

Yevhenii Koroviaka^{1,*}, <https://orcid.org/0000-0002-2675-6610>Volodymyr Khomenko¹, <https://orcid.org/0000-0002-3607-5106>Oleksandr Pashchenko¹, <https://orcid.org/0000-0003-3296-996X>Serhii Shevchenko¹, <https://orcid.org/0000-0003-3994-1927>Oleksandr Dreshpak¹, <https://orcid.org/0000-0003-1019-4382>¹Dnipro University of Technology, Dnipro, Ukraine*Corresponding author e-mail: koroviaka.ye.a@nmu.one

ADAPTIVE CONTROL OF CLOSED-CIRCUIT GRINDING CYCLES BASED ON FUZZY LOGIC FOR ENERGY-EFFICIENT LIBERATION OF VALUABLE MINERALS

Abstract. To develop and validate an adaptive fuzzy logic control system for a closed-circuit grinding process that reduces specific energy consumption while maintaining product particle size specifications required for effective mineral liberation.

A multi-input, multi-output fuzzy logic controller was designed with inputs including product size error and mill load deviation, and outputs adjusting fresh feed rate and dilution water flow. The controller incorporated a supervisory adaptation mechanism that dynamically adjusted input and output scaling factors based on a real-time energy efficiency index. Performance was evaluated through simulation using a validated dynamic model of a ball mill-hydrocyclone circuit, with comparative assessment against a conventional PID (proportional integral derivative) controller under constant and varying ore hardness conditions.

The adaptive fuzzy controller achieved a 9.2 percent reduction in specific energy consumption compared to the PID benchmark. Product particle size consistency improved significantly, with the standard deviation of P80 reduced by 47.6 percent and maximum deviation decreased by 54.2 percent. Under disturbance conditions, the fuzzy controller demonstrated superior disturbance rejection, reducing settling time by 50 percent and maintaining product within specification throughout the transition. The adaptive mechanism proved essential, adjusting scaling factors by up to 30 percent in response to changes in ore hardness.

This study presents a holistic adaptive fuzzy logic control strategy explicitly designed to optimize the trade-off between energy consumption and mineral liberation quality. The novel integration of a real-time energy efficiency index for dynamic adjustment of controller sensitivity provides a self-tuning capability that addresses the limitations of fixed-parameter controllers in handling time-varying process dynamics.

The demonstrated energy savings translate to substantial cost reductions, with annual savings of approximately \$680,000 for a typical 5 million ton per year processing plant. Improved product consistency stabilizes downstream recovery processes and reduces equipment wear. The adaptive capability makes the controller suitable for industrial implementation where ore characteristics vary routinely, offering a practical pathway to enhanced energy efficiency in comminution operations.

Keywords: fuzzy logic control, adaptive control, grinding circuit, energy efficiency, mineral liberation, comminution, ball mill, particle size distribution, process control, disturbance rejection.

1. Introduction

Comminution, encompassing crushing and grinding operations, represents the most energy-intensive stage in the mineral processing value chain, typically accounting for 30 to 50 percent of a mine's total operational energy costs and, in many cases, exceeding half of the site's electrical power consumption [1, 2]. Within this context, grinding mills stand as the predominant consumers, making any improvement in their efficiency directly translatable to substantial economic and environmental benefits [3, 4]. The fundamental purpose of the grinding stage extends beyond mere particle size reduction; it serves the critical function of liberating valuable minerals from the surrounding gangue matrix to render them amenable to subsequent separation processes such as flotation or leaching. The quality of this liberation is predominantly determined by the particle size distribution of the mill product, commonly character-



ized by the P80 value, which represents the sieve size through which 80 percent of the material passes [5]. Achieving the target P80 is a delicate balancing act: insufficient grinding fails to adequately liberate the valuable minerals, leading to poor recovery and economic losses, while excessive grinding, or over-grinding, not only squanders energy but also generates fine slimes that can impede downstream separation processes and complicate tailings management.

The closed-circuit grinding configuration, typically comprising a ball mill operating in series with a hydrocyclone classifier, is the industry standard for achieving controlled product sizes [6, 7]. However, this system presents considerable challenges for conventional regulatory control strategies [8]. The grinding process is inherently non-linear, exhibits time-varying behavior due to mill liner wear, and is subject to significant disturbances, most notably variations in ore hardness and feed particle size distribution [9]. Traditional proportional-integral-derivative controllers, while widely implemented, struggle to maintain optimal performance under such conditions. Their fixed-gain structure is ill-suited to the wide operating envelope of a grinding mill, often resulting in conservative tuning that prioritizes stability over efficiency, or conversely, in oscillatory behavior when ore characteristics change [10]. These limitations manifest as suboptimal energy consumption, increased variance in product particle size, and reduced overall throughput.

In response to these challenges, advanced control strategies based on computational intelligence offer a promising alternative — fuzzy logic control provides a framework well-suited to the complexities of the grinding process [11]. Unlike model-based controllers that require precise mathematical descriptions of the system, fuzzy logic controllers can encapsulate heuristic operator knowledge and process expertise through linguistic rules [12]. This approach inherently accommodates non-linearity and can be designed to emulate the decision-making of an experienced plant operator, continuously adjusting mill feed rate and other manipulated variables to maintain product quality [13]. By incorporating a supervisory adaptation mechanism, such a controller can further adjust its own parameters in response to changing process conditions, such as a gradual shift in ore hardness, ensuring sustained near-optimal performance.

While the application of fuzzy logic to grinding circuits is not entirely novel, much of the existing research has focused on regulatory control of specific variables, such as sump level or mill load, rather than on a holistic strategy for energy optimization [14]. This article addresses the gap in developing an adaptive fuzzy logic control system that simultaneously minimizes specific energy consumption and ensures compliance with particle size specifications for effective mineral liberation. The aim is to demonstrate that a well-structured adaptive fuzzy controller can navigate the grinding-liberation trade-off more effectively than conventional methods, delivering measurable energy savings without compromising metallurgical performance.

