Process Optimization: from Software Sensor to New Control Strategy and Applicability of Artificial Intelligence

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Abstract

Mineração Paragominas' operations involve the extraction, beneficiation, and hydraulic transport of bauxite to the Hydro Alunorte alumina refinery. This study focuses on the beneficiation stage, which comprises two parallel processing plants that treat homogenized ore independently. Through various unit operations, including cycloning, high-frequency screening, milling, crushing, and thickening, the desired mineral is separated and concentrated. The final product is composed of three streams: the underflow from the secondary cycloning of superfines, undeflow from the thickening cycloning, and underlow from the concentrate thickening. The latter, which contains the finest ore fractions, represents approximately 30% of the total output. These streams are stored in slurry tanks and pumped through a 244 km pipeline from the beneficiation plant to the alumina refinery.

Occasionally, fluctuations in the physical quality of the slurry batches impact the final product quality. In response, a set of control engineering strategies was developed to improve process stability and product consistency. The main initiatives included:

1. Development of a software-based density sensor enabling closed-loop control in the cycloning stage.
2. Implementation of an override control strategy to enhance process responsiveness and reliability.
3. Application of artificial intelligence (AI) techniques – specifically, fuzzy logic control – to optimize slurry tank composition by dynamically adjusting the mass flow rate of the Concentrate Thickening underflow.

The density software sensor leverages mass balance principles to overcome instrumentation limitations, effectively closing the control loop. The AI-driven system predicts the physical quality of the slurry in real time and adjusts the setpoints to ensure consistent blending within quality limits. These innovations have resulted in improved product quality, increased productivity, enhanced thickener performance, and overall gains in process efficiency at the refinery – delivering value across the entire production chain.

Keywords: Regulatory Control, Advanced Control, Fuzzy Logic, Process Optimization, Bauxite processing.

1. Introduction

Mineração Paragominas S.A. (MPSA), a bauxite beneficiation facility located in Pará state, Brazil, is currently in full operation. The bauxite is processed in two parallel plants that operate independently, undergoing comminution, classification, and thickening stages, which are the main unit operations in mineral processing. The product is transported via a 244 km long slurry pipeline to the Hydro Alunorte alumina refinery, located in the municipality of Barcarena, Pará.

Mining constantly faces challenges related to process variability and the need to produce materials with increasingly strict granulometric and chemical specifications, especially due to its integration into a production chain for slurry transport and feeding the Bayer process.

The product from the bauxite beneficiation plants is composed of three main streams: secondary hydrocycloning of superfines, thickening hydrocycloning, and concentrate thickening, as shown in the flow diagram in Figure 1. Approximately 70% of the product corresponds to the alumina-rich particle size fraction composed of coarser particles above 37 µm, obtained through classification operations using hydrocyclones. These devices separate particles based on differences in their behavior in a fluid medium (water), featuring an inlet, an upper outlet (vortex finder), and a lower outlet (apex). The concentrate thickening stream consists of the finer fractions of the ore, between 45 µm and 10 µm, which significantly impact the final quality of the material sent to the refinery. This fraction is directed to concentrate thickeners, which are responsible for increasing the solids content of the slurry through sedimentation. The underflow mass from these thickeners represents about 30 % of the total product.

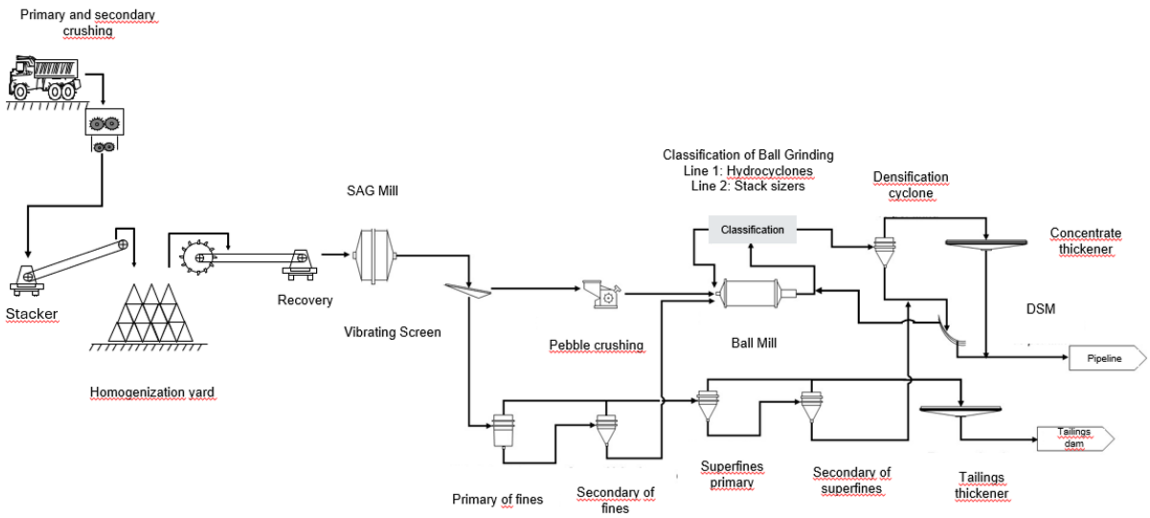


Figure 1. Simplified flowchart of the product formation streams at MPSA.

However, variability in the physical properties of the slurry batches pumped to Hydro Alunorte can compromise the performance of the refining process, affecting, for example, the efficiency of the digestion stage, and posing risks to the integrity of the slurry pipeline, such as accelerated wear, which occurs due to larger particles, as they promote more intense impacts on the internal wall of the pipeline, in addition to causing abrasion by scraping when in contact with the bottom of the pipe, significantly reducing the useful life of the pipeline.

In the current configuration of the hydrocycloning circuits, the operation aims to control three main variables: slurry density, battery pressure, and feed box level, through the adjustment of water addition flow into the box and the speed of the slurry pumps. However, while pressure is controlled by varying the pump speed and the box level is regulated by the water flow, the slurry density remains without direct control, being merely a consequence of water addition, as represented on Figure 2. This limitation makes the cycloning circuit susceptible to operational instabilities, potentially resulting in out-of-spec particle size distribution and high variability in control variables.

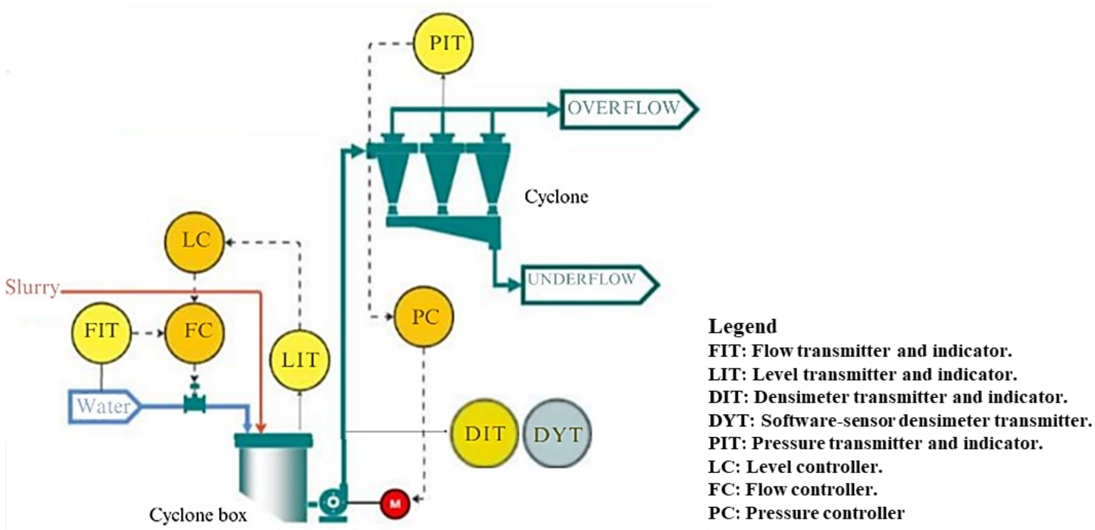


Figure 2. Cycloning operation instrumentation diagram before project.

