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Artificial intelligence-based control system for the analysis of metal casting properties

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Analysis and modelling

ABSTRACT

Purpose: The metal casting process requires testing equipment that along with customized computer software properly supports the analysis of casting component characteristic properties. Due to the fact that this evaluation process involves the control of complex and multi-variable melting, casting and solidification factors, it is necessary to develop dedicated software.
Design/methodology/approach: The integration of Statistical Process Control methods and Artificial Intelligence techniques (Case-Based Reasoning) into Thermal Analysis Data Acquisition Software (NI LabView) was developed to analyze casting component properties. The thermal data was tested in terms of accuracy, reliability and timeliness in order to secure metal casting process effectiveness.
Findings: Quantitative values were defined as “Low”, “Medium” and “High” to assess the level of improvement in the metal casting analysis by means of the Artificial Intelligence-Based Control System (AIBCS). The traditional process was used as a reference to measure such improvement. As a result, the accuracy, reliability and timeliness were significantly increased to the “High” level.
Research limitations/implications: Presently, the AIBCS predicts a limited number of casting properties. Due to its flexible design more properties could be added.
Practical implications: The AIBCS has been successfully used at the Ford/Nemak Windsor Aluminum Plant (WAP) to analyze Al casting properties of the engine blocks.
Originality/value: The metal casting research community has immensely benefited from these developed information technologies that support the metal casting process.
Keywords: Casting; Artificial intelligence methods; Metallurgy; Statistical process control; Properties

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1. Introduction

Based on the current demands in the metal casting industry for advanced and “intelligent” computing architectures, the present research focuses on the implementation of an Artificial Intelligence-Based Control System (AIBCS) that integrates a Statistical Process Control System for quality control purposes and an Artificial Intelligence System into the acquisition of Thermal Analysis data for the analysis and prediction of metal cast component properties.

The AIBCS Thermal Analysis Platform is designed to support aluminum casting processes, faulty components and unexpectedly higher scrap rates, even when chemical analysis, pouring temperatures and times on the Statistical Process Control charts are identical to other cases. These situations could be caused by the fact that the solidification process parameters vary due to the differences in the melt treatment procedures, etc.

In the late 1980s, the application of Artificial Intelligence (AI) in metal casting problems was suggested. Since then several developments have been reported including applications in casting design [1], mould selection [2], casting defect diagnosis and prevention [3, 4], design of mould filling and feeding systems, process monitoring, and prediction of casting characteristics [5]. The AIBCS presented in this paper differs from previous work as it integrates three core functions (data acquisition, statistical control and properties prediction) into one use for melt solidification process characterization.

This System captures metal casting characteristics since the melt is poured into the mould until it is solidified as a component. The Statistical Process Control sub-system monitors variables and provides warnings when out-of-control values are presented in the process. Artificial Intelligence predicts alloy properties and detects abnormalities that lead to corrective and preventive actions.

The System is complemented with more informative and intuitive graphical interfaces to make the process more understandable for all operators and engineers, providing easy and rapid identification of errors and variables. The outstanding feature of the AIBCS is the prediction of casting properties, which are very relevant to the quality of the component during its service.

The main engine of the Artificial Intelligence System is Case-Based Reasoning (CBR) logic and representation [6]. This approach is similar to the nature of Thermal Analysis data analysis in the solidification process and casting characteristics. The CBR representation has the advantage that beside the prediction of numerical and non-numerical parameters, it gives an explanation of the results through some recommendations and comments [7]. This technique has been widely used in a variety of applications due to the fact that its capabilities of adaptation and explanation are easily implemented. This feature overcomes shortcomings presented in other Artificial Intelligence techniques such as Artificial Neural Networks [8].

