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HOW TO SAVE MONEY IN A FOUNDRY PRODUCTION WITH OPPORTUNITIES OFFERED BY INDUSTRY 4.0 AND ISO9001:2015 STANDARD

КАК СЭКОНОМИТЬ СРЕДСТВА В ЛИТЕЙНОМ ПРОИЗВОДСТВЕ В СВЯЗИ С ВОЗМОЖНОСТЯМИ, ПРЕДЛАГАЕМЫМИ ПРОГРАММОЙ «ПРОМЫШЛЕННОСТЬ 4.0» И СТАНДАРТОМ ISO9001:2015

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Пункты 6.1 (основанные на риске взгляды) и 9.3 (обзор управления) стандарта качества ISO9001:2015 и программы «Промышленность 4.0» скоро станут одним из самых важных факторов, чтобы вызвать необходимые изменения в культуре деятельности литейных заводов для их перспективного развития.

В данной статье рассматривается практическое тематическое исследование о том, как литейные заводы могут включить основанные на риске взгляды и улучшить аналитику получаемых данных, чтобы обнаружить возможности для улучшения деятельности завода. Статья вводит такие понятия, как «риски», «неуверенность» и «дефицит данных», которые используется в стандарте качества ISO9001:2015 и связаны с анализом данных в стандарте качества VDA6.3. Вводятся элементы 7Epsilon, которые создают системный подход для незавершенного анализа данных и организационного управления знаниями в контексте ISO9001:2015. Разъясняется новая матрица потерь основанная на методе визуализации данных и ассоциация ценностей штрафа с основанными на риске данными.

Приводится пример действий по уменьшению эффекта влияния дефектов при изготовлении стального литья. Статья также вводит простую, но полезную технику для определения качественных факторов, таких как качество литейного потока, непрерывная/прерванная заливка и т. д. Возможности экономии на литье приводятся по данным, которые ведут к методам принятия решения, и объясняет, почему у предложенной методологии есть возможность произвести новые гипотезы для достижения непрерывного совершенствования процесса и инноваций.

The clauses 6.1 (risk based thinking) and 9.3 (management review) of the quality standard ISO9001:2015 and Industry 4.0 expectations are set to become one of the most important driving factors to trigger a necessary cultural change in making foundries as data driven companies.

The paper discusses a practical case study on how foundries can embed risk based thinking and advanced in-process data analytics to discover opportunities for improvement across foundry operations. The paper introduces concepts such as 'risks', 'uncertainty' and 'deficiency of knowledge' as used in the ISO9001:2015 quality standard and relates it to the expectations on data analysis in the VDA6.3 quality standard. It introduces 7Epsilon steps that take a system approach for in-process data analysis and organizational knowledge management in ISO9001:2015 context. A novel penalty matrix based data visualization technique has been explained and the association of penalty values with risk based thinking highlighted.

An example of reducing the rework effort to minimize the effect of inclusion defects in the manufacture of steel castings is discussed. The paper also introduces a simple but useful technique for quantifying qualitative factors such as quality of pouring stream, continuous/interrupted pouring etc. The paper focuses on the saving opportunities foundries can realise with data driven decision making methods and explains how the proposed methodology has ability to generate new hypotheses for achieving continual process improvement and innovation.

Ключевые слова. *ISO9001:2015, VDA6.3, Совершенствование процесса, 7Epsilon, Шесть Сигм.*

Keywords. *ISO9001:2015, VDA6.3, Process Improvement, 7Epsilon, Six Sigma.*

DATA DRIVEN DECISION MAKING

Many foundries are either investing in, or already using, continuous process monitoring technologies using internet of things (IoT) style connected devices. However, the savings will not be realized by just monitoring process inputs and outputs for specified control limits with conventional statistical process control techniques. The next step is to use advanced machine learning and data visualization algorithms along with clever organizational knowledge management techniques to gain real-time insights, take necessary action(s) for improvement, monitor the effectiveness of actions and record insights gained, as organizational knowledge, for reuse.