For the concentrate thickeners, the focus is on product densification, aiming for efficient pumping and compliance with the required particle size distributions. Variables such as reagent dosage, slurry level, torque, rake lift, and underflow density are essential for optimizing the operation. Pumping control depends on manual adjustments made in the control room, which can lead to high variability in particle size composition, delays in decision-making to correct deviations, and consequently, negative impacts on product quality.

Given this scenario, the development and enhancement of more robust, adaptive, and automated process control solutions become essential. These systems must be capable of handling the dynamics and uncertainties of mineral processing, thereby ensuring operational stability, product quality, and system safety.

Three process control strategies were implemented:

1. The development of a software-based density sensor on cycloning feed, Figure 2, represented by DYT to enable closed-loop control in cycloning operations, even in the presence of instrumental limitations;
2. The adoption of the control strategy known as "Override Control," applied to cycloning operations;
3. The use of artificial intelligence through fuzzy logic, aimed at optimizing the physical quality in the slurry tanks by dynamically adjusting the mass flow of the underflow from the concentrate thickeners.

These approaches have resulted in tangible benefits for the operation, including improved stability in slurry composition, optimization of the physical quality of the product within process specification limits, reduced variability of critical variables, and enhanced preservation of industrial assets. Thus, this work aims to describe these strategies, their technical foundations, implementation challenges, and the impacts observed at the MPSA beneficiation plant.

2. Optimizing Cycloning and Concentrate Storage Thanks through Enhanced Process Control

Several methodologies and technologies were used to enhance process control. This included developing virtual sensors for closed-loop control strategies and implementing a new advanced regulatory control logic based on Proportional-Integral-Derivative control (PID) for cycloning operations. Additionally, an Advanced Process Control (APC) system was introduced in the blending process of the final concentrate tanks during the beneficiation stage. These integrated initiatives focus on reducing variability in critical process variables and guiding operations within ranges that optimize the physical quality of the final concentrate.

2.1 Software-based Sensor of Density

The development of the density estimators was based on the application of mass balance engineering principles, directly integrated into the plant's control system. This approach was adopted to enable the use of virtual sensors as active elements in the new process control strategy for cycloning operations. Figure 3 shows where the software-based sensor was implemented, the DYT highlighted. In addition to applying mass balance, the model incorporated flow residence time and the use of an exponential filter [1], with the aim of more accurately representing the hydraulic dynamics of the cyclone feed boxes.

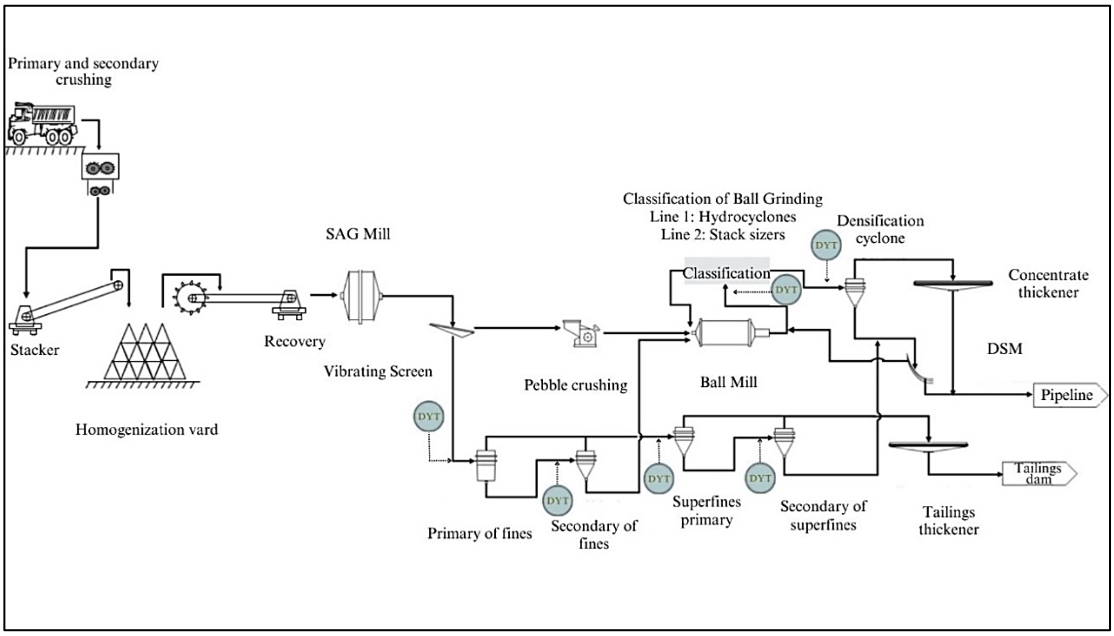


Figure 3. Simplified flowchart of beneficiation plant highlighted where software sensor was implemented. Legend: DYT: Software-sensor densimeter transmitter.

The use of virtual sensors based on mass balance has proven to be an increasingly common practice in the mining industry, showing statistically satisfactory results. Besides contributing directly to operational control, these estimators have also proven useful as a predictive maintenance support tool, signaling deviations that may indicate the need for calibration or intervention in physical instruments [2].

The implementation of the estimators was carried out directly within the control system, considering their integration as an essential component of the new control strategy architecture for cycloning. To exemplify, Figure 4 shows an example of the mass balance calculation implemented in the SAG mill operation, and Table 1 lists the parameters used in this calculation.

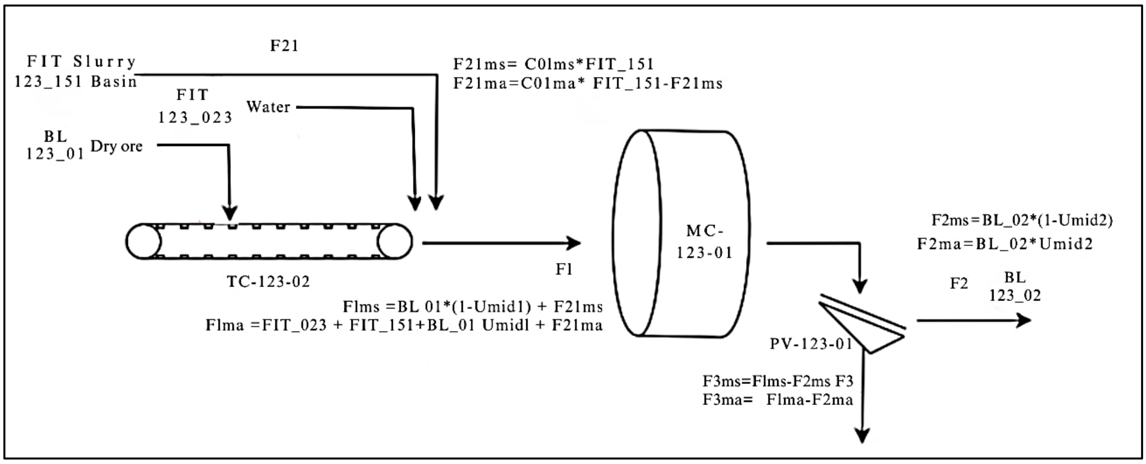


Figure 4. SAG Mill – Example of mass balance equations implemented on the SAG mill operation.