In order to ensure that the AIBCS provides the outcomes required in both industrial and research labs, it was evaluated in terms of accuracy, reliability and timeliness. The AIBCS outcomes were compared to the traditional process parameters commonly used for analysis, control and prediction of characteristics in the casting process. In this traditional approach, the site for the solidification process is a large continuous casting facility where automatic devices collect data on variables across the casting line every few seconds. The monitoring of melt processing and quality control of components consists primarily of operators and engineers periodically checking a few variables. Experts predict the casting properties will enhance the final product's quality and performance.

The AIBCS provides the process engineer with a meaningful interpretation of the Thermal Analysis cooling curve parameters, including capabilities for a continuous increase of knowledge on the casting process and component. This approach allows for early adjustments to the process parameters preventing melt related defects.

2. Methodology

The Statistical Process Control System and the Artificial Intelligence-Based System are integrated into the National Instruments LabView graphical user interface. This tool is commonly used to capture data from complex instruments. In this project, several thermocouples capture data during the solidification process. Labview has the ability to represent this data in Control Charts by defining Upper and Lower Control Limits (UCL and LCL) that in turn will determine out-of-control values. By applying Western AT&T rules, alarms are presented to the operator to warn of the severity of out-of-control values.

The Artificial Intelligence System is a separate application developed in C++ named Caspian [9] using Casa-Based Reasoning representation. This executable application is called by LabView using metal casting values as parameters. The Case-Based Reasoning knowledge base was populated with information from experiments carried out by G. Pelayo et al at the University of Windsor [10].

The methodology to assess the AIBCS outcomes in terms of accuracy, reliability and timeliness is based on probability and statistics. The Standard Deviation, the Analysis of Variance (ANOVA) and the Cochran Test are calculated to measure the results. The assessment is carried out in the following components of the AIBCS:

- Real-Time Data Acquisition System (RTDA),
- Statistical Process Control System (SPC),
- Case-Based Reasoning System (CBRS).

3. High-level architecture of the AIBCS

The Real-Time Data Acquisition System (RTDAS) captures the thermal analysis data during the solidification process along with the environmental conditions around the melt sample. The Statistical Process Control System controls the casting parameters and provides melt evaluation. Indeed, it warns of abnormal conditions and advises of corrective actions. The Case-Based Reasoning System (CBRS) predicts parameters of the component during service.

The AIBCS combines statistical algorithms, Artificial Intelligence techniques and mathematical models to provide a tool that assists the demanding metal casting research specifications (Fig. 1).

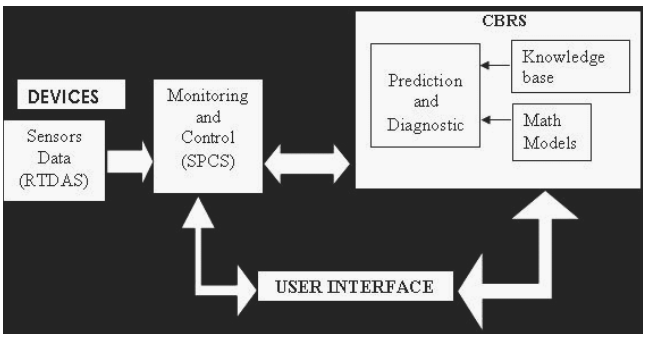

Fig. 1. AIBCS components

3.1. Real-Time Data Acquisition System (RTDAS)

The RTDAS is the sensing component that monitors the melt casting process through the simultaneous measurement and recording of melt temperature in five different locations (using K-type thermocouples) and environmental conditions around the melt such as pressure and airflow by connecting two valves to the equipment. Flow rates vary from 0 (no flow) to 800 cubic feet per meter (cfm), and elevated pressures of 0-15 pounds square per inch (psi), simulate metallostatic head pressure (Fig. 2).

