

Article

Expert System Framework for Vertical Roller Mills Start-Up Automation in Cement Manufacturing

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Abstract

Vertical Roller Mills (VRMs) are extensively used in the cement industry for their high energy efficiency. Nonetheless, the start-up phase remains a critical operational challenge due to its pronounced sensitivity to changing process conditions. Such variations frequently induce excessive vibrations, which can trigger unplanned shutdowns, mechanical damage, and diminished throughput. The underlying cause lies in the intrinsic variability of raw materials, particularly in parameters such as moisture, particle size distribution, and hardness, which exert a direct influence on the mill's dynamic response during the transition to steady-state operation. This study presents the real-world implementation of an Expert System designed to automate the start-up sequence. By applying logical reasoning to key process setpoints, the system enables a controlled and gradual ramp-up, minimizing transient instabilities. Seamlessly integrated into the plant's control infrastructure, it facilitates remote unattended operation, enhancing process reliability and operational efficiency. The proposed architecture addresses a key challenge in cement production and enables advanced control and intelligent optimization.

Keywords: Expert Systems; advanced process control (APC); process optimization; vertical roller mill; cement industry

1. Introduction

The cement industry is one of the most energy-intensive sectors of manufacturing, with energy accounting for up to 70% of the total variable production costs of a cement plant, comprising approximately 33% for thermal energy used in clinker production and 37% for electrical energy [1]. This substantial contribution makes energy consumption a major factor in the overall economic performance and competitiveness of cement plants. According to the European Cement Research Academy (ECRA), earlier assessments estimated that comminution processes account for approximately 60–70% of the electrical energy demand of cement production, depending on cement properties [2]. Updated ECRA data indicates that, in modern dry-process cement plants, approximately 68% of the total electrical energy demand is associated with raw-material preparation and cement grinding, with 25% allocated to raw-material preparation and grinding and 43% to cement grinding [3]. This distribution underscores the pivotal role of comminution stages in shaping the plant's overall electrical energy demand. Grinding operations are inherently inefficient and energy-intensive [4], as a considerable portion of the input energy is dissipated as heat due to friction between the grinding media and the feed material. Moreover, the grinding stage exerts a decisive influence on the final product's quality and



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uniformity, directly affecting the performance of clinker hydration and the energy efficiency of subsequent pyro-processing stages. Improving the efficiency and controllability of this operation is therefore a strategic priority for reducing energy consumption and carbon emissions across the cement value chain.

Over the past decades, the Vertical Roller Mill (VRM) has emerged as the dominant technology for raw-meal and cement grinding, owing to its superior energy performance and multifunctional process integration [5]. Unlike conventional ball mills, VRMs simultaneously perform drying, grinding, separation, and pneumatic transport within a single compact unit, thereby minimizing plant footprint and eliminating auxiliary equipment such as external separators or conveyors [6]. Industrial evaluations consistently report energy savings of 40–50% compared with closed-circuit ball-mill systems, along with lower noise emissions, reduced wear rates, and improved operational stability [7,8]. Their capability to process raw feeds containing up to 20% moisture while achieving product fineness below 90 μm has established VRMs as the preferred solution for new-generation, energy-efficient cement plants [9]. Furthermore, its modular design facilitates rapid product changeover and supports advanced automation, aligning seamlessly with the cement industry's broader goals of decarbonization and digital transformation.

Despite its technological maturity, the start-up phase of a VRM continues to be one of the most critical and least automated operations in cement manufacturing. The process is characterized by strongly nonlinear dynamics and a pronounced sensitivity to fluctuations in feed moisture, particle-size distribution, and hardness, factors that directly determine the formation of the grinding bed and the stability of the pressure field within the mill [10,11]. Even minor deviations in these parameters can generate excessive vibration amplitudes, which may trigger automatic shutdowns or, in severe cases, lead to mechanical failures in rollers, hydraulic actuators, or gearboxes [12]. During the transient transition from idle to loaded operation, precise coordination among the hydraulic, pneumatic, and thermal subsystems is essential to maintain process stability. Empirical investigations have shown that improper sequencing or premature feed introduction frequently causes collapsed grinding beds, abrupt power surges, and unstable airflow patterns, all of which increase energy consumption, accelerate component wear, and impose additional mechanical stress on the drive system [13]. Because the variability of raw-material properties cannot be fully controlled, each start-up event presents a unique dynamic scenario that continues to challenge both human operators and automated control architectures, underscoring the need for intelligent, adaptive start-up strategies in modern VRM systems.

Conventional start-up procedures in VRMs are still performed under direct operator supervision, relying on manual control and empirical expertise. Experienced operators typically initiate roller descent, gradually introduce the feed and water spray, and continuously adjust separator and fan speeds while monitoring critical process indicators such as vibration velocity, differential pressure, and main motor current [12,14]. These operations depend heavily on tacit knowledge and heuristic rules accumulated through years of hands-on experience. Although skilled personnel can eventually achieve process stabilization, this manual approach is inherently non-reproducible: start-up durations vary considerably, typically between 15 and 40 min—and transient energy peaks may exceed nominal consumption by as much as 15% [11]. The reliance on individual operator judgment limits the scalability and standardization of the process, preventing consistent performance across shifts or plants. Moreover, manual interventions during transient conditions may introduce delayed or inconsistent adjustments, potentially affecting process stability [13]. In addition, safety interlocks and other safety-instrumented functions may be inadvertently placed or left in bypass during operational or maintenance activities, reducing the availability of critical safeguards and increasing process risk [15].

The progressive shift from manual supervision to knowledge-based automation in cement manufacturing has led to the development of Expert Systems and fuzzy-logic controllers aimed at replicating operator decision-making logic and improving process stability [16]. Early implementations combined model-based control with heuristic reasoning, embedding the experiential knowledge of skilled engineers into supervisory frameworks that enhanced process robustness and consistency [14,17]. In the operation of a VRM, fuzzy-PID and rule-based control architectures have achieved remarkable success in maintaining the stability of key operational variables such as outlet temperature, differential pressure, and classifier rotor speed. These systems employ linguistic inference rules that emulate the reasoning of experienced operators; for instance, when vibration increases together with differential pressure, the controller responds by reducing the feed rate [17]. These symbolic systems offer significant advantages in interpretability, transparency, and implementation feasibility [9,18], as they execute deterministic control actions with low computational demand and can be seamlessly integrated into the existing control system architecture.

Recent progress in data-driven modeling has introduced advanced machine-learning methods capable of representing the nonlinear dynamics inherent to VRM circuits. By leveraging large industrial datasets, ensemble algorithms have demonstrated strong predictive capabilities for critical output variables such as energy consumption, feed rate, and motor power, achieving high correlation accuracy in cement grinding applications [19,20]. A SHapley Additive exPlanations–Extreme Gradient Boosting (SHAP–XGBoost) framework applied to an industrial VRM successfully modeled outlet temperature and power demand with high determination coefficients, identifying working pressure and airflow as dominant influencing factors [19]. Similarly, a hybrid Light Gradient Boosting Machine (LightGBM) and Shapley Additive Explanations (SHAP) approach captured the interplay between feed rate, hydraulic pressure, and differential pressure, enabling precise estimation of mill load and energy performance [20]. In parallel, Computational Fluid Dynamics–Discrete Phase Model (CFD–DPM) multi-objective optimization has proven effective in refining air velocity, separator speed, and thermal profiles to maximize grinding efficiency and product quality [9].