Table 1. List of parameters considered on mass balance calculation on SAG Mill operation.

Unit Operation	Flow direction	Parameter	Description	Unit
SAG Mill	Inflow	FIT_123_151	Slurry flow from basin	m^3/h
	Inflow	FIT_123_023	Water flow	m^3/h
	Inflow	C01ms	Constant from calculation of dry mass from slurry basin	-
	Inflow	C01ma	Constant from calculation of water mass from slurry basin	-
	Inflow	BL_123_01	Bauxite ore mass rate from scale	t/h
	Inflow	Umid1	Constant of humidity of bauxite ore	-
	Inflow	F1ma	Calculation of bauxite ore mass rate wet	t/h
	Inflow	F1ms	Calculation of bauxite ore mass rate dry	t/h
	Outflow	F2ma	Bauxite ore mass rate wet from sieve overflow	t/h
	Outflow	F2ms	Bauxite ore mass rate dry from sieve overflow	t/h
	Outflow	BL_123_02	Bauxite ore mass rate from scale	t/h
	Outflow	Umid2	Constant of humidity of bauxite ore from sieve overflow	-
	Outflow	F3ms	Calculation of slurry mass rate from sieve underflow	t/h
	Outflow	F3ma	Calculation of water flow from sieve underflow	t/h

Considering the wet nature of the process where dry material is converted into slurry in the initial stages of beneficiation the flows were broken down into two main streams: solids rate (dry mass) and water rate. This segmentation allowed for the differentiated application of mass balance to each component, with parameters determined either from design values or estimated using regression models. For parameter estimation, an optimization method using a solver was applied, with the objective of minimizing the model's root mean square error (RMSE) [3]. Based on the principle of mass conservation and the fundamental relationship between mass, density, and volume, a weighted contribution of the solid and liquid streams was applied, this enabled the calculation of slurry density and the corresponding solids concentration [4, 5].

$$\sum massflow_{dry}(in) = \sum massflow_{dry}(out) \tag{1}$$

$$\sum massflow_{wet}(in) = \sum massflow_{wet}(out) \tag{2}$$

$$mass_{slurry} = mass_{wet} + mass_{dry} \tag{3}$$

$$\rho_{slurry} = \frac{\rho_{dry} * Vol_{dry} + \rho_{wet} * Vol_{wet}}{Vol_{dry} + Vol_{wet}} \tag{4}$$

where;

$massflow_{dry}$	Mass flow dry, t/h
$massflow_{wet}$	Mass flow wet, t/h
$mass_{slurry}$	Mass slurry, t
$mass_{wet}$	Mass water, t
$mass_{dry}$	Mass solid, t
ρ_{slurry}	Density slurry, g/cm^3
ρ_{dry}	Density solid, g/cm^3
Vol_{dry}	Volume solid, m^3
ρ_{wet}	Density water, g/cm^3
Vol_{wet}	Volume water, m^3

For the calculations, the density of water was assumed to be 1.0 g/cm^3, while the density of the dry bauxite ore was considered to be 2.6 g/cm^3, in accordance with typical values reported in the literature and commonly used in industrial practice [6].

2.1 Override Strategy to Cycloning Operation

To support the implementation of the override strategy, calibration and maintenance activities were carried out on the instrumentation associated with the controllers. These actions are essential to enable both the adoption and the effectiveness of the proposed strategy.

In parallel, operational teams were engaged in continuous improvement programs, fostering the recognition and encouragement of best operational practices. These efforts were essential and foundational to ensure the success of the changes introduced in the control strategy.

All of these actions were focused to optimizing cyclone operations. At Paragominas Mining, there are eleven cyclone circuits distributed across two beneficiation plants. Although the new control strategy has been implemented in only two of these operations so far (Figure 5), the project is ongoing, with plans to scale up the strategy to the remaining cyclone circuits.

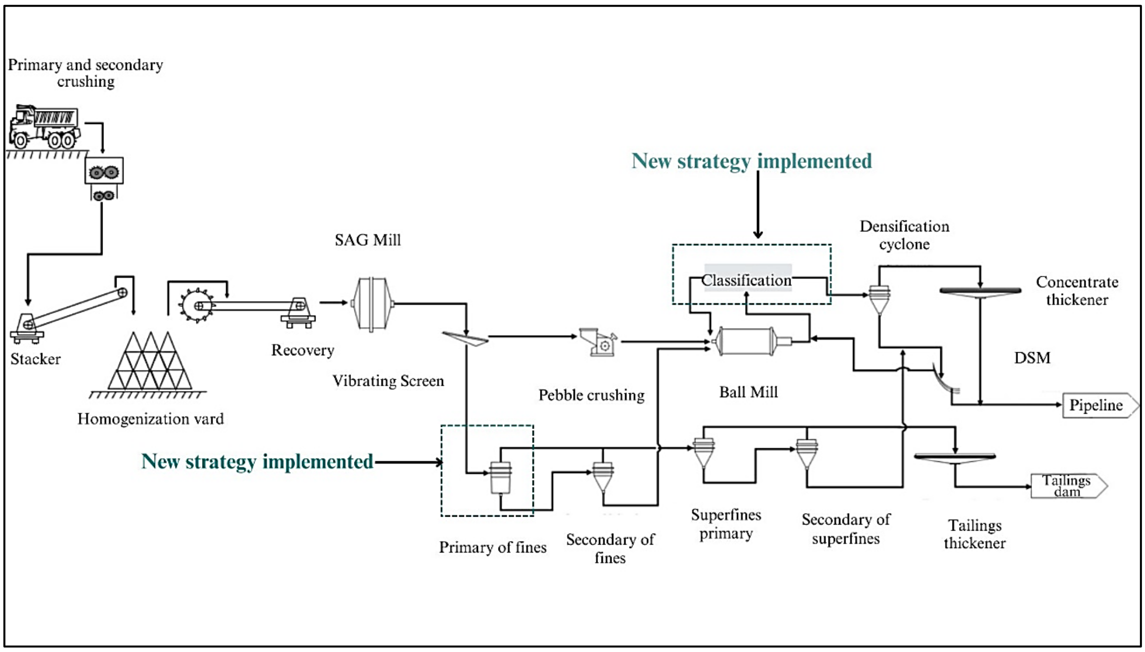


Figure 5. Simplified beneficiation plant flowchart – highlighted operations where override strategy was applied.

The cycloning operations are influenced by several factors that affect the characteristics of the underflow and overflow products, including:

- Cyclone geometry variables: apex and vortex diameters, shape and size of the feed inlet;
- Operating conditions: feed pressure, solids concentration in the slurry, particle size distribution, slurry density and viscosity.