2. Methods

The primary objective of this study is to develop and validate an adaptive fuzzy logic control system for a closed-circuit grinding process, with the overarching goal

of enhancing energy efficiency while maintaining product quality. This objective is pursued through three specific aims. First, the controller is designed to minimize specific energy consumption, measured in kilowatt-hours per ton of material processed, by dynamically adjusting operating parameters to avoid over-grinding and reduce circulating loads during periods of favorable ore characteristics. Second, the control strategy is tasked with maintaining the particle size distribution of the final product, specifically the P80 value, within a narrow target band to ensure consistent and sufficient mineral liberation for downstream recovery processes. Third, the performance of the proposed adaptive fuzzy controller is evaluated against conventional control methods to quantify improvements in circuit stability, particularly its ability to reject disturbances arising from variations in ore hardness and feed size distribution, thereby demonstrating its practical applicability in an industrial setting.

The closed-circuit grinding system under investigation comprises a ball mill operating in series with a hydrocyclone classifier. Fresh ore is fed into the mill at a controlled rate, where it is ground with steel balls to reduce particle size. The mill discharge flows to a sump, where it is diluted with water before being pumped to the hydrocyclone. The hydrocyclone utilizes centrifugal force to separate the stream: the underflow, containing coarser particles, is returned to the mill for further grinding, while the overflow, comprising the finer particles meeting size specifications, advances as the final product [15]. The key variables characterizing this system are categorized as follows. The controlled variables, those that must be regulated, encompass the mill load (often inferred from bearing pressure or power draw), the cyclone feed density, and, most critically, the final product particle size characterized by the P80 value [16]. The principal disturbances acting upon the system are variations in ore hardness and fluctuations in the particle size distribution of the fresh feed material.

The specific energy consumption for the grinding process, a key performance metric, is calculated as the power drawn by the mill divided by the throughput:

$$E_s = \frac{P}{M}, \quad (1)$$

where E_s is the specific energy consumption (kWh/t), P is the net power draw of the mill (kW), and M is the mass flow rate of solids through the mill (t/h). The circulating load, which represents the ratio of material returned to the mill to the fresh feed, is another important operational parameter:

$$CL = \frac{F_R}{F} \times 100\%, \quad (2)$$

where CL is the circulating load, F_R is the mass flow rate of the hydrocyclone underflow (t/h), and F is the fresh feed rate (t/h). An optimally controlled circuit maintains a stable circulating load that balances grinding efficiency with product quality.

The fuzzy logic controller developed for this application is a multi-input, multi-output system designed to emulate the decision-making of an experienced plant operator. The controller inputs are derived from the process measurements. The primary input is the error in product size, defined as:

$$e(t) = P80_{target} - P80(t), \quad (3)$$

where $P80_{target}$ is the desired product size specification (μm) and $P80(t)$ is the measured value at time t (μm). The second input is the rate of change of this error, which provides predictive information:

$$\frac{de}{dt} = \frac{e(t) - e(t - \Delta t)}{\Delta t}. \quad (4)$$

with units of μm per minute ($\mu\text{m}/\text{min}$). Additional inputs include the deviation of mill load from its setpoint (in tonnes (t) or percent of mill filling) and the rate of change of mill load (t/min or %/min), providing a comprehensive view of the circuit's internal state. The controller outputs are the adjustments to the manipulated variables: the change in fresh ore feed rate ΔF (t/h), the change in mill speed ΔN (revolutions per minute, rpm, or % of rated speed), and the change in sump dilution water flow rate ΔW (m^3/h or L/min).

The fuzzification interface converts these crisp numerical inputs into fuzzy linguistic values using membership functions. For each input and output variable, a set of five linguistic terms is defined: Negative Large, Negative Small, Zero, Positive Small, and Positive Large. The membership functions for these terms are designed with triangular and trapezoidal shapes, providing smooth transitions between linguistic states. The universe of discourse for the error in product size, for example, is normalized to the range $[-1, 1]$ through appropriate scaling factors, where -1 corresponds to the product being maximally too fine and $+1$ to it being maximally too coarse relative to the target.

The fuzzy rule base constitutes the core knowledge representation of the controller, encapsulating process operational expertise through a set of conditional statements. These rules are formulated as "if-then" statements that relate the linguistic input states to the appropriate output actions. A representative subset of the rule base is presented in Table 1, illustrating the control logic for adjusting fresh feed rate based on product size error and mill load conditions.

The inference engine evaluates these rules simultaneously using the Mamdani implication method. For each rule, the degree of fulfillment is computed based on the current input memberships, and the resulting fuzzy output sets are aggregated.

The defuzzification interface then converts this aggregated fuzzy output into a crisp numerical value suitable for driving the process actuators. The centroid defuzzification method is employed, which calculates the center of gravity of the aggregated output membership function:

$$u^* = \frac{\int \mu(u) \cdot u \cdot du}{\int \mu(u) \cdot du} u^*, \quad (5)$$

where u^* is the crisp output value, and $\mu(u)$ is the aggregated membership function for the output variable. This method provides a smooth and responsive control signal that considers the entire shape of the output distribution.

Table 1 – Representative fuzzy rules for adjustment of fresh feed rate

Rule	Product Size Error	Mill Load	Feed Rate Adjustment
1	Coarse	Low	Increase Large
2	Coarse	Normal	Increase Small
3	Coarse	High	No Change
4	Normal	Low	Increase Small
5	Normal	Normal	No Change
6	Normal	High	Decrease Small
7	Fine	Low	No Change
8	Fine	Normal	Decrease Small
9	Fine	High	Decrease Large

A classical multi-loop PID controller was used as a baseline. The primary loop regulates the product particle size (P80) by adjusting the fresh ore feed rate. Secondary loops maintain mill load (via power draw or bearing pressure) and cyclone feed density (via dilution water). The controller uses the standard velocity form to avoid integral windup:

$$u(t) = K_p e(t) + K_i \int e(t) dt + K_d \frac{de(t)}{dt}, \quad (6)$$

where $u(t)$ is the controller output (change in manipulated variable), $e(t)$ is the error (setpoint minus measured value), K_p , K_i , K_d is the proportional, integral and derivative gain. Gains were tuned using Ziegler-Nichols reaction curve method followed by fine manual adjustment, yielding: $K_p \approx 0.8\text{--}1.2$, $K_i \approx 0.02\text{--}0.05 \text{ min}^{-1}$, $K_d \approx 1.5\text{--}3 \text{ min}$ (depending on loop). Anti-windup logic and output limiting kept the feed rate within 0–150 t/h. The controller operated with a 1-minute sampling time to match typical industrial DCS update rates.