Despite their predictive strength, these data-driven systems remain limited by dependence on historical datasets and reduced interpretability under uncharacterized process conditions. When exposed to novel feed chemistries or extreme moisture variations, their accuracy declines significantly, and the absence of embedded constraints restricts their applicability to safety-critical phases such as mill start-up, where deterministic and rule-based control remains indispensable [10,14]. Moreover, Computational Fluid Dynamics (CFD) studies have confirmed that unregulated air ingress and particle recirculation during milling can severely compromise throughput and efficiency, further underscoring the importance of structured, logic-based coordination during transient phases [21].

The literature reveals a clear research gap: although Expert Systems, fuzzy controllers, and data-driven methods have previously been investigated for cement grinding, the available studies predominantly address steady-state optimization, variable prediction, or simulated control scenarios. Industrial-scale implementations specifically addressing the automated execution of the VRM start-up sequence, together with long-term plant-level validation, remain scarcely documented. Data-driven models predict operating variables but do not manage sequential transitions, while existing fuzzy or rule-based controllers target continuous operation rather than transient conditions [11,14,22,23]. Manual start-up thus remains standard practice, characterized by inconsistent reproducibility, prolonged ramp-up times, and mechanical risk. There is a need for a hybrid Expert System that codifies the procedural logic of experienced operators, embeds safety interlocks, and interacts

directly with the plant distributed control system (DCS) to achieve reliable, repeatable start-ups without continuous operator supervision.

This study presents an Expert System framework designed to automate the start-up of VRMs in cement manufacturing. The system applies symbolic artificial intelligence, translating the tacit knowledge of process engineers into a rule-based architecture integrated within the Siemens PCS7 control environment [11,20]. Unlike traditional sequential automation, the proposed framework continuously evaluates process feedback—such as vibration, temperature, differential pressure, and hydraulic load—before authorizing each operational step. The rule base establishes dynamic safety thresholds and conditional transitions to ensure stable roll-down and controlled feed ramp-up under variable raw-material conditions. Its novelty resides in four core aspects: symbolic transparency, which provides explicit and traceable reasoning paths that facilitate interpretability and compliance with industrial validation standards [24]; adaptive knowledge refinement, achieved through the continuous updating of rules using post-start-up diagnostics and operator feedback [11]; industrial implementation; and long-term validation. The system operates natively within the existing DCS infrastructure, enabling remote supervision and seamless interaction with advanced process-control layers. By merging symbolic reasoning with deterministic control logic, the framework bridges the gap between human expertise and automated execution, representing a transition from data-driven prediction to knowledge-driven decision-making. It enables unattended execution of the VRM start-up sequence while preserving the existing alarm, interlock, trip, and operator-supervision functions, thereby supporting centralized and remote plant operation.

2. Process Description

VRMs constitute the core grinding technology in modern cement manufacturing due to their compact design, superior energy efficiency, and capability to integrate multiple unit operations within a single mechanical system. In contrast to conventional ball mills, these units carry out comminution, drying, and classification simultaneously, which substantially reduces specific energy demand and improves overall process robustness. In this configuration, raw materials are delivered centrally onto a horizontally rotating table, where centrifugal forces spread the material uniformly to form a stable grinding bed. Hydraulically loaded rollers apply high compressive stresses that promote interparticle crushing, generating effective size reduction while limiting impact forces and associated wear. This grinding mechanism ensures efficient material breakage, supports consistent bed formation, and contributes to the operational stability required for continuous, high-throughput cement production.

As illustrated in Figure 1, the typical architecture of this type of mill comprises the grinding table, multiple rollers mounted in rocker arms, and an integrated dynamic separator positioned above the main body. Hot process gases, originating either from the kiln system or from an auxiliary hot-gas generator, enter through the nozzle ring beneath the table and establish the drying and pneumatic conveying environment required for efficient operation. As the gas stream rises, it entrains the freshly ground particles and transports them toward the separator, where the rotor speed defines the effective cut size and regulates the classification boundary. Fine material is directed toward the product outlet, while coarser fragments are returned to the grinding zone, forming a well-balanced internal loop. This controlled circulation promotes stable bed formation, enhances operational robustness, and supports high drying efficiency. Furthermore, the integrated grinding, drying, and classification arrangement enables the mill to accommodate variations in feed moisture and particle-size distribution through coordinated adjustment of the process condition.

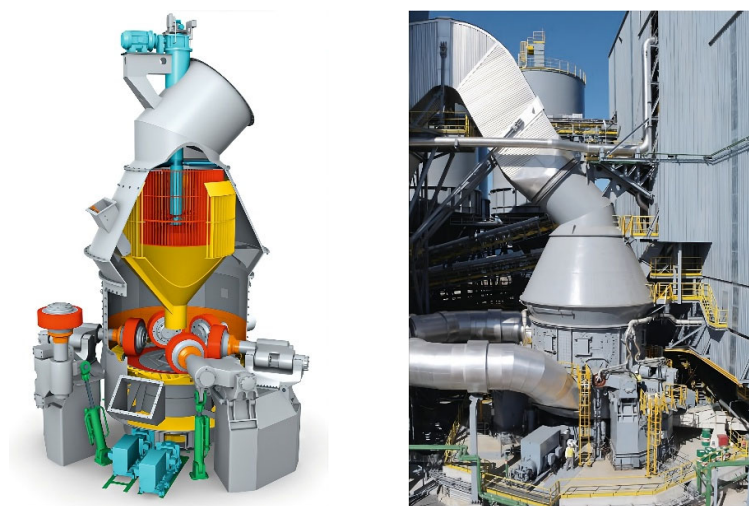


Figure 1. Pfeiffer MVR 6000 C-6 model coupled with a Multidrive® system (Gebr. Pfeiffer SE).

The model illustrated in Figure 1 represents a Pfeiffer MVR 6000 C-6 vertical roller mill (Gebr. Pfeiffer SE, Kaiserslautern, Germany) equipped with six grinding rollers, each 2120 mm in diameter, and a MultiDrive® system (Gebr. Pfeiffer SE, Kaiserslautern, Germany) with a total installed drive power of 6700 kW. In this configuration, the grinding-table drive is distributed among several independent drive modules, providing active mechanical and electrical redundancy. Together with the six-roller arrangement, this modular drive concept allows individual rollers or drive units to be taken out of service for maintenance while mill operation continues at reduced throughput. These specifications refer exclusively to the representative configuration shown in the figure and may vary depending on the material being processed, the required product fineness, and plant-specific design requirements [25].

The global process flow of the installation is depicted in Figure 2, which outlines the main mass and gas streams together with their actuators and controlled variables. Red squares identify process variables, whereas blue squares identify actuators. Blue lines represent fluid-flow paths, including the gas and water circuits, while black lines represent solid-material transport paths. The raw mix components—typically limestone, slate, pyrite, and gravel—are proportioned by independent weigh feeders, thereby regulating the fresh feed rate entering the grinding chamber. On the rotating table, the rollers generate interparticle compression, while a finely metered water injection contributes to bed stabilization and thermal management. The ground material is entrained by the upward gas stream toward the dynamic separator; particles rejected by the separator form the internal recirculation loop, returning directly to the table. Externally, a bucket elevator mechanically conveys the mill discharge back to the feed chute, closing the overall solids circuit and maintaining consistent circulation ratios.

The gas circuit governs the thermal behavior and aerodynamic conditions of the unit, with the main process fan establishing the overall gas flow and system draft, while the recirculation damper and fresh-air valve provide precise adjustments to pressure drop and particle residence time. After leaving the mill, the gas–solid suspension enters the bag filter, where the finished product is separated and collected. Temperatures and pressures at the inlets and outlets of both the mill and the filter are continuously monitored to maintain a stable thermal balance, which is essential for achieving complete drying, preventing excessive vibrations, and preserving the integrity of the grinding bed. Because grinding mechanics, gas flow, classification efficiency, and thermal regulation interact strongly, their coordination is critical. Fluctuations in moisture, grindability, or feed composition propagate through the system, altering bed thickness, separator loading, and gas velocities.