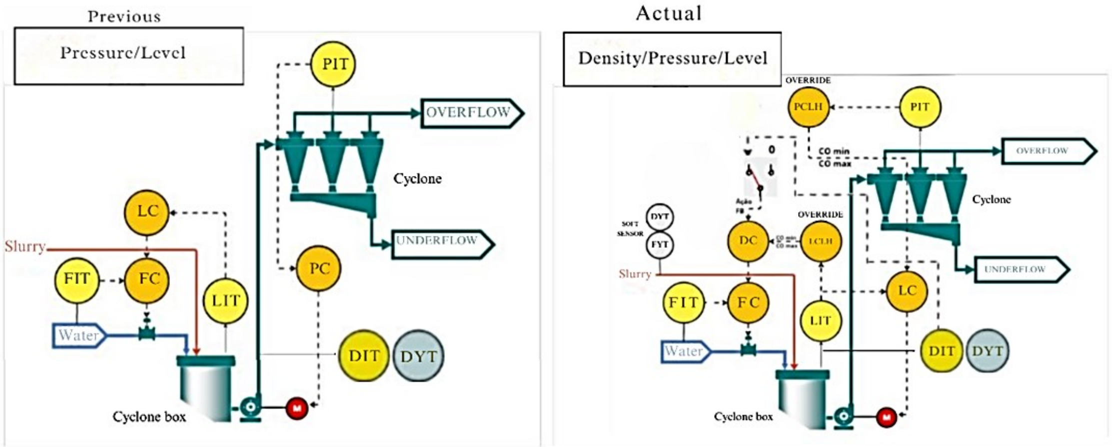
Density is one of the variables that has a direct impact on the performance of cyclone products. In circuits without a physical densimeter installed, virtual densimeters were developed to enable closed-loop density control [7]. Prior to the project, there was no closed-loop density control, leading to high variability in the slurry density fed into the circuit due to fluctuations in the feed slurry density to the feed box and oscillations in the water addition rate to the same box.

Currently, all cyclone operations involve monitoring and controlling three main variables: pressure, density, and feed box level. However, only two manipulated variables are available: regulating the cyclone feed pump speed and adjusting water addition into the cyclone surge box. The strategy does not include automating the on/off branches of the cyclone battery, a decision made by the operations team.

This situation presents a classic challenge in process control where the number of controlled variables exceeds the number of manipulated variables. To overcome this limitation, a multi-loop advanced regulatory control strategy, known as override control, was adopted [8]. Figure 6 illustrates the cyclone control strategies before and after the project's implementation.

The previous strategy was based on two main closed-loop control objectives:

1. Regulation of cyclone feed pressure: achieved through feedback control to maintain the feed line pressure at a fixed setpoint by adjusting the speed of the feed pump.
2. Maintenance of the cyclone feed box level: controlled by two loops in a master-slave configuration. The master loop, based on level, determines the required flow to maintain the level, which serves as the setpoint for the slave loop controlling water flow and modulating a control valve.



Legend

FIT: Flow transmitter and indicator.
FYT: Software-sensor flow transmitter.
LIT: Level transmitter and indicator.
DIT: Densimeter transmitter and indicator.
DYT: Software-sensor densimeter transmitter.
PIT: Pressure transmitter and indicator.
LC: Level controller.
FC: Flow controller.
PC: Pressure controller.
DC: Densimeter controller.
LCLH: Limiter controller Low/High.
PCLH: Primary controller Low/High.

Figure 6. Cycloning regulatory control strategy.
Left: Previous strategy, Right: new strategy.

The new approach incorporates additional objectives and priorities, adjusting operations according to load conditions:

1. Simultaneous regulation of feed box level and slurry density: under stable load conditions, density and level are controlled by modulating water addition to the feed box. The control follows a master-slave logic, where the flow control loop is the slave to the master density control loop, while the level is maintained via feedback control by modulating the speed of the feed pump.
2. Regulation of feed box level and cyclone feed pressure: in scenarios with load variations that cause significant deviations in feed pressure, selective control acts by modulating pump speed to regulate pressure. Simultaneously, the feed box level is controlled by the master-slave strategy for water addition, following the same logic used prior to the project.

These improvements in control strategy have significantly enhanced the stability and efficiency of cyclone operations. By enabling dynamic prioritization of control objectives and leveraging the available manipulated variables more effectively, the system is now better equipped to handle process disturbances and maintain key operational parameters within optimal ranges. This advancement not only reduces process variability but also lays the groundwork for future optimization initiatives in the grinding circuit.

2.2 Fuzzy APC to Storage Tank Blending

With the primary goal of reducing variability and improving the physical quality of the final bauxite concentrate, an advanced controller based on fuzzy logic was implemented as part of the process optimization program. This technology has been widely adopted in industrial processes, especially in mining, showing satisfactory results across various control objectives [9]. In this case, the fuzzy controller is primarily aimed at minimizing variability in the physical characteristics of the finer concentrate fractions 45 µm and 10 µm as well as the density of the final concentrate. Maintaining these specifications significantly contributes to the efficiency of subsequent stages in the alumina production chain.

The controller's action is focused on recommending the ideal setpoint for controlling the underflow flow rate of the final product from the concentrate thickeners Figure 7. This stream represents about 30 % of the total production of each unit and contains the highest concentrations of fine fractions (10 µm and 45 µm), as well as a more diluted slurry compared to other final concentrate streams.

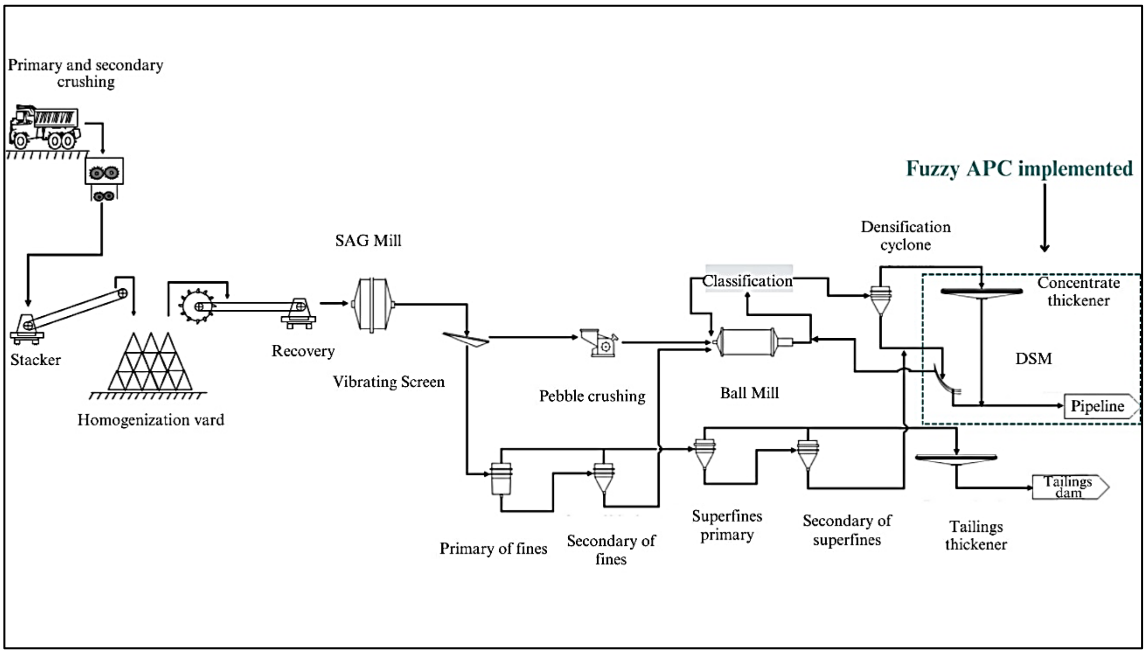


Figure 7. Simplified beneficiation plant flowchart – highlighted where APC Fuzzy controller was implemented.

