WebCADAS: A New Online Education System for Casting Defect Identification, Analysis and Optimisation of Parameters

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Abstract- In this paper the author has made use of E learning technology for the benefit of foundry industry located in Kolhapur area. Each casting produced in a foundry is a research experiment, since no two castings have the exactly same values of their geometric, material and process parameters. By the time, castings are inspected the link to the originating (influencing) parameters is lost, since they are never systematically recorded and correlated with quality characteristics. The defects analysis system includes an expandable library of images to facilitate correct identification of a given defect, and presents the various causes and remedies based on the user inputs. The entire system is implemented in a web-based environment for wide access to practicing foundry engineers. The system named WebCaDAS, forms the basis for recognizing the casting defect, which is the major cause of rejection leading to considerable loss of investment, and its analysis and correction using E learning techniques.

Keywords – Foundry, casting, rejection, e learning, casting parameters, optimization.

I. INTRODUCTION

The Indian foundry industry is a leading engineering sector with annual production of over 7 million tonnes of castings, accounting for about 8–9% of total castings production in the world. There are approximately 4,500 foundry units in the country out of which 90% can be classified as small-scale units, 8% as medium-scale units, and 2% as large-scale units. The foundry industry is dispersed across various geographical clusters, of which the Kolhapur cluster is one of the major ones. Kolhapur was traditionally an agro-based economy. Demand for oil engines and agricultural implements grew with industrialization in the region. This led to the emergence of the foundry industry which evolved around the 1960s. Today Kolhapur is a leading foundry cluster, renowned for manufacturing quality castings. There are approximately 300 foundry units located in the Kolhapur and Sangli districts of the region. While units in Sangli are located mainly in the Miraj and Palus industrial areas, foundries in the Kolhapur district are spread across eight major industrial estates. The cluster primarily manufactures ferrous (iron) castings covering both SG iron and grey-iron castings. The total production of the Kolhapur foundry cluster is estimated to be 600,000 tonnes per annum. A majority of the foundry units in the cluster cater to the automotive sector along with other sectors such pumps/valves, sugar, textiles, etc. The cluster has experienced growth in turnover, employment and exports over the past few years. Almost 30% of production is being exported to several countries and catering to numerous industries [1].

In many manufacturing companies large amount of data is collected and stored, related to designs, products, equipment, materials, manufacturing processes etc. This data can be a source of valuable information. The extracting useful knowledge from that data, using intelligent and partly automated techniques, is called data mining. It is important that data mining techniques can provide various types of information. Much work has been done to develop methods of automated knowledge extraction from the recorded past data, usually in the form of logic rules of the type "if … then…".

Metal casting involves a large number of activities and process parameters related to toolmaking, sand preparation, moulding, core-making, metal melting, pouring, solidification, fettling, cleaning, inspection, heat treatment, machining and shipping. It is virtually impossible to maintain the same values of each parameter, for example the composition of metal and mold material, and the pouring temperature and rate. Thus each casting produced in a foundry is a research experiment, since no two castings have the exactly the same values of their dimension, material properties and process parameters. Casting defects can be traced back to incorrect values and improper control of these parameters.

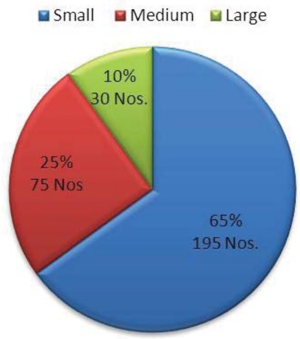


Figure. 1: Distribution of foundry units in Kolhapur cluster [1]

In the foundry area there are several types of important practical problems that can be solved through extracting knowledge from a recorded past data, such as [2]:

a. Prediction of results of manufacturing process change, including indication of optimal or critical process parameters, e.g. combination of time and temperature for heat treatment, influence of variations of chemical composition of an alloy on its mechanical properties, etc.

b. Detection of causes of deteriorating product quality. This can apply to the final products, e.g. increasing percent of defective castings, or intermediate products, e.g. lowered strength of molding sand.

c. Establishing rules for design of casting processes, e.g. rigging systems, or for process operations, e.g. molding sand preparation, melting procedures etc.