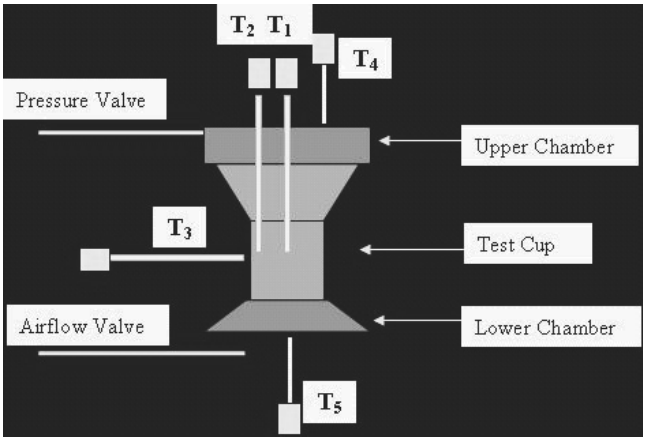

Fig. 2. Location of thermocouples and position of servo valves

The model obtains data from devices at regular time intervals, recording sensor information in a database for query and retrieval. This data repository includes thermal analysis parameters, ambient conditions, process settings and melts chemical composition.

The range of temperatures is defined in the RTDAS. When the central temperature (TC1) falls between this range the RTDAS automatically adjusts the hardware (pressure and airflow valves) to those values defined as the target. The thermocouples continuously monitor characteristic points. Based on the sensor readings, the RTDAS generates integral information for the analysis of the cooling curve (Fig. 3). The time-temperature data, as well as the input and output values of the environmental conditions are automatically saved and time stamped for traceability in order to make it feasible to generate graphical plots of various melt samples.

The assessment of the RTDAS data in the AIBCS in terms of accuracy is determined by the deviation of measured values from temperature sensors against the precise value (average value). Reliability is given by the analysis of the variability of the recorded temperature values in a set of samples. An ANOVA model is used to determine if any of the tests shows variability. The Cochran Test determines if the variability in the process is significant. Timeliness is given by the measurement of time in the acquisition of temperature signals.

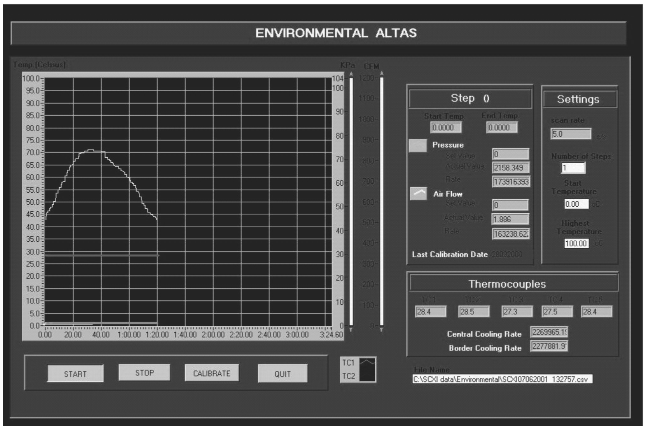

Fig. 3. RTDAS data monitoring

3.2. Statistical Process Control System (SPCS)

Once the temperature signals are recorded by the RTDAS, they are statistically analyzed in the SPCS module. The SPCS monitors, measures, and evaluates melt quality based on pre-defined criteria. The SPCS evaluates three variables out of 45 Thermal Analysis parameters selected from the RTDAS. These parameters are simultaneously evaluated to detect Out-of-Control situations. The selection of the subset of default parameters is done as part of the design of the quality control policy using expert opinion from process engineers, who each day run a series of tests that emulate the behaviour of the melt during casting and solidification. The data subgroups are retrieved from a database with information from experimental Thermal Analysis runs. The algorithms are calculated in the SPC toolkit library functions available in LabView.

The SPCS presents the following charts (Fig. 4).

- The X-Bar Chart,
- The Range Moving Average Control Chart,
- Exponentially Weighted Moving Average Control Chart (EWMA) [11].

