



Article

An Innovative Self-Adaptive Expert System for Improving Energy Efficiency in Cement Mill Grinding Operation

Raimundo Fernández Gassó * , Lorenzo Sevilla Hurtado and Juan Miguel Cañero-Nieto

Civil, Materials and Manufacturing Engineering Department, Universidad de Málaga, 29071 Málaga, Spain; lsevilla@uma.es (L.S.H.); jmcanero@uma.es (J.M.C.-N.)

* Correspondence: r.fernandez@uma.es

Abstract

The cement industry, responsible for 26% of industrial CO₂ emissions and 8% of global emissions, is under growing pressure to reduce its environmental footprint while maintaining profitability. In this context, optimizing grinding processes is essential to enhance both the efficiency and sustainability of cement production. This study presents the development of a self-adaptive expert system for closed-loop control, integrating symbolic Artificial Intelligence (AI) and Advanced Process Control (APC) techniques. The system dynamically adjusts operational parameters in real time to minimize the specific energy consumption of cement grinding while meeting quality targets. Notably, it enables autonomous plant operation without direct human supervision, thereby reallocating personnel to higher-value tasks and maintaining optimal performance continuously. The benefits observed following industrial implementation are discussed, alongside an analysis of the key factors influencing grinding performance and productivity. Furthermore, the integration of Artificial Neural Networks (ANNs) and genetic algorithms is proposed as a future enhancement, complementing the expert system through neuro-symbolic approaches. This fusion represents a significant step toward the digital transformation of industrial operations.

Keywords: expert systems; self-adaptive systems; advanced process control (APC); process optimization; energy efficiency; cement industry

1. Introduction

The industrial sector is increasingly required to adopt more sustainable production practices in response not only to market expectations but also to environmental legislation and progressively stricter regulatory requirements. These obligations concern emissions reduction, energy efficiency, resource conservation, recycling, and the responsible handling, treatment, and use of raw materials. Compliance with these requirements has therefore become a major driver of technological innovation, particularly in energy- and emissions-intensive industries such as cement manufacturing.

The cement industry is one of the largest industrial sources of CO₂ emissions, accounting for approximately 26% of industrial CO₂ emissions and about 8% of global emissions [1]. Its environmental impact, together with its intensive use of energy and natural resources, has increased the need for technological solutions capable of reducing greenhouse-gas emissions while maintaining production performance.

A considerable portion of the emissions from the manufacturing process and the energy consumption associated with the manufacture of cement are unavoidable because



Academic Editor: Shuting Lei

Received: 6 July 2026

Revised: 21 July 2026

Accepted: 27 July 2026

Published: 29 July 2026

Copyright: © 2026 by the authors.

Licensee MDPI, Basel, Switzerland.

This article is an open access article distributed under the terms and

conditions of the [Creative Commons Attribution \(CC BY\)](https://creativecommons.org/licenses/by/4.0/) license.

of the associated chemical processes and the intensive nature of the processes that make it up [2]. This significantly contributes to the footprint of the final product.

Energy represents a substantial proportion of variable cement-manufacturing costs. Approximately 33% corresponds to thermal energy used primarily in clinker production, whereas approximately 37% corresponds to electrical energy consumed by plant equipment and grinding operations. Together, these components account for approximately 70% of variable manufacturing costs [3].

In this context, for corporate social responsibility and to reduce the associated high energy costs, an increase in energy efficiency and carbon capture, use, and storage (CCUS) have become key points in the cement industry sector, directly impacting manufacturing costs and companies' strategic plan efficiency [3]. As a result, over the years, there have been important evolutions in cement manufacturing technologies with the aim of minimizing its environmental impact, reducing its carbon footprint, and promoting energy [4].

Grinding is one of the most critical stages in cement manufacturing because it strongly influences final product quality while accounting for a large share of total electricity demand. Owing to frictional losses, grinding remains an energy-intensive process, with 60–70% of total plant energy use associated with raw material and cement comminution stages [5,6]. Improving the operation of grinding circuits therefore offers a direct opportunity to reduce specific energy consumption, operating costs, and the indirect emissions associated with electricity use.

The continuous process industry, particularly the cement industry, traditionally relies on the knowledge and experience accumulated by operators and technicians in manual control [7]. This dependence is reflected in the need for specialized skills and practical experience to ensure the efficiency and safety of processes, presenting challenges such as variability in performance and the constant need for training and knowledge transfer. Therefore, management of the knowledge base is a fundamental pillar of the operation of industrial facilities [8].

Traditional control systems allow for improved mill driving by adjusting the independent adjustment loops. Although effective, these systems always require constant supervision by the operator to ensure optimal operation, because the operating instructions must be established manually and periodically. Human intervention is crucial to make fine adjustments and respond to unexpected variations in the process [9]. However, the availability and experience of the Process Engineer in defining the operating conditions, operating ratios, and performance of the installation must be considered.

The cement industry has become a promising field for the implementation of APC techniques to ensure long-term efficiency and sustainability in its operations and to reduce dependence on operators and engineers [10].

In recent years, AI techniques have become valuable tools for optimizing industrial processes [11]. These techniques seek to imitate human behavior while reducing the energy consumption associated with the process and ensuring the quality of cement [12].

AI is divided into two main branches: symbolic and sub-symbolic. Symbolic AI relies on the manipulation of explicit symbols and rules, whereas sub-symbolic AI uses mathematical and statistical models to learn patterns from data [13].

Expert Systems (ES) are a branch of Artificial Intelligence that use explicit knowledge bases and inference rules to support decision-making in specialized domains. Since their early development, they have been widely applied to complex industrial problems requiring transparent and structured reasoning [14–16].

Since then, the cement industry has employed symbolic AI to create increasingly advanced Expert Systems that leverage the knowledge of process engineers and constant observation-based refinement as an optimization engine [17,18]. This AI technique, based

on logical rules, attempts to replicate human reasoning through a process of constant adaptation and refinement of its application. However, it has certain limitations as it cannot adapt to changing situations. Frequently, these systems combine fuzzy logic with Proportional–Integral–Derivative (PID) controllers or Model Predictive Control (MPC) models [19].

One of the first documented examples in the cement industry was developed in 1987 by Vanderstichelen [20], who created a diagnostic program for use in cement mills using KEE (Knowledge Engineering Environment) software. Also in 1987, the CemExpert system was introduced [21], specifically designed to optimize the cement grinding process. Rather than relying on logical rules, CemExpert integrates process models, parameter estimators, simulators, and predictors based on algorithmic calculations. The system was designed to support operators in process monitoring and decision-making.

Since its origins, the applications of Expert Systems have been extensive and well documented [22,23]. The development of digital communication and online scientific databases further facilitated the dissemination of knowledge and collaboration among researchers and practitioners.