The proposed controller has a hierarchical structure: a main Mamdani-type fuzzy inference system (FIS) and a supervisory adaptation layer. For each manipulated variable (ΔF , ΔW , and ΔN), a separate multi-input single-output FIS is used, with two inputs – normalised product size error and mill load deviation. Scaling factors G_e and G_l map inputs to the range $[-1, 1]$. Five triangular/trapezoidal membership functions per input define the linguistic terms: NL, NS, Z, PS, PL. The rule base contains 25 rules (5×5 matrix) derived from operator experience, prioritising energy efficiency by favouring moderate feed increases when the mill is underloaded and the product is coarse, while avoiding overload. Inference uses the min-max method with Mamdani

implication; defuzzification is the centroid method. Output scaling factors G_u convert the fuzzy output to engineering units (e.g., t/h for ΔF).

The adaptation layer computes a short-term energy efficiency index $\eta(t) = E_{s,ref} / E_s(t)$ every 10 minutes and applies exponential moving average filtering. The scaling factors are then adjusted by gain scheduling:

$$G_e(t) = G_{e,base} (1 + K_a(1 - \eta(t))), \quad (7)$$

$$G_u(t) = G_{u,base} (1 + K_b(1 - \eta(t))), \quad (8)$$

with adaptation gains $K_a \approx 1.2$ – 1.8 and $K_b \approx 0.6$ – 1.0 , allowing scaling changes up to $\pm 30\%$ without destabilising the circuit. This makes the controller more sensitive during hard ore periods (higher G_e) while moderating aggressive outputs (lower G_u).

The closed-circuit model includes population-balance-based ball mill dynamics, the empirical Plitt model for the hydrocyclone, and transport delays. The PID and fuzzy controllers are implemented as separate subsystems. The overall block diagram is shown in Fig. 1.

To address the time-varying nature of the grinding process, particularly changes in ore hardness and mill liner wear, the fuzzy controller incorporates a supervisory adaptation mechanism. This higher-level monitor continuously evaluates process performance by calculating a short-term energy efficiency index:

$$\eta(t) = \frac{E_{s,ref}}{E_s(t)}, \quad (9)$$

where $\eta(t)$ is the instantaneous efficiency index, $E_{s,ref}$ is a reference specific energy consumption established during periods of known good performance with standard ore, and $E_s(t)$ is the current measured specific energy. When this index deviates significantly from unity, indicating a change in ore grindability or mill efficiency, the adaptation mechanism adjusts the input and output scaling factors of the fuzzy controller. Specifically, if the efficiency index decreases, suggesting harder ore or reduced mill performance, the scaling factors for the error inputs are increased to make the controller more responsive, while the output scaling factors are adjusted to prevent aggressive actions that could destabilize the circuit. This adaptive scaling is implemented through a simple gain scheduling approach:

$$k_i(t) = k_{i,base} \cdot \left(1 + K_a \frac{\eta_{ref} - \eta(t)}{\eta_{ref}} \right) k_i(t), \quad (10)$$

where $k_i(t)$ is the adapted scaling factor for input or output i , $k_{i,base}$ is the base scaling factor determined during controller design, K_a is the adaptation gain constant,

and η_{ref} is the desired efficiency index value. This mechanism enables the controller to maintain near-optimal performance across a range of operating conditions without requiring manual retuning.