Visualization tools are often treated as supplementary methods, providing better understanding and easier to interpret the knowledge discovered by the models. Examples of such tools are flow charts, run charts, Pareto charts, Ishikawa diagrams, histograms, scatter plots, identification of outliers and others. However, some of those methods can be also extremely valuable for initial analysis of the problem, aimed at the right choice of the mode’s variables, i.e. identification of potential process parameters and interdependencies between them, which could play important role in the process. Statistical regression models are probably the most popular in continuous type data analysis and generalization, often used in the form of so called empirical relationships. It is important that a particular form of the function must be assumed which requires a certain amount of knowledge about the modeled process. The cause of defects is often a combination of several factors rather than a single one. When these various factors are combined, the root cause of a casting defect can actually become a mystery. By the time quality engineers inspect the castings, the link to the originating (influencing) parameters is lost, since they are never systematically recorded for each casting, and correlated with quality characteristics. Thus, a vast amount of valuable knowledge is generated in the foundries every day, but is never fully utilized for quality improvement.

II. Literature Review

It is said that practice makes man perfect and experience over a wide period of time adds to it. But getting such experienced human resource is always not possible. In past few years attempts were made to implement the human knowledge and experience available in the form of expert system.
Chokkalingam and Nazirudeen [3] demonstrated a systematic procedure to identify and analyze a major casting defect (mould crush in that case) for automated transfer case casting. Mane et al. [4] advocated the need to correctly identify and characterize the casting defect. They stressed on the fact that unless a defect is correctly identified procedure to analyze the defect cannot be rightly followed. Ransing et al. [5] developed the intelligent computer aided defect analysis (ICADA) system, based on artificial intelligence technique, to identify design, process or material parameters which would be responsible for occurrence of defective casting in a manufacturing campaign. Yang and Hwang [6] developed the computerized diagnostic system for casting defects. For this system user enters the facts and sketch of casting defect to system. Dwivedi and Sharan [7] developed a knowledge based engineering module for the diagnosis of defect in a cylinder block casting. On the same lines Alagarsamy [8] suggested a new

way to defect analysis. It is based on elimination of causes and then arriving at particular root cause. It also made use of design of experiments. Gorny et al. [9] proposed development of attribute table as a new tool. The approach in our work is envisaged to overcome the limitations of earlier expert systems, enable continuous expansion of knowledge base, and provide wide access for its use through the Internet.

III. Casting Defect Analysis (11)

The overall approach for the analysis of casting defects is illustrated below (Refer fig. 2). It is separated in two stages namely diagnosis and remedies. The approach starts with the detection of defects in casting components, followed by identification of their attributes and classification. The second stage involves determining the possible causes and suggestion of the remedies. The casting defects analysis system is implemented in an interactive web-based environment. It includes an expandable library of casting defect images to facilitate correct identification of a given defect. The analysis ends with suggesting remedies to eliminate the defects from casting.

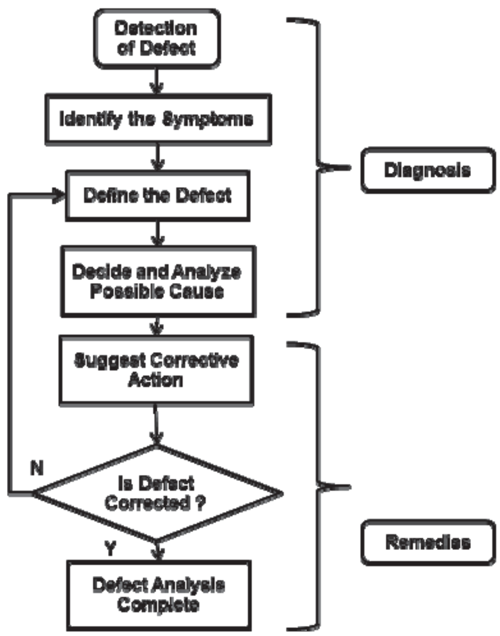
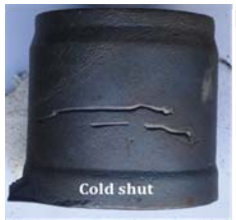