In recent years, with the increase in computing capacity and new machine learning techniques, Subsymbolic AI techniques have become excellent tools for the optimization of industrial processes because of their autonomy, learning capacity, and adaptability, which are fundamental aspects in the development of intelligent systems [24]. The objective of subsymbolic AI techniques is to create models that interrelate input variables with output variables using machine learning mechanisms. Two prominent examples in this area are Artificial Neural Networks (ANNs) [25], first proposed in 1943 [26], and the Genetic Algorithms introduced by J.H. Holland in the 1960s, inspired by the processes of natural selection and biological evolution [27].

In this context, subsymbolic AI techniques have proven to be particularly useful in enabling the creation of systems that not only automate complex tasks but also continuously improve as they receive more data. This is especially relevant in industrial environments, where efficiency and sustainability are fundamental pillars. Moreover, the integration of these techniques with emerging technologies, such as the Internet of Things (IoT) and cloud computing, has further expanded their applicability.

ANNs are suitable for analyzing real-time data from sensors in a plant, optimizing the performance, and reducing the downtime. In the cement industry, they can be used to predict the particle size distribution of the final product [28], managing the variability in ore properties and operating conditions. This information can be used in real time to improve the operating setpoints, reduce the standard deviation of the quality parameters associated with cement manufacturing, and reduce energy consumption.

Similarly, Genetic Algorithms can be used to find optimal solutions to planning and scheduling problems [29], adapting quickly to changes in the operating conditions. These algorithms can optimize the manufacturing cost function [3] by selecting the most suitable products and assigning production lines and manufacturing sequences. The implementation of hybrid crossover and mutation operators in Genetic Algorithms improves the quality of solutions and reduces calculation time, outperforming other optimization methods.

Symbolic and subsymbolic methods provide complementary capabilities [13]. Symbolic approaches generate conclusions from explicit rules and formal structures, which facilitate transparency and the incorporation of expert knowledge. Subsymbolic approaches learn associative relationships from data and can identify complex patterns in large or noisy datasets. However, purely data-driven methods may be limited when relevant process disturbances are not directly measured or when the available data do not adequately represent all operating conditions.

On the other hand, neurosymbolic computing (SNC) combines subsymbolic learning algorithms with symbolic reasoning methods to achieve a balance between the ability to learn from data and interpretability. This integration allows complex problems to be addressed more effectively, allowing for a transversal and innovative approach to operate in an optimized manner, guaranteeing energy efficiency and process stability [30,31].

The cement industry is showing increasing interest in combining symbolic and subsymbolic AI to optimize production processes and improve final-product quality. Research in this field continues to expand, supporting the development of more adaptive and interpretable industrial systems [32].

Previous applications of expert systems and advanced control in cement grinding have reported improvements in energy efficiency and productivity. Nevertheless, many approaches remain dependent on fixed parameterization, isolated control modules, periodic operator retuning, or continuous supervision. The available literature provides limited evidence of full-scale industrial systems that integrate supervisory rule-based reasoning, closed-loop regulatory control, and continuous recalibration within a unified architecture capable of sustained autonomous operation.

The principal contribution of this study is the development and industrial implementation of a self-adaptive expert system that continuously updates its operating references according to the observed process response. The architecture combines explicit process knowledge, supervisory decision rules, regulatory control, and recursive setpoint correction. It is therefore able to compensate for gradual or abrupt disturbances, including grinding-media wear, diaphragm clogging, sensor drift, and variations in raw-material properties, without relying exclusively on directly measured variables or recurrent manual retuning.

The system was implemented in two full-scale cement mills processing multiple commercial cement recipes under routine production conditions. The study evaluates whether this architecture can reduce specific energy consumption and increase production performance while maintaining operational continuity and compliance with product-quality requirements. The industrial validation also examines whether continuous recalibration can sustain system performance under changing plant conditions. These characteristics distinguish the proposed approach from static or purely data-driven control solutions and define its scientific and practical added value.

2. Process Description

The cement manufacturing process involves several stages from the extraction of raw materials to the final grinding of the product. This process includes crushing, homogenizing the materials, and grinding the clinker along with its addition to obtaining the final product [2]. Figure 1 summarizes the different processes involved in cement manufacturing:

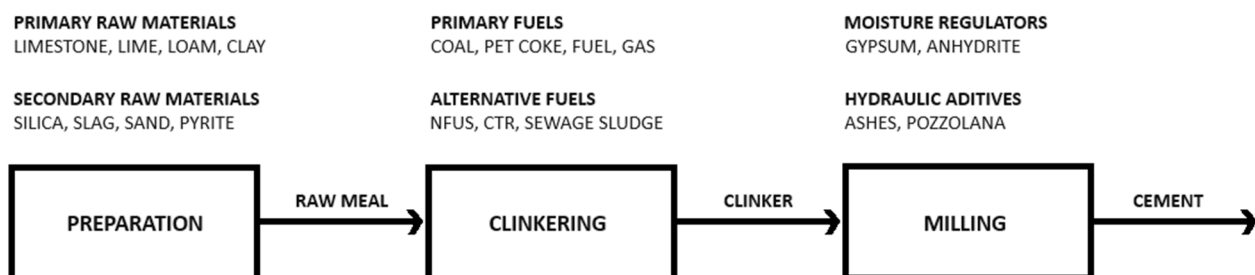


Figure 1. Cement manufacturing: processes, raw materials, and fuels.

The grinding stage determines the final granulometry and strongly influences cement quality. It is also one of the most energy-intensive stages of the process [5]. To contextualize

the importance of the grinding stage in terms of energy consumption and its impact on manufacturing costs and emissions, Figure 2 provides a detailed analysis that allows us to identify, in percentage terms, the specific energy requirements associated with each stage of the complex cement manufacturing process.

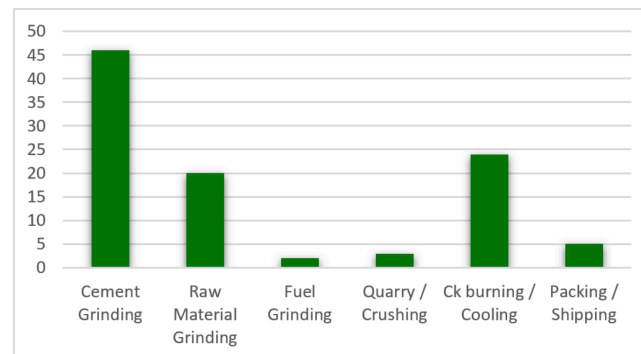


Figure 2. % Energy demand in the cement industry [33].

