Advanced Data Analytics Tools to Identify the Root Cause of Filter Clogging During Casthouse Operation

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Abstract

During DC casting of aluminium, some products require filtration to remove impurities and inclusions from the liquid metal before solidification. Various technologies exist for this filtration, ensuring adequate cleanliness of the metal. The advanced compact filter (ACF) is an online filtration system using porous ceramic filter tiles, directly installed upstream of the casting unit. This system is widely used in the industry, offering numerous advantages such as its high and consistent filtration efficiency. However, the filter priming quality is critical. In some cases, the filter could clog prematurely and reduce the flow of liquid metal that could result in aborting the cast. The casthouse that produces rolling ingots using the ACF filtration technology experienced a significant increase in clogging frequency during a given period. A comprehensive data analysis approach was conducted to diagnose and identify the main factors associated with this phenomenon. The objective was to identify the root cause and implement corrective actions and resume the initial casting performance.

To achieve this objective, advanced data science tools were successfully applied. A systematic and methodical approach was used to analyze several inputs. Each step of the process was scrutinized in detail, including batch preparation, liquid metal chemistry and various process parameters. Several key process indicators were defined and calculated. Different data science tools were selected and applied, including Seeq® Dataiku™, and Minitab® The analyses provided a better understanding of the fundamental causes and mechanisms of clogging. Furthermore, it was possible to identify a specific change in the operational practice that played a crucial role in increasing clogging frequency. This better understanding of clogging phenomena, using powerful data science tools and data-driven decisions, leads to more targeted corrective actions. It is worth mentioning that the data valorisation represents the first step that makes possible the use of these analytic tools. This article will present the integration of available analytic tools combined with a deep understanding of the process parameters as key elements to solving complex operational challenges by fully leveraging valuable data assets.

Keywords: DC Casting, Filter clogging, Root cause, Data driven decision, Advanced data science tools.

1. Introduction

Various configurations exist for the semi-continuous DC casting process of rolling ingots. Basically, these include batching furnaces, in-line metal treatment units and a casting pit. All these elements must function adequately to ensure both the quality of the final product and the productivity of the casthouse. One of the critical elements in the production line is the filtration unit. This equipment is required on certain products to remove impurities and inclusions. The proper functioning of the filtration unit is crucial for the overall productivity and cast ingots quality. In some cases, the filter could clog prematurely and the casting must be immediately stopped. Several factors might influence the quality of filtration including thermo-physical parameters of the metal, type of alloys, the initial metal cleanliness and some thermal aspects. Consequently, all these governing factors must be compliant to ensure a good cast start and to maintain a high-quality filtration.

Figure 1 shows a typical diagram of a casting centre. The filtration unit, located upstream of the casting table, is a critical element to ensure the quality of the metal, and its proper functioning is required for a successful casting. At the site of interest, the filtration system used was an advanced compact filter (ACF). This type of filter, widely used in the industry, is explained in detail by Breton [1]. The filter priming upon cast start-up is a critical step particularly sensitive to clogging.

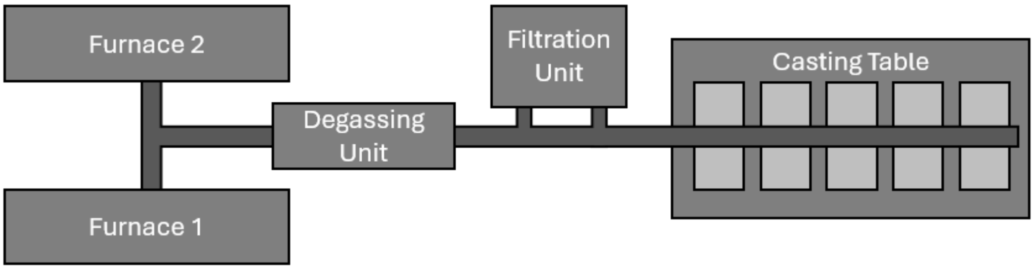


Figure 1. Diagram of a casting center, showing the furnaces, in-line metal treatment, and the casting pit.

For some reason, the site has experienced a significant increase in clogging frequency, resulting in premature casting abort. Two types of clogging were observed: at the start (casting length < 500 mm) and during steady state (casting length > 500 mm). Figure 2 shows the monthly clogging frequency for the site. A significant increase in clogging frequency was observed starting from the fifteenth month, rising from nearly 0 % to 0.49 %.

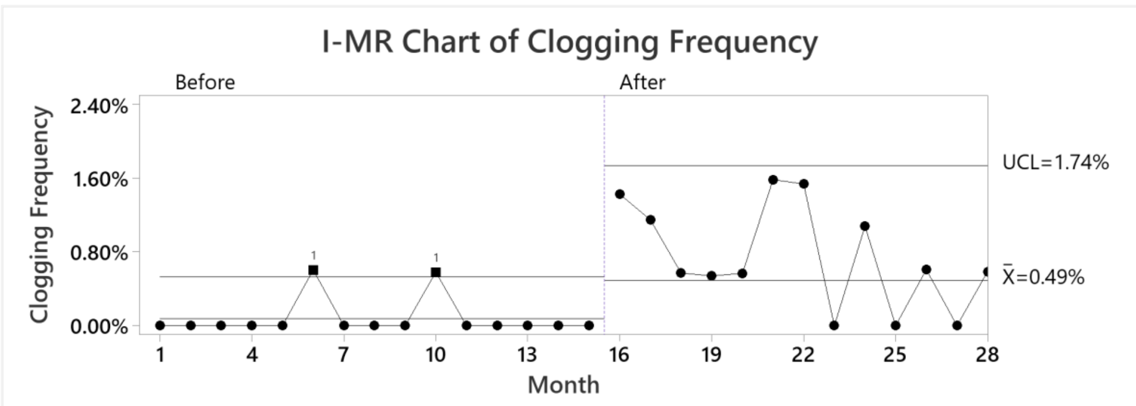


Figure 2. ACF monthly clogging frequency.

The objective of this study was to identify a correlation between process inputs and the head loss/clogging of the ACF through data analysis. We were aiming to gain a better understanding of the root causes to implement effective data-driven solutions.