The traditional six sigma process improvement techniques rely on improving a 'subset of the process' rather than taking the factory wide optimization approach. Low cost sensors coupled with affordable data storage and communication technologies is enabling IoT based devices to connect foundry in a way not seen before. It is possible to capture variability in the process at every stage in the foundry. The 7Epsilon steps (www.7epsilon.org) give process engineer a template to connect data sets in meaningful ways that may exist within numerous data silo's in a foundry. In Industry 4.0 and ISO9001:2015 quality standard context, the in-process data from multiple sources across the connected foundry needs to be analysed as a whole rather than in parts.

ISO 9001:2015 quality standard gives explicit definitions of all concepts. It defines risk as 'an effect of uncertainty'. Uncertainty is the state, even partial, of deficiency of information related to understanding or knowledge of an event, its consequences or likelihood. In short, this is deficiency of knowledge. Knowledge is (actionable) information being a justified belief and having a high certainty to be true. Information is defined as 'meaningful data' whereas data is 'facts about an object'. Hence, the ISO 9001:2015 definition of risk can be reworded as 'deviation from the expected result or desired outcome caused by the deficiency of knowledge (uncertainty). If the deviation from the expected result is quantified by a penalty value, then a data transformation technique based on bubble diagrams and penalty matrices[1] can help to quantify the deficiency of knowledge.

In the context of foundry processes, the product specific process knowledge is defined as the actionable information in the form optimal list of measurable factors and their ranges (e. g. C: 0.28–0.33; Mn: 0.60–0.90; S: 0.020 max, P: 0.020 max; Ni: 0.40–0.70; Cr: 0.40–0.70; Mo: 0.15–0.25; Al: 0.03–0.06;) in order to meet desired business goals (process responses or expected results) e. g. minimize defect rates, porosity scores or rework time etc and/or maximize mechanical properties[1].

The clause 6.1 of the ISO9001:2015 quality standard requires organizations to analyze in-process data to discover risks and opportunities. The objective is to minimize undesired effects in the process and enhance, or repeat, the process conditions when expected results occur. Risk is interpreted as the negative effect of uncertainty and an opportunity is the positive effect of uncertainty. In other words, it gives guidance on how to repeat 'good days' and avoid 'bad days'.

The German automotive standard VDA6.3 has prepared an auditable process analysis questionnaire. In addition to the usual process control requirements, the latest version requires auditors to ask following sample questions:

(a) Is quality and process data collected in a way that allows analysis?

(b) Are process specific targets for effectiveness, efficiency and elimination of waste defined, monitored and communicated?

(c) In the case of deviations from product and process requirements, are the causes analysed and the corrective action checked for effectiveness?

(d) Are changes to the product or process in the course of serial production tracked and documented?

(e) Are processes and products audited regularly?

This paper illustrates how penalty matrix approach[1,4] was employed to embed risk based thinking in a foundry. Both risks and opportunities, as required by the clause 6.1 of the ISO9001:2015 quality standard, were discovered which led to enhanced operator training and improved tolerance specification for one process factor. The novelty, and the usefulness of this work for foundry industry, is identified as follows:

- Demonstration of an example of the risk based thinking, as defined by clause 6.1 of the ISO9001:2015 quality standard, using a foundry scenario,
- Improved transparency by publishing the original in-process data set used in this case study along with factor names and responses,
- Identification of new process factors by innovatively quantifying pouring operations as bad (1), tolerable (2) and good (3) and use them in the analysis.

The next Section describes a foundry scenario for the in-process quality improvement project and explains how to embed risk based thinking for in-process data analysis. Even though the foundry scenario is specific to melt chemistry and pouring operations in a steel foundry, the methodology is transferable to other foundry scenarios. This discussion is followed by conclusion.

IN-PROCESS QUALITY IMPROVEMENT PROJECT: AN EXAMPLE FOUNDRY SCENARIO

Inclusions, bi-film defects, oxides, distributed and/or subsurface porosity are among the internal defects that have always challenged process engineers and metallurgists. With the advancement of industrial computed tomography (CT) or industrial radiography techniques and its increasing use by casting users, the pressure on foundrymen to address the challenge of internal defects can only increase. Whether the scrap rate is measured in percentages, or parts per million, there is increasing trend of casting users tightening up product specifications and process control and pass on the liability of field failures to foundries who control the manufacturing process.