As a result, stable operation depends on rigorous control of feed rate, gas flow, separator speed, and water injection to ensure consistent product quality, reliable performance, and optimal energy efficiency.

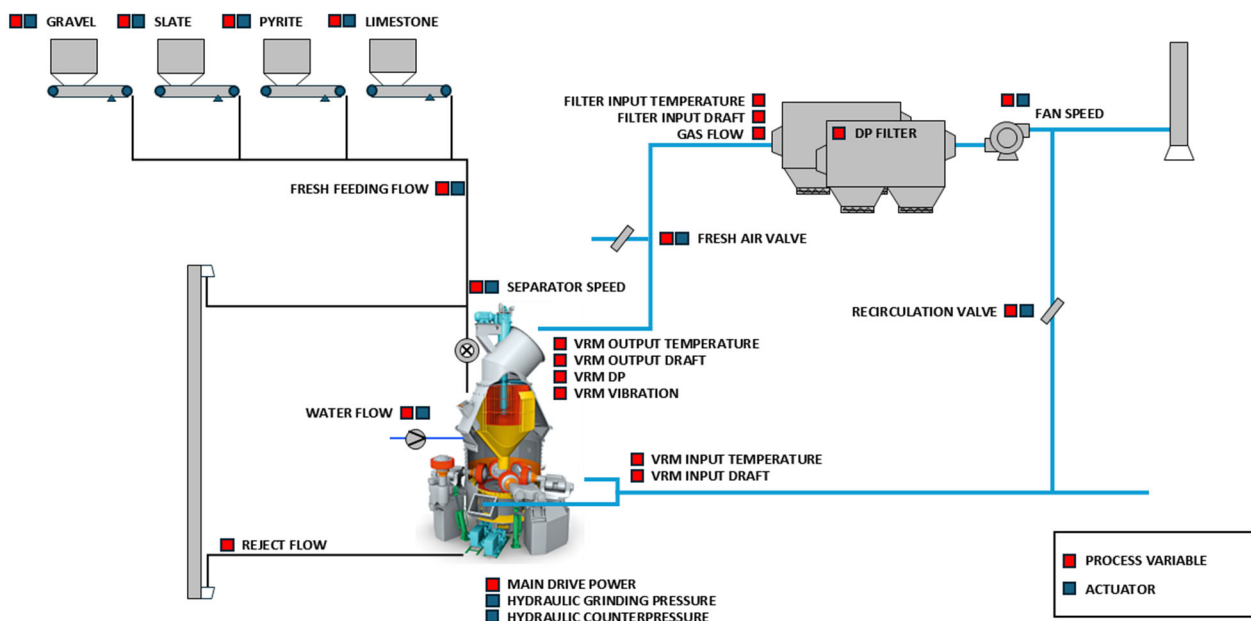


Figure 2. VRM process diagram.

3. Methodology

The methodology presented in this study is conceived as a structured strategy to overcome the automation challenges inherent to the start-up of VRMs. Rather than relying exclusively on conventional PID-based regulation or manual operator intervention, this approach incorporates a symbolic Expert System to orchestrate the transition from idle to full-load operation. This supervisory layer governs the sequence of setpoint applications, actuator engagement, and logical interlocks based on rule-based reasoning derived from best operational practices and validated plant data. Its implementation addresses the broader goal of translating experiential process knowledge into a deterministic, replicable control structure compatible with the DCS.

The rationale behind this methodology stems from the recognition that start-up complexity arises not only from equipment dynamics, but also from the need to ensure procedural consistency, safety, and efficiency across variable raw material and plant conditions. The integration of symbolic logic into the Siemens PCS7 control architecture enables standardized decision-making, while supporting transparency and traceability. This knowledge-driven approach elevates mill start-up from a reactive, experience-dependent task to a proactive, systematized operation embedded in the plant's automation layer.

The methodological architecture is structured in six interconnected stages:

- Contextualization and objective definition;
- Data acquisition and process characterization;
- Knowledge elicitation;
- Expert System architecture definition;
- Software preparation;
- Industrial implementation.

Each stage is grounded in both theoretical rigor and industrial feasibility, ensuring compatibility with standard plant instrumentation and operator workflows. This framework not only allows transparent automation of the start-up sequence but also ensures

adaptability to varying operational scenarios through the formal encoding of engineering heuristics and historical process behavior.

3.1. Contextualization and Objective Definition

The start-up phase of VRM represents one of the most critical periods in cement manufacturing from both a mechanical and process control perspective. During this transient interval, the system is subject to elevated instability due to unsteady material flow, delayed heat transfer equilibrium, and rapid variations in hydraulic pressure, gas flow, and feed composition. This volatility is particularly problematic because most industrial VRMs are equipped with vibration protection systems based on high-threshold alarms. When these limits are exceeded—even momentarily—the system executes an emergency shutdown to prevent mechanical damage, leading to production interruptions and substantial operational inefficiencies.

These repeated trips are not only detrimental to equipment health and throughput, but also severely compromise energy efficiency. The start-up sequence consumes a disproportionately high amount of energy per ton of product due to suboptimal grinding conditions and delayed process stabilization. Consequently, minimizing the duration of this phase is critical for improving overall plant performance. Furthermore, maximizing system availability by reducing unplanned shutdowns enhances the plant's ability to schedule production during periods of lower electricity tariffs, thereby reducing energy costs and improving economic performance.

Considering these challenges, a collaborative initiative was established between plant process engineers and the automation development team to design a symbolic Expert System that would ensure a consistent and repeatable start-up procedure. The aim was to formalize the accumulated best practices, previously dependent on individual operator expertise, into a deterministic rule-based framework capable of executing the entire sequence autonomously. By eliminating inter-operator variability, the system provides a reliable, transparent, and standardized methodology for start-up execution. The decision to embed this system within the PCS7 architecture further ensured its compatibility with existing instrumentation, safety interlocks, and supervisory control layers.

To ensure traceable and objective evaluation of the system's impact, a set of performance metrics was defined and consistently applied throughout the validation stage. These include:

- Specific energy consumption (kWh/t), as the main indicator of grinding efficiency, normalized to output.
- Specific CO₂ emissions (kg CO₂/t), as a proxy for environmental performance based on standardized emission factors.
- Improvement percentage, comparing average consumption before and after automation.

These metrics were selected to quantify the energy, environmental, and operational impact of automating the start-up sequence. Their inclusion allows a comprehensive assessment of system effectiveness under real-world production variability.

3.2. Data Acquisition and Process Characterization

A critical foundation for developing the Expert System was the systematic identification and characterization of the process variables that influence VRM stability during start-up and transition to steady-state operation. Unlike conventional modeling approaches that rely solely on sensor-derived data, this methodology integrates industrial operating records, incident reports, and empirical observations with domain-specific expertise from plant engineers, equipment manufacturers, and experienced operators. Table 1 summarizes

the identified parameters affecting VRM stability and classifies them according to their process category, real-time adjustability, and operational role.

Table 1. Parameters affecting VRM stability.