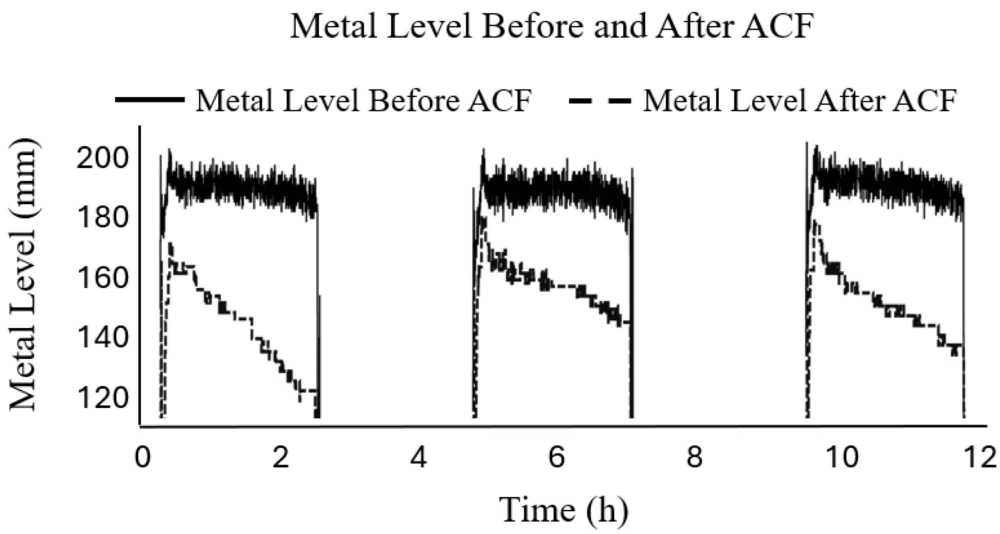
To conduct the analysis, a brainstorming session was first held to identify the process inputs that could potentially impact ACF clogging. Next, the data from the past two years for these inputs were collected. An initial data preparation step was required to clean and transform the data. In some cases, intermediate indicators needed to be calculated. To model the data, the castings, aborted due to clogging, were divided into two categories: first with clogging at the start of casting and second, during the steady-state regime. The main hypothesis was that these clogging incidents had likely different mechanisms. The approach was data-driven based on the analysis of process data through standard statistical methods. It embodies a pragmatic approach, aiming to combine data analysis with process knowledge seamlessly. Several reference books can be consulted for this statistical analysis approach [2]. With the advent of powerful and efficient data analysis tools, this approach is becoming increasingly accessible [3]. This paper is giving details on the approach used, the results of the analysis, and the main conclusions as well as some discussion about the implications and solutions.

2. Methodology

2.1 Data Collection and Preparation

Initially, raw data collection was conducted. Data spanning a two-year period between 2021 and 2023 were collected. The data originated from various sources and production systems, primarily from the OSIsoft PI for process inputs and SQL tables for metal chemistry. All relevant data and signals were consolidated onto the same platform. Contextual data, batch preparation and metal treatment parameters, indicators from in-line metal treatment equipment (including degassing, refining, and the filtration system), metal chemistry, inter-casting time, and metal flow rate were all included.

The difference in metal level between the inlet and outlet of the ACF was defined as the output to analyzed. Commonly referred to as head loss, this indicator represents the filter's resistance. It was hypothesized that the head loss is correlated with the number of cloggings, a hypothesis widely supported by the literature [4, 5]. Each casting was then divided into two periods: the start (< 500 mm) and the steady-state (> 500 mm), as it was suspected that cloggings originated from different mechanisms depending on the casting regime. Finally, for each of the two casting phases, the maximum head loss was calculated. Data manipulation was facilitated using Seeq^{TM} software. Figure 2 on the top shows the raw metal level signals before and after the ACF, and at the bottom, casting phases, calculated head loss, and maximum head loss for each phase are added. The visual representation at the bottom was also adjusted to highlight only the periods of interest, which is during casting.



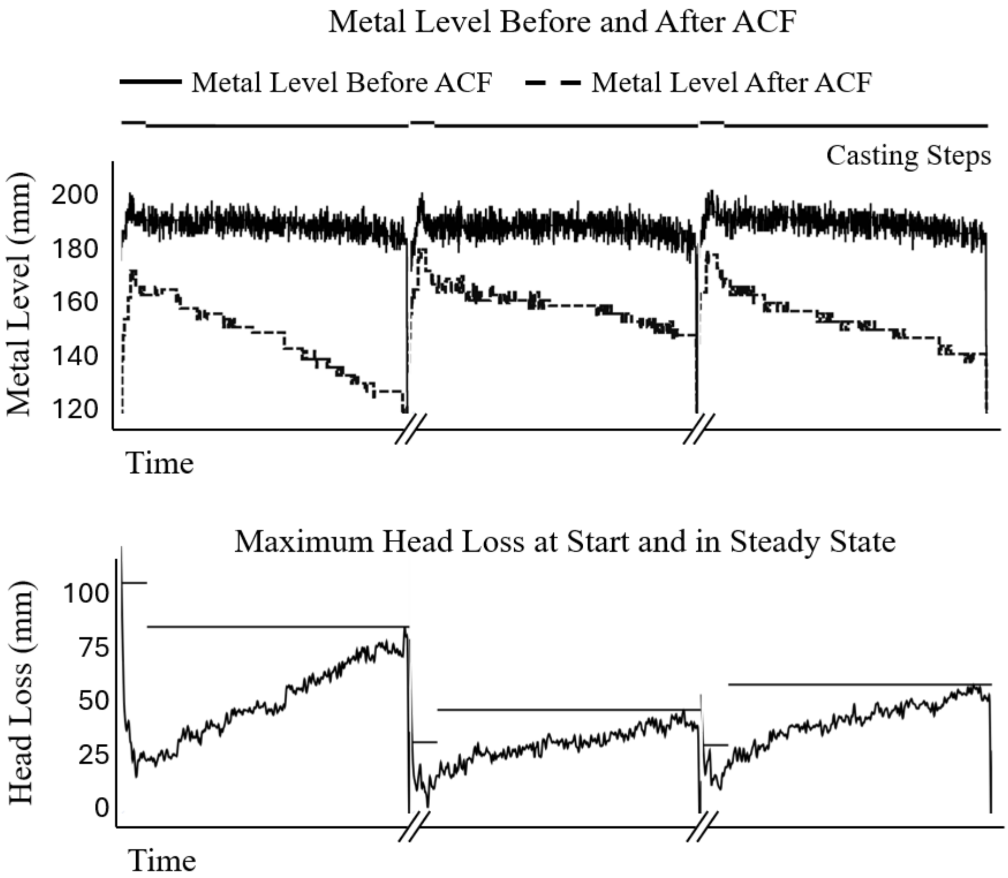


Figure 3. Output definition signals. Top and middle: metal level before and after ACF, Bottom: calculated head loss and phase identification.

A total of 27 variables were investigated. The following table presents the list of variables included in the analysis. These variables are known in the literature to have a direct or indirect effect on the cleanliness of the metal or on the thermal aspect of filtration [1, 5, 6]. For each of these inputs, different statistics were calculated per state of cast; minimum, maximum, average, and standard deviation.

Table 1. Analysed inputs variables.

Context	Furnace	Degassing	Grain Refiner	ACF	Chemistry %	Casting
Alloy	Spout temperature	Chlorine flow	Quantity	Vacuum time	Ti	Interdrop time
Size	Spout metal level	Rotor pressure	Type	ACF temperature	Ca	Metal flow
Casting practice	Resting time	SF_6 flow		ACF level at start	Mg	
Furnace use	Fluxing time			Preheating time	Na	
ACF use				Holding time	V	
					B	

The same data processing exercise was then conducted for each of the inputs. For every process signal or data point, a per-casting indicator was calculated. Consequently, for each input, a statistic was computed over the period of interest and reported per casting. Figure 4 provides an illustration using the metal temperature at the furnace spout as an example. It displays the average temperature for both the start and steady-state phases.