Figure. 2: Process for analysis of casting defects [10]

IV. New Classification of Defects [4]

The new classification is hierarchical and more comprehensive than previous approaches. It classifies casting defects in terms of their appearance, size, location, consistency, discovery stage and identifying method. Traditionally defects have been classified based on the location or the external appearance of the defect but it is required to classify the casting defects in terms of its effect on the casting. The classification of defects can be considered as of mixed type and multi-phase type as it not only classifies the defects but also links them to causes and remedies.

In the first phase, the defect is classified on the basis of geometric, integrity and material/property related defects. In phase II, they are further classified on the basis of identifying stage, type, size/severity and identifying method, taking into account the different types of controls performed on cast parts to reveal defects. A sample classification of coldshut is showed as per new system of classification (Refer fig. 3).



TYPE	Geometry
Appearance	Material partings primarily in thinner wall thicknesses and castings with large surfaces. Material partings with rounded edges.
Defect Size	Medium to large
Location	Thin walls and casting parts with long flow paths.
Consistency	On the outer surfaces with thin walls
Discovery at	Cleaning stage
Inspection	Visual

Meta-cause	Root cause
Low fluidity of molten metal	Increase the pouring temperature of molten metal
	Metal sections too thin for area involved
Rapid fall of temperature	Improper sizing of gates, runner and sprue-ingates too small or too few
	Excess moisture , Permeability too low
	Too rapid heat transfer of molding material

Figure. 3: Hierarchical classification of coldshut

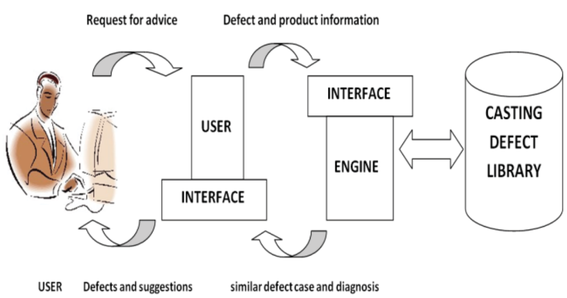


Figure. 4 : Structure of system

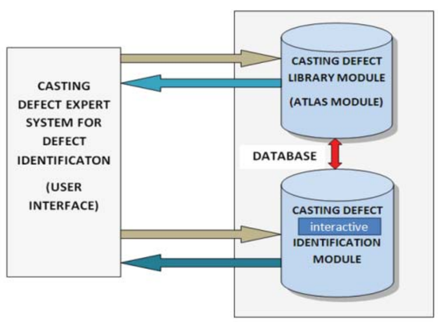
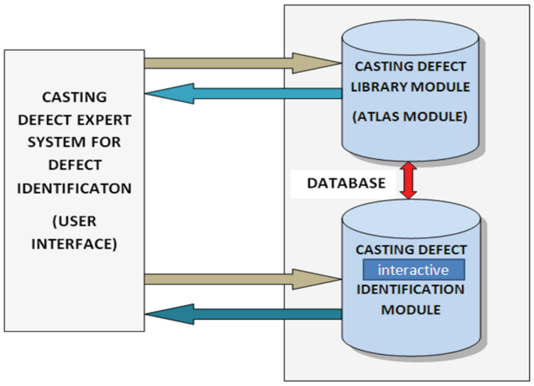


Figure. 5: Working of the system through user interface

V. WebBased Casting Defect Analysis System (WebCADAS)

The system of casting defects analysis is implemented in a web-based environment with a user friendly interface . The casting defects expert system consists of two modules: Atlas module and identification & Diagnosis module. The Atlas module classifies the defects, and Identification and Diagnosis module provides causes and their remedies. Both modules can be employed by inspectors in quality assurance departments of foundries (Refer fig. 4). The system works through the systematic process. User seeks for the advice. The information regarding the casting defects, their cause and remedial measures etc. is stored in database. This information is fetched and then presented to the user through user interface as above (Refer fig. 5).