The process of grinding raw materials in the cement industry is conducted using horizontal ball mills, vertical roller mills, or hydraulic presses. Numerous studies have studied and compared different grinding technologies [6] and concluded that vertical roller mills can save up to 30% of grinding energy compared to the use of conventional ball mills [34].

Historically, ball mills have been the predominant choice for cement grinding and are widely used. These mills, known for their robustness and reliability, allow for a wide particle size distribution, which is beneficial for cement workability [2]. However, they have high energy demand and lower grinding efficiency than vertical mills. Despite these disadvantages, ball mills are still popular because of their ability to produce high-quality cement with increased specific surface areas required for certain types of cement and their lower initial cost.

Cement grinding uses two main horizontal mill configurations: an open circuit, where the material passes once, and a closed circuit, where it recirculates until it reaches the desired fineness. Closed-circuit mills offer key benefits including higher energy efficiency, better control of particle size, improved cement quality, and lower operating costs. This study focused on optimizing the closed loop grinding process, as illustrated in Figure 3, where the arrowheads indicate the direction of material and gas flow.

Raw material feeders initially supply material to the grinding circuit in appropriate quantities and proportions. The dosed material was transported inside a ball mill using a belt system. Inside the mill, the material was dried by the flow of hot air that ventilated it and crushed by the impact and friction generated by the steel balls, which were lifted by the plates fixed to the interior of the rotating mill, thus reducing the size of the particles.

The distribution of the balls along the mill was optimized to allow the grinding of raw materials of great hardness and size in the first chamber, and at the same time to achieve a particle size suitable for the quality of cement to be manufactured in the second chamber. When the material reduces in size sufficiently, it is carried by the flow of warm air through the mill to the separator located at the top, which is responsible for classifying the particles according to their size. Finally, the airflow with the ground material particles was filtered to recover the material stored in the homogenization silos.

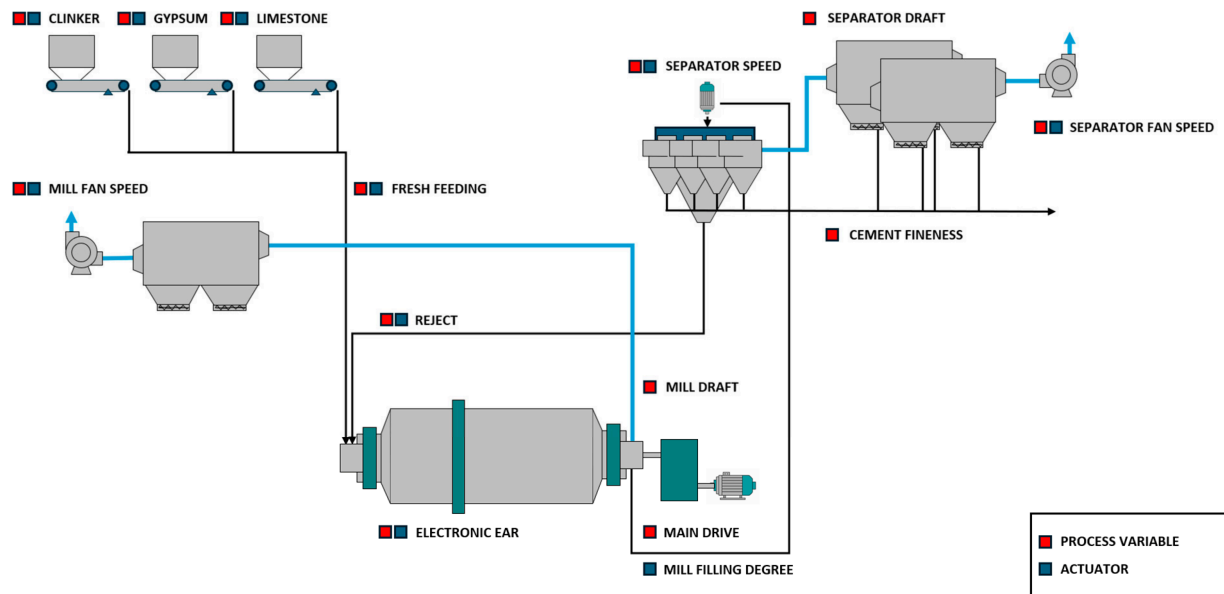


Figure 3. Flow diagram of a closed-loop cement grinding plant.

From an operational perspective, the closed-loop configuration creates a strong dynamic interaction between grinding capacity, separator efficiency, and material recirculation. If classification efficiency decreases, the reject flow increases, raising the internal mill load and specific energy demand. Conversely, stable separation and controlled recirculation improve throughput, reduce overgrinding, and enhance product consistency. This behaviour explains why simultaneous regulation of feed rate, separator conditions, and internal load is essential for efficient mill operation.

In general, the performance of a horizontal ball mill is strongly influenced by multiple uncontrolled variables that directly affect process efficiency and operational stability. The main influencing factors are as follows:

- Target cement fineness and quality requirements.
- Material hardness.
- Feed particle size distribution.
- Material moisture content.
- Wear condition of the grinding media.
- Mill diaphragm condition and clogging level.
- Internal mill temperature.
- Temperature of the material entering the mill.
- Ambient and seasonal operating conditions.
- Sensor drift and measurement reliability.

In addition, operators traditionally adjusted several actuators to compensate for disturbances, maintain stable operation, and maximize performance. The principal manipulated variables were as follows:

- Fresh feed setpoint to the mill.
- Total feed setpoint to the mill.
- Grinding additive dosage setpoint.
- Separator filter fan speed setpoint.
- Mill fan speed setpoint.
- Separator rotational speed setpoint.
- Reject flow setpoint.
- Total mill filling degree setpoint.

- Electronic ear setpoint.
- Mill outlet draft/inlet depression setpoint.

Owing to multiple uncontrolled variables, a complete mathematical model of cement grinding remains difficult to establish. However, available data, operational experience, and appropriate analytical tools can still be used to determine efficient operating conditions [35].

3. Methods

This study was designed to evaluate whether a self-adaptive expert system can improve the operational performance of industrial cement grinding under real production conditions. In particular, it addresses the following research questions: (RQ1) Can a self-adaptive expert system improve the energy efficiency of industrial cement grinding under real operating conditions? (RQ2) Can the proposed system increase production performance while maintaining process stability and product quality? (RQ3) Can autonomous recalibration mechanisms sustain effective operation under changing plant conditions such as wear, clogging, sensor drift, and raw material variability? Based on these questions, the following hypotheses were formulated:

- H1.** *the implementation of the proposed system reduces specific energy consumption compared with conventional manual operation;*
- H2.** *the proposed system increases production throughput without compromising operational stability; and*
- H3.** *continuous adaptive recalibration enables sustained performance without frequent manual retuning.*

To test these hypotheses, an industrial validation design was implemented under real production conditions in two cement mills operating with multiple commercial cement recipes and variable process conditions representative of normal plant operation. Performance was assessed by comparing manual and Expert System operation using production rate and specific energy consumption as the principal measured indicators. The study did not include CO₂-circulation, capture, or removal experiments. Any associated reduction in companies' carbon footprint was estimated indirectly from the measured electricity savings using the stated electricity-emission factor. The use of two independent mills and several product types increased the representativeness of the validation and allowed the robustness of the proposed approach to be evaluated across different operating scenarios.