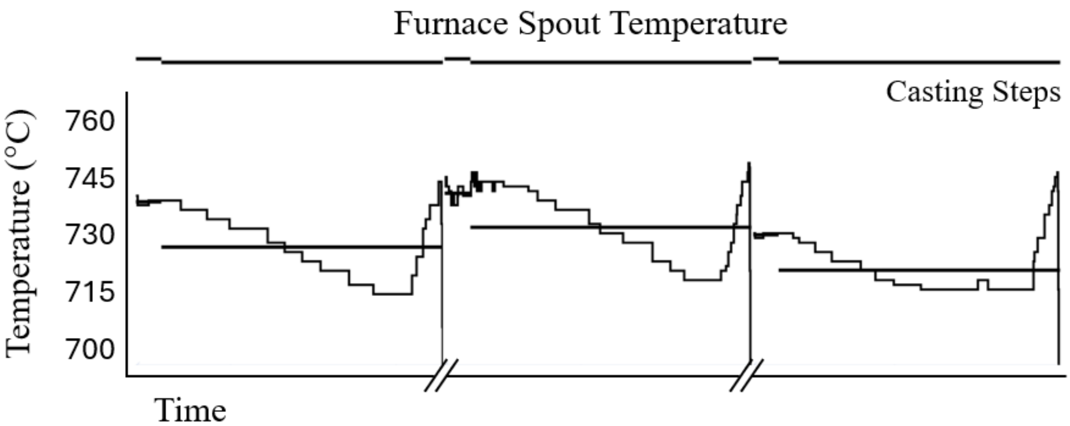


Figure 4. Average furnace spout temperature, example of KPI calculations for start and steady state.

At the end of the exercise, a database was built including ACF head loss at the start and in steady state regime for each casting, along with several calculated inputs. Data were analyzed from two perspectives: 1) context, determining if there is a higher frequency under certain conditions or equipment, and 2) regarding process variables. Figure 5 outlines the approach.

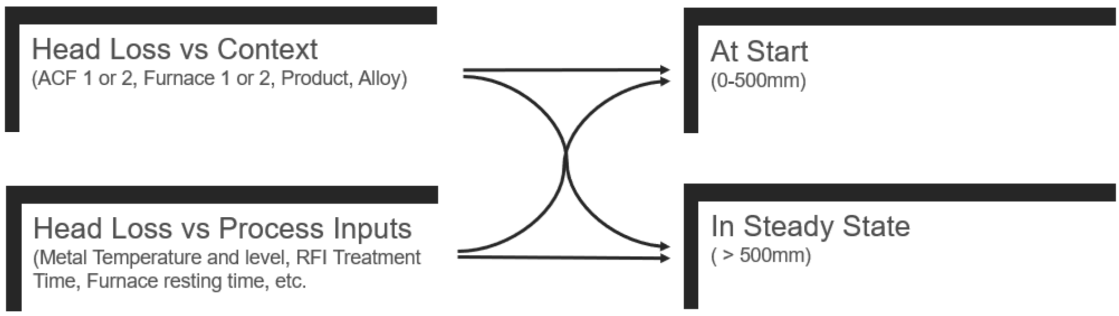
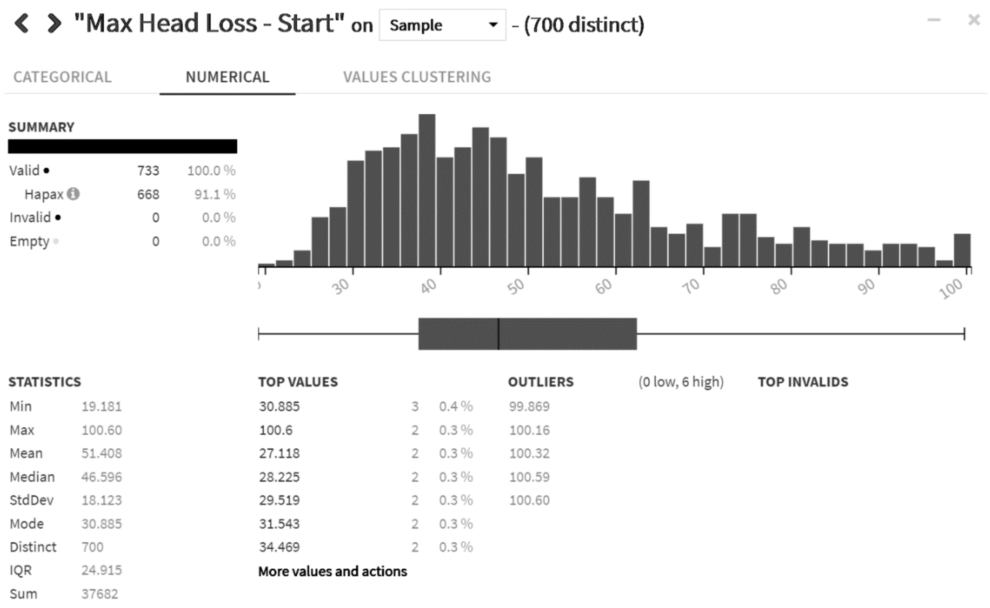
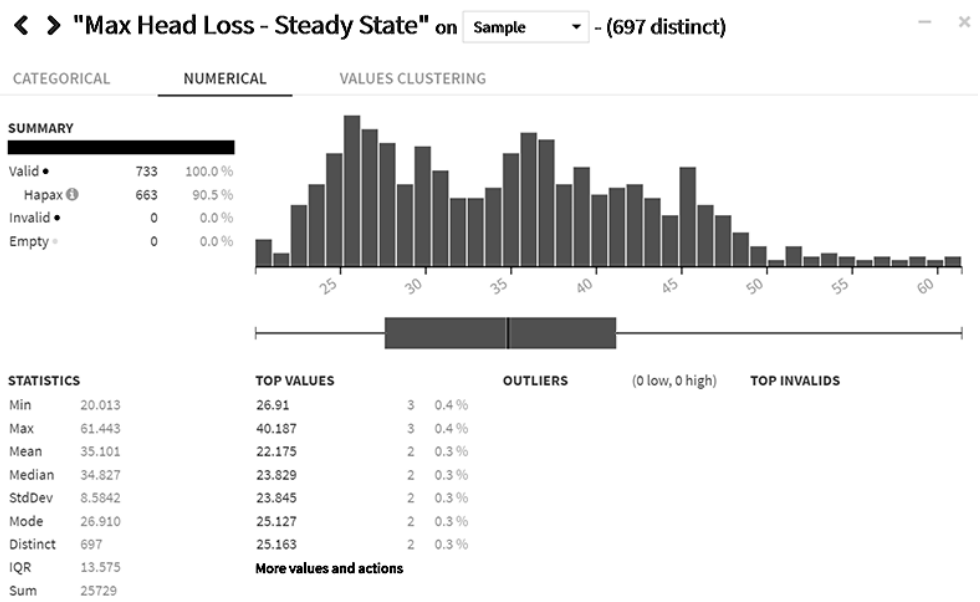