Melt preparation, melting process, filling and feeding process are designed with principles, guidelines and various casting rules given by foundry experts. Gating systems are optimised using simulation software. The designs minimize the velocities at the time of entry of molten metal into the mold cavity and also make sure that there is a minimal surface area contact with air in the mold cavity. First article castings are produced using an optimal gating design. However, during production castings, inclusions and internal defects still occur on, or in, the castings. This observation is true for almost all precision ferrous and non-ferrous foundries.

Steel, for example, is a very highly oxidizable metal. In this context, inclusions are: reoxidation inclusions, sand inclusions, slag inclusions and de-oxidation inclusions. It has been established that 90% inclusions in foundries are due to re-oxidation. It means good metal leaving the bottom pour ladle can still end up getting re-oxidised in mold cavity giving rise to inclusions that require welding for salvage. Average cost of welding for steel foundries is US$ 60 per hour per operator. The average welding hours per ton of steel casting for a particular type of casting was 3.5 hours with a minimum value 0.3 hours/ton to a maximum of 13 hours/ton. With an example of 1000 tons per month production, the average welding costs are US$210,000 per month with a maximum exposure of US$780,000 per month. Once the pain point is identified and the financial opportunity quantified, the goal of analysis is defined as discovering opportunities for minimising welding hours per ton of steel castings. A pareto analysis identified a casting part which was chosen for further analysis. Most of the data used in this sample case study was manually observed and entered.

It was decided to use risk based thinking approach, as described by clause 6.1 of ISO9001:2015 quality standard, for exploring additional ways of minimising these costs. The following 7Epsilon steps briefly describe how to satisfy requirements of ISO 9001:2015's clauses 4.4 (*a-h*), 6.1, 7.1.6, 7.2, 7.5, 9.3.1 d & e, 9.3.2, 10.2 & 10.3 in easy to understand way. These steps build onto the 10 step approach defined earlier[2].

The generalized 7Steps of 7Epsilon to **ERADICATE** Non-conformities go beyond the DMAIC (Define, Measure, Analyze, Implement and Control) steps of Six Sigma in that they are designed for computers to interpret in-process data to gain product specific organizational knowledge and reuse it.

Step 1: **E**stablish process knowledge [*x's*], [*y's*]
Step 2: **R**efine process knowledge [$y = f(x's)$]
Step 3: **A**nalyse data using penalty matrices
Step 4: **D**evelop hypotheses (potential solutions)
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*]

The objective of this step is to define process inputs [*x's*], and outputs [*y's*] by acquiring team members' knowledge about processes, factors (process inputs) and responses (process outputs). Also, develop the corresponding cause and effect relationships by studying process maps, SIPOC diagrams, fish bone diagrams etc.

Organizations keep electronic record of the knowledge generated in this step. The records may include photographs of flip charts used in brain storming sessions, electronic files, word/excel files, scanned copies of papers (if used), photographs of defects, and any references to external sources of knowledge including any copies that are in organizations possession. It is suggested that this information is stored with meta tags and relevant file descriptions so that they become reusable and can be found easily.

During the brainstorming session for the proposed example of reducing weld hours, pouring practice was identified as a key process variable in addition to the melt chemistry (Table 1). In-process data was collected for

59 heats. The process inputs from Ladle leaks to Riser Powdered in Table 1 quantify pouring practice. An inspector evaluated each pour and ranked the corresponding process input as bad (1), tolerable (2) and good (3). This categorization is subjective and based on experts' opinion. The chemistry values are shown as percentages.

The tasks undertaken in this step satisfy the requirements of clause 4.4 *a*.

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

The objective of this step is to understand how [*x's*] influence [*y's*] by using internal and external sources of knowledge (clause 7.1.6 *a*, *b*). The output from this step is a systematic research on process inputs (factors), how they affect each response with a written description, proposed tolerance limits and a plan with, how [*x's*] and [*y's*] are measured and at what sampling frequency. All relevant best practice guidelines should also be documented and included. This needs to be done for every process input [*x*] and output [*y*] combination.