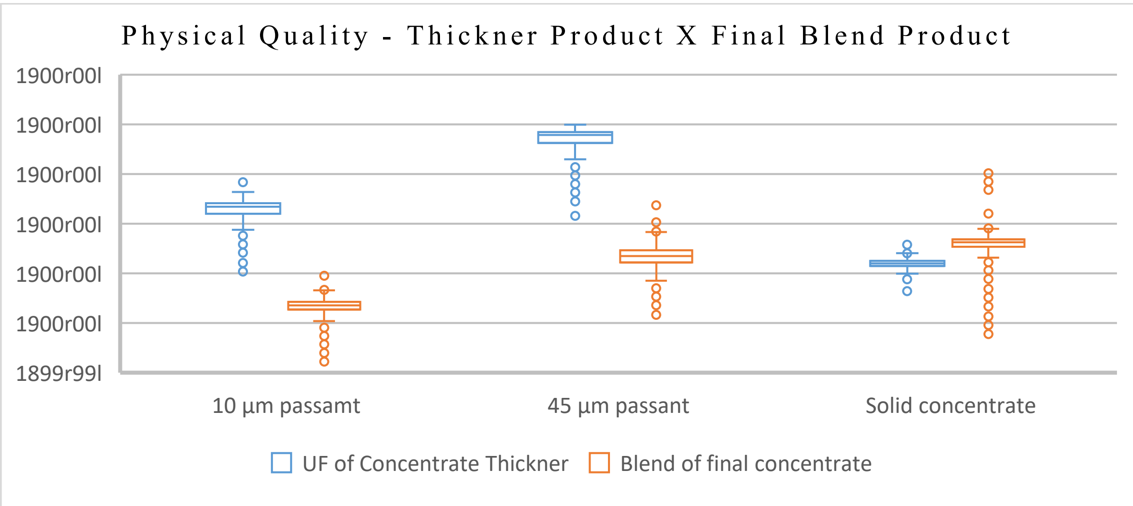


Figure 8. Physical quality comparative between product of Concentrate Thickener and the final product blended.

The fuzzy controller processes data from the control system in real time, including operational and process variables, and also integrates laboratory information obtained from the Laboratory Information Management System (LIMS) [10]. The diagram below illustrates the set of parameters used by the fuzzy system.

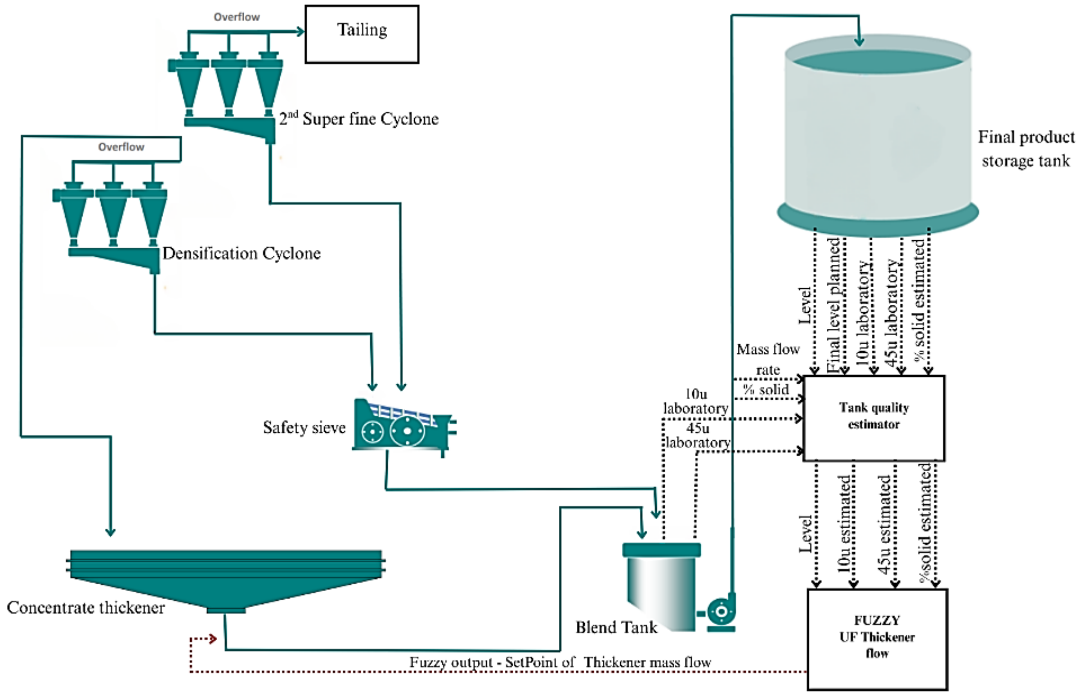


Figure 9. General vision of fuzzy parameters. Process diagram simplified.

The definition of the fuzzy variables' universes of discourse was based on a historical analysis of data accumulated over two years. The membership functions for both antecedents and consequent as well as the structure of the rule base, were developed with the support of interviews and workshops conducted with process and operations experts from the beneficiation plant and below is represented the final fuzzy rules consolidating the membership functions for each antecedent with response desired on consequent.

Table 2. Fuzzy rule table – solid concentrate on tank x derived of solid concentrate on tank

	Low low	**Low**	**Good**	**High**	**High high**
Very negative	Low low	Low low	Low	Normal	High
Negative	Low low	Low	Low	High	High
Stable	Low	Low	Normal	High	High high
Positive	Low	Normal	High	High	High high
Very positive	Normal	Normal	High	High high	High high

Table 3. Fuzzy rule table – 10 µm estimated on tank x derived of 10 µm estimated on tank

	Low low	**Low**	**Good**	**High**	**High high**
Very negative	High high	High high	High	Normal	Low
Negative	High high	High	High	Low	Low
Stable	High	High	Normal	Low	Low low
Positive	High	Normal	Low	Low	Low Low
Very positive	Normal	Normal	Low	Low low	Low low

Table 4. Fuzzy rule table – 45µm estimated on tank x derived of 45 µm estimated on tank

	Low low	**Low**	**Good**	**High**	**High high**
Very negative	High high	High high	High	Normal	Low
Negative	High high	High	High	Low	Low
Stable	High	High	Normal	Low	Low low
Positive	High	Normal	Low	Low	Low Low
Very positive	Normal	Normal	Low	Low low	Low low

The rule tables presented reflects a moderate tuning of the controller. Additionally, variants of the rule base with smoother or more aggressive tuning were developed. The selection of the appropriate tuning is done dynamically, considering the relationship between the current tank level and the planned level for closure. This approach aims to ensure the integrity and operational safety of the thickeners, allowing more aggressive actions only in cases of significant deviations in quality or when the tank levels are high.

The controller algorithm was configured to run every 5 minutes. The online quality of the concentrate in the tank is estimated through a weighting that combines the last quality sample measured in the tank along with its corresponding level, together with the quality of the final concentrates-from the two plants feeding the tank, weighted by the instantaneous mass produced by each unit. Figure 9 presents the diagram, highlighting the block named tank quality estimator.

3. Results and Discussion

3.1 Software-based Density Sensor – Multi-loop Override Strategy

3.1.1 Software-based Density Sensor

The new control strategy was first introduced in the fine primary operations and ball mill classification of Plant 1, *Figure* 3 illustrate where software-based sensor was implemented and *Figure* 5 where the new strategy was implemented. To successfully implement the new control strategy using the virtual density sensor, it is crucial that the estimated variable accurately represents the measured variable. Out of all the operations that were implemented, only the ball mill classification circuit had a physical densitometer in place. As a result, a comparison was conducted between the calculated and measured densities in the ball mill classification circuit for validation purposes. The calculated and measured densities exhibited similar and therefore satisfactory behavior, indicating the efficiency of the virtual density sensor. The results are now presented in Figure 10.