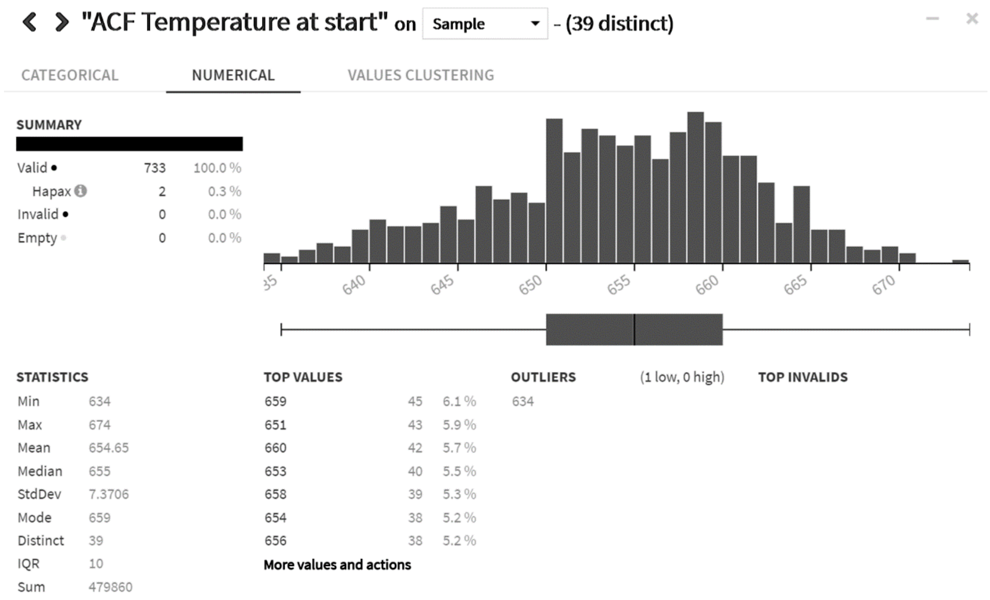
Figure 5. Schematization of the approach used.

2.2 Data Exploration and Analysis

After aggregating and preparing the data, an initial exploration step was conducted. For each variable and output, the distribution was plotted. It was verified that the data distributions were, as expected, based on process knowledge that there were no outliers. In cases of extreme or suspicious values, the data points were individually checked. The Dataiku™ data science software was used for this step. Figure 6 shows examples of data distributions for the maximum head loss, temperature, and the metal level in the ACF at the start of the cast.


"Max Head Loss - Start" on Sample - (700 distinct)
CATEGORICAL
NUMERICAL
VALUES CLUSTERING
SUMMARY
Valid 733 100.0 %
Hapax 668 91.1 %
Invalid 0 0.0 %
Empty 0 0.0 %
30 40 50 60 70 80 90 100
STATISTICS
Min 19.181
Max 100.60
Mean 51.408
Median 46.596
StdDev 18.123
Mode 30.885
Distinct 700
IQR 24.915
Sum 37682
TOP VALUES
30.885 3 0.4 %
100.6 2 0.3 %
27.118 2 0.3 %
28.225 2 0.3 %
29.519 2 0.3 %
31.543 2 0.3 %
34.469 2 0.3 %
More values and actions
OUTLIERS (0 low, 6 high)
99.869
100.16
100.32
100.59
100.60
TOP INVALIDS


"Max Head Loss - Steady State" on Sample - (697 distinct)
CATEGORICAL
NUMERICAL
VALUES CLUSTERING
SUMMARY
Valid 733 100.0 %
Hapax 663 90.5 %
Invalid 0 0.0 %
Empty 0 0.0 %
25 30 35 40 45 50 55 60
STATISTICS
Min 20.013
Max 61.443
Mean 35.101
Median 34.827
StdDev 8.5842
Mode 26.910
Distinct 697
IQR 13.575
Sum 25729
TOP VALUES
26.91 3 0.4 %
40.187 3 0.4 %
22.175 2 0.3 %
23.829 2 0.3 %
23.845 2 0.3 %
25.127 2 0.3 %
25.163 2 0.3 %
More values and actions
OUTLIERS (0 low, 0 high)
TOP INVALIDS



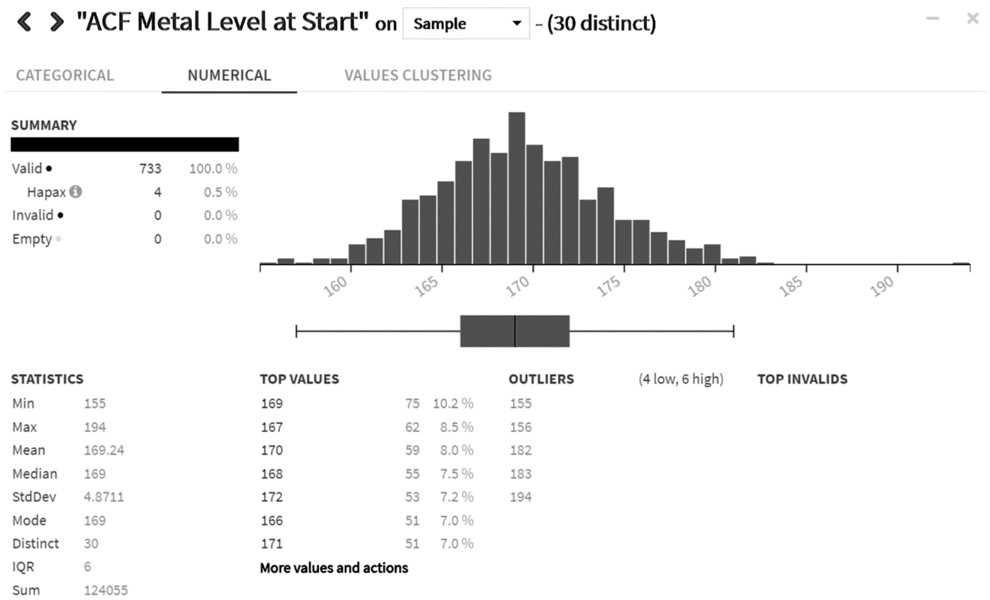


Figure 6. Data investigation: Example of distribution for maximum head loss, temperature, and metal level in the ACF at the start.

To analyze whether head loss was more significant in certain contexts, pie charts were primarily used. Castings with higher head loss were filtered, and a pie chart was created for the relevant context identifier, such as alloy family or the specific furnace used.

For the process variables, various charts were utilized. Boxplots and interval plots were particularly effective for the initial exploration since they illustrated the distribution of the variables according to head loss groupings. This step helped to identifying major high-level trends. When a potential correlation was observed, the analysis was further refined using statistical software such as Minitab™. Advanced statistical methods and control charts were then subsequently applied to the variables that indicated a potential correlation.

3. Results et Discussion

3.1 Context

3.1.1 Cast Start Regime

Figure 7 shows the distribution of head losses as a function of alloy family or alloy series during the cast start regime. The data has been filtered to include only the casts showing head losses exceeding 65 mm, and representing the third quartile of the dataset (see Figure 6). The objective was to determine which alloys experienced the highest head losses.