Parameters	Category	Real-Time Adjustment	Description
Table and roller liner wear	Installation	Not possible	Alters grinding surface uniformity and energy transfer.
Table rotation speed	Installation	Not possible	Controls material movement and residence time on table.
Dam ring height (mm)	Installation	Not possible	Limits bed depth and constrains material accumulation.
Mill body resonance	Installation	Not possible	Amplifies structural response to internal dynamic forces.
Separator efficiency (%)	Installation	Not possible	Defines coarse return rate and grinding bed texture.
Feed particle size distribution	Material property	Not possible	Modifies bed formation and contact pressure profile.
Feed moisture content (%)	Material property	Not possible	Changes cohesion and drying balance during grinding.
Feed material hardness (HB)	Material property	Not possible	Determines resistance to compression under roller load.
Mill outlet temperature (°C)	Process values	Indirect	Controls gas density and particle entrainment potential.
Mill outlet gas draft (mbar)	Process values	Indirect	Influences pneumatic transport and flow stability.
Airflow through mill (Nm ³ /h)	Process values	Indirect	Regulates drying rate and internal suspension behavior.
Mill differential pressure (mbar)	Process values	Indirect	Indicates internal load and circulation resistance.
Mill main drive power (kW)	Process values	Indirect	Indicates grinding load and energy transfer efficiency.
Recirculation rate (t/h)	Process values	Indirect	Indicates material fallback and internal loading stability.
Mill vibration (mm/s)	Process values	Indirect	Represents dynamic instability and mechanical imbalance.
Bed thickness (mm)	Process value	Indirect	Governs force absorption zone and bed stability.
Start-up material load (t)	Process values	Indirect	Sets initial bed condition for ramp-up stability.
Fresh feed rate (t/h)	Actuator	Direct	Determines material input and bed build-up dynamics.
Separator speed (%)	Actuator	Direct	Alters cut size and product fineness distribution.
Fan speed (%)	Actuator	Direct	Regulates airflow rate and system pressure profile.
Recirculation valve (%)	Actuator	Direct	Adjusts hot gas return and internal flow balance.
Fresh air valve (%)	Actuator	Direct	Controls inlet air for cooling and dilution effect.
Hydraulic grinding pressure (bar)	Actuator	Direct	Sets roller load applied to the grinding bed.
Hydraulic counterpressure (bar)	Actuator	Direct	Dampens load fluctuations and stabilizes roller contact.
Water injection flow (m ³ /h)	Actuator	Direct	Adjusts moisture and cooling at the grinding zone.

The operational data used in this study were provided by the plant owner and extracted from the company's official production-reporting tools. The datasets consisted of industrial production and energy-performance records that had been anonymized by the data owner before being made available to the authors. The authors did not have access to the original raw sensor-level DCS data or to the internal data-processing procedures applied within the reporting environment. Consequently, no additional filtering of abnormal measurements, missing-value imputation, outlier removal, or time synchronization was performed by the authors.

A critical distinction was established between variables that can be directly manipulated in real time and those that are adjusted only indirectly because of broader process dynamics. Parameters such as material hardness or liner wear, while not accessible for online control, were nonetheless integrated into the system as boundary conditions that constrain operational thresholds and influence control decisions. This classification played a central role in shaping the structure of the Expert System's rule base, enabling a clear differentiation between actively controllable levers and contextual state indicators used to assess system readiness and trigger transitions between operational phases. The resulting taxonomy of variables, developed from operational records, empirical observations, and domain-specific expert knowledge, forms the foundational layer in which the subsequent rule formalization and decision-making logic are built.

3.3. Knowledge Elicitation

Among all methodological stages, the knowledge elicitation phase proved to be the most time-intensive and critical for the successful design of the Expert System. This is attributable to the inherent complexity of the VRM, which has historically been the most demanding unit in cement production plants in terms of control and supervision. Its multi-variable nature, sensitivity to raw material variation, and interaction between hydraulic,

pneumatic, and thermal subsystems required constant operator attention—particularly during start-up—resulting in a highly operator-dependent process. Over a period exceeding four years, plant engineers systematically gathered operational records, performance logs, incident reports, and empirical observations to compile a comprehensive basis for further knowledge formalization.

A crucial conceptual distinction was made between explicit knowledge—such as written Standard Operating Procedures (SOPs), alarm setpoints, and interlock diagrams—and tacit knowledge, which resided in the experiential intuition and situational awareness of veteran operators. While explicit information provided the structural foundation for rule formulation, tacit knowledge proved essential for capturing the nuances of real-world process behavior, including how operators interpret evolving trends and anticipate system responses not easily captured by sensors. Tacit knowledge was elicited through structured interviews, collaborative sessions, and interactive walkthroughs during actual start-up operations. Operators were encouraged to verbalize their decision-making processes, describe reaction patterns under different scenarios, and highlight conditions that historically led to vibration alarms or unstable behavior. These qualitative insights were then cross-referenced with logged process data to identify reproducible logic patterns.

The combination of both knowledge forms enabled the creation of a hierarchical rule base composed of conditional statements, temporal interlocks, and dynamic thresholds. Particular attention was paid to resolving potential rule conflicts, redundancies, or operator disagreements through iterative validation loops and simulation-based testing. As a result, the Expert System's logic structure captures both the formalized control philosophy of the plant and the embedded operational experience, ensuring robust and context-aware decision-making under variable process conditions.

3.4. Expert System Architecture Definition

Building on the structured knowledge extracted from plant personnel and formalized in the preceding stages, the architecture of the Expert System was designed to operationalize this knowledge into an executable control framework. At the core of the proposed automation strategy lies a symbolic Expert System specifically configured to manage the start-up sequence of the VRM in a safe, consistent, and adaptive manner. The system comprises three primary components: an inference engine, responsible for executing logical reasoning based on real-time process conditions; a knowledge base, which encodes conditional rules, heuristics, and empirically derived control thresholds; and an interface layer, which facilitates bidirectional communication with the DCS, implemented here through Siemens PCS7. The overall architecture adheres to recognized industrial standards for process safety, traceability, and operator intervention, ensuring both robustness and transparency in its supervisory function.

From an implementation perspective, the Expert System acts as a supervisory layer interfacing seamlessly with the Siemens PCS7 control environment. Communication with lower-level Programmable Logic Controllers (PLCs) and field instruments is handled via industrial protocols such as OPC DA/UA and Profibus, ensuring robust real-time data exchange. All system transitions are logged and visualized through the Human–Machine Interface (HMI), facilitating full traceability and operator awareness. Internally, the rule base relies on symbolic reasoning, Boolean conditions, and timers to enforce interlocks and limit compliance. These features ensure consistent operation within mechanical and thermal constraints while supporting unattended automated execution of the start-up sequence within the plant's existing supervisory and safety framework.

The parameter classification previously introduced in Table 1, especially the delineation between directly adjustable variables and those influenced indirectly through dy-

dynamic process, played a decisive role in shaping the structure of the Expert System's rule base. This taxonomy not only informed the prioritization of control levers but also established the conditional dependencies and interlocks required for safe progression through the start-up sequence. Each rule was formulated with explicit reference to the manipulability, latency, and process impact of the associated variable, ensuring that transitions occur only under verifiable and stable operating conditions.

The decision thresholds and operating setpoints are configured and periodically reviewed by plant personnel within the control system when changes in raw-material characteristics, equipment condition, or operating requirements make adjustment necessary. Their initial values were established primarily based on the industrial experience of the plant process engineers, supported by historical operating records and observations collected during previous start-up events. During commissioning, these values were reviewed and progressively refined through iterative validation under actual process conditions. This configuration-based approach allows the thresholds to be adapted to changes in raw-material characteristics, equipment condition, and plant operating requirements while preserving operator oversight and process safety. In the future evolution of the system, this manually supervised configuration could be complemented by a data-driven, subsymbolic AI layer capable of recommending or dynamically refining threshold values, while retaining the symbolic rule base as the transparent and safety-constrained decision layer.

The resulting control logic is represented schematically in Figure 3, which outlines the Expert System's sequential decision-making structure. The start-up procedure is articulated through nine interdependent stages, each governed by predefined criteria and real-time process validation.