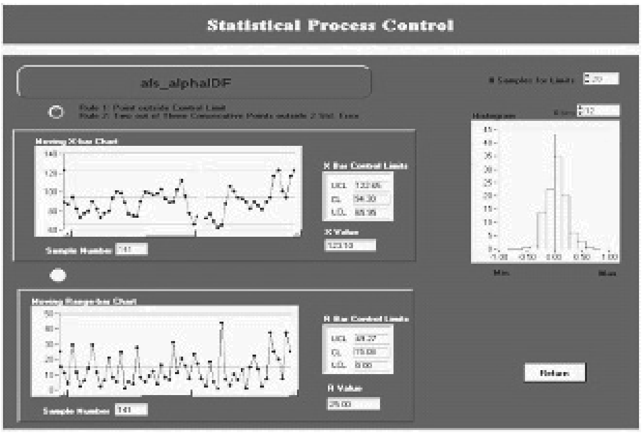

Fig. 4. X-Bar and Range Moving Average Control Charts

For a complete analysis of the SPC charts, a histogram is included showing the frequency of values.

Variable values such as the number of samples for recalculation of control limits and lambda (λ) are specified by the user. Default values of these parameters are presented to the operator, which are set to be optimal. In moving average charts, the plotted points are not independent of each other. The points are interrelated through a "distance" that depends on the number of samples used for the averages. This must be kept in mind while interpreting the alarms.

In the EWMA control chart, the λ and L optimal values were established by analyzing the tables provided by Lucas and Saccucci [12]. Therefore, default values were λ=0.10 and L=2.814. These values yield a steady state ARL = 492, allowing for the detection of shifts in the process lower than 0.25σ.

Western AT&T Electrical Rules [13] are applied in the control of evaluated characteristics. When the control chart approaches or exceeds the control limits, some alarms are presented to the operator that may require a corrective action. When the variable value falls within the control limits, no correction is made and the process receives a go-ahead signal for the next product. However, control charts by themselves cannot indicate the causes of the abnormality. It is necessary to combine a complete understanding of the concepts of control charts and a comprehensive knowledge on manufacturing processes.

The SPCS accuracy measures the frequency of an out-of-control condition. Reliability is given by the analysis of the variability of the out-of-control warnings. Timeliness is given by the average time taken in the thermal analysis process necessary to analyze the control charts.

The SPCS assists in identifying abnormalities in the melt improving the quality of castings. However, go and no-go data merely indicates that parts are "good" or "bad", but an important question for corrective action is "how good" or "how bad"? Thus, there remains the need to integrate an "intelligent" system that predicts casting properties and provides recommendations and actions to the operator for the improvement of the process.

3.3. Case-Based Reasoning System (CBRS)

The CBRS has been used in manufacturing processes to provide effective process control with on-line, real-time data. Its prediction capability provides early warnings of failure and can be trained to build accurate, sophisticated and dynamic models.

A series of experimental work carried out by G. Pelayo [10] provided the parameters, values and solutions to be included in the case base. The case base contains 19 cases in the Thermal Analysis domain of castings, which were obtained from experts and engineers in metallurgy. The case base is implemented in a text file utilized by the Caspian shell, being easily accessed to solve problems and to append new cases in the prediction of casting characteristics.

The set of parameters that characterize the main metallurgical reactions are the attributes included in the structure of each case (Table 1). Attribute weights are defined in a scale from 0 to 20 depending on how critical the parameters are in the definition of the shape of the cooling curve. Index fields (Solidification/Cooling Rate Factor and Silicon Modification Level) are assigned a weight value of zero.

Table 1.
Casting Attributes Included in the Case Base

Casting Characteristic	Property
Porosity and Resistance	Area_Percent_Porosity (%) TwoPercent_YieldStrength (%) Percent_Elongation (%) Hydrogen_Level
Quality of the Melt in the Sample	Sample_Quality Test_Sample_Mass (Grams) Test_Sample_Temperature (°C)
Characteristics of the Cu Rich Phases	Area_Percent_CooperBased_Phases (%) Maximum_Recommended_Thermal SandRemoval_Temp
Modification Level of the Silicon Particles	AFS_Silicon_Modification_Level Strontium_Content_(PPM) Silicon Morphology
Mechanical Properties	Matrix_MicroHardness_µHV Percent_Elongation UTS TwoPercent_YieldStrength Brinell_Hardness Sample_Microstructure