Particular attention was given to potential confounding variables that could influence the comparison, including variations in raw material hardness, moisture, and granulometry; differences among cement recipes and target fineness; seasonal or ambient operating conditions; progressive wear of grinding media and internal components; sensor drift; and occasional operator interventions. Their effect was mitigated by analysing results under normal industrial operation across multiple products, using two independent mills, disaggregating performance by recipe, and evaluating improvements only after sufficiently stable operating periods. The methodological framework adopted for the expert system was structured to ensure technical rigor, practical applicability, and long-term sustainability within the industrial cement grinding context.

The process began with a thorough examination of the facility's operational conditions, with the aim of identifying inefficiencies, sources of variability, and opportunities for optimization. This initial diagnostic stage provided a foundation for defining key performance indicators and aligning project goals with broader priorities such as energy efficiency, process stability, and product quality. Close collaboration with process engineers, plant

operators, and automation specialists ensured the resulting system would be compatible with the existing control environment and responsive to site-specific operational dynamics.

A critical component of the methodology was the early identification and analysis of potential challenges that could undermine implementation success. These included technical difficulties—such as changes in grinding media load, sensor drift, diaphragm obstructions, and non-linear process behavior—as well as human and organizational factors like operator acceptance, insufficient training, and disengagement over time. Addressing these risks from the outset enabled the design of a resilient and flexible control architecture capable of real-time adaptation, self-adjustment, and reliable performance under diverse operating conditions. Emphasis was placed on integrating predictive logic, adaptive setpoint calibration, and autonomous fault detection to reduce dependency on fixed rule sets. The system's modular and transparent design allows for seamless updates and future scalability.

Based on this foundation, the implementation proceeded through a structured engineering cycle including conceptual modeling, knowledge acquisition, control algorithm configuration, simulation testing, and real-world deployment. Each phase incorporated validation and refinement to ensure consistency with operational requirements and adaptability across different production scenarios.

3.1. Identification of Implementation Challenges

Despite the clear advantages of incorporating an expert system, significant challenges must be overcome to ensure its success. One of the main challenges is integrating the system with the existing infrastructure, which requires meticulous planning and coordination. In addition, the complexity of the grinding process requires the development of highly accurate models that require continuous refinement and validation to ensure their accuracy. No less important is the need to foster cultural change within the organization, training operators, and engineers to understand and trust the system and promote a sustained commitment to continuous process improvement.

Experience has shown that many expert systems lose effectiveness after the first months of operation because they are based on fixed assumptions that gradually diverge from real plant conditions. To overcome this limitation, the proposed self-adaptive expert system was designed using a cascade control architecture in which the only fixed supervisory reference is the reject flow rate. This variable represents the desired recirculation condition of the grinding circuit. All other setpoints are continuously recalculated by subordinate control loops according to real-time plant response. As a result, the system is inherently robust against sensor drift, wear phenomena, and changing operating conditions:

Modification of the load of grinding bodies inside the mill. The absorbed motor power depends not only on the material hold-up but also on the grinding media charge, which changes progressively because of wear and periodic replenishment. Instead of using a permanent fixed power target, the system adapts the filling-degree references according to the reject-flow response and achieved process performance. This allows stable optimization even when the grinding media condition changes over time.

Electronic ear decalibration. The electronic ear is an important indirect indicator of first-chamber filling degree; however, its signal may drift because of changes in ball load, material properties, humidity, or sensor aging. For this reason, the expert system does not operate with a fixed electronic-ear reference. Once the total filling objective is achieved, the electronic ear setpoint is synchronized dynamically with the current validated operating value, allowing automatic compensation for progressive decalibration or changing acoustic conditions.

Partial occlusion of the mill diaphragm. During prolonged operation, the outlet diaphragm may progressively become obstructed, reducing discharge capacity and affecting reject circulation. When this occurs, the reject-flow controller detects that the desired recirculation target cannot be maintained under previous conditions. The system then increases the total mill filling degree, within safe operating limits, to raise the internal transport of material and recover the outlet flow. After maintenance or cleaning, the setpoints are automatically readjusted to the new plant condition.

Total occlusion of the mill diaphragm. In severe cases, sudden blockage may interrupt material discharge completely. Conventional controllers may react incorrectly by increasing feed rate. In contrast, the proposed expert system recognizes the abnormal collapse of reject flow together with filling-related constraints and executes protective actions, including rapid feed reduction and stabilization logic, to prevent prolonged stoppages and facilitate recovery.

Unidentified potential problems. Because the architecture is modular and transparent, new rules and supervisory conditions can be incorporated whenever plant engineers identify additional sources of inefficiency or instability. This ensures long-term adaptability and continuous improvement without redesigning the complete control structure.

3.2. Definition of the Control Strategy and Modelling Approach

To evaluate the impact of the proposed implementation on operational efficiency and, consequently, on the reduction in variable cement manufacturing costs, two key performance indicators were selected: Production rate was defined as the average cement output of the mill, measured in tonnes per hour (t/h) using the plant weighing and material flow measurement systems. Specific energy consumption was defined as the electrical energy demand of the grinding circuit per unit of produced cement, expressed in kilowatt-hours per tonne (kWh/t). Both variables were continuously recorded through the plant automation and supervisory monitoring system using the standard industrial instrumentation available at the facility. In general, an increase in production rate reflects a more efficient and cost-effective operation, whereas a reduction in specific energy consumption indicates more efficient energy use and contributes to the sustainability of the cement manufacturing process.

Among the variables governing grinding performance, the most critical are the mill filling degree and the recirculation factor. Within an appropriate operating range, increasing the recirculation factor may enhance system performance; however, an excessive filling degree can reduce grinding efficiency. When the operating limit is exceeded, the potential energy of the grinding media becomes insufficient to effectively fracture the material. Grinding energy demand is also influenced by particle size, material hardness, and the distribution of the grinding bodies. Because these operating conditions vary continuously, the optimal operating point must be continuously adjusted to maintain stable and efficient performance.