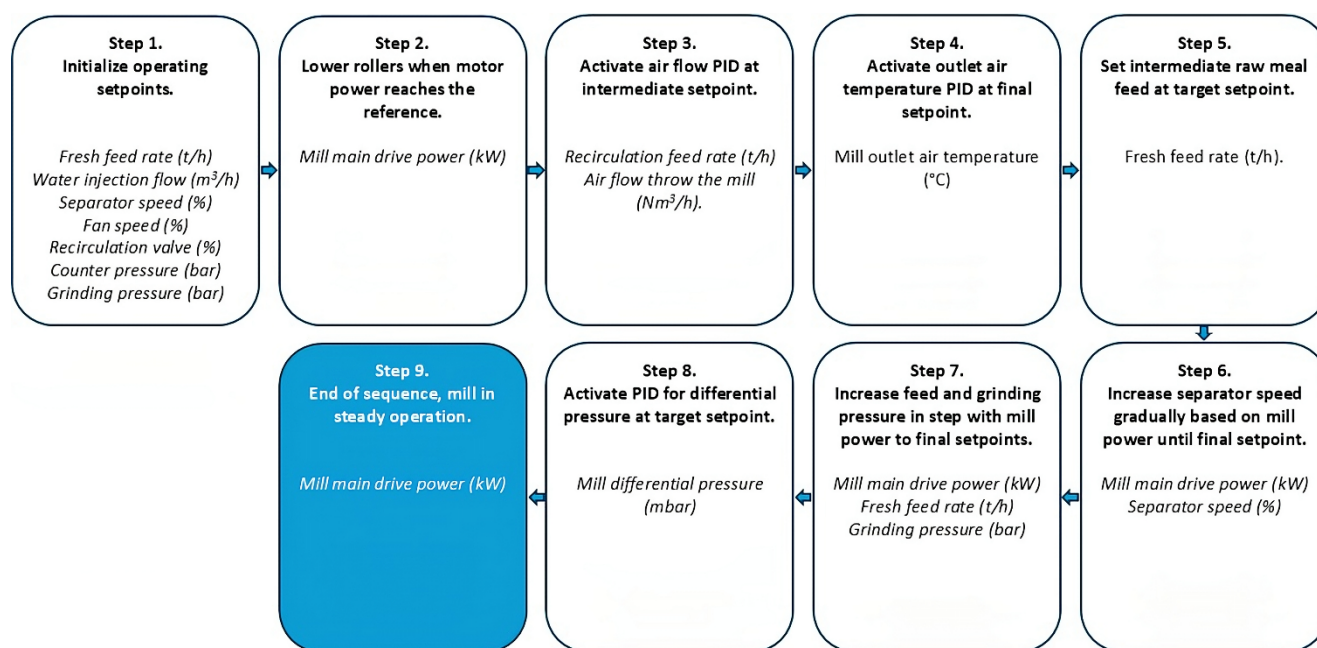


Figure 3. Sequential flowchart of the automatic start-up procedure for a VRM.

- *Step 1: Initialize operating setpoints.* The system loads the active validated configuration for the main actuators, including fresh feed rate, water injection, separator speed, fan speed, recirculation valve position, grinding pressure, and counterpressure. These parameters are configurable and may be periodically reviewed by plant personnel when changes in raw-material characteristics, equipment condition, or operating requirements make adjustment necessary. During routine start-up, the Expert System

applies the active configuration automatically and proceeds according to the real-time process conditions.

- *Step 2: Lower rollers when motor power reaches reference.* The descent of the grinding rollers is initiated once the main drive power reaches a predefined threshold, indicating sufficient material accumulation on the grinding table and adequate torque to support the grinding process. This condition ensures mechanical engagement under stable load conditions, preventing premature contact between rollers and table that could induce vibration or mechanical stress.
- *Step 3: Activate airflow PID at intermediate setpoint.* Once the rollers are fully engaged and the internal recirculation rate is sufficiently low, the airflow through the mill is regulated to an intermediate setpoint via a PID controller. This staged control stabilizes the internal gas dynamics and material suspension, reducing the risk of pressure surges or excessive velocity that could destabilize the grinding bed.
- *Step 4: Activate outlet air temperature PID at final setpoint.* Once the mill airflow reaches the intermediate target and the recirculation rate remains below the defined threshold, the outlet air temperature control loop is activated at its final setpoint. This step enables progressive reduction in the initial excess water dosage defined in Step 1, stabilizing thermal conditions across the grinding zone. Achieving the target outlet temperature is essential to ensure proper material drying and promote the formation of a uniform and stable grinding bed.
- *Step 5: Set Intermediate raw meal feed at target setpoint.* The raw meal feed rate gradually increased to an intermediate setpoint defined during initialization. This controlled ramp-up promotes consistent grinding bed formation and facilitates thermal equilibrium within the mill, ensuring stable conditions for the subsequent increase in process load.
- *Step 6: Increase separator speed gradually based on mill power.* Separator speed is progressively increased in discrete steps to approach the target fineness as early as feasible, while ensuring that the absorbed motor power remains within safe operating limits. Ramp-up is conditioned on mill power exceeding a defined threshold, guaranteeing sufficient grinding energy before intensifying particle classification.
- *Step 7: Increase feeding and grinding pressure based on mill power.* Once the separator reaches its nominal speed, both the raw meal feed rate and hydraulic grinding pressure are increased concurrently, following a ramp profile driven by the mill's main drive power. This ensures that the grinding load rises in coordination with the system's energy capacity, avoiding mechanical overload and maintaining process stability.
- *Step 8: Activate PID for differential pressure at target setpoint.* Once the feeding rate, grinding pressure, and separator speed have stabilized, the Expert System activates closed-loop control of the mill differential pressure. This regulation ensures balanced internal circulation and maintains the pressure gradient required for efficient material transport and particle separation.
- *Step 9: End of sequence, mill in steady operation.* After completing all transitional stages, the Expert System concludes the start-up sequence and transfers control to standard regulatory loops. At this point, the mill operates under steady-state conditions, with all process variables stabilized and maintained automatically through conventional PID control.

This architecture guarantees that each transition within the start-up sequence is both condition-driven and reversible. Should any monitored process variable, such as excessive vibration, abnormal differential pressure, or unstable airflow, deviate beyond its designated operational envelope, the system halts progression, triggers alarms, and may initiate rollback procedures. These safeguards prevent premature or unsafe transitions, ensuring

mechanical integrity and protecting critical components during the most sensitive phases of start-up.

A fundamental strength of the Expert System lies in its capacity to adapt to a wide range of operational scenarios and raw material conditions. Before initiating the automated sequence, operators are granted full flexibility to configure the reference setpoints for each of the primary actuators. This capability enables precise adjustment of the start-up logic in response to specific material characteristics, including moisture content, particle size distribution, and grinding resistance, as well as to the mechanical condition of internal components such as the grinding rollers and table liners. In addition, the modular architecture of the rule base facilitates future enhancements or reconfigurations without compromising the integrity or stability of the core control logic. This feature is particularly valuable for long-term maintainability and supports transfer to other VRM installations, provided that plant-specific process variables, thresholds, interlocks, actuator limits, and operating sequences are revalidated before deployment. New rule layers, including those accounting for environmental factors such as external temperature and humidity or upstream process variables like silo levels and feed availability, can be seamlessly incorporated. As a result, the Expert System provides not only robust execution of the start-up procedure but also a framework for continuous improvement and cross-process coordination.

3.5. Industrial Implementation

The final phase of the methodological framework involved the structured implementation of the Expert System within the industrial control architecture. This step was designed not only as a technical integration exercise but also as an organizational process requiring close coordination with plant operators, maintenance engineers, and automation specialists. The objective was to ensure that the symbolic Expert System—developed in prior stages through rule formalization and logic design—could be deployed safely, transparently, and sustainably within the real-time constraints of a working cement plant.