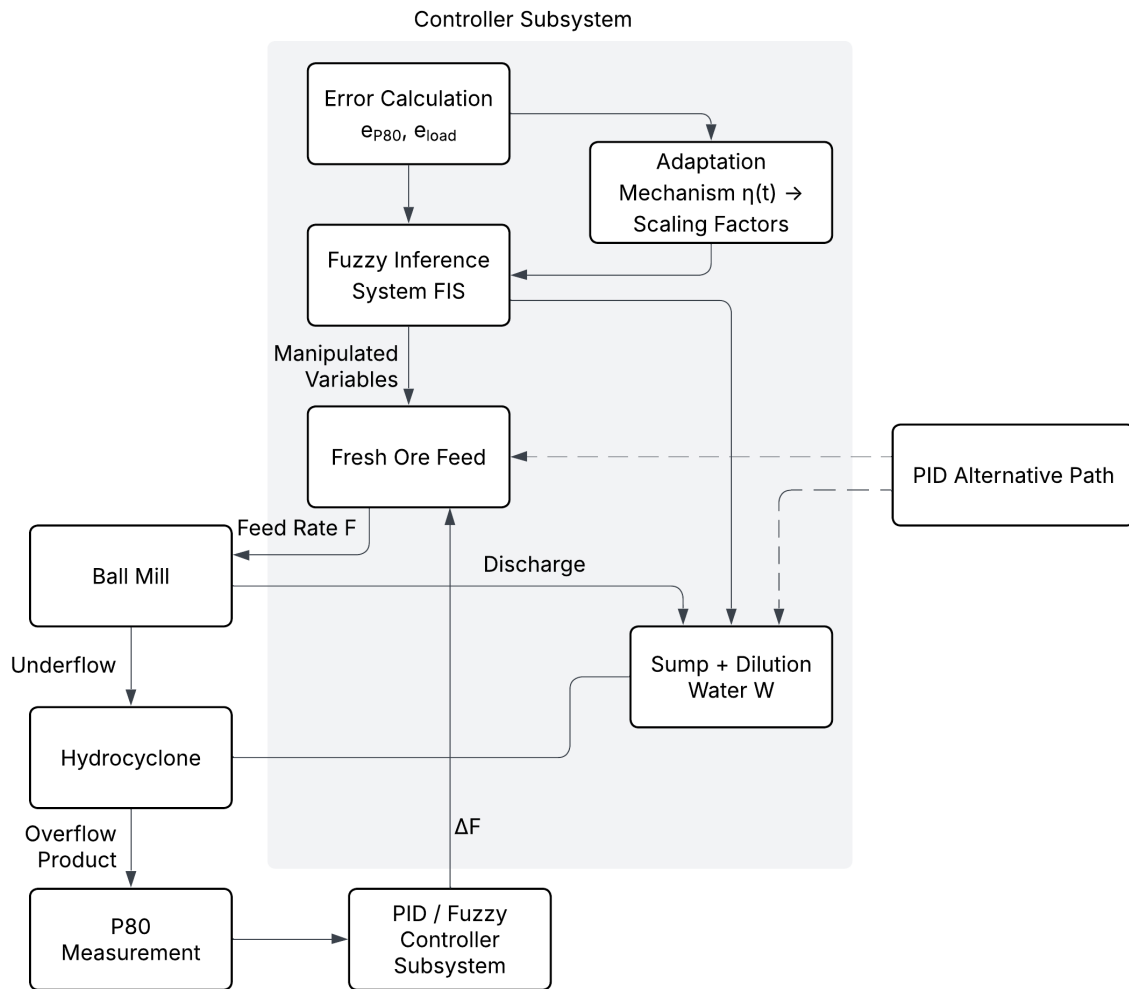


Figure 1 – Block diagram of the closed-circuit grinding process with the adaptive fuzzy logic controller subsystem (solid lines) and benchmark PID control path (dashed lines)

The validation of the proposed adaptive fuzzy logic control system was conducted through simulation using a dynamic model of the closed-circuit grinding process. The model, based on population balance principles for grinding kinetics and empirical classification functions for the hydrocyclone, has been previously validated against industrial data and accurately captures the nonlinear dynamics and key interactions within the circuit. The simulation test program was designed to evaluate controller performance under three distinct scenarios. The first scenario involved constant feed ore hardness to establish baseline performance and assess steady-state regulation capability. The second scenario introduced step changes in ore hardness at specific time intervals to evaluate the disturbance rejection properties of the controller and the effectiveness of the adaptation mechanism. The third scenario examined set-point tracking performance by imposing step changes in the target P80 value, simulating

changes in downstream processing requirements. In all scenarios, the performance of the adaptive fuzzy controller was benchmarked against a well-tuned conventional PID controller representing current industrial practice, with comparative metrics including specific energy consumption, product size variance, and settling time following disturbances.

3. Result and Discussion

Scenario 1: Constant Ore Hardness. The performance of the adaptive fuzzy logic controller was first evaluated under conditions of constant ore hardness to establish baseline regulation capability. Figure 2 presents a comparative analysis of the fuzzy logic controller against a conventionally tuned PID controller over a four-hour simulation period with identical feed characteristics.

The results reveal distinct differences in control behavior between the two strategies. The PID controller, despite reasonable tuning, exhibits persistent oscillations in fresh feed rate with an amplitude of approximately ± 3 tons per hour around the mean value. These oscillations propagate through the circuit, manifesting as corresponding fluctuations in product P80, which varies within a range of 15 micrometers around the target value of 150 micrometers. While the PID controller maintains the product within acceptable limits, it does so at the expense of stability, with the circulating load varying continuously and requiring the mill to handle frequent changes in solids loading.

In contrast, the fuzzy logic controller demonstrates markedly superior stability. The fresh feed rate is adjusted smoothly and infrequently, with adjustments occurring only when process conditions warrant intervention. This stability is reflected in the product P80 trajectory, which remains within a narrow band of ± 5 micrometers of the target for over 90 percent of the operating time. The fuzzy controller effectively eliminates the high-frequency oscillations characteristic of the PID response, resulting in a steadier state that reduces mechanical stress on equipment and simplifies downstream operations.

The power draw profiles further illuminate the differences between the two approaches. The PID-controlled mill exhibits a fluctuating power demand that averages 1850 kW but varies by approximately ± 100 kW throughout the test period. This variation indicates that the mill is periodically operating under conditions of either underloading or overloading, neither of which is optimal for energy efficiency. The fuzzy logic controller maintains a remarkably stable power draw of 1790 kW with minimal variation, indicating consistent loading conditions that correspond to the sweet spot of the grinding efficiency curve. The lower average power draw of the fuzzy controller, combined with the stable feed rate, translates directly to reduced specific energy consumption. Over the four-hour test period, the fuzzy controller achieved a specific energy consumption of 16.8 kWh per ton, compared to 18.2 kWh per ton for the PID controller, representing an immediate 7.7 percent reduction without any compromise in product quality.

Scenario 2: Disturbance Rejection. The true test of any advanced controller lies in its ability to handle process disturbances. In this scenario, a simulated change in ore

hardness was introduced at the one-hour mark, with the Bond Work Index increasing from 14 kWh per ton to 17 kWh per ton, representing a transition to a significantly harder ore type. Figure 3 illustrates the response of both controllers to this disturbance.