Table 1. **Process inputs (factors, [x's]) chosen to analyze process output 'weld hours' [y].**

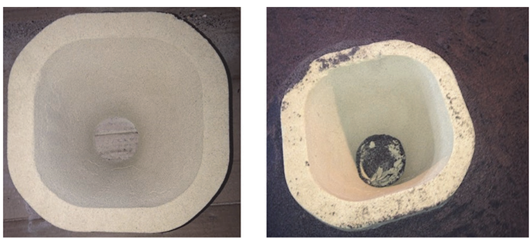
C	Mn	Cr	P	Si	Ni	S	B	Cu
Fe	Mo	V	Ti	Al	Ca	Nitrogen Content, PPM	Carbon Drop	
Pouring Time (sec)	Ladle leaks	Tap Temp (F)	Nozzle Alignment	Pouring Cup Flash	Pouring Stream	Pouring Continuous	Nozzle Distance	Powder level of Risers

For example external sources of knowledge, or peer reviewed journal papers, are studied to highlight trends in the variation of process inputs near the operating conditions. E. g. Aluminum is an important chemical element when it comes to formation of oxides. It has higher attraction for oxygen as compared to other elements. Lino et al.[3] plot two binary aluminum vs calcium phase diagrams for 0.02%Si and 0.2%Si. Carbon and Sulphur composition was maintained at 0.2% and 0.05% respectively. The%Aluminum was increased from 0.01% until 0.06% and Calcium was varied from 0.0005% to 0.005%. The binary phase diagram shows the presence of predominant aluminum oxide at the simulation temperature used (1550 deg C or 2822 deg F). The study highlighted that aluminum, sulphur, silicon, carbon and calcium influence the equilibrium between the oxides and sulphides phases present in steel. However, it also showed that the aluminum variation from 0.01% to 0.03% had little influence on the equilibrium of the system. Authors explained an example of castability window to minimize the occurrence of inclusions in a continuous steel casting operation. An increase in carbon, aluminium and sulphur content reduced the castability window due to formation of oxides other than the slag whereas the increase in silicon content was preferred.

Every foundry has different operating conditions and may have a completely different set of chemical compositions. However, it is important to underline the qualitative trends among variations in process inputs that can potentially explain the correlations discovered in the in-process data. The explanation given above is an example of how external source of knowledge (clause 7.1.6 *b*) is compiled in order to interpret a potential correlation related to the operating range of aluminum.

One of the novelties of this paper is the quantification of manual pouring operations to develop new process inputs e. g. Pouring Cup Splash, Nozzle Alignment, Pouring Continuous etc. These inputs are explained below. The pouring basin used in this example is shown in Figure 1a. Figure 1b illustrates the pouring basin mounted on the mold.

Pouring Cup Splash: The pourer needs to ensure that the nozzle of the bottom pour ladle is straight above the pouring basin. If the pourer does not control the bottom pour ladle properly, the metal leaving the ladle can hit the sides of the pouring cup and cause splash. Splash breaks the metal stream and steel gets oxidized at the time of entering the mold cavity causing reoxidation inclusions. These inclusions are removed initially by grinding and filling them by welding. The welding hours are indicative of the time spent on repairing the defects due to inclusions.



(a) *(b)*

Fig. 1. Pouring basin used in the production of castings (*a*): Pouring basin kept on a table; (*b*): Pouring basin mounted on a mold

Nozzle Alignment: When the ladle is brought to the pouring station the pourer needs to adjust the nozzle to be aligned exactly above the sprue cavity in the pouring basin. Untrained pourer can shake the ladle and cause misalignment resulting pouring cup splash.

Pouring Continuous: In general, the pourer is trained to open and close the nozzle without any need for interruptions during pouring. Any interruptions in pouring will result in breakage of metal stream resulting reoxidation of steel and the incidents of inclusions needing weld repair for salvaging the casting.