The proposed Expert System was developed to ensure stable operation through dynamic adjustment of the key process variables, with the objectives of maximizing production, improving grinding efficiency, and maintaining final product quality. The system adapts to process variations through a hierarchical self-adaptive control architecture composed of three complementary algorithms operating simultaneously. First, a rule-based supervisory layer translates the empirical knowledge of experienced process engineers into transparent decision rules. This layer evaluates current operating conditions, production targets, and plant constraints—such as maximum reject flow, mill draft limits, motor load, and quality requirements—to determine feasible control actions while preventing unsafe or inefficient operating states.

Second, recursive setpoint correction routines continuously update the reference values of key variables, including reject flow, total mill filling degree, separator speed, and electronic ear targets, according to the recent dynamic response of the process. Rather than relying on fixed calibration values, the system learns from observed operating behaviour and progressively compensates for slow disturbances such as grinding media wear, partial diaphragm clogging, sensor drift, seasonal variations in material moisture, and changes in clinker hardness or granulometry. This adaptive mechanism preserves control stability and process performance over time without repeated manual recalibration.

Third, a multivariable gradient optimization routine searches for improved operating conditions by applying small, coordinated changes to selected variables and evaluating their effect on the performance indicators under sufficiently stable conditions. Only modifications that produce a statistically significant reduction in kWh/t, an increase in throughput, or a simultaneous improvement in both objectives are retained. If performance deteriorates, the change is rejected and the previous setpoints are restored.

Through the coordinated interaction of these three layers, the system continuously regulates feed rate, ventilation, recirculation factor, mill filling degree, and classification conditions in real time, allowing the mill to operate close to its instantaneous optimum despite nonlinear dynamics and changing process conditions.

The development of the proposed model required a detailed analysis of the facility and of the interactions among the key variables, which is a fundamental step in the design of any Expert System based on Symbolic AI. This modelling process was carried out in collaboration with process engineers and plant operators to define the most appropriate control strategy for maximizing operational efficiency. To address the complexity of the installation, a comprehensive framework was established to evaluate both the individual subprocesses and the interdependence among the variables, including the performance indicators defined above. This methodology enables integrated process management and ensures accurate and efficient control under all operating scenarios considered.

Figure 4 presents a block diagram of the dynamic improvement strategy implemented by the self-adaptive Expert System, highlighting the regulators and control loops involved in cement grinding optimization. The diagram integrates advanced process control (APC), fuzzy logic, and conventional PID regulation within a unified framework. It illustrates the real-time interaction among key operating variables such as mill filling degree (%), separator speed (%), reject flow (t/h), and specific energy consumption (kWh/t), together with critical constraints including inlet depression (mbar) and maximum allowable reject (t/h). The adaptability of the system is reflected in its ability to dynamically adjust fresh feed according to total feed and process feedback, thereby enabling continuous optimization of energy efficiency and production stability. In the diagram, the different colors distinguish the control modules and process variables, while the arrows indicate the direction of information, reference, and feedback signals between the system components.

The different control modules operate in a coordinated hierarchical structure rather than as independent loops. At the supervisory level, the optimization layer determines the most suitable operating targets according to energy efficiency, throughput, and process constraints. These targets are then implemented by the regulatory modules. The filling degree controller stabilizes the internal material load of the mill, while the electronic ear loop provides a real-time indicator of first-chamber conditions and enables rapid correction of feed disturbances. In parallel, separator control regulates classification efficiency and recirculation behavior, directly influencing reject flow and final product fineness. Because these variables are strongly coupled, changes in one module affect the others; therefore, the proposed architecture continuously updates their references in a coordinated manner to maintain stable and efficient operation under changing industrial conditions.

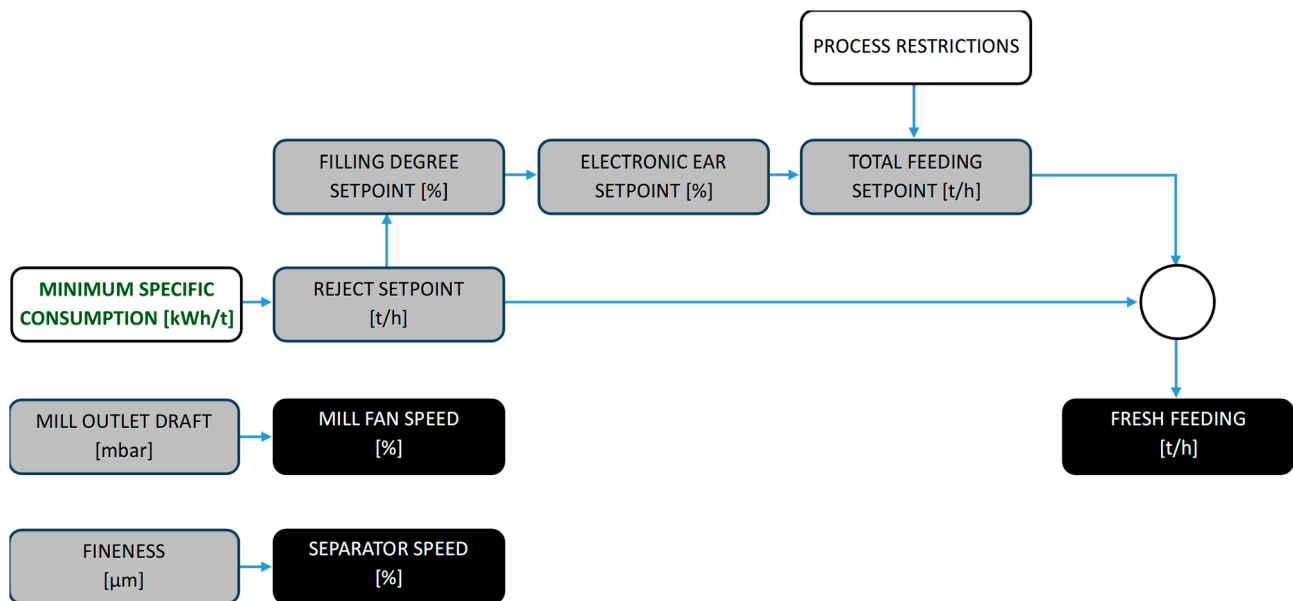


Figure 4. Block diagram of the regulation of the Self-Adaptive Expert System.

This coordinated strategy improves system behaviour under industrial disturbances such as variations in feed properties, moisture, or grinding media condition. Fast regulatory loops absorb short-term fluctuations, whereas the supervisory layer progressively shifts the operating point toward lower specific energy consumption and higher production. As a result, the control structure combines local stability with continuous plant-wide optimization.