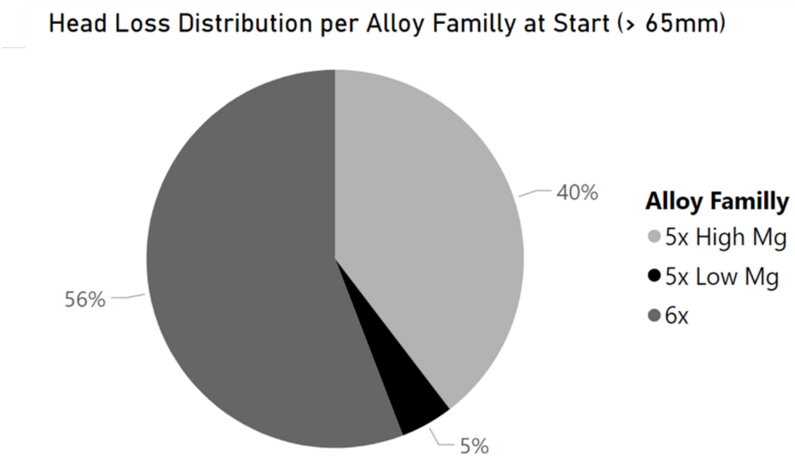


Figure 7. High metal head loss distribution per alloy family at start.

Figure 7 shows that 56 % of head losses during the cast start regimes occur on the 6xxx series alloys. This result could be attributed to a thermal issue at the beginning of the start. Indeed, 6xxx series alloys have a slightly higher liquidus temperature than those of the 5xxx series, making them more sensitive to colder conditions at the beginning of the casting process. Figure 8 presents the solidification curves of three common alloys in each of the two series. In addition, this graph also highlights that the 6xxx series alloys has a shorter solidification range than the 5xxx series alloys. The curves in the figure were calculated using the Thermo-Calc™ software according to the Scheil solidification model [7].

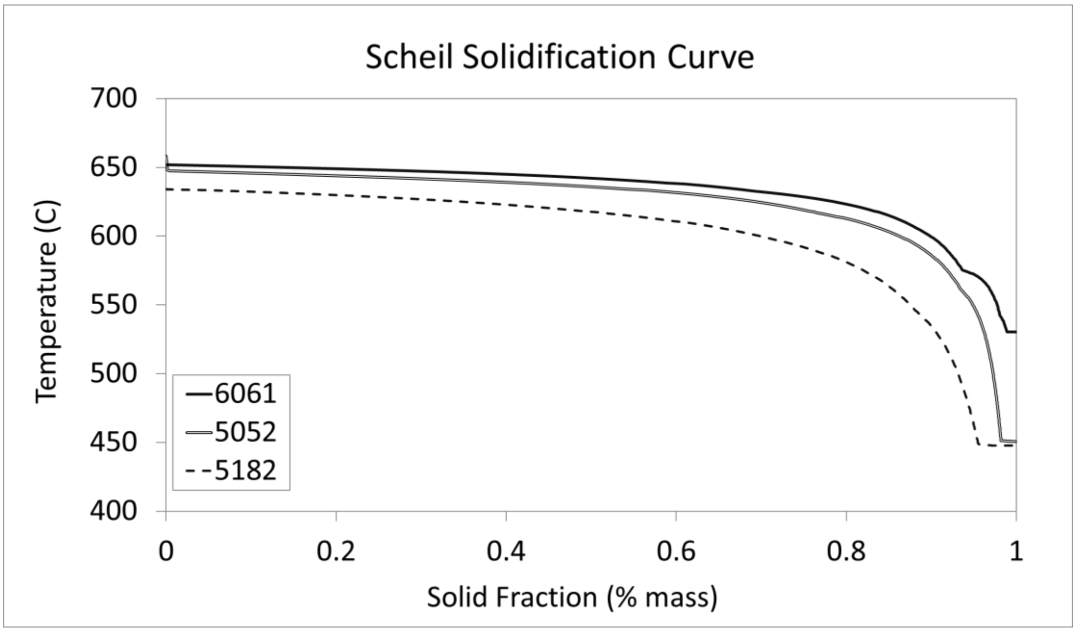


Figure 8. Scheil solidification curve for common, low Mg (5052), High Mg (5182) and 6x (6061) alloys.

These data highlight the importance of managing the thermal aspect at the start of casting. If the metal temperature drops below the liquidus, solidification will begin and increase the risk of clogging. Therefore, it is crucial to properly preheat the ACF and the casting trough to maintain a sufficient metal temperature during the initial priming step. Figure 9 shows the maximum head loss at the start of casting for two groups: the 25 % of casts with the coldest metal temperatures and the 25 % with the highest temperatures at the casting spout. It is evident from this graph that the head losses are, on average, higher for all casts with lower metal temperatures, and this confirming the importance of the thermal managing aspect.

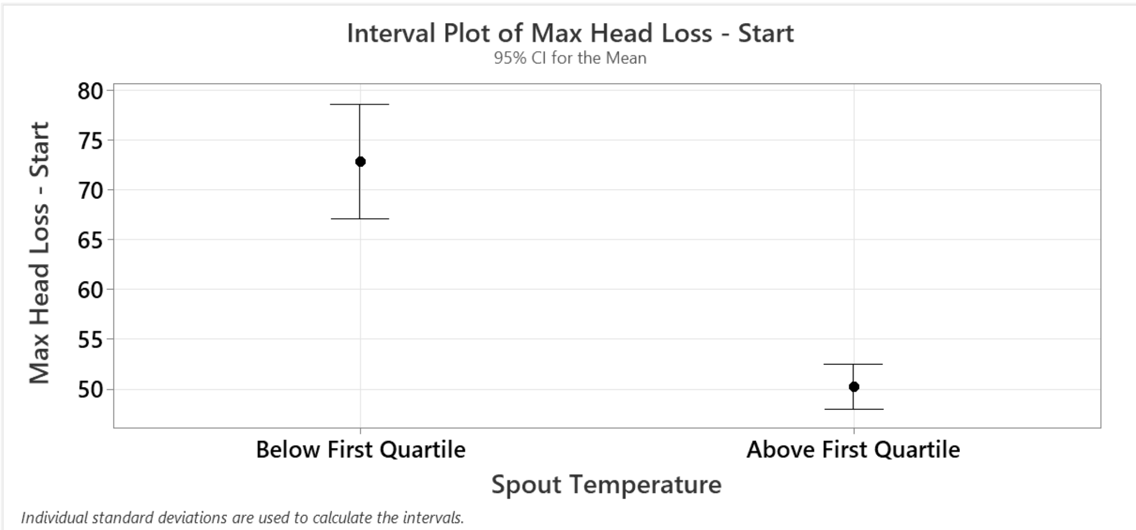


Figure 9. Head loss distribution at the start of the cast upon spout temperature category.

3.1.2 Steady State Regime

Figure 10 shows the distribution by alloy series with high head losses during steady-state conditions. For this analysis, only casts with head losses exceeding 45mm, representing the third quartile, were included (see figure 6). In steady-state conditions, high head losses are primarily associated with 5xxx series alloys with high magnesium content.