The information encoded in Step2 was already made available within the foundry and is being kept up to date. This is an essential step but is rarely done systematically. It is important again to store this information with meta tags and relevant file descriptors so that the information is easily accessible and can be reused.

The tasks undertaken in this step satisfy the requirements of clauses 4.4 b, c & g and also clause 7.1.6 on organizational knowledge. The outputs from this step can be used to enhance the competence of relevant persons by creating an organization specific training material and also satisfy requirements of clauses 7.2 b & c.

Step 3: Analyse data using penalty matrices

The objective of this step is to discover correlations and trends in the data to highlight new opportunities for continual process improvement. A specific cast component was chosen and in-process data on weld hours as well as associated factors was collected for 59 heats.

The risk based thinking as described in Section 1 focuses on developing an ability to repeat the performance for ‘good days’ and to avoid ‘bad days’. Good and bad days are defined with respect to whether expected results were achieved or not. The deviation from expected results is quantified by a penalty value.

The in-process data is analysed using following 4 sub-steps.

(i) Plot response scatter to define acceptable and unacceptable response values (Figures 2).

(ii) Plot scatter diagram for each process input (Figure 3).

(iii) Penalise deviation from acceptable response using 0 to 100 penalty values represented as small and large bubbles respectively (Figure 4).

(iv) Transfer response penalty values onto corresponding process inputs. This converts the process input scatter diagram into a bubble diagram (Figure 5).

(v) Transfer bubble diagram into Main Effects penalty matrix to discover correlations (Figure 6).

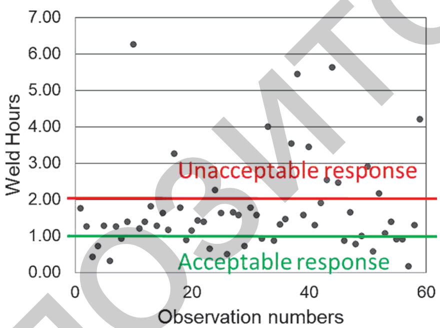


Fig. 2. Heat wise variation for process output ‘weld hours’ is shown as a scatter diagram with acceptable and unacceptable response categorization

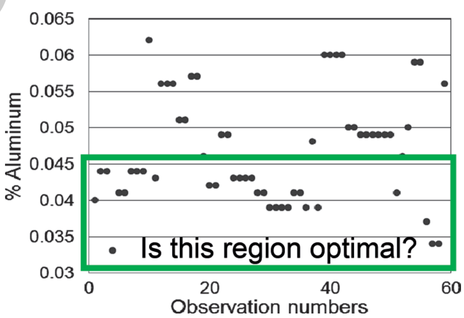


Fig. 3. Scatter diagram of Aluminium data points

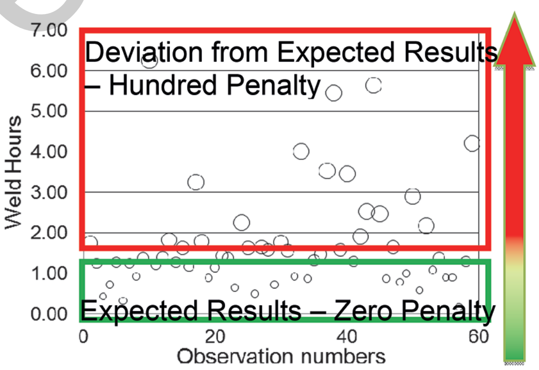


Fig. 4. The deviation from expected results (i. e. desired or acceptable response values) is penalized and shown as a bubble diameter