3.2.1. Advanced Process Control (APC) Module: Minimization of Specific Electrical Consumption

The control strategy implemented in the plant begins with an Advanced Process Control (APC) module specifically designed to minimize specific electrical consumption (kWh/t) while preserving throughput, process stability, and final cement quality. This supervisory optimization layer continuously monitors the operating state of the grinding circuit and updates the most influential manipulated variables, including mill ventilation airflow, reject-flow target, separator operating conditions, and other related setpoints that directly affect grinding efficiency. Because electrical consumption is strongly coupled with production rate and classification performance, improvements achieved in this module also enhance the overall productivity and consistency of the installation.

The optimization logic is based on a multivariable gradient-search procedure executed online under real production conditions. At each iteration, the system applies small, coordinated perturbations to one or more selected variables and observes the resulting response of the key performance indicators, particularly kWh/t and production rate (t/h). The direction and magnitude of subsequent moves are determined from the measured trend of these indicators, allowing the controller to progress toward more efficient operating regions without requiring a complete first-principles model of the process.

To ensure reliable decisions, each proposed operating point is evaluated only after a sufficiently long period of stable operation. This filtering stage reduces the influence of transient effects and uncontrolled disturbances such as variations in clinker hardness, material moisture, internal mill temperature, feed granulometry, or separator adjustments. A new set of references is accepted only when the measured improvement exceeds the recent natural variability of the indicator, represented by its standard deviation, and all operating constraints remain satisfied.

If no statistically significant benefit is confirmed, the previous setpoints are restored and an alternative search direction is tested. Through this conservative and adaptive strategy, the APC module continuously tracks improved operating conditions over time and maintains robust performance under changing industrial conditions.

3.2.2. Reject Control Module

The reject flow setpoint set by the advanced control module defines the recirculation factor of the grinding plant. This parameter represents the proportion of material that, in relation to the total feed, does not reach the desired fineness after passing through the mill, and therefore must be recirculated. Because the recirculation factor directly influences the efficiency of the separator and the overall installation performance, effective control is essential.

The reject flow rate was regulated by a fuzzy controller that used the total filling degree of the mill as its main actuator. Generally, an increase in this grade is required to increase the reject flow. However, occasionally, the mill outlet partition can become clogged, preventing material from being ejected, even with proper filling. In such situations, the system makes an opposite adjustment, reducing the degree of filling to facilitate the exit of the material.

When the regulator reaches its setpoint, the system records the actuator value, specifically the degree of the total mill fill associated with each recipe. This procedure not only establishes a new value but also ensures that the facility operates efficiently, even during scheduled changes in material quality.

3.2.3. Filling Degree Control Module

The total filling degree of the mill is defined as the sum of the filling degrees of the first and second chambers, calculated from the power absorbed by the motor, and normalized using the maximum and minimum historical values. This provided a dynamic reference adjusted for real-time operating conditions. The optimization of this parameter is particularly complex because of the influence of the ball load, which varies over time and affects the calculation of the reference. Therefore, the system dynamically adjusts the setpoint of the total filling degree to ensure an adequate reject flow in all circumstances.

The advanced control system employs a PID regulator that precisely adjusts the total fill rate, using the fill rate in the first chamber as an actuator. This regulator considers at the same time some operational restrictions, such as inlet depression and the maximum height of material allowed in the first chamber, to avoid overloads or imbalances. Once the optimum filling degree is reached, the system synchronizes the setpoint of the electronic ear with its actual value, thus ensuring the process stability and efficient operation of the system.

3.2.4. Electronic Ear First Chamber Control Module

The degree of filling in the first chamber is determined by an instrument known as an electronic ear, which records the sound generated by the impact of the balls against the material inside the mill. The data collected by this sensor establishes a direct correlation with the amount of material present, so that variations in sound reflect changes in the level of filling. It is important to note that the sound captured is influenced by several factors, such as humidity, fineness of the material, and load of the balls.

For this reason, the proposed Expert System does not rely on a fixed calibration value. Instead, the electronic ear reference is continuously synchronized with the current stable operating condition of the mill, and its target is dynamically updated according to process response and supervisory control objectives. This adaptive recalibration mechanism allows

the signal to remain meaningful over time while preserving stable filling control under changing production conditions.

To control the degree of filling in the first chamber, a cascade PID regulator was used to adjust the total feed to the mill, consisting of the reject material flow rate and fresh feed flow. This method not only ensures effective control of the fill but also mitigates fluctuations in the reject, considering constraints such as the maximum allowable reject, minimum inlet depression, and maximum power in the reject elevator. The regulator operates in three working ranges, adapting to the magnitude of the error and its trend, allowing it to adjust its behavior according to the conditions of the mill, thus favoring stability and reducing transitions caused by feed cuts or stoppages.

3.2.5. Fresh Feed Compensation Calculation

A key control objective is to determine the appropriate balance between fresh feed and recirculated reject material entering the mill. Because fluctuations in reject flow can disturb the filling degree of the first chamber, the control system continuously compensates for the effect of the return stream when calculating the fresh feed setpoint. In this way, the regulator acts on the effective total feed to the mill, improving process stability and minimizing unnecessary oscillations during normal operation. The corresponding control parameters are established during commissioning and refined according to plant behavior and production requirements.

3.3. System Development

The following is a description of the fundamental stages implemented throughout the development and implementation of the proposed self-adaptive expert system aimed at ensuring the optimization of the industrial cement grinding process and its effective integration into the production environment:

1. Analysis of the context and needs.
2. Problem choice.
3. Conceptualization.
4. Acquisition of knowledge.
5. Selection of tools.
6. Application development.
7. Computer simulation and validation.
8. Implementation in an industrial environment.
9. Validation of performance results.
10. Maintenance and continuous improvement.

3.3.1. Analysis of the Context and Needs

Context and needs analysis were the critical initial stage in the development of the expert system, providing a detailed understanding of the operating environment and the specific challenges of the facility. At this stage, a thorough evaluation of the cement grinding process was conducted, covering both the operating procedures and the characteristics of the equipment and its potential limitations. Key operating variables, nature of the processed material, performance indicators, and quality parameters were analyzed in depth, with the aim of identifying critical areas that required improvement.

This analysis made it possible to determine the key aspects that the new system had to address, such as the optimization of energy efficiency, stabilization of operating conditions, and rigorous control of product quality. In addition, bottlenecks and workflow deficiencies that affected productivity and increased operating costs were identified, providing clear guidance for the design of targeted interventions. In this way, a solid foundation was

established for the subsequent phases of the project, ensuring that the system responded to the strategic needs of the plant and incentivized the process of continuous operational improvement at the facility.