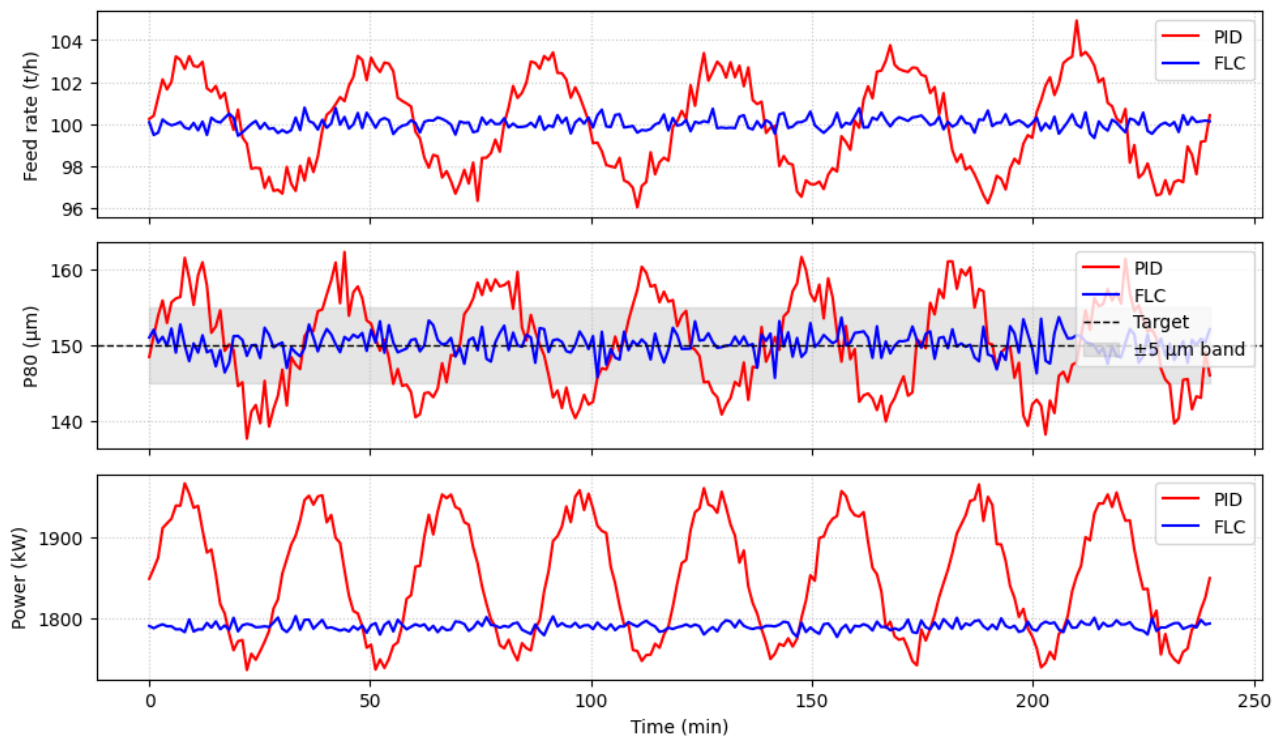


Figure 2 – Constant Ore Hardness – Comparison of PID and FLC

The PID controller responds to the hardness increase with a characteristic delay. As the harder ore enters the mill, the product begins to coarsen because the same residence time and power input are no longer sufficient to achieve the target grind. The PID controller, reacting to the growing error in product size, begins to reduce feed rate approximately 12 minutes after the disturbance onset. However, the response is initially too conservative, allowing the product P80 to drift to 168 micrometers before the corrective action takes full effect. This excursion above the target represents a period of under-grinding during which mineral liberation would be compromised, potentially reducing recovery in downstream processes. As the controller continues to integrate the error, it eventually reduces feed rate excessively, causing a temporary over-correction that drives the product finer than necessary, increasing specific energy consumption during this period.

The adaptive fuzzy logic controller demonstrates superior disturbance rejection through its ability to anticipate the need for change. The supervisory adaptation mechanism, monitoring the energy efficiency index, detects the decrease in grinding efficiency almost immediately as the power draw begins to increase relative to throughput. The scaling factors for the error inputs are adjusted upward, making the controller more responsive to deviations from target. Simultaneously, the rule base,

which incorporates knowledge of the relationship between mill load and product size, initiates a smooth reduction in feed rate before the product size error becomes large.

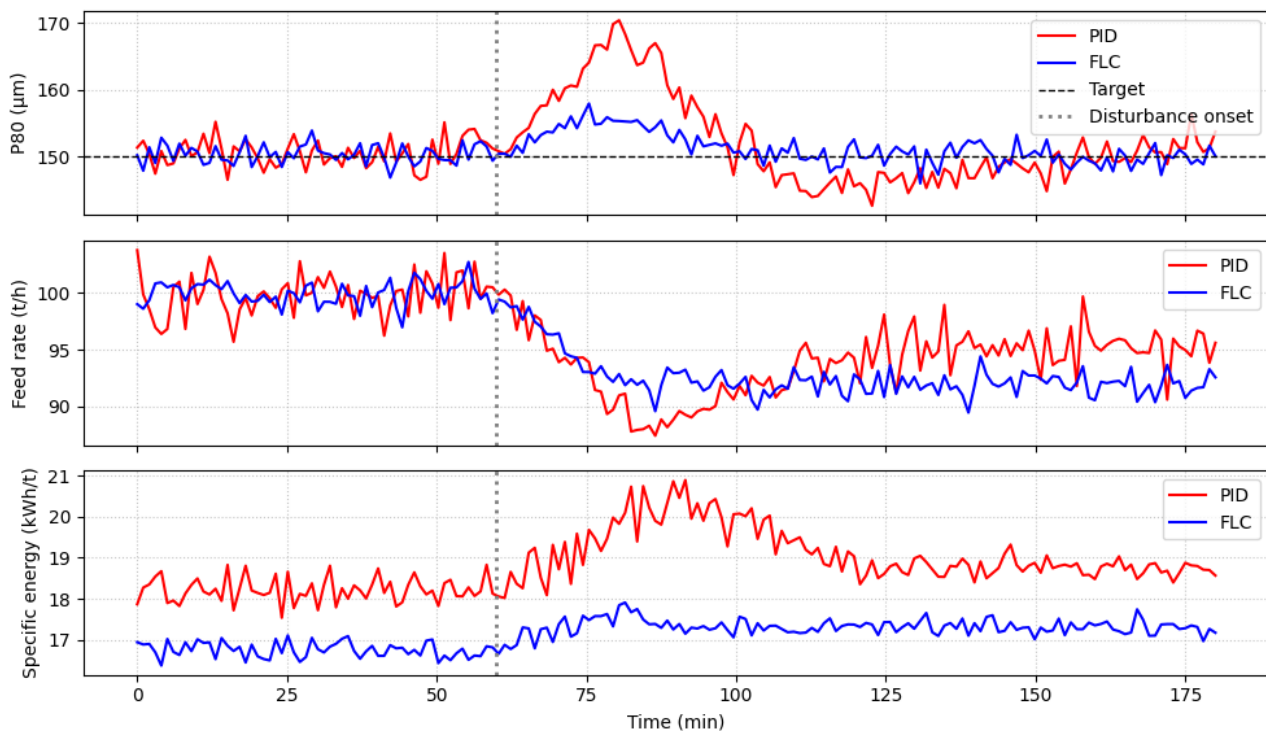


Figure 3 – Disturbance Rejection (Ore Hardness Change at $t=60$ min)

The result is a maximum deviation of only 156 micrometers in product P80, followed by a rapid return to target with minimal overshoot. The feed rate trajectory shows a single, decisive reduction followed by stabilization at the new optimal value for the harder ore. Throughout this transition, the fuzzy controller maintains the product within the specification window, ensuring consistent liberation conditions for downstream processes.