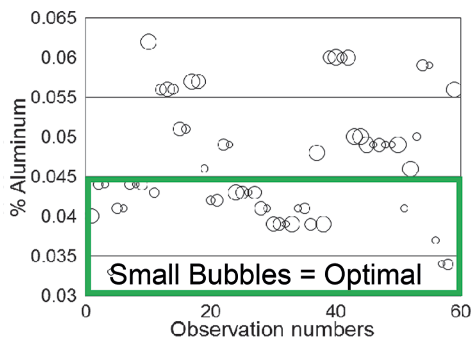


Fig. 5. The penalty values are transferred onto factor scatter diagrams

% Al

Q1	Q2		Q3	Q4
Minimum		Median		Maximum
0.033	0.041	0.044	0.05	0.062

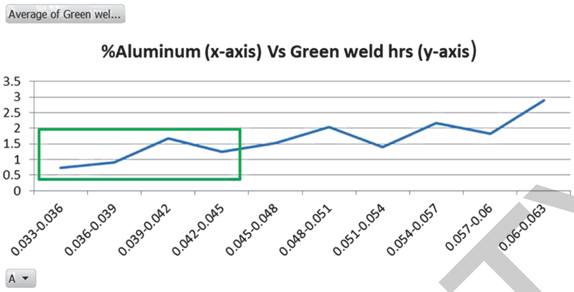
Q1 & Q2: Optimal; Range: Bottom 50%, [>=0.033 & <=0.044];

Q4: Avoid; Range: Top 25%, {>=0.05 & <=0.062}; Strength: 2.7;

Q3 & Q4: Avoid; Range: Top 50%, [>0.044 & <=0.062]; Strengt

Penalty	Q1	Q2	Q3	Q4
80-100	2		2	5
60-80		1	2	1
40-60	2			3
20-40		2	1	1
0-20	14	9	6	8

(a)



(b)

Fig. 6. (*a*) Transforming bubble diagrams (Fig. 5) into a Main Effects penalty matrix. Green rectangle shows bottom 50 percentile as optimal region as it has more number of points with lower penalty value, (*b*) Pivot chart showing variation in Green Weld Hours w. r. t. %Aluminum input values

(i) Plot response scatter to define acceptable and unacceptable response values.

The risk based approach requires organizations to quantify process outputs as acceptable and unacceptable outputs. Acceptable process outputs are expected results and the deviation from expected results is defined by studying scatter diagram of process output for each process observation. In this example, response values from 0 to 1 are acceptable response and above 2 are unacceptable Weld hours (Figure 2).

(ii) Plot scatter diagram for each process input.

The deviation from expected results is interpreted as an effect of the possible deficiency of process knowledge (or uncertainty). The deficiency in the process knowledge is linked to process oriented tolerancing approach where the hypothesis is that optimal regions exist within the tolerance range (or minimum and maximum values observed for process inputs for all values of process outputs). This is further illustrated by plotting scatter diagrams for all process inputs. In this example, we consider scatter for Aluminum as shown in Figure 3.

Here, the uncertainty or the deficiency of knowledge is the hypothesis of existence of optimal regions within the tolerance limits of process inputs. Few examples of uncertainty are:

a. Should the target value of% aluminum be 0.04, 0.05 or 0.06?[1]

b. Is the range robust? Or should it be changed?

c. Should the lower or upper limit be changed simultaneously or individually?

d. In terms of quartiles, is the top 25%, top 50%, bottom 50%, bottom 25% or middle 50% quartile any better than the current range?

The effect of this uncertainty is the deviation from the expected results. However, if the process engineer has the knowledge (justified belief with high certainty to be true) that the proposed aluminum range for his or her foundry is correct then it is easily inferred that there should not be any correlation between aluminum range and occurrence of high or low weld hours. In this situation, the tolerance limit for aluminum will be considered as 'robust'.

The discovery of correlations in in-process data is not a straightforward task. Sometimes, it may not be possible to combine categorical and continuous process inputs. A penalty matrix approach has been suggested that undertakes various transformations on raw process input and output data. Refer to Ransing et al.[1] and Ransing et al.[4] for details and discussions on how to combine both types of process inputs that take continuous and discrete values.

(iii) Penalise deviation from acceptable response using 0 to 100 penalty values represented as small and large bubbles respectively.

The deviation from the expected results is quantified by a penalty value. A penalty value of zero is assigned to a region of acceptable process output values (E. g. weld hours less than one). The process response values in the unacceptable process output region are given a hundred penalty value (E. g. weld hours greater than two.). Remaining process outputs are given a penalty value between zero and hundred (Figure 4).