To initiate the integration, a joint evaluation of the existing DCS, built on Siemens PCS7, was carried out in close coordination with the plant's automation team. This phase involved selecting appropriate PLCs to host the Expert System, assessing computational capacity, and verifying process cycle times to ensure real-time operability. Prior to engaging live actuators, the system was deployed in open-loop mode, allowing its decisions to be simulated and monitored without impacting physical equipment. This virtual environment provided a robust platform for validating rule logic, testing communication interfaces, and assessing failure responses. Comparable strategies based on digital twin technology [26] have proven effective for validating control logic and optimizing process conditions in mill operations, underscoring the advantages of virtual commissioning as a safe and efficient precursor to full-scale deployment.

In parallel, dedicated sessions were held with control room staff and process engineers to validate the symbolic rule base under actual process conditions. Feedback collected during this stage was used to refine logical thresholds and adapt sequences to specific operational constraints. Only after multiple validation rounds and risk assessments—in line with standard Failure Mode and Effects Analysis (FMEA) methodology—was the system gradually transitioned to closed-loop control.

Crucially, implementation was not limited to technical deployment. Special emphasis was placed on building operational familiarity through training and cross-functional collaboration. Operators were encouraged to contribute to the refinement of rules and thresholds, fostering a sense of shared ownership. This participatory approach ensured that the system was not only integrated, but also understood, trusted, and maintainable by local teams, setting the foundation for long-term operability and future expansion.

4. Result and Discussion

The evaluation of the proposed Expert System was carried out under real industrial operating conditions in a full-scale cement production facility equipped with a VRM for raw material grinding. The study covered several years of operation and therefore provided a dataset reflecting realistic process variability. However, the extended observation period also introduced potential sources of temporal variability that could not be controlled independently, including changes in feed composition, raw-material moisture, ambient conditions, production schedules, maintenance activities, equipment condition, and operating strategies. Moreover, because the intervention directly addressed the start-up sequence, while the reported energy indicator reflects overall mill operation, the contribution of start-up automation to the observed reduction in annual specific electrical energy consumption could not be quantified independently. Accordingly, the observed reduction should be interpreted as a temporal association with the Expert System operating period rather than as an effect attributable exclusively to the automated start-up procedure.

The baseline configuration corresponded to the conventional manual ramp-up routine performed by experienced operators. This procedure was characterized by high dependence on operator judgment, inconsistent ramp trajectories, and frequent vibration events requiring corrective intervention. After the deployment of the expert-rule framework, the start-up sequence was executed automatically without continuous operator supervision, through a rule-based reasoning structure embedded in the Siemens PCS7 control environment, ensuring continuous coordination with existing process control loops. The analysis therefore focused on quantifying, through long-term operational data, the extent to which symbolic logic enhanced electrical performance, process stability, and overall reliability of the installation.

4.1. Operational Performance

The evaluation of operational performance was based on multi-year datasets extracted from the plant owner's official production-reporting system. The anonymized records consisted of validated production and energy-performance data rather than raw sensor-level DCS signals. They provide an extensive retrospective view of operation under actual industrial conditions, covering both the start-up and steady-state phases before and after implementation of the Expert System.

Two operating periods were defined for comparative analysis. The traditional-operation period comprised Years 1–3, whereas the Expert System period comprised Years 5–6. Year 4 was excluded from the direct comparison because it represented a transition period during which manual operation and progressive implementation of the Expert System coexisted. Months with zero production were classified as non-operating periods and were excluded from the monthly statistical analysis.

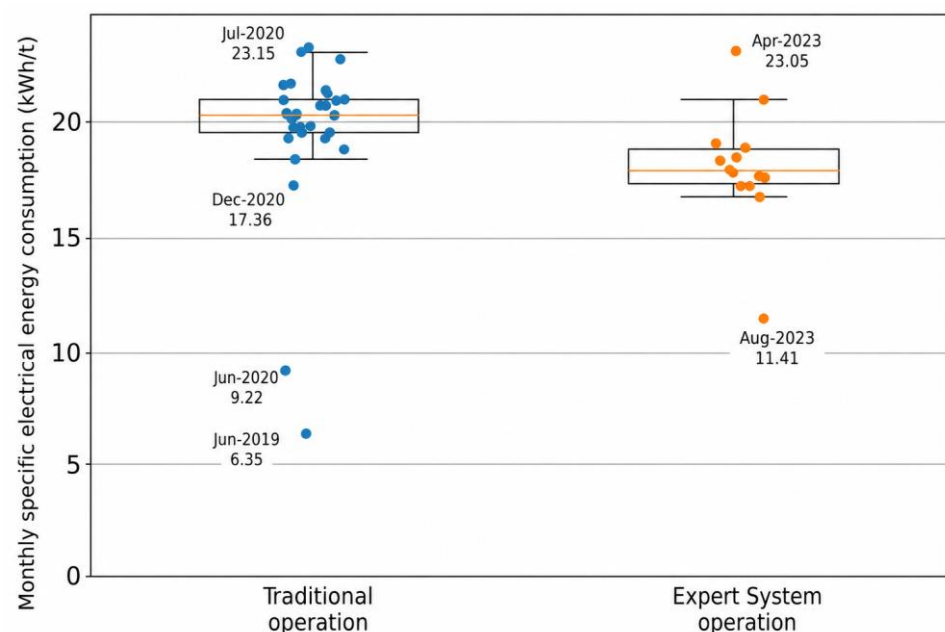
To characterize the central tendency and variability of the specific electrical energy consumption data, monthly observations were analysed separately for the traditional-operation and Expert System periods. The traditional-operation period comprised 29 productive months, whereas the Expert System period comprised 14 productive months. The resulting descriptive statistics are presented in Table 2.

As shown in Table 2, mean monthly specific electrical energy consumption was 19.56 kWh/t during traditional operation and 18.10 kWh/t during Expert System operation. Median consumption was 20.30 and 17.98 kWh/t, respectively. In addition, the standard deviation decreased from 3.52 to 2.52 kWh/t, while the coefficient of variation decreased from 18.01% to 13.91%. These descriptive results, together with the monthly distributions shown in Figure 4, indicate that the Expert System operating period was associated with lower monthly specific electrical energy consumption and reduced variability.

Table 2. Descriptive statistical comparison of monthly specific electrical energy consumption.

Statistic	Traditional Operation	Expert System Operation
Productive months, <i>n</i>	29	14
Mean, kWh/t	19.56	18.10
Standard deviation, kWh/t	3.52	2.52
Coefficient of variation, %	18.01	13.91
Median, kWh/t	20.30	17.98
Interquartile range, kWh/t	19.57–20.96	17.43–18.87

Figure 4 presents the monthly distributions for the two operating periods. The boxes represent the interquartile range, the horizontal lines indicate the median, the whiskers extend to the most extreme observations within $1.5 \times \text{IQR}$, and the labelled points identify statistical outliers according to the Tukey criterion. The figure shows that the relatively large standard deviations compared with the interquartile ranges are primarily associated with a small number of observations located outside the central concentration of the monthly data. Using this criterion, June 2019, June 2020, July 2020, and December 2020 were identified as statistical outliers during traditional operation, whereas April 2023 and August 2023 were identified during Expert System operation. Most observations in both periods remained concentrated within substantially narrower interquartile ranges. These statistical outliers should not necessarily be interpreted as measurement errors or invalid operating records. The outlying observations were retained because they correspond to productive months included in the plant owner's validated reporting dataset and could not be confirmed as measurement errors from the available information.