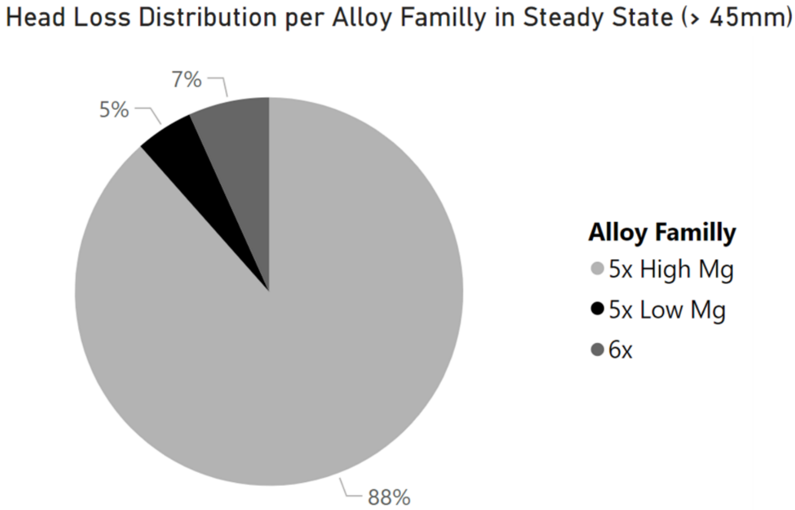


Figure 10. High head loss distribution per alloy family in steady state

The oxidation of magnesium alloys could also explain this phenomenon. Due to their high magnesium content, these alloys are more susceptible to oxidation. Under certain conditions, inclusions and impurities form over time and could degrade the metal quality. This could potentially lead to the formation of a buildup at the filter surface. If this buildup becomes too thick, it could create excessive resistance to the metal flow and the head loss will gradually increase to eventually leading to a cast abort. Figure 11 compares the head loss evolution of two different casts. The one on the left shows a normal casting, while the one on the right shows a gradually increasing head loss, and at risk of clogging, during casting due to accumulation on the filter surface. The latter is attributed to the oxidation of magnesium in aluminum alloys and this mechanism of buildup formation on the filter surface have been extensively studied [8, 9].

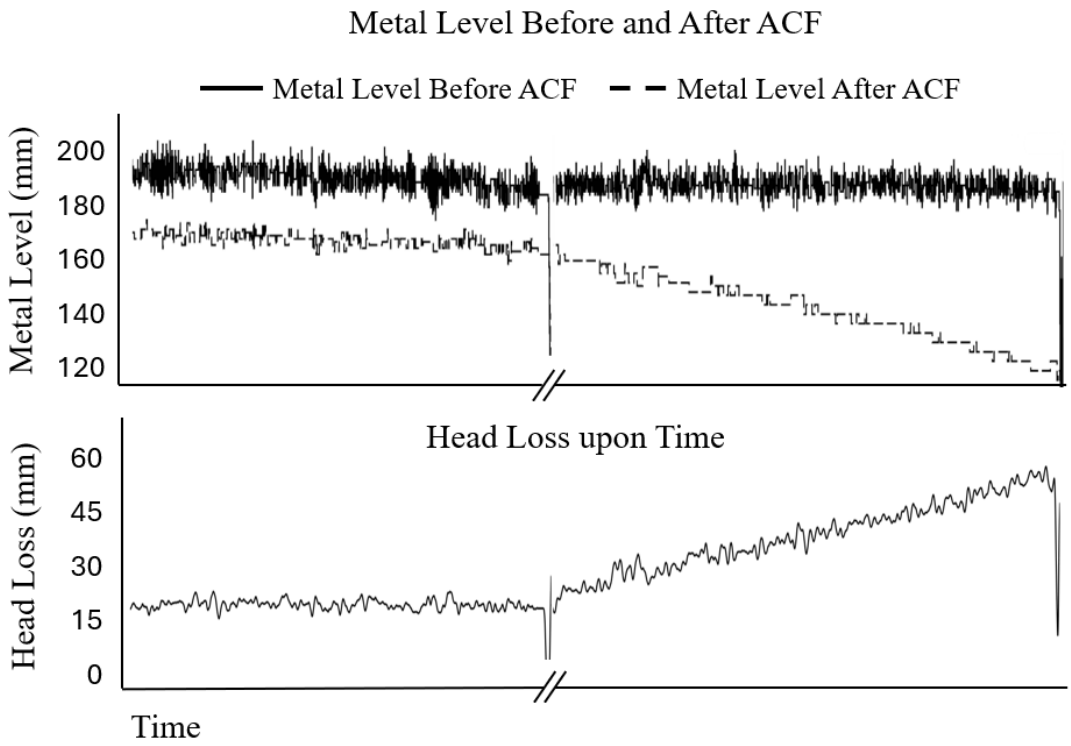


Figure 11. Steady state head comparison for High Mg 5x.
Left: good cast, Right: at risk of clogging cast.

3.2 Process Variable

The variable that has demonstrated the highest correlation with head losses was the furnace fluxing time using a typical rotary flux injector (RFI). The RFI is a metal processing unit that is widely used in the industry since many years. It is known for its effective removing of alkalis and impurities from molten metal. Numerous references highlight its efficiency and characteristics [10, 11]. Figure 12 shows the maximum head loss during casting as a function of the RFI processing time. This graph groups the variables by deciles, with each point representing a population containing 10 % of the data. It shows an inverse relationship between head loss and processing time. Consequently, this graph allows for highlighting major trends, at a high level, to assess whether a correlation exists in this case. However, it does not permit refining a model or obtaining a precise correlation rate. These observations highlight the importance of the cleanliness of the metal being filtered by the ACF to prevent clogging and premature cast abort.