[1] Note that such small adjustments to various process inputs are outside the scope of traditional design of experiments. A typical design of experiment study is more likely to choose a much wider range of %aluminum values e.g. 0.01%, 0.05% and 0.1%.

(iv) Transfer response penalty values onto corresponding process inputs. This converts the process input scatter diagram into a bubble diagram.

Each process output value (response value) has a corresponding factor value. The response penalty values are transferred onto factor (process input) scatter diagram of Figure 3 in order to convert it into a bubble diagram (Figure 5). Small bubbles represent process inputs corresponding to acceptable output whereas large bubbles represent those inputs corresponding to unacceptable output. The region with more number of small bubbles is the optimal region for Aluminum as highlighted in Figure 5.

(v) Transfer bubble diagram into **Main Effects penalty matrix** to discover correlations.

However, it is not always practical to visualize in-process data using bubble diagrams as shown in Figures 4 and 5. The visualization becomes difficult when the number of observations increase and/or when two or more observations have same value i. e. if they overlap. Hence, the information is transferred into a penalty matrix.

Penalty matrices discretize the data in terms of quartiles for continuous inputs and levels for discrete inputs and align it with five bins of response penalty values viz: 0–20, 20–40, 40–60, 60–80 and 80–100. The numbers in the corresponding cells of a penalty matrix are the number of observations that correspond to the response penalty value bin and the quartile or level of the process input (Figure 7). Blue colour represents number of data points related to acceptable response and red colour represents number of data points related to unacceptable response. It is clear that the bottom 50 percentile of aluminum is optimal.

The correlation discovered from penalty matrices are cross validated using pivot tables and charts as shown in Figure 6b. The%Aluminum input values are grouped at the interval of 0.003% and the corresponding average green weld hour values are plotted in Figure 6.2(b). The variation of%Aluminum in bottom 50% region, shown as green rectangle, can be seen to be associated with lower Green weld hours.

The tasks undertaken in Step3 satisfy requirements of clauses 4.4 f, h & 6.1.1 b.

The visualization of in-process data in this way uncovers underlying correlations that may convert into new opportunities for continual process improvements. This process helps to quantify the uncertainty in knowledge and creates hypotheses (or potential solutions) that process experts need to answer by referring to internal (clause 7.1.6 a) as well as external (clause 7.1.6 b) sources of knowledge. In simple terms, the qualitative trends discovered in step 2 are applied to correlations discovered in the step 3 to create hypotheses for step 4.

Wherever necessary, this methodology may also be used in conjunction with, or in addition to, the existing process improvements tools based on design of experiments, statistical process control or Six Sigma could also be employed. For manufacturing processes, including foundry processes, data analysis may also involve the use of process simulation software tools to discover opportunities.

Step 4: Develop hypotheses (potential solutions)

The objective of Step4 is to determine optimal process settings or opportunities for corrective actions that are likely to minimize instance of producing undesired process outcomes or effects. This step is normally implemented during a 7Epsilon quality control meeting. Prior to the meeting, every team member interprets the results of Step 3 as per his/her competence and by accessing the knowledge stored in Step 2 and turns insights into actionable information and electronically passes on all suggestions to the chair of the meeting. The chair reviews and compiles ALL suggestions and calls for a meeting.

The team members may review both internal and external sources of knowledge and give their own explanations on why the suggested correlations be chosen or not chosen. The team member requests the chair of the quality control meeting to review the source of information. The chair discusses the findings in the meeting, and if necessary, seeks external professional help from domain experts to refine the knowledge and update the process knowledge description on factors selected so that it can be reused.

The meeting discusses the suggestions and takes one or more of the following decisions:

1. Agree to a corrective action plan for a confirmation trial
2. Decide to collect more in-process data for the same or additional factors
3. Decide to conduct one or more design of experiments or further process simulations
4. Recommend a fundamental review of the process with help from external consultants with or without additional Six Sigma projects.
5. Close the project with justified and documented reasons.
6. Update process knowledge documented in Step 2.