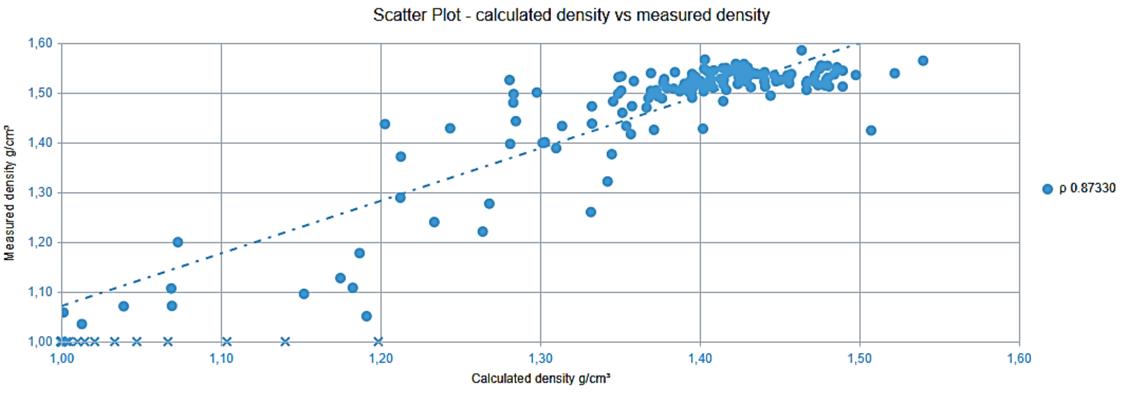


Figure 10. Scatter plot - censity measured versus density estimated – classification circuit – beneficiation 1.

3.1.2 Controled Variable

One of the main outcomes achieved with the implementation of the new strategy was the reduction in the standard deviation of the most relevant control variables. In the fines primary circuit, a 24.2 % decrease in the standard deviation of water addition was observed, while in the classification circuit, this reduction reached 42.1 %, as illustrated in Figures 11 and 12, respectively. Previously, water addition was controlled in a closed loop based on the tank level, a parameter with greater tolerance for variability. With the new approach, water addition became primarily regulated based on pulp density, a parameter directly linked to the performance of the classification process. This strategic shift provided greater process stability, significantly reducing fluctuations in water addition and, consequently, in density. As a result, a more efficient classification operation was achieved, with lower variability in one of the key variables that directly impact system efficiency.

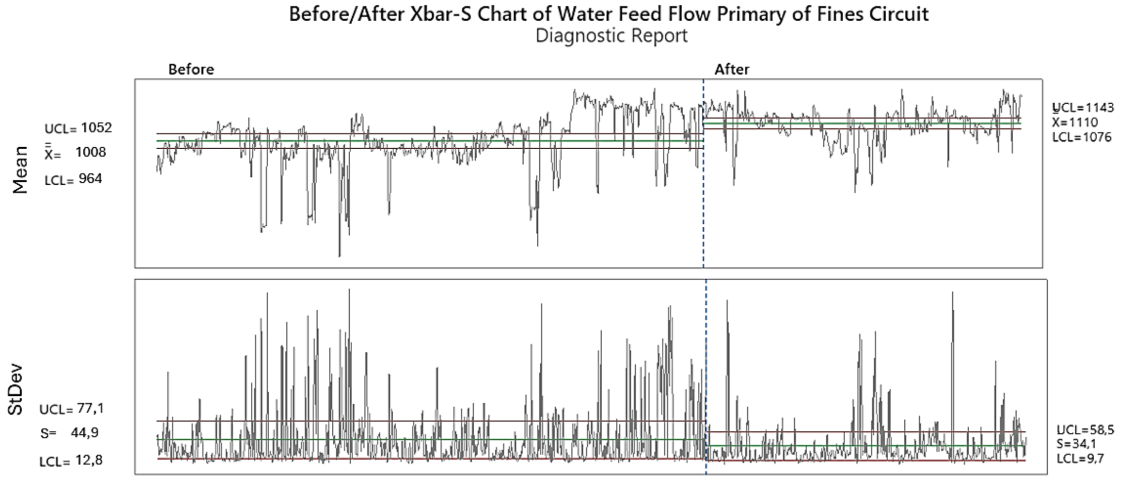


Figure 11. Before x after - water feed flow variability – primary of fines circuit – beneficiation 1.

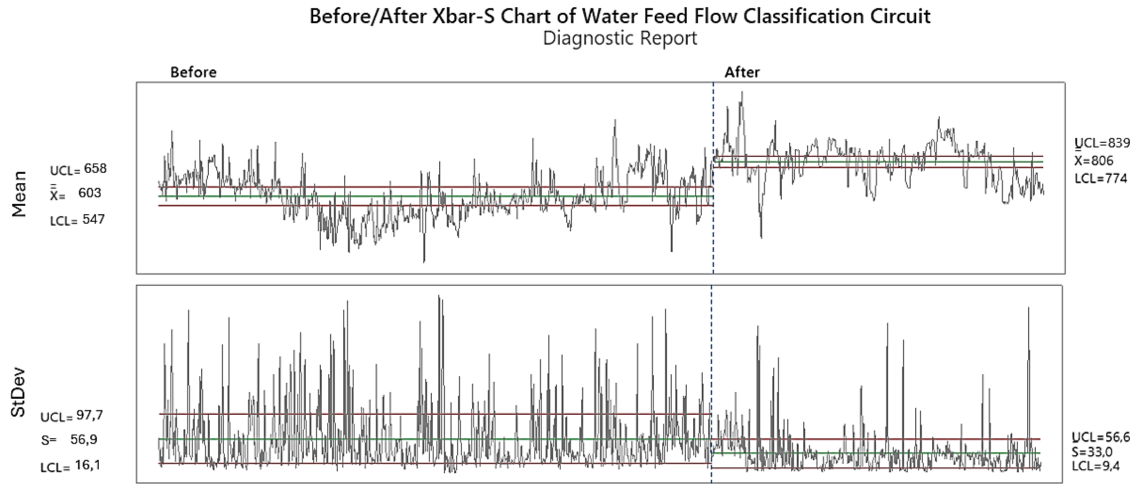


Figure 12. Before x after - water feed flow variability – classification circuit – beneficiation 1.

In addition to the improved stability in the water dosing circuit for the cycloning operations, another result achieved was the reduction in classification density. Operating at excessively high density negatively impacts the cyclone's cut efficiency and, as a consequence, may lead to increased circulating load in the circuit. Therefore, as shown in Figure 13, there was not only a reduction in the standard deviation, but also a decrease in density from 1.53 to 1.50 t/m^3. This opens the way for a more efficient particle size classification operation.