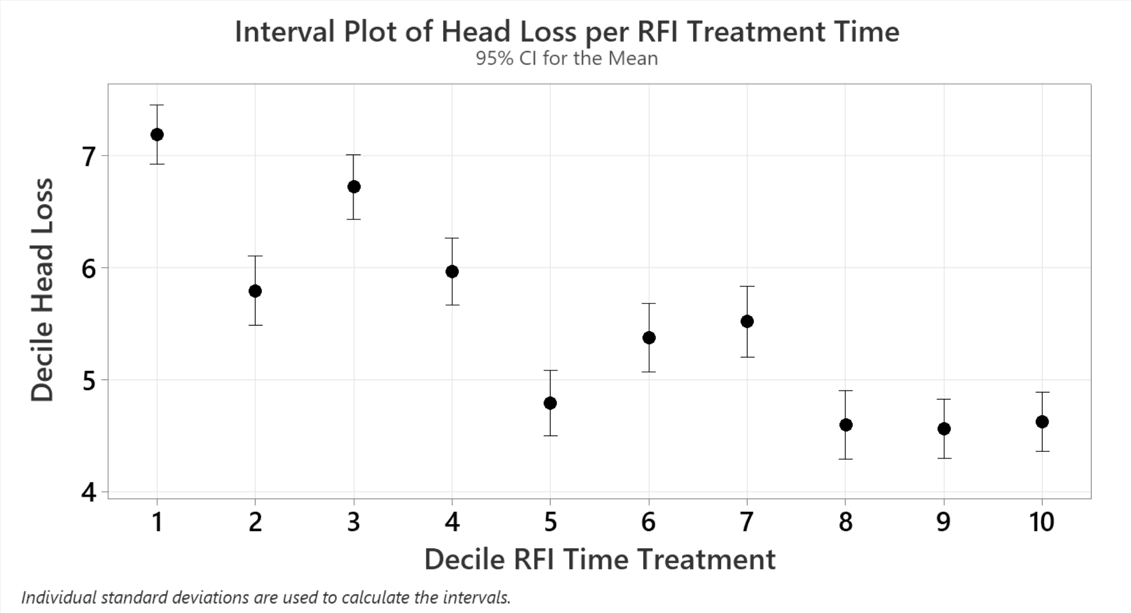
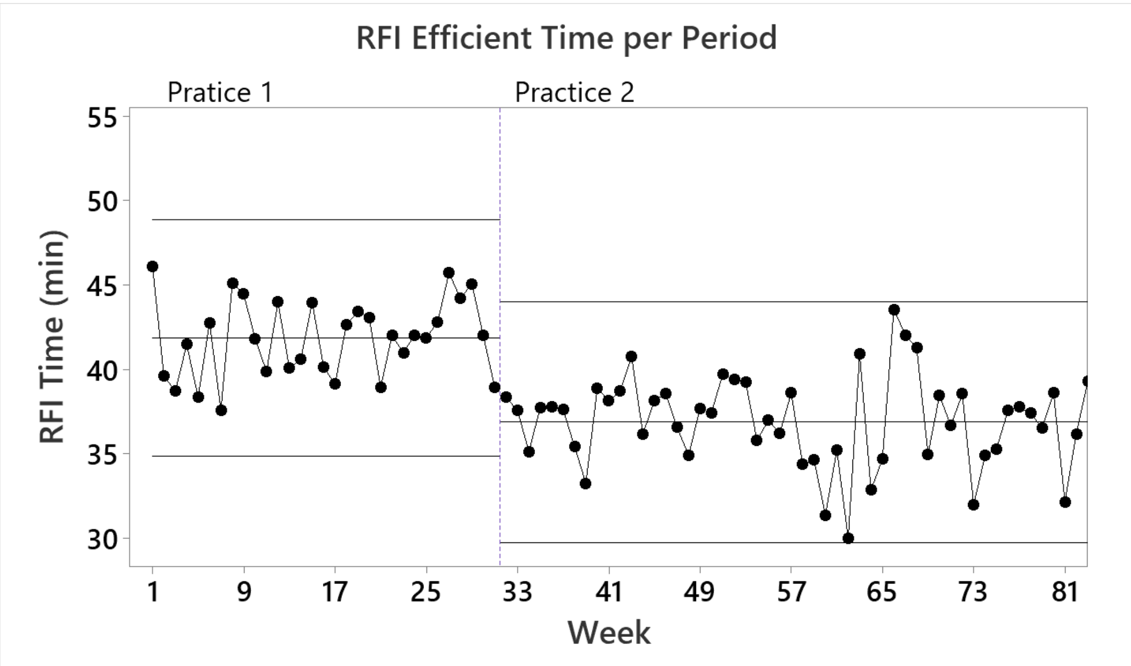


Figure 12. Interval plot showing ACF head loss upon RFI treatment time.

Following these results, the impact of the RFI treatment on head losses was explored in greater depth. Control charts were plotted to show the evolution of head losses over time, in parallel with the changes in RFI treatment. Figure 13 illustrates these results. These charts allowed us to identify a breaking point where operational practices had been changed. These periods are labeled as « Practice 1 » and « Practice 2 » on the graphs below. The maximum head loss also increased with this change in RFI practice. To validate the hypothesis of the impact of the change in practice on head losses, interval plots were also created (shown at the bottom in Figure 13). The p-values from hypothesis 2 samples t test are both < 0.005 for the RFI treatment time and head losses. Therefore, we can conclude that the change in practice significantly altered the efficient RFI treatment time as well as the head losses.



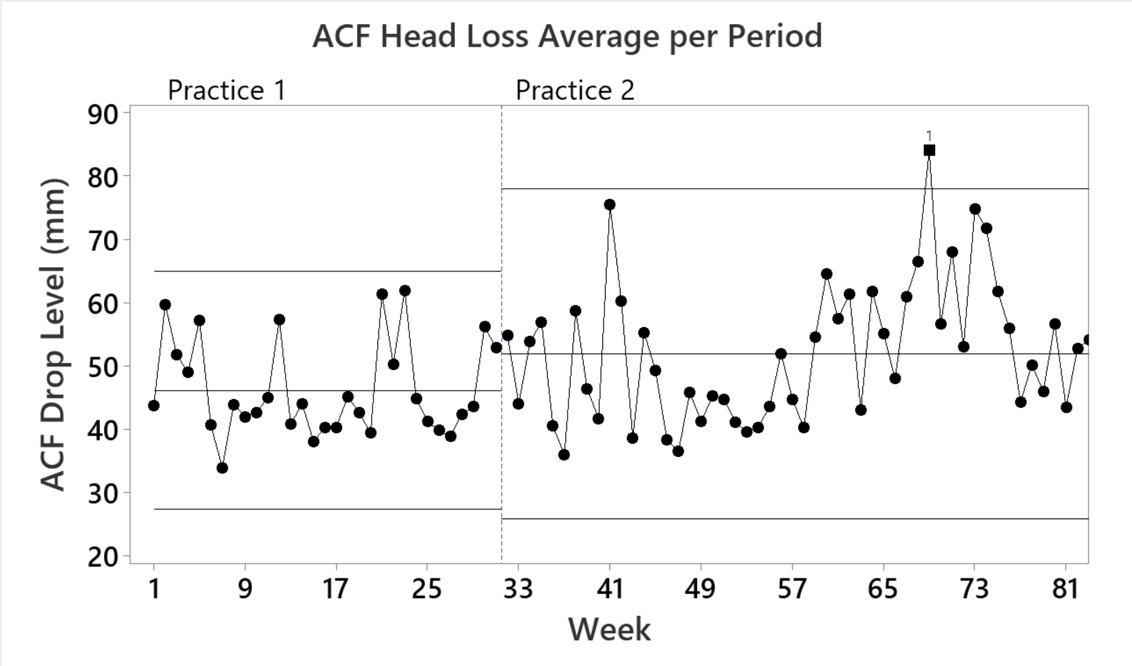


Figure 13. Control chart of RFI treatment time and ACF head loss for different periods.