3.3.2. Problem Choice

Interviews were conducted with specialized personnel from plants involved in industrial development to precisely define the objectives of the new facility. The identification of the problem, in collaboration with experts from the European Technical Centre, was based on rigorous criteria of operational efficiency, sustainability, and economic viability. The detailed analysis concluded that the priority should be to minimize specific energy consumption in cement grinding and reduce associated emissions while maintaining the quality of the final product, which is essential to compete in a highly demanding industrial context, where operating margins are critical for competitive viability and adaptation to increasingly stringent environmental regulations.

In addition, considering that many applications lose functionality over time owing to their lack of adaptation to changing conditions, it was concluded that the system should be flexible and self-adaptive and capable of automatically adjusting its parameters in response to operational variations. Finally, the importance of the system being integrated in a transparent manner into the plant's control infrastructure is highlighted, making it easier for personnel to manage, maintain, and optimize the system without interrupting the production process. This ensures long-term sustainability and efficiency, ensuring that the system evolves along with the production needs.

3.3.3. Conceptualization

The conceptualization stage focused on developing a detailed structure of the expert system based on the results obtained in the previous phases of analysis and selection of the problem. The fundamental components of the system, its overall architecture, and the interrelationships between them are defined to ensure that everything is aligned with the strategic and operational objectives of the plant.

A conceptual model was developed that represented the information flows and control mechanisms of key variables, which facilitated the identification of critical areas and made it possible to foresee bottlenecks in the process. This anticipation of operational difficulties allowed the integration of preventive solutions from the beginning, thereby optimizing the design of the system.

On the other hand, the interdependencies between the different subsystems were evaluated, and the necessary protocols were defined to ensure efficient control and fluid communication. Priority was given to the design of a modular and flexible structure capable of adapting to future adjustments or expansions without compromising operational stability. Taken together, the conceptualization provided a coherent framework that guided the detailed design, ensuring the effective integration of the system into the plant's existing infrastructure and its long-term viability.

3.3.4. Acquisition of Knowledge

Knowledge acquisition is a fundamental stage in system development and focuses on gathering the expertise needed to build the rule base. This includes the collection of historical data and interviews with operators and cement production experts, as well as documentation on best practices and ideal operating conditions.

An analysis of the historical records was conducted, considering critical parameters, such as specific energy consumption (kWh/t), mill operating conditions, material properties, and product quality. This analysis makes it possible to identify key correlations and establish an empirical framework for generating operating rules. Likewise, structured

elicitation techniques were used to capture the tacit knowledge of operators and engineers derived from their experience in process management. Through interviews and workshops, effective heuristics and strategies were identified to oversee operational variations such as fluctuations in material properties and production demands. Finally, the collected information was structured through systems based on rules and decision trees, which are typical of Symbolic AI. These tools provide a logical and transparent framework that allows modelling of the relationships between operational variables, ensuring the system's ability to adapt in real time and maintain interpretability and efficiency under changing production conditions.

The resulting rules were initially formulated from this combined knowledge base and subsequently reviewed by experienced process engineers and plant operators to verify their technical consistency, operational relevance, and compatibility with plant constraints. Before industrial deployment, the rules were tested under simulated operating scenarios to evaluate their expected responses to disturbances, changing production demands, and abnormal conditions. Following implementation, the rule base was further refined during commissioning through iterative adjustments based on the observed plant behaviour and measured process performance. This staged validation procedure ensured that the final rule set was both theoretically coherent and practically effective under real industrial conditions.

3.3.5. Selection of Tools

In a highly competitive industrial environment, it is critical to ensure that applications are easily maintainable and that specialized plant personnel promote continuous improvement. For this purpose and to simplify the programming process, it was decided to develop the application on top of the existing control system, the Siemens PCS7 V10 SP1 suite, a widely recognized platform in the industry that offers a comprehensive set of tools for automation and process control.

The choice of PCS7 made it easier to incorporate the application into the operating environment of the plant, highlighting its robustness and flexibility. Within this suite, tools such as Simatic Step 7 V5.4 and WinCC V8.0 were used. The Simatic Manager offered an advanced environment for the development and configuration of Programmable Logic Controllers (PLCs) responsible for processing the code of the expert system. This approach simplified programming, allowed for better understanding and acceptance of the system by specialized personnel, and ensured its long-term maintenance. In addition, by ensuring efficient interaction between components, communication problems between applications are avoided, thereby optimizing the flow of information.

In contrast, the WinCC tool was used for the development of graphical Human-Machine Interfaces (HMIs), which are essential for visualizing and understanding the process and behavior of the system in real time. Owing to its ability to manage large volumes of data and its seamless integration into the PCS7 suite, WinCC enables a clear and accessible visualization of key operating parameters, making it easier for control room operators to make informed decisions and evaluate application performance in an effortless manner.

3.3.6. Application Development

The development stage of the application focused on the construction and programming of the expert system following the specifications and conceptual bases previously defined. This process involved the implementation of inference engine logic designed to process the system rules and generate concrete actions that optimize the performance of the cement grinding process. The algorithms were structured to analyze data in real time,

allowing dynamic adjustments to the operating parameters, such as the recirculation factor or the degree of mill filling.

The implementation was supported by Siemens' APL V10.0 SP1 (Advanced Process Library), which allowed the selected algorithms to be efficiently integrated into PLCs. These were configured using Simatic Manager to ensure smooth interaction with the sensors and actuators involved in the process. As part of this stage, specialized modules capable of interpreting the rules of the expert system and responding accurately and efficiently to variations in the operating conditions were programmed.

In parallel and in close collaboration with plant personnel, graphical interfaces were developed using the WinCC application. These interfaces were designed with a focus on simplicity and adaptability, providing operators with an intuitive tool to monitor the key operational variables in real time. In addition, the necessary functionality was included for operators to interact with the expert system, allowing them to make informed decisions and adjust when circumstances are required.

3.3.7. Computer Simulation and Validation

Next, a computer simulation of the application was carried out to validate its operation and ensure the correct integration of all components of the system in a controlled environment. The main objective of this phase was to minimize operational risks and maximize the chances of success before actual implementation in the plant. To do this, the Siemens' S7-PLCSIM V5.4 simulation tool was used, which allowed the precise recreation of the operating conditions of the industrial process. Advanced simulation models were used to replicate various situations, simulate variations in operating parameters, and evaluate how inference algorithms adjust operational setpoints in real-time. This process makes it possible to observe how the system responds to different combinations of conditions, making it easier to identify failures or areas for improvement. Consequently, adjustments were made to the algorithms to further optimize the performance and efficiency of the system, ensuring that the model operated within the desired margins.

In parallel, exhaustive validation of the designed graphic interfaces was conducted to evaluate their ability to present the data in a clear and accessible way. The ease of use for operators was also evaluated to ensure that they could efficiently interact with the system during operation. This phase was crucial to ensure that all the tools were functional and robust for the final implementation.