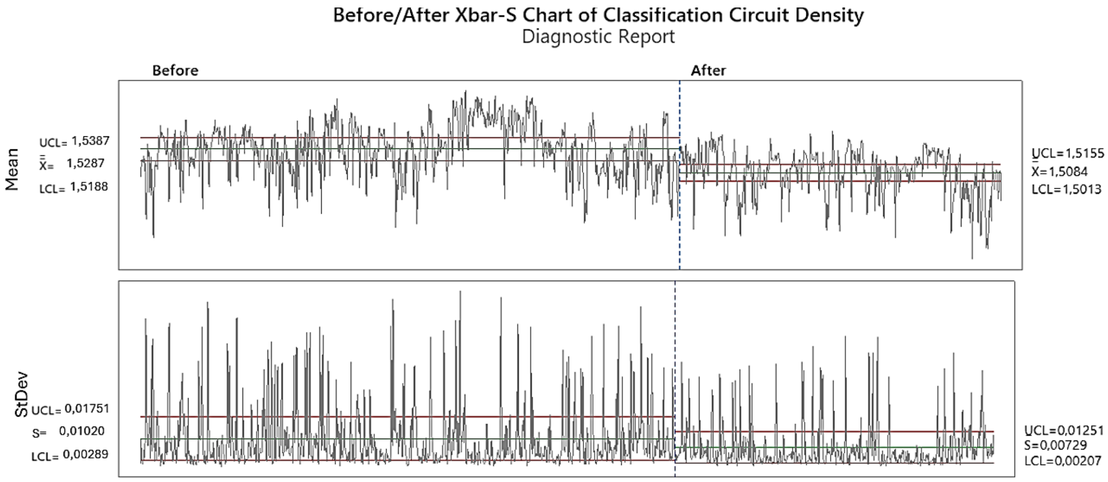


Figure 13. Before x after – density variability – classification circuit – beneficiation 1.

3.1.3 Physical Quality

In the particle size control loop of the plant's product, the 500 µm fraction is the most critical in terms of pipeline pumping. Particles larger than 500 µm accelerate pipeline wear and reduce its service life. Figure 14 illustrates that after implementing the new control strategy, there was an increase in the percentage of the plant's product passing through. This improvement is a result of operational stability and more efficient particle size classification, which significantly contributes to meeting and exceeding the required quality specifications.

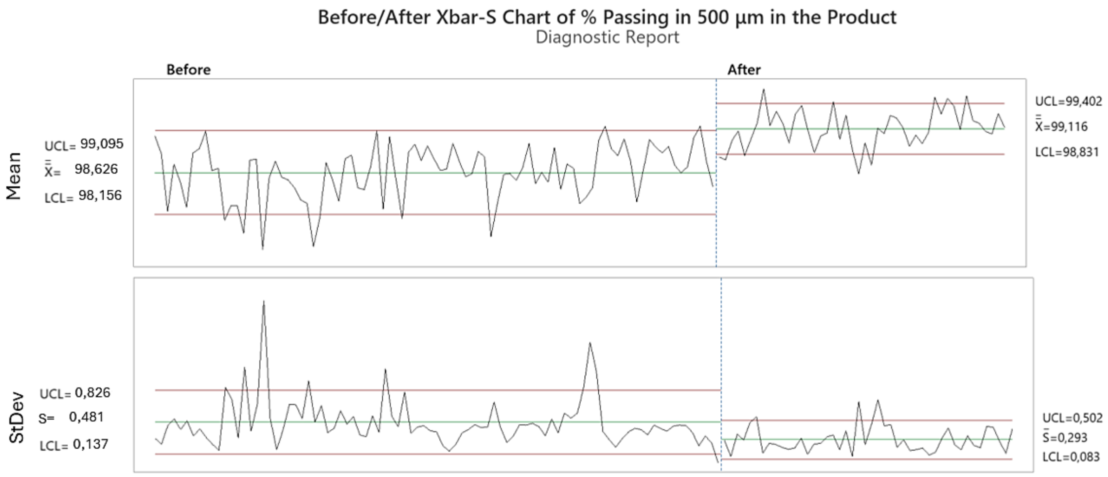


Figure 14. Before x after - % passing in 500 µm of product – beneficiation 1.

Therefore, the importance of closed-loop process control becomes evident. It not only leads to greater operational efficiency and enhanced stability in the circuits where the new strategy was implemented but also ensures more consistent water addition to the cyclone feed boxes, a reduction in classification feed density, and improved compliance with the required physical quality standards. This benefits downstream processes in a positive and significant way.

3.2 Fuzzy APC to Storage Tank Blending

The implementation of the advanced Fuzzy Logic controller at the product tank formation stage aimed primarily at reducing variability in the physical characteristics of the final concentrate, with a particular focus on the finer fractions (10 µm and 45 µm) and slurry density.

After deployment, data were collected over a three-month period and analyzed using Minitab statistical software (version 2020) to compare process performance before and after the controller implementation. For the analyses, and to standardize comparison conditions, only results with over 70% adherence to the fuzzy logic recommendations regarding the incorporation of thickener underflow mass into the product tanks were considered. Additionally, only periods with plant feed stability above 75% were included.

The first criterion ensures that, for most of the time, the fuzzy inference system was effectively applied, making it possible to attribute the resulting tank quality to the fuzzy logic recommendations.

The application of the controller resulted in significant improvements in the stability of quality variables, reducing fluctuations and deviations that previously impacted compliance with the quality-requirements, as shown in Figures 15, 16, and 17.

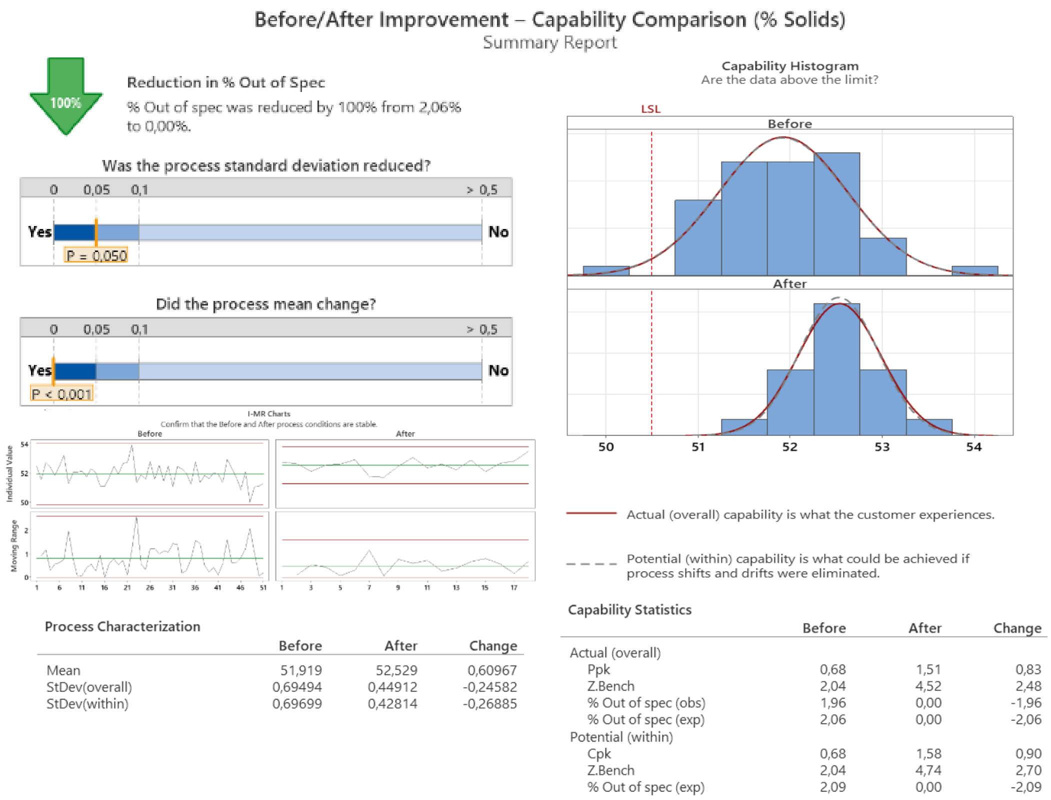


Figure 15. Statistical analysis of the % solids results before and after the implementation of fuzzy logic.