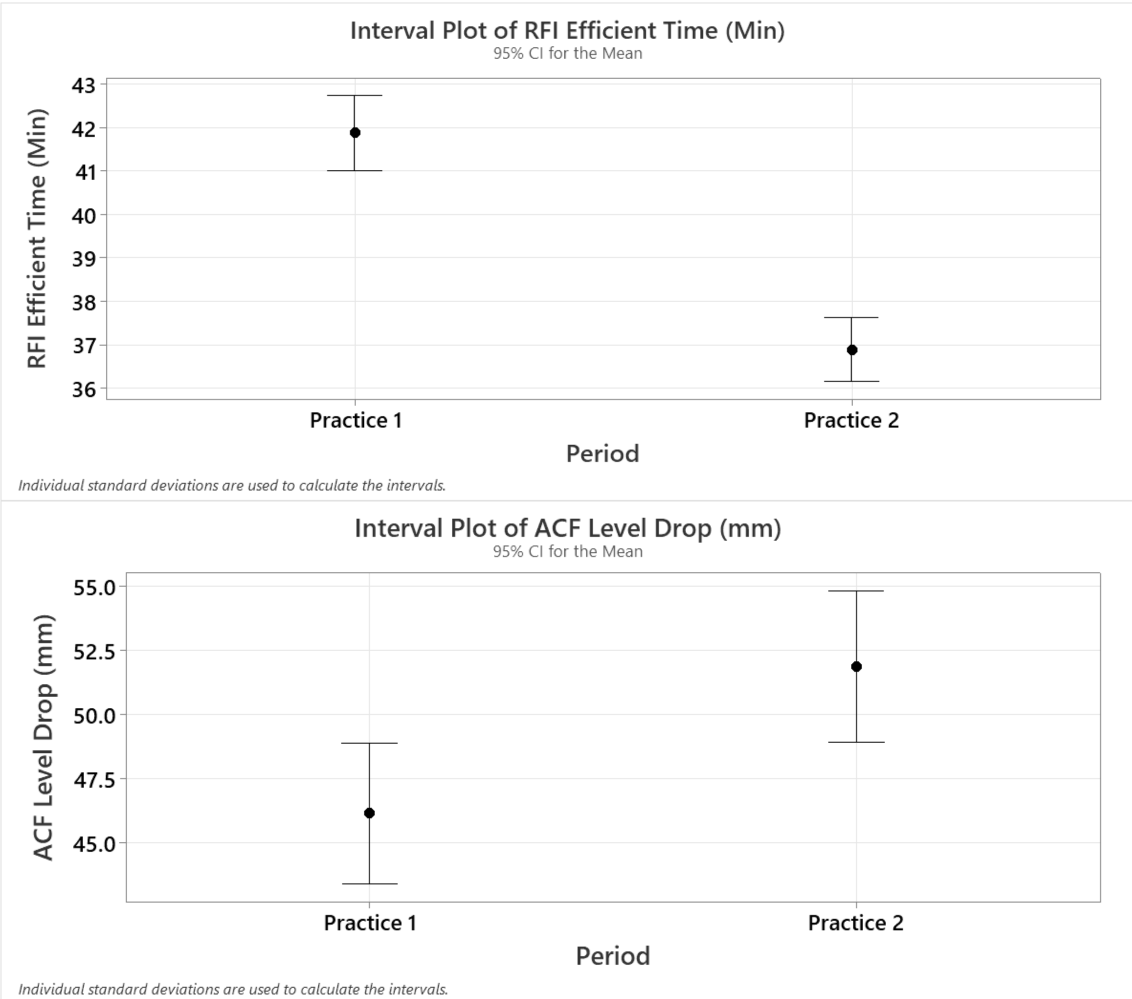


Figure 14. Interval plot of RFI treatment time and ACF head loss for the different periods.

Following these results, the site made immediate changes to its operational practices and, primarily at the RFI treatment level. The original RFI treatment practice or method was optimized with the new insights to define the optimal conditions and identified as Practice 3 in Figure 15. This figure illustrates the evolution of clogging frequency per month and identifies each of the RFI methods used. This graph clearly shows that the process improvements have significantly reduced the clogging rates and returned to an acceptable and typical level (< 0.2 %). The use of powerful data analysis tools (Seeq™, Dataiku™, and Minitab™) greatly facilitated and accelerated the analysis by enabling the rapid targeting of the problem's root cause and the implementation of effective corrective actions. In-depth knowledge of the process by the teams involved in the analysis was also a key element in this challenging problem solving.

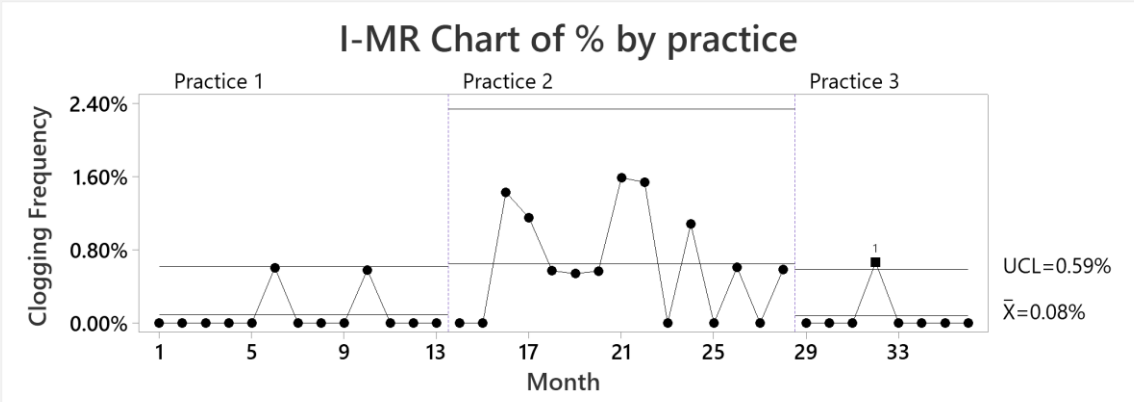


Figure 14. ACF Monthly clogging frequency; showing frequency reduction after improvement implementation.

4. Conclusions

In conclusion, the study was focused on investigating the phenomena of increase clogging frequency experienced by a casthouse using the advanced compact filtration technology (ACF) for aluminium DC casting. By utilizing advanced data science tools and a systematic analytical approach combined with a deep knowledge of the DC casting process and metallurgy, the study successfully identified the root causes of the increased clogging frequency and implemented effective corrective actions. The analysis revealed that operational practices, particularly changes in the metal treatment conditions using the RFI, significantly influenced the clogging frequency. While this study adopted a pragmatic, data-driven approach to enhance productivity, further metallographic and metal quality analyses could further support and enrich our fundamental understanding. For instance, a more in-depth analysis of metal cleanliness and oxide formation and its correlation with RFI efficiency could be beneficial.

In is clear that the integration of data analysis tools such as Seeq™, Dataiku™, and Minitab™ greatly facilitated the identification of these critical factors and accelerated the problem-solving process. Moreover, the study emphasized the importance of leveraging both, the in-depth process knowledge along with the data-driven decision-making to address complex operational challenges. Subsequent data-driven decision to improve the operational practices, particularly with in RFI treatment, resulted in a substantial reduction in clogging rates while restoring the casting performance to their previous levels. This study highlights also the unquestionable value of combining advanced analytics with process expertise in solving operational issues and optimizing casting processes in aluminium production facilities.

5. Acknowledgements

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