	5	38	2942	2861	4	0.18	1.01	0.011	0.011	0.46	1.68	1.04	0.4	0.144	0.03	0.0109	92	0.0033	0.0019	58
26	10	26	2925	2875	2	0.21	1	0.01	0.011	0.48	1.6	1.09	0.41	0.140	0.04	0.0134	100	0.0038	0.0036	103
27	15	47	3028	2865	2	0.18	0.93	0.011	0.015	0.44	1.64	1.06	0.4	0.160	0.03	0.0121	85	0.0029	0.0013	48
28	30	13	3034	2850	15	0.22	0.93	0.012	0.017	0.41	1.68	1.01	0.43	0.149	0.02	0.0058	78	0.0015	0.0008	44
29	5	40	2913	2850	2	0.17	0.93	0.009	0.016	0.42	1.66	1.01	0.41	0.145	0.04	0.0125	103	0.0032	0.0037	95
30	20	58	2940	2855	6	0.2	1.02	0.011	0.014	0.48	1.63	1.12	0.41	0.153	0.03	0.0142	93	0.0030	0.0023	68
31	0	30	3020	2850	6	0.19	1.04	0.01	0.013	0.46	1.6	1.04	0.41	0.146	0.04	0.0135	104	0.0044	0.0023	62
32	10	39	2993	2850	5	0.22	0.96	0.01	0.013	0.41	1.67	1.02	0.41	0.117	0.04	0.0153	96	0.0039	0.0045	115
33	5	49	2944	2850	3	0.18	1.03	0.013	0.013	0.39	1.69	1.01	0.42	0.164	0.03	0.0090	79	0.0029	0.0003	12
34	3	37	3045	2870	12	0.23	1.18	0.013	0.015	0.52	1.64	1.13	0.42	0.127	0.03	0.0097	91	0.0032	0.0032	110
35	5	46	2933	2850	6	0.19	0.92	0.012	0.011	0.46	1.68	1.08	0.42	0.110	0.03	0.0109	77	0.0034	0.0024	73