**Figure 4.** Distribution of monthly specific electrical energy consumption by operating period.

A limitation of this long-term assessment is that sufficiently granular time-series data were not consistently available for all relevant start-up and process variables. Consequently, the specific operating conditions associated with the statistical outliers shown in Figure 4 could not be reconstructed or independently verified. Given the extended period covered by the study, the individual effects of these variables could not be reliably isolated from other temporal and operational influences. Nevertheless, the assessment was based on anonymized real-world data from production reports validated by the plant owner, and all

productive-month observations were retained in the analysis. Together with the statistical metrics presented, these data support a comparative assessment of the operational impact associated with the implementation of the Expert System.

To complement the monthly descriptive and distributional analyses presented in Table 2 and Figure 4, annual production, electrical energy consumption, specific electrical energy consumption, estimated CO₂ emissions, and the descriptive improvement indicator were also examined. Because total production, energy use, and CO₂ emissions may vary as a result of plant demand, feed characteristics, operating schedules, and other production conditions, the absolute annual values are provided primarily for contextual interpretation. The annual indicators are summarized in Table 3.

Table 3. Comparison of performance before and after implementation of the VRM start-up Expert System.

Years	Production [t]	Energy [MWh]	CO ₂ Emissions [t]	CO ₂ Emissions [kg CO ₂ /t]	Electrical Consumption [kWh/t]	Improvement [%]	Type of Control
1	494,295	10,079	2906	5.88	20.39	Reference	Traditional
2	455,859	9090	2621	5.75	19.94		Traditional
3	471,035	9666	2787	5.92	20.52		Traditional
4	439,764	8514	2455	5.58	19.36	Transition	Transition
5	475,879	8604	2481	5.21	18.08	9.97	Expert System
6	122,834	2333	672	5.47	18.99		Expert System

The comparison between operating regimes indicated lower specific electrical energy consumption during the Expert System period. The analysis considered two distinct phases: traditional operation during Years 1–3 and Expert System operation during Years 5–6, while Year 4 was excluded from the direct comparison because it represented a transitional period in which both operating modes coexisted. Year 6 corresponds to a partial-year dataset comprising only March, April, and May, during which the raw mill produced 122,834 t. Plant operation subsequently ceased temporarily as part of its transformation into a grinding centre, which explains the markedly lower production reported for that year.

The improvement in specific electrical energy consumption was calculated using a production-weighted average based on the aggregated energy consumption and total production of each operating period. This calculation showed a 9.97% reduction during Expert System operation compared with manual operation. Given the retrospective and observational nature of the comparison, this reduction should be interpreted as an association with the Expert System operating period rather than as an effect attributable exclusively to the automated start-up procedure.

Comparable improvements in energy performance have been reported in the recent literature, further validating the relevance of the results achieved. Ma et al. [17] demonstrated that fuzzy predictive control applied to cement grinding can significantly enhance process stability and energy efficiency, underscoring the capability of symbolic-logic-based control strategies to manage highly nonlinear and transient operating conditions. Paredes et al. [27] observed up to 14% savings in specific energy consumption through the optimization of VRM parameters, although these improvements were partly attributable to circuit design adjustments. In contrast, the symbolic Expert System presented here achieved stable performance across varying raw-material conditions without requiring structural modifications to the grinding circuit. Notably, no previous study was identified that explicitly addressed the mitigation of mechanical vibrations and enhancement of operational reliability during the start-up phase, reinforcing the novelty and industrial significance of the proposed contribution.

Beyond the direct reduction in energy demand, automation generated additional operational benefits that strengthened overall plant performance. The Expert System enhanced process reliability and equipment availability, reducing unplanned interruptions and improving production scheduling flexibility. This increased stability allowed the plant to align mill operation with periods of lower electricity tariffs, thereby lowering the specific manufacturing cost and reinforcing the economic viability of the automation strategy. These outcomes confirm that the integration of symbolic artificial intelligence not only improved energy efficiency but also enhanced the predictability and continuity of industrial operation.

From an environmental standpoint, the decrease in specific energy consumption brought a proportional reduction in indirect CO₂ emissions, which declined from an average of 5.85 to 5.27 kg CO₂ per ton of raw meal. Although calculated using standard emission factors for electrical energy, this reduction provides a reliable indication of the system's contribution to the facility's decarbonization objectives and alignment with international efficiency standards. Furthermore, the Expert System introduced qualitative improvements in operational consistency by standardizing the start-up logic and minimizing dependence on operator judgment. This reproducibility increased the Mean Time Between Failures (MTBF), reduced maintenance interventions associated with transient mechanical stress and consolidated the long-term sustainability of the grinding process.

The improvement originated from the Expert System's capacity to manage the start-up sequence as a progressive, self-regulating process, continuously adapting key control variables, such as separator speed, hydraulic pressure, and feed rate, according to real-time feedback from the mill. This adaptive coordination maintained optimal grinding conditions during the critical transition phase, preventing abrupt load variations and stabilizing material flow within the grinding bed. Consequently, the start-up evolved in a controlled and predictable manner, characterized by smoother acceleration profiles and faster attainment of steady-state operation. These dynamic adjustments effectively suppressed transient oscillations, eliminating energy peaks, reducing mechanical stress and vibration levels, and lowering the occurrence of safety-triggered shutdowns.

Critically, the symbolic reasoning framework deployed in this study demonstrated superior adaptability under real-world process variability, particularly when compared to black-box neural models. Belmajdoub et al. [11] emphasized that variations in operational parameters such as hydraulic pressure, feed rate, and mill outlet temperature substantially influence both energy consumption and mill vibration yet are often under-characterized in standard datasets. Fatahi et al. [19] further confirm that working pressure and gas input are the dominant contributors to VRM energy demand, highlighting the limitations of purely data-driven models when raw-material conditions fluctuate. In contrast, the symbolic system implemented here encodes expert knowledge into explicit rules that can be adjusted as operating conditions evolve. This knowledge-driven approach supports transparent and robust decision-making in industrial settings, particularly during transient regimes in which purely data-driven models may encounter previously unseen operating conditions.

4.2. Challenges Encountered

Despite the successful deployment and demonstrated performance gains of the Expert System, several challenges emerged during its development and implementation that required iterative refinement and engineering adaptations. One of the primary difficulties stemmed from the inherent variability of the raw material feed. Although the Expert System was designed to interpret moisture, particle size distribution, and hardness as rule inputs, the lack of real-time, high-resolution measurements for these parameters constrained the precision of inference during the initial deployment stages. As highlighted

by Sahasrabudhe et al. [14], fluctuations in raw material properties, especially in terms of chemical and mineralogical composition, remain one of the major sources of instability in cement manufacturing and must be explicitly addressed by control architectures to avoid energy and quality penalties.

Another key challenge involved integrating the symbolic logic into the Siemens PCS7 control infrastructure while preserving both system responsiveness and adherence to safety interlocks. This demanded the development of a robust interface layer capable of synchronizing the Expert System's supervisory logic with the underlying PID loops. Special care was required to prevent conflicts between rule-based decisions and protective control actions triggered by vibration, torque, or pressure thresholds. Multiple tuning iterations were carried out to balance energy efficiency with operational safety, particularly during unstable feed conditions and post-maintenance restarts. The mechanical vulnerability of VRM components under adverse conditions—such as unbalanced pressure distribution or irregular ramp-up—is well documented in recent failure analysis studies [28], reinforcing the importance of structured, logic-based start-up strategies. These integration challenges align with broader safety automation principles for safety-critical systems, where embedded logic must be designed to ensure fail-safe operation without introducing latent hazards [29,30].