After the SPCS evaluates the quality of the melt characteristics, it sends the metallurgical reaction parameters as input to the Knowledge-Based System. The option "Analysis", which performs the CBR functionality is only enabled until the operator is done with the SPCS. Once this selection is made, the screen presented in Figure 5 appears to the operator to enter the casting section to predict (solidification rate), the chemical composition and the expected modification level. Then the CBRS compares cases from the knowledge base and if a case with similar characteristics is found, the CBR provides the predicted properties and suggested actions (Fig. 6).

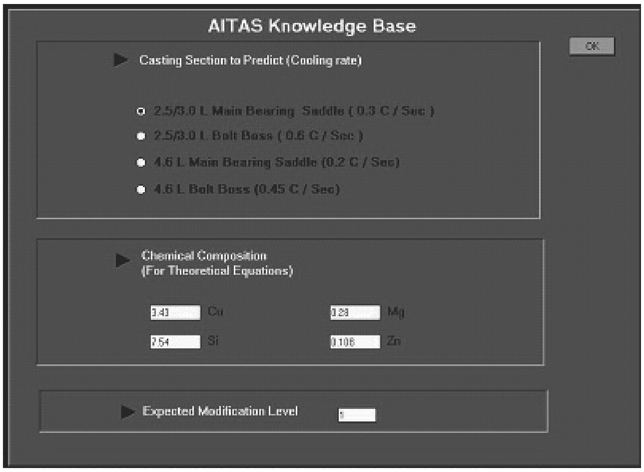

Fig. 5. Selection of casting section to predict

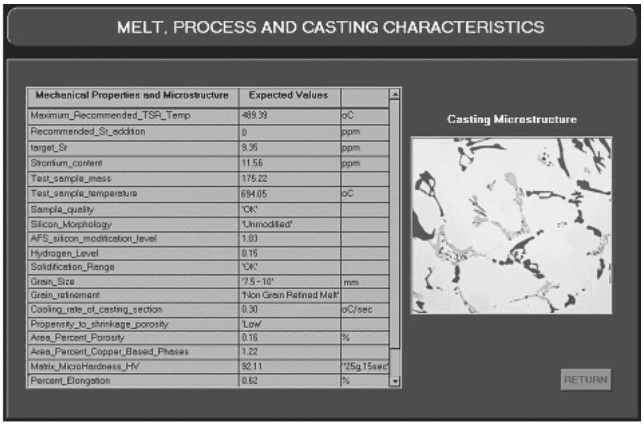

Fig. 6. Predicted casting properties and microstructure

Measurement of CBRS accuracy is given by the analysis of the deviation of predicted values from the real casting properties. Reliability is given by the analysis of the variability of the predicted values in a set of samples. In order to probe this reliability, the Relative Error (RE) for each parameter in the solution part of the case was calculated and added. The overall RE is the proportion of this cumulative RE and the total possible error, which was calculated allowing a maximum RE of 100% for each parameter. If the RE is within the Result Acceptability Criteria (RAC) the test is considered reliable. The RAC is a parameter that serves as an acceptability threshold for each of the test cases executed during the reliability procedure.

The RAC is defined as the Relative Error (Eq. 1) of the solution when compared to a standard. The results are classified as optimal (RE = 0 %), acceptable (RE=1%) or unacceptable (RE=2 %).

$$RE = \underline{(|a-b|)} * 100 \qquad (1)$$

where:
a is the calculated value of the parameter,
b is the real value of the parameter.

Timeliness is measured by the average time taken to retrieve cases by the CBRS.

4. Assessment and achieved results

In order to evaluate the effectiveness of each one of the AIBCS components in the analysis of metal casting properties, the following hypotheses were defined. The Traditional Control System (TCS) was taken as a reference to measure the AIBCS improvement.