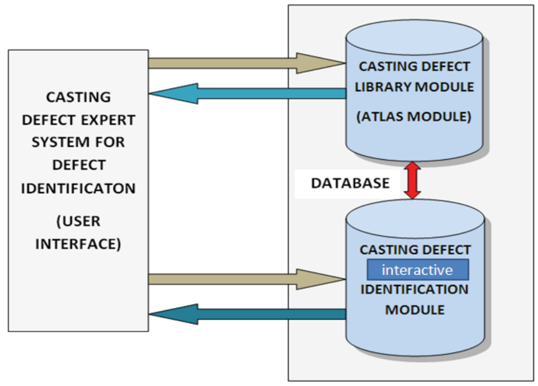


Figure. 6: Information of casting defect – coldshut

Fig. 7: Image library for enhanced defect understanding

VI. CASTING PARAMETER OPTMISATION

Process optimisation is the identification and control of the input process parameters (factors) to achieve the desired output (response) in any process. The foundries need to have Pareto charts for different parts showing the loss of

revenue due to scrap or rework (not meeting the product specifications) and identifying the parts that adversely affect the profitability of the company. Once the parts are identified, the foundries need to identify all the process variables that could be related to the defects and collect data with traceability. The analysis of such data should be able to give the ranges of process variables that have positive effect, negative effect, and no effect on the product characteristics. Such analysis should result in the validation experiment to verify the results of the analysis. The experimentation can also be done with the simulation packages available for designing of methoding systems, analysis.
A software prototype is built up for the implementation of data mining. This prototype creates new files of casting, input the selected parameters on the daily basis, will input the rejection data, process the data and then present the optimized values to the user for particular casting. A case base logic is used to find the similar match between existing castings and a new casting. The system can find out similar match and the user thus can directly get the initial startup values of parameters for new casting thus avoiding the experimentation.

VI. Limitations of design of experiments

In view of the large number of factors that are responsible for casting defects, the general statistical approach is not always the best [12]. The various limitations of DoE are as follows:
a. In DoE, the number of experiments needed depends on the number of factors. In the 2^K design, each factor is varied over two levels and the numbers of experiments needed are 2^K where K is the number of factors. For 3 factors, 8 experiments are needed and for 4 factors, 16 experiments are needed. As the number of factors increase, the number of experiments needed increase exponentially. Even if fractional factorial designs or Taguchi design of experiments are used, the number of experiments needed become very large. Generally the number of factors is more in a metal casting process.
b. The need to carry out controlled experiments to collect the required data interrupts regular production.
c. These needs to be considerable difference in the levels of factors in order to have meaningful results, hence the results could be biased.
d. The use of statistical techniques to design and interpret results requires significant training and expertise, making it expensive and time-consuming.

This optimisation of parameters can be achieved through mining and processing of historical data. Historical data is the data which is recorded in the foundry on the continuous basis. This data mainly includes the information related to the composition, pouring parameters, melting parameters, moulding parameters, number of castings poured, number of castings rejected, and number of defects. Such information in major or minor / small scale foundries is recorded on periodical basis. This information is gathered as a when a particular component is poured. This large amount of data remains unprocessed over the period of time. The basic idea behind making use of historical data is to not to waste human efforts in experimenting and then coming out with some rejection etc but have a controlled set of parameters values optimized for particular component which gives minimal rejection. Historical data plays important role as hidden experiments are accumulated in those practices. The historical data can be seen as the experiences accumulated over the period of time. This experience needs to be extracted from these values by proper processing. Each casting in the foundry is a research experiment. Experimenting with facts takes lot of time consumed. So, then it calls for the processing of historical data. Historical data can give the information regarding the different permutations combinations that were carried out.