Moreover, expert knowledge codification posed a critical challenge in translating tacit operational strategies into formal logic constructs. While experienced process engineers provided invaluable heuristics, their integration into an automated reasoning framework required multiple validation cycles. Certain decision rules, particularly those involving sequencing of separator speed and feed rate under specific ambient conditions, had to be redefined to capture their intended behavior under edge-case scenarios. This iterative knowledge engineering process proved essential in enhancing the system's reliability and reducing false-positive rule triggers.

Finally, organizational and human-factor considerations also played a role in the initial adoption phase. Operators accustomed to manual start-up routines expressed reservations about the transparency and controllability of the automated logic. To address these concerns, a visualization layer was developed within the PCS7 interface to provide real-time insight into rule activations and system decisions, which improved user acceptance and trust. Collectively, these challenges informed refinements that strengthened the system's robustness under the operating conditions considered during implementation. Nevertheless, the retrospective nature of the long-term comparison did not allow the influence of changes in raw materials, maintenance, equipment condition, production strategy, auxiliary systems, or seasonal conditions to be isolated independently.

4.3. Technical Implications

The implementation of a symbolic Expert System for VRM start-up entails significant technical implications that extend beyond immediate performance enhancements. By formalizing expert decision logic into structured, rule-based sequences, the system introduces a mechanism for standardizing complex control procedures across industrial units. This codification enables not only local performance gains but also facilitates broader replication and consistency across facilities. When integrated into a distributed control system like Siemens PCS7, the expert rules function as a supervisory layer interacting in real time with underlying PID loops, preserving process continuity while guiding strategic decisions. This integration must be engineered with care to maintain compliance with real-time execution and safety interlocks, but once established, it supports seamless interaction between human-expert-derived logic and automated process control.

The deployment has demonstrated how knowledge-based automation can enforce procedural consistency across start-up operations. By eliminating variability associated with human-dependent sequences, the Expert System ensures that the mill transitions predictably to stable operating conditions, regardless of external disturbances. This uniformity simplifies training requirements and enhances transparency in operation, a key factor for regulatory compliance and quality assurance frameworks. By embedding energy consumption constraints and operational safeguards directly into the decision logic, the system contributes to the plant's environmental compliance efforts, offering a traceable and auditable route to reducing energy-related emissions.

Another critical implication lies in the scalability of the rule-based architecture. The modularity of symbolic logic permits straightforward expansion of the knowledge base, whether for future mill upgrades, integration with other grinding lines, or application in other process units. This creates a pathway toward standardizing automation strategies across production lines while still allowing localized rule adjustments based on material properties or plant-specific configurations. Furthermore, this modular design provides a natural foundation for the development of hybrid control architectures that merge symbolic reasoning with data-driven statistical models, an approach increasingly recognized as essential for robust monitoring and decision-making in complex industrial environments [31]. While symbolic logic provides deterministic and explainable behavior under known conditions, historical data from system operation can inform machine learning models that fine-tune parameters, predict anomalies, or suggest improvements to rule definitions. This symbiotic architecture enhances adaptability without sacrificing transparency, addressing a known limitation of purely black-box approaches in safety-critical systems.

The broader applicability of this framework extends to other industrial sectors that employ VRMs in energy-intensive grinding operations, where start-up phases are particularly sensitive to inefficiencies and mechanical stress. Beyond cement manufacturing, VRMs are increasingly adopted in the production of slag cement, industrial minerals, and coal grinding for power generation, contexts that similarly require tight coordination of load, pressure, and feed parameters during ramp-up. In these applications, symbolic Expert Systems offer a compelling solution by embedding domain-specific heuristics into the automation layer, enhancing process stability while minimizing equipment wear. The case of the VRM start-up illustrates how codified expert knowledge becomes a durable and transferable digital asset. This not only reinforces control system resilience but also advances strategic objectives such as energy optimization, reliability, and intelligent process standardization. By translating operator expertise into formal logic, the approach establishes a scalable and transparent automation model that supports long-term efficiency and sustainability across VRM-equipped facilities.

4.4. Study Limitations

This study has several limitations that should be considered when interpreting its findings. First, the Expert System framework was implemented and evaluated in a single cement plant and for one specific VRM configuration. Consequently, the numerical thresholds, actuator ranges, safety interlocks, and individual decision rules are plant-specific and cannot be transferred directly to other installations without local adaptation and validation. Second, the comparison was conducted under actual plant operating conditions over an extended period, during which raw-material properties, ambient conditions, maintenance activities, equipment condition, production schedules, and operating strategies varied. These factors could not be controlled independently and may have influenced the observed differences between the manual and automated operating periods. Third, the availability and temporal resolution of some process measurements were limited, particularly for

certain feed properties and start-up variables, preventing a detailed time-series assessment of their individual effects. Finally, the evaluation was retrospective and observational rather than based on a controlled experimental design. The reported results should therefore be interpreted as evidence of an association between Expert System implementation and the observed operational improvements, rather than as definitive proof of causality. Further validation across multiple plants, VRM configurations, and prospectively controlled operating periods is required to confirm the generalizability and causal contribution of the proposed framework.

5. Conclusions

This study presented the industrial-scale implementation and long-term plant-level evaluation of a symbolic Expert System for automating the start-up of a vertical roller mill. The proposed framework translates process-engineering knowledge into deterministic rules, operating thresholds, and sequential safety conditions integrated within the existing Siemens PCS7 control environment. Its main contribution lies not merely in the use of rule-based control, but in demonstrating its deployment under sustained full-scale industrial operating conditions to standardize a complex and highly operator-dependent procedure without replacing the underlying regulatory and protection layers. Once the validated control configuration is active, the system executes the start-up sequence without continuous operator supervision, while the existing alarm, interlock, trip, and operator-intervention functions remain available throughout the procedure. The comparison between the manual and automated operating periods showed a production-weighted reduction of 9.97% in specific electrical energy consumption during Expert System operation, together with lower monthly variability and a corresponding reduction in estimated indirect CO₂ emissions. Given the retrospective and observational nature of the evaluation, these results should be interpreted as evidence of an association with the implementation rather than as definitive proof of causality.

From a practical perspective, the deployment shows that symbolic expert logic can be incorporated into an existing industrial control system while preserving conventional PID loops, safety interlocks, operator supervision, and plant-specific operating constraints. This unattended automated execution releases the operator from continuous start-up monitoring, allowing attention to be directed toward other operational tasks and supporting centralized supervision and remote operation. The configurable structure of the rule base enables process engineers to adapt thresholds and start-up conditions to changes in raw-material characteristics, equipment condition, and production requirements. The implementation also highlights the importance of involving plant personnel in knowledge elicitation, rule validation, commissioning, and iterative refinement, both to ensure technical robustness and to support operational acceptance and long-term maintainability.

The framework was evaluated in a single plant and for one VRM configuration; therefore, transfer to other installations requires local adaptation and validation of the rules, thresholds, instrumentation, actuator limits, and safety constraints. Future work should extend the evaluation to additional plants and VRM configurations and investigate hybrid symbolic–data-driven approaches capable of supporting threshold refinement, disturbance prediction, and improved adaptability while preserving interpretability, operator oversight, and process safety.

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methodology, participated in validation and evaluation, provided supervision, and contributed to manuscript review and editing. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement: The data presented in this study are available on request from the corresponding author. The aggregated production and energy-performance data used in the comparative analysis are presented in the article. The underlying operational datasets, raw process records, complete Expert System rule base, plant-specific threshold values, and software implementation contain confidential, proprietary, and sensitive information from an industrial cement plant and are therefore not publicly available. Additional information may be requested from the corresponding author upon reasonable request and will be subject to approval by the data owner and the applicable intellectual-property and confidentiality restrictions.

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