- Accuracy → $H_0 : \sigma_{TCS} \geq \sigma_{AIBCS}$
- Reliability → $H_0 : \sigma^2_{TCS} \geq \sigma^2_{AIBCS}$
- Timeliness → $H_0 : \mu\tau_{TCS} \geq \mu\tau_{AIBCS}$

It could be concluded that the AIBCS performs better than the Traditional Control System only if the null hypotheses are accepted. Table 2 shows the results after performing a set of runs.

Table 2.
Comparative results in the assessment of the AIBCS versus the TCS

Performance	Monitoring of the melt solidification process	Statistical Process Control of melt characteristics	Prediction of casting characteristics	Qualitative Measuring Scale
Accuracy (Standard Deviation σ)	$\sigma_{TCS} = 0.220$ $\sigma_{RTDAS} = 0.123$	$\sigma_{TCS} = 3.1168$ $\sigma_{SPCS} = 0.2399$	$\sigma_{TCS} = 0.761$ $\sigma_{CBRS} = 0.278$	High - Precision of values ($\sigma \leq 0.25$) Medium - Precision of values ($0.25 \leq \sigma \leq 0.75$) Low - Precision of values ($\sigma \geq 0.75$)
Reliability (Variability σ^2)	$\sigma^2_{TCS} = 0.2068$ $\sigma^2_{RTDAS} = 0.075$	$\sigma^2_{TCS} = 0.2068$ $\sigma^2_{SPC} = 0.0753$	$\sigma^2_{TCS} = 0.6228$ $\sigma^2_{CBRS} = 0.0872$	High - Reliability of values ($\sigma^2 \leq 0.25$) Medium - Reliability of values ($0.25 \leq \sigma^2 \leq 0.75$) Low - Reliability of values ($\sigma^2 \geq 0.75$)
Timeliness (Average Time $\mu\tau$)	$\mu\tau_{TCS} = 0.1116$ $\mu\tau_{RTDAS} = 0.020$	$\mu\tau_{TCS} = 1.00$ $\mu\tau_{SPCS} = 0.075$	$\mu\tau_{TCS} = 4.5$ $\mu\tau_{CBRS} = 0.0002$	Short Time - Execution time ($\mu\tau \leq 0.25$) Medium Time - Execution time ($0.25 \leq \mu\tau \leq 0.75$) Long Time - Execution time ($\mu\tau \geq 0.75$)

According to the assessment results, the RTDAS does not show statistically significant improvement in the acquisition of casting parameters. However, the main contribution of the RTDAS is the acquisition and monitoring of temperatures around the test cup and the control of environmental conditions (pressure and airflow). It allows the metallurgist to control and simulate the behaviour of the cooling curve in the casting of components.

The SPCS assessment was clearly superior providing significant improvements in quality control during the solidification process. The SPCS detects abnormalities in the process sooner, resulting in faster process correction and less casting defects.

The CBRS provides considerable improvement in the prediction of casting properties. The execution time is significantly shorter compared to the traditional approach. In addition, the CBRS seems to be highly reliable. Table 3 presents the qualitative assessment results in terms of High, Medium and Low levels.

Table 3.
Qualitative results in the assessment of the AIBCS

Process	Accuracy	Reliability	Timeliness
Data Acquisition	High	High	High
Statistical Process Control	High	High	High
Prediction of Casting Properties	Medium	High	High

5. Conclusions

In conclusion, the null hypotheses defined for accuracy, reliability and timeliness are accepted.

- Accuracy → $H_0 : \sigma_{TCS} \geq \sigma_{AIBCS}$ → Accepted,
- Reliability → $H_0 : \sigma^2_{TCS} \geq \sigma^2_{AIBCS}$ → Accepted,
- Timeliness → $H_0 : \mu\tau_{TCS} \geq \mu\tau_{AIBCS}$ → Accepted.

The utilization of the AIBCS enables metal casting analysis to be accurate, reliable and timely which in turn leads to better quality without the need for judgmental speculation or expensive trial-and-error testing.

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