These tasks satisfy requirements of clauses 4.4 f, 6.1.2 a, 7.1.6 and 10.3. The clauses 9.3.1 c1 & e and 9.3.2 require the decisions of 7Epsilon quality control meeting on the potential opportunities for continual improvement be discussed in the management review which is also required to authorize actions/decisions including any resource needs. Note that clause 10.3 requires organizations to address all opportunities and areas of underperformance as part of continual improvement and clause 7.1 commits top management to provide resources needed.

The data analysis in Step 3 highlighted the following correlations.

1. The bottom 50 percentile of Aluminum (>= 0.033 and <= 0.044) was chosen as an optimal range.

2. Nozzle Alignment, Pouring Cup Splash, Pouring Stream, Pouring Continuous, Nozzle distance and Powder level of Risers were classified into three categories bad (1), tolerable (2) and good (3).

It was discovered that the classification value of 3 for Pouring Cup Splash, Pouring Continuous and Nozzle Alignment was optimal. In other words, these parameters must be closely monitored to achieve a perfect pour. Whereas, Pouring Stream, Nozzle distance and Powder level of Risers will require less monitoring.

3. Correlations were also discovered for top 25 percentiles of Titanium and Chromium but they were weak and hence, not selected for confirmation trial. A detailed mathematical formulation for discovering these correlations and interactions is given by Ransing et al.[4] and Batbooti et al[5].

Step 5: Innovate using rootcause analysis and conducting confirmation trials

The objective of this step is to create new product specific process knowledge based on the hypotheses (potential solutions) outlined in Step 4. The tasks may involve conducting one or more confirmation trials, design of experiments, new Six Sigma projects etc.

These tasks satisfy the requirements of clauses 4.4 f & g, 6.1.2 b2 and 10.2.1 b2 & d. The clause 9.3.1d requires the effectiveness of the actions taken be reported back to the management review. This process may iteratively continue as the management review may suggest new actions.

Step 6: Corrective actions and update process knowledge

If the additional knowledge is gained then all changes are reflected in the organizational knowledge as documented in Step 2 along with the necessary justification so that the experience is reusable in the future.

After a successful confirmation trial, it was decided to provide operator training and monitoring to ensure a good score for Pouring Cup Splash, Nozzle Alignment and Pouring Continuous factors and the target value for percentage aluminum was lowered. The process knowledge was updated and the foundry being a jobbing foundry, it was decided to use this knowledge for repeat or similar orders in the future.

These tasks satisfy the requirements for clauses 4.4 f & g; 6.1.2 b1 & 6.1.1 c, 7.1.6, 10.2.1 c & e.

Step 7: Build Aspiring Teams and Environments by monitoring performance

The objective of this step is to build aspiring teams to achieve the following:

- Continually monitor performance and maintain accountability (4.4 e).
- Ensure sustainability of this initiative with adequate resources (4.4 d).
- The foundry specific process knowledge repository can also be used to train operators and process engineers (7.2).
- Store knowledge in computer repositories so that they are easily accessible (7.5, 10.2.2, 10.3).
- Determine the knowledge necessary for the operation of its processes and to achieve conformity of products and services and make it available to the extent necessary.

CONCLUSIONS

ISO 9001:2015 has explicitly made creation of risk based thinking environment and enhancing organization's ability to reuse, retain and continually discover and update organizational knowledge as a requirement. However it has not specified how organizations can implement these solutions. With the advent of Industry 4.0 and connected enterprise initiatives, foundries will record more in-process data in future. Converting in-process data into actionable information is a challenge that has been addressed in this paper.

A seven step approach based on penalty matrices has been illustrated with the help of an actual foundry based in-process quality improvement project. The paper explained the methodology and demonstrated how to embed the risk based thinking as required by the clause 6.1 of the ISO9001:2015 quality standard. It was also discussed how every step of the seven steps satisfied one or more ISO9001:2015 requirements. The foundry was able to discover process improvement opportunities. Opportunities were discovered for operator training based on the correlations discovered in the in-process data. New tolerance limits for one of the process input was also suggested.

The methodology described in this paper is generic and applicable to many other foundry scenarios. It is expected that this paper becomes a useful template for future foundry based risk based thinking in-process quality improvement projects.

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