VII. Selection of Correct Parameters for Optmisation

Some of the major parameters that are required to be considered for analysis of casting defects are presented under different categories in Table 1. These parameters play crucial role in production of defect free casting. A slight imbalance of these parameters is also responsible for defect generation in cast component. For selection of these parameters mechanism of formation of a casting defect is taken into the consideration i.e. when a coldshut is formed, it occurs mainly due to excess moisture, weak sand, low permeability, too rapid heat transfer to mould, changed chemical composition, cold melting, low pouring temperature, interrupted pouring, cold ladles etc. Same is the case with the design parameters. This means that every factor contributes to the defect formation in more or less amount. This amount changes with relative proportions. The defect under consideration are: Inclusions, Blow hole, Scab, Shrinkage, Hot Tear, Cracks, Cold shut, etc.

The parameters included can be grouped in to following types as:
1. Melting parameters

2. Chemical composition
3. Sand parameters
4. Design parameters

VIII. Process of Comparison of Paramters

In this process the step by step comparison method is followed as follows [13]:

a. First the rejection rates lower than allowed rejection rate specified by user are screened and only those readings which fulfil the conditions are accepted.

b. Next amongst the allowed parameter values defect wise rejection is calculated and is compared with the specific value entered by user. This process ensures that % rejection due to specific defect can be lowered. Thus, it is possible to control the rejection of specific defect. The range value for every parameter is depicted based on the set of accepted values specifying the rejection limit criterion. This range will include P_{max}, P_{min} *and* P_{avg}.

c. A defect can be traced based on its percentage deviation from normal working range that gives minimum rejection. For this if there are five parameters in the consideration then either the reading will be accepted or not. If accepted then it is checked for each parameter whether the value lies within the range depicted or not. If it lies in the range then the defect which may be generated due to the imbalance of the said parameter will be absent. If it lies outside the range then it can be concluded that the rejection will contain more defects due to these parameters as compared to the parameter within the range. Also based on the deviation from the maximum or minimum value of particular parameters the severity of the defects can be understood.

d. For the working of above concept it is essential to find out or ascertain the impacting parameters for particular defect. Here it is assumed that the defect is generated due to the combined imbalance of the parameter governing the defect generation (theory of combined imbalance). Foundry is unpredictable science. No two moulds are similar. The parameter levels in one mould are different than that in the different mould. Thus, it can be thought of as the relative imbalance of the parameters causes defect in the particular mould.

e. For casting defect analysis relative imbalance for the parameter ascertained for generation of particular defect is calculated. This imbalance is monitored over a period of time as more and more readings get accumulated. More the readings more the accuracy is the principle behind this. Thus, the aim for the casting defect analysis is to reduce the relative imbalance of these parameters. By making use of this theory the factors responsible for defect generation can be identified to tackled separately so as to take care of the nuisance parameters. This theory helps to improve production by reducing amount of rejection.

IX. Benefits

The defects analysis system provides the following benefits:

1. The system can be used for defect identification and classification.
2. The interactive casting defect library can be used as a teaching resource for industrial as well as academic institutions.
3. It can become the basis for developing an Indian Atlas of casting defects.

The system, as it is prototype, is under further development to refine the classification system, and add more reference images to the casting defects library. Collaborations with industry and other academic institutes are being sought to generate more case studies.

X. CONCLUSIONS

In this paper an attempt is made to put forward a hierarchical and comprehensive classification system for casting defects, for a more scientific and user-friendly approach to casting defects analysis. The Atlas module facilitates defects classification, whereas the Identification & Diagnosis module presents the causes and remedies of the defect. An expandable library of reference images of casting defects allows accurate identification and classification of the defects. It has been implemented in an interactive web-based environment of expert system that is being further refined with industry support.

In this paper an attempt is made to advocate and justify the use of historical data of casting for optimizing the casting parameters and thus leading to minimum rejection without performing much of experimentation. This historical data can be processed and suitable ranges of parameters can be identified for minimum rejection. The defects can be related with the imbalance of particular parameters, which can be achieved with a large pool of database of casting parameters values recorded systematically. This can eliminate the design of experiments for new casting development when applied with case based reasoning for similar castings.

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