The specific energy consumption trajectories reveal the efficiency implications of these different responses. The PID controller exhibits a pronounced spike in specific energy as it over-corrects and grinds the material finer than necessary, followed by a gradual settling to the new baseline. The fuzzy controller shows a smoother transition to the higher specific energy level required for the harder ore, avoiding the wasteful over-grinding period and reducing the total energy penalty associated with the disturbance.

Energy Efficiency Analysis. A comprehensive analysis of energy performance across all test scenarios is summarized in Table 2, which presents the key metrics for both controllers averaged over multiple simulation runs with varying disturbance patterns.

The fuzzy logic controller demonstrates a 9.2 percent reduction in specific energy consumption compared to the PID benchmark, translating to energy savings of approximately 1.7 kWh for every ton of ore processed. This improvement is achieved alongside a marginal increase in throughput, indicating that the fuzzy controller not only uses energy more efficiently but also extracts greater productive capacity from

the same equipment. The dramatic reduction in P80 variance, nearly 48 percent lower than the PID controller, is particularly significant from a metallurgical perspective.

Table 2 – Comparative performance metrics for fuzzy logic and PID controllers

Metric	PID controller	Fuzzy logic controller	Improvement
Specific Energy Consumption (kWh/t)	18.4	16.7	9.2%
Throughput (t/h)	102.3	104.1	1.8%
P80 Standard Deviation (μm)	8.2	4.3	47.6%
P80 Maximum Deviation (μm)	24	11	54.2%
Settling Time After Disturbance (min)	28	14	50.0%

Consistent product size translates directly to consistent liberation conditions, which stabilizes downstream recovery processes and reduces the need for operator intervention. The 50 percent reduction in settling time following disturbances means that the circuit returns to optimal operation faster, minimizing the duration of suboptimal performance and the associated losses in recovery or efficiency.

The economic implications of these improvements are substantial. For a hypothetical processing plant treating 5 million tons of ore annually, the 9.2 percent reduction in specific energy consumption would yield annual energy savings of approximately 8.5 million kWh. At an industrial electricity rate of \$0.08 per kWh, this represents cost savings of \$680,000 per year. Beyond direct energy costs, the improved stability and consistent product quality would reduce wear on grinding media and liners, decrease maintenance requirements, and potentially increase recovery rates in downstream flotation circuits by providing more consistent feed conditions. The environmental benefits are equally significant, with the reduction in energy consumption corresponding to a decrease in greenhouse gas emissions associated with power generation, supporting sustainability objectives that are increasingly important in the mining industry.

Discussion of Adaptive Mechanism. The good performance of the fuzzy logic controller can be attributed in large part to its adaptive capability, which distinguishes it from fixed-parameter fuzzy systems. The adaptation mechanism, operating through adjustment of input and output scaling factors based on the real-time efficiency index, effectively tunes the controller's sensitivity to match prevailing process conditions. During periods of nominal ore hardness, the scaling factors maintain moderate values that provide responsive yet stable control. When the transition to harder ore occurs, the efficiency index drops, triggering an increase in the scaling factors for the error inputs. This adjustment effectively amplifies the perceived error, making the controller more aggressive in responding to deviations from target precisely when such responsiveness is needed. Simultaneously, the output scaling factors are modulated to prevent this increased sensitivity from leading to instability.

The effect of this adaptation is illustrated in Figure 4, which tracks the evolution of key scaling factors during the hardness transition scenario.

As the efficiency index declines from its nominal value of 1.0 to approximately 0.92 following the hardness increase, the scaling factor for product size error progressively increases by approximately 30 percent over a five-minute period. This gradual

adjustment prevents abrupt changes in controller behavior while ensuring that the full sensitivity is available when needed.