For the solids percentage, the standard deviation decreased from 0.69 to 0.44, demonstrating the effectiveness of the multivariable control. The Process Performance Index (Ppk), which reflects the actual process performance against specifications, increased from 0.68 to 1.51, indicating greater stability and the ability to produce within the specified limits, even when considering process shifts [11]. The Process Capability Index (Cpk), which measures the process potential under the assumption of being stable and centered, also improved, rising from 0.68 to 1.58, confirming the reduction in variability [11].

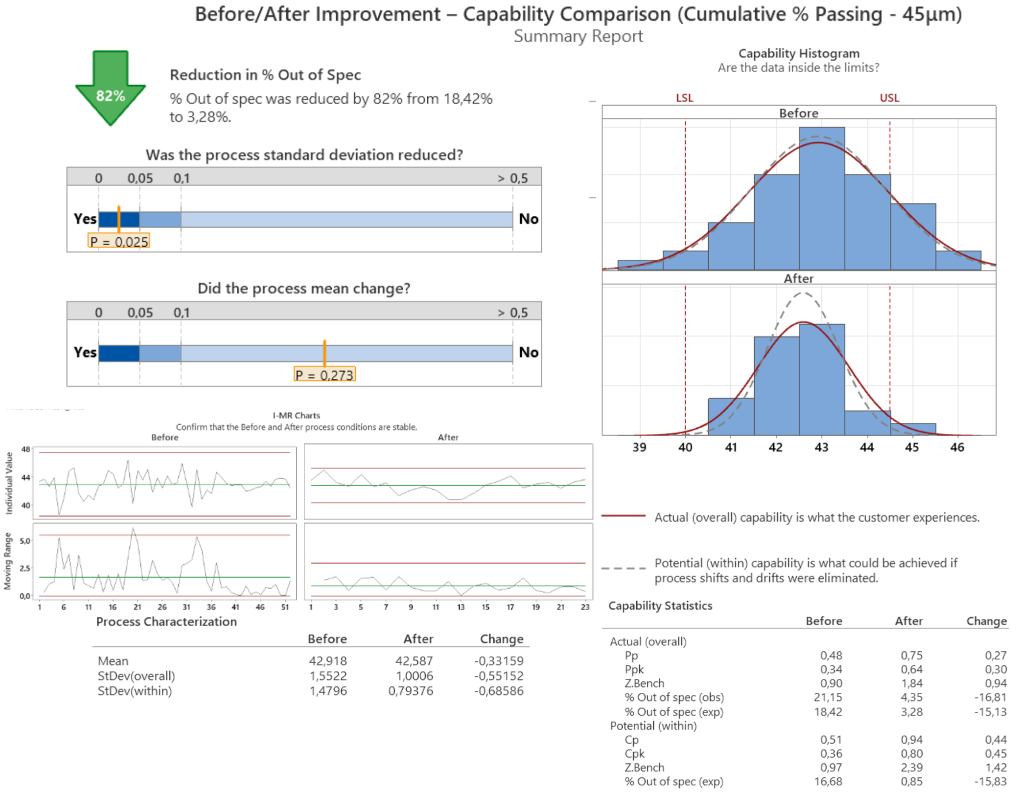


Figure 16. Statistical analysis of the 45 µm passing results before and after the implementation of fuzzy logic.

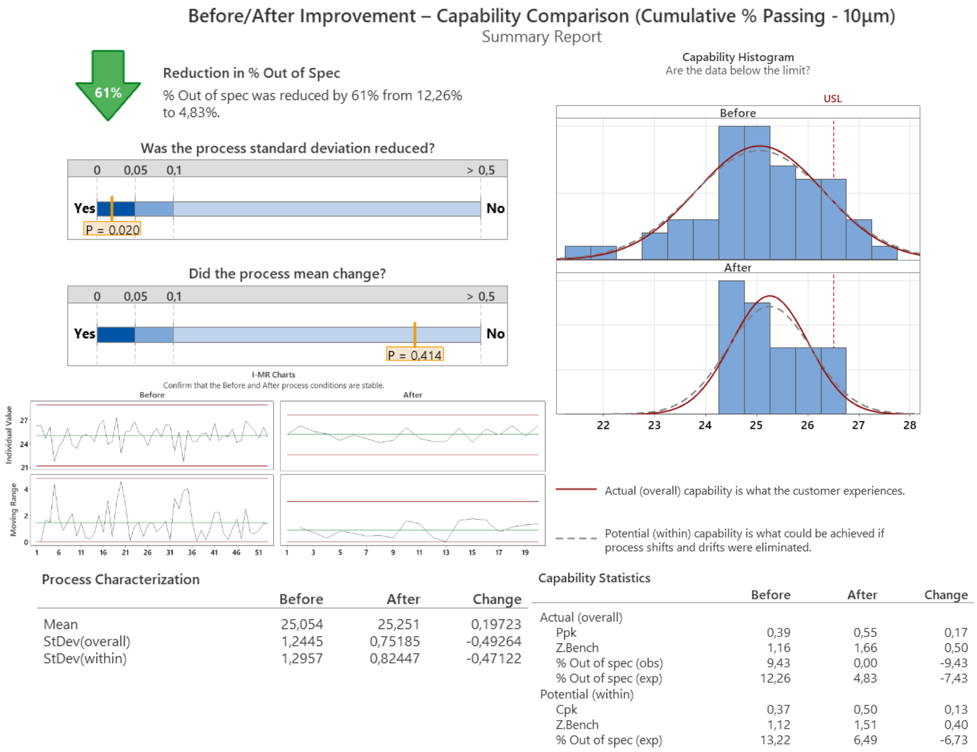


Figure 17. Statistical analysis of the 10 µm passing results before and after the implementation of fuzzy logic.

Similar results were observed in the granulometric fractions:

- **45 µm**: standard deviation reduced from 1.55 to 1.00; Ppk increased by 0.27; Cpk increased by 0.44.
- **10 µm**: standard deviation reduced from 1.24 to 0.75; Ppk increased by 0.17; Cpk increased by 0.13.

These results demonstrate that the Fuzzy controller contributed significantly to homogenizing the quality of the final concentrate, mitigating the impact of fine fractions originating from the thickener underflow.

Furthermore, the hypothesis tests (t-test) with 95 % confidence confirmed the accuracy between predicted and actual data, validating the fuzzy logic model.

Overall, these results highlight the effectiveness of Fuzzy logic as a complementary tool to traditional control systems, delivering tangible improvements in quality, operational stability, and beneficiation process efficiency.

4. Conclusion

The integrated adoption of technologies such as virtual sensors, advanced regulatory control strategies (such as override control or similar), and intelligent advanced control systems like fuzzy logic, represents a significant advancement in the management of industrial beneficiation processes. When applied in a complementary manner, these solutions enable greater operational stability, improved control of critical variables, and increased adaptability to the inherent fluctuations of mineral operations.

Virtual sensors make it possible to obtain reliable information even in environments with instrumental limitations, allowing the applicability of loop controls, reducing the usage of open control loops. The override control strategy provides robustness in systems with multiple control variables and limited actuation options, ensuring safer and more effective automatic decisions across various operational scenarios. Finally, the use of artificial intelligence with fuzzy logic enables predictive and real-time adjusted actions, reducing variability and ensuring greater compliance with established quality standards.

Together, these approaches contribute to a more efficient, safer, and standardized operation throughout the beneficiation process. Their outcomes point to consistent gains in productivity, product quality, asset preservation, and readiness for future advancements in automation and digitalization paving a promising path toward intelligent mining.

5. References

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