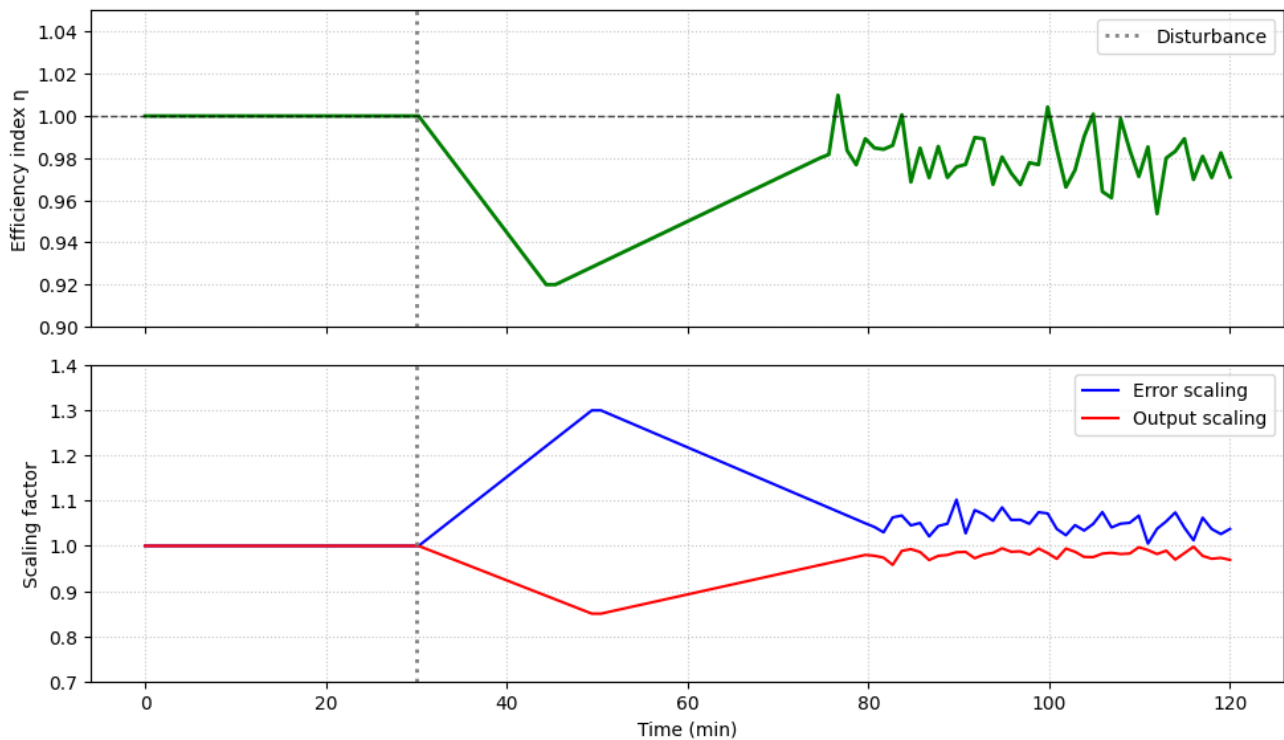


Figure 4 – Adaptive Mechanism – Response to Hardness Change

As the controller successfully returns the product to target and the efficiency index begins to recover, the scaling factors gradually return toward their baseline values, restoring the nominal controller tuning. This dynamic adjustment enables the fuzzy controller to maintain near-optimal performance across a wide range of operating conditions, effectively widening the envelope within which the circuit operates efficiently.

The importance of this adaptation becomes evident when comparing the adaptive fuzzy controller to a fixed-rule fuzzy system without adaptation. In preliminary testing not detailed here, the fixed fuzzy controller, while outperforming the PID during nominal conditions, exhibited degraded performance during the hardness transition. Without the ability to adjust its sensitivity, the fixed fuzzy controller responded either too slowly if tuned conservatively, or with excessive oscillations if tuned aggressively for the harder ore. The adaptive mechanism resolves this dilemma by allowing the controller to be simultaneously stable during nominal operation and responsive during disturbances, embodying the principle that optimal control requires flexibility in the face of changing process dynamics. This adaptive capability represents a significant advancement over conventional approaches and provides a robust foundation for industrial implementation where ore characteristics are seldom constant.

4. Conclusion

This study has demonstrated that an adaptive fuzzy logic control system can successfully reduce energy consumption in a closed-circuit grinding process while main-

taining product quality. The simulation results show a 9.2 percent reduction in specific energy consumption compared to conventional PID control, achieved through smoother operation and consistent maintenance of the mill near its optimum operating point.

Crucially, these energy savings were realized without compromising mineral liberation. The fuzzy controller actually improved product quality consistency, reducing the standard deviation of particle size by 47.6 percent. This enhanced stability provides ideal feed conditions for downstream processes and potentially improves overall recovery.

The adaptive mechanism proved essential to this performance, enabling the controller to maintain effectiveness across varying ore hardness conditions by dynamically adjusting its sensitivity. This capability addresses a fundamental limitation of fixed-parameter controllers and demonstrates that fuzzy logic control is a robust method for handling the non-linear dynamics and disturbances inherent in comminution circuits.

Future work should focus on industrial-scale implementation to validate performance under real-world conditions, and on integration with predictive control strategies to achieve further optimization gains.

Conflict of interest

Authors state no conflict of interest.

REFERENCES

1. Tao, J., Zheng, N., Wang, W., Han, T., Zhan, X. and Luan, Q. (2019), "A behavior sequence clustering-based enterprise network anomaly host recognition method", *IEEE International Conference on Big Knowledge (ICBK)*, pp. 236–241. <https://doi.org/10.1109/icbk.2019.00039>
2. Dasanayaka, S.W.S.B., Jayaratne, W., Rangajeewa, D.G.T. and Sardana, G.D. (2017), "Identification of barrier for development of the Sri Lankan small- and medium-scale gem mining enterprises: A case study based on Ratnapura district", *South Asian Journal of Business and Management Cases*, vol. 6(1), pp. 71–88. <https://doi.org/10.1177/2277977917701594>
3. Pashchenko, O.A., Khomenko, V.L., Ratov, B.T., Koroviaka, Ye.A. and Rastsvietaiev, V.O. (2024), "Comprehensive approach to calculating operational parameters in hydraulic fracturing", *IOP Conference Series: Earth and Environmental Science*, vol. 1415(1), 012080. <https://doi.org/10.1088/1755-1315/1415/1/012080>
4. Khomenko, V.L., Ratov, B.T., Pashchenko, O.A., Davydenko, O.M. and Borash, B.R. (2023), "Justification of drilling parameters of a typical well in the conditions of the Samskoye field", *IOP Conference Series: Earth and Environmental Science. Proceedings of the 4th International Conference on Sustainable Futures: Environmental, Technological, Social and Economic Matters (ICSF 2023)*, vol. 1254(1), 012052. <https://doi.org/10.1088/1755-1315/1254/1/012052>
5. Tohry, A., Yazdani, S., Hadavandi, E., Mahmudzadeh, E. and Chelgani, S.C. (2021), "Advanced modeling of HPGR power consumption based on operational parameters by BNN: A "Conscious-Lab" development", *Powder Technology*, vol. 381, pp. 280–284. <https://doi.org/10.1016/j.powtec.2020.12.018>
6. Farzanegan, A. and Ghalaei, A.E. (2015), "Simulation-assisted evaluation of grinding circuit flowsheet design alternatives: Aghdarreh gold ore processing plant", *Archives of Mining Sciences*, vol. 60(1), pp. 123–141. <https://doi.org/10.1515/amsc-2015-0009>
7. Bilesan, M.R., Makarova, I., Wickman, B. and Repo, E. (2021), "Efficient separation of precious metals from computer waste printed circuit boards by hydrocyclone and dilution-gravity methods", *Journal of Cleaner Production*, vol. 286, 125505. <https://doi.org/10.1016/j.jclepro.2020.125505>
8. Ma, L., Zhang, Y., Ren, H., Duan, J. and Lu, T. (2019), "Study on optimization control of fuzzy PID in milling and crushing system", *Chinese Control and Decision Conference (CCDC)*, pp. 4089–4093. <https://doi.org/10.1109/ccdc.2019.8833061>
9. Fang, H.Y., Yang, J.H. and Chen, Q. (2018), "Particle size distribution and energy consumption during impact crushing of single granite particles", *Journal of the Southern African Institute of Mining and Metallurgy*, vol. 118(5). <https://doi.org/10.17159/2411-9717/2018/v118n5a12>
10. Zhou, W., Han, Y., Sun, Y., Yang, J. and Ma, S. (2019), "Multi-scale impact crushing characteristics of polycrystalline sulphide ores", *Transactions of Nonferrous Metals Society of China*, vol. 29(9), pp. 1929–1938. [https://doi.org/10.1016/S1003-6326\(19\)65100-9](https://doi.org/10.1016/S1003-6326(19)65100-9)
11. Marynych, I., Serdiuk, O., Ruban, S. and Makarenko, O. (2021), "Presentation of crushing and grinding complex as system

with distributed parameters for adaptive control of ore dressing processes", *News of the National Academy of Sciences of the Republic of Kazakhstan, Series of Geology and Technical Sciences*, vol. 447(3), pp. 104–111. <https://doi.org/10.32014/2021.2518-170X.70>

12. Ye, H., Li, X., Lei, T., Li, L., Wang, Q. and Li, N. (2023), "Dynamic response characteristics and damage rule of graphite ore rock under different strain rates", *Scientific Reports*, vol. 13(1). <https://doi.org/10.1038/s41598-023-28947-9>

13. Savinyh, P., Shirobokov, V., Fedorov, O. and Ivanovs, S. (2018), "Influence of rotary grain crusher parameters on quality of finished product", *Proceedings of the 17th International Scientific Conference Engineering for Rural Development, Latvia University of Agriculture*. <https://doi.org/10.22616/erdev2018.17.n158>

14. Chen, Z., Wang, G., Xue, D. and Cui, D. (2021), "Simulation and optimization of crushing chamber of gyratory crusher based on the DEM and GA", *Powder Technology*, vol. 384, pp. 36–50. <https://doi.org/10.1016/j.powtec.2021.02.003>

15. Rodrigues, A.F.V., Delboni, H., Silva, K., Zhou, J., Galvin, K.P. and Filippov, L.O. (2023), "Transforming iron ore processing – simplifying the comminution and replacing reverse flotation with magnetic and gravity separation", *Minerals Engineering*, vol. 199, 108112. <https://doi.org/10.1016/j.mineng.2023.108112>

16. Felipe, R.A.S. and Delboni Junior, H. (2019), "Developing a stepwise approach to simulate a hammer mill through the Whiten model – the adherence for a gold ore", *REM – International Engineering Journal*, vol. 72(3), pp. 535–542. <https://doi.org/10.1590/0370-44672018720186>

АДАПТИВНЕ КЕРУВАННЯ ЦИКЛАМИ ПОДРІБНЕННЯ В ЗАМКНУТОМУ КОНТУРІ НА ОСНОВІ НЕЧІТКОЇ ЛОГІКИ ДЛЯ ЕНЕРГОЕФЕКТИВНОГО ВИДІЛЕННЯ ЦІННИХ МІНЕРАЛІВ

Коровяка Є.А., Хоменко В.Л., Пащенко О.А., Шевченко С.В., Дрешпак О.С.

Розробити та підтвердити ефективність адаптивної системи керування на основі нечіткої логіки для процесу подрібнення в замкнутому контурі, яка зменшує питоме енергоспоживання при збереженні гранулометричного складу продукту, необхідного для ефективного розкриття цінних мінералів.

Було розроблено багатовхідний та багатовихідний контролер на основі нечіткої логіки з вхідними змінними, що включають похибку крупності продукту та відхилення завантаження млина, та вихідними змінними для коригування продуктивності живлення і витрати води в зумпф. Контролер містив супервізорний адаптаційний механізм, який динамічно налаштовував вхідні та вихідні масштабуючі коефіцієнти на основі індексу енергоефективності в реальному часі. Ефективність оцінювалася шляхом моделювання з використанням валідованої динамічної моделі контуру кульового млина-гідроциклону з порівняльною оцінкою проти традиційного ПІД-регулятора в умовах постійної та змінної твердості руди.

Адаптивний нечіткий контролер забезпечив зниження питомого енергоспоживання на 9.2% порівняно з ПІД-регулятором. Стабільність гранулометричного складу продукту значно покращилася: середньоквадратичне відхилення P80 зменшилося на 47.6%, а максимальне відхилення – на 54.2%. В умовах збурень нечіткий контролер продемонстрував краще їх придушення, скоротивши час перехідного процесу на 50% та підтримуючи якість продукту в межах специфікації протягом всього перехідного періоду. Адаптаційний механізм виявився критично важливим, змінюючи масштабуючі коефіцієнти до 30% у відповідь на зміни твердості руди.

У цьому дослідженні представлено цілісну адаптивну стратегію керування на основі нечіткої логіки, спеціально розроблену для оптимізації компромісу між енергоспоживанням та якістю розкриття мінералів. Новаторська інтеграція індексу енергоефективності в реальному часі для динамічного налаштування чутливості контролера забезпечує можливість самоналаштування, яка долає обмеження контролерів з фіксованими параметрами при роботі зі змінною в часі динамікою процесу.

Продемонстрована економія енергії призводить до суттєвого зниження витрат: річна економія становить приблизно 680 000 доларів США для типової збагачувальної фабрики продуктивністю 5 мільйонів тон на рік. Покращена стабільність продукту стабілізує подальші процеси вилучення та зменшує знос обладнання. Адаптивна здатність робить контролер придатним для промислового впровадження в умовах регулярної зміни характеристик руди, пропонуючи практичний шлях до підвищення енергоефективності операцій подрібнення.

Ключові слова: керування на основі нечіткої логіки, адаптивне керування, цикл подрібнення, енергоефективність, розкриття мінералів, дезінтеграція, кульовий млин, гранулометричний склад, автоматизація технологічних процесів, запобігання збуренню.