3.3.8. Implementation in an Industrial Environment

Once the simulation and validation in a controlled environment were completed, the self-adaptive expert system was implemented in a real plant, which involved a meticulous transition from a test environment to an industrial operating environment. The process began with the physical installation of PLCs and the connection of sensors and actuators to the plant's existing infrastructure, using the Siemens PCS7 platform to ensure compatibility and stability of the system within the control environment.

The implementation was carried out gradually with the aim of minimizing any impact on the plant's day-to-day operations. The expert system is integrated step-by-step into the grinding process, continuously monitoring the key process parameters. During this phase, the behavior of the system and its interaction with the industrial process were monitored in real time, allowing any variation in the operating conditions to be detected and programming adjusted according to needs.

Particular attention was paid to the correct interaction of the system with existing infrastructure and equipment. In addition, the operational staff were trained to ensure that they could operate the graphical interfaces effectively. This allowed operators to monitor

the system performance and make manual adjustments when necessary, ensuring that the system is operated effectively within the industrial environment.

3.3.9. Validation of Performance Results

The performance results were validated to evaluate the direct impact of the self-adaptive expert system on the cement grinding process after implementation in an industrial environment. This phase was crucial for confirming that the objectives previously set by the plant personnel were being met effectively.

During the validation process, continuous measurements were made of key indicators such as energy consumption, production capacity, and cement quality. These data were compared with the values prior to the implementation of the system, allowing a comparative analysis of performance. Special attention was also paid to the stability of the process, ensuring that the system could adapt autonomously to operational variations without compromising the results.

In addition, specific tests were conducted to verify the system's ability to manage contingencies and unforeseen variations in operating conditions, such as fluctuations in material quality or production demands. The results confirmed that the system optimized the use of resources and improved the consistency of the process, contributing to a significant reduction in operating costs and an increase in the overall productivity of the plant.

3.3.10. Maintenance and Continuous Improvement

Despite the capabilities of applications based on symbolic AI to manage complex industrial facilities, their main limitation is the absence of machine learning. This makes constant maintenance and updating of the system critical for ensuring its relevance and long-term effectiveness.

The maintenance of the expert system aims to incorporate new knowledge and adjust its inference rules to respond to changes in operating conditions or the demands of the production process. These adjustments allow the system to not only retain its original functionality but also improve its performance, adapt to emerging technologies, and optimize cement grinding in the face of future challenges.

Concurrently, the constant training of operational personnel is key to maximizing the benefits of the system. Through management- and diagnostics-oriented training, it is ensured that the team is prepared to take full advantage of the system's capabilities, adjust when necessary, and participate in its evolution.

This comprehensive approach, which combines technical upgrades with the strengthening of human skills, ensures that a self-adaptive expert system maintains its strategic value over time. By operating effectively under changing conditions and promoting a process of continuous improvement, it consolidates itself as an indispensable resource for the plant, promoting sustainability, efficiency, and competitiveness in the long term.

4. Results and Discussion

The system presented in this study was designed to address the dynamic complexities of cement grinding, which is characterized by nonlinear interdependencies and variable conditions. The results obtained under real operating conditions provide an assessment of the impact of the proposed self-adaptive expert system on key performance indicators in cement grinding.

This system is distinguished from existing solutions by its ability to integrate symbolic AI with advanced closed-loop process control algorithms, thereby providing real-time adjustments based on a modular and adaptable model. Unlike traditional systems that rely on fixed configurations and constant operator monitoring, the self-adaptive approach allows

for a dynamic response to changes in raw material properties and operating conditions, thereby significantly reducing human intervention and associated costs.

4.1. Operational Performance

The implementation of a self-adaptive expert system in cement grinding presents a significant opportunity to optimize the performance and energy efficiency in an industry characterized by its high demand for resources. However, to accurately assess its impact, it is essential to analyze a sufficiently extended period that considers the variations inherent in the process. Factors such as the chemical composition and physical properties of the raw materials, such as grain size, hardness, and moisture, directly affect the system performance.

In this study, the results obtained under two operational scenarios were analyzed: with the Expert System activated and in conventional manual mode. The manual reference condition corresponded to normal industrial operation conducted by trained and experienced control-room operators following the plant's established procedures and using the same instrumentation available to the automated system. Therefore, the comparison does not reflect a contrast with suboptimal operation, but rather an evaluation of the additional benefits provided by continuous supervisory optimization, faster response to process changes, and more consistent setpoint adjustment. Additionally, two cement mills operating under comparable industrial conditions were included to ensure that the findings were sufficiently representative.

To correctly analyze the real impact of the implementation carried out in the operation, it is essential to analyze the results in a disaggregated manner, since each cement recipe has needs in terms of material fineness, recirculation factor, clinker content, and grinding additive that affect the specific associated energy consumption and therefore the potential results. This variability makes it necessary to adapt optimization strategies to address the specific requirements of each type of product.

The data presented below were continuously recorded in real time by the Expert System during normal industrial operation and consolidated into monthly integrated performance records through the system's statistical interface. The monitored variables were sampled automatically by the plant automation system and aggregated for comparative analysis using standard production reporting procedures. These records include the main operating indicators used for validation and covering two cement mills, multiple commercial cement recipes, and different production conditions representative of routine plant operation. This dataset enabled detailed performance comparisons under diverse industrial scenarios while also supporting the continuous improvement of the application over time.

Tables 1 and 2 present the disaggregated performance data by recipe and installation, enabling the identification of a general improvement in the main operating indicators under different production scenarios. Considering all valid comparative cases reported for the two facilities, the Expert System (ES) achieved an average increase in output of 33.3% and an average reduction in specific energy consumption of 20.0%. These aggregate results correspond to the unweighted arithmetic mean of the 12 valid recipe-level comparisons reported in Tables 1 and 2. In addition, for CEM IV/A (V) 42.5 R/SR, one of the most representative products analyzed in this study, output increased by 11.0%, while specific energy consumption decreased by 9.3% during the evaluated period.

These initial gains were particularly significant because they corresponded to the implementation phase, during which intensive real-time supervision and continuous fine-tuning were carried out to consolidate the new control strategy. Over extended operation, the system continued to maintain positive improvements in energy efficiency compared with the previous historical performance of the plant, confirming the long-term robustness,

adaptability, and practical relevance of the proposed self-adaptive system under normal production conditions.

Table 1. Disaggregated operating results for different Mill 3 recipes, with and without the Expert System (ES) activated.

	Previous Month					Current Month					ES Improvement		
	ES Off t/h	ES On t/h	ES Off kWh/t	ES On kWh/t	ES On %	ES Off t/h	ES On t/h	ES Off kWh/t	ES On kWh/t	ES On %	Output %	Energy %	ES On %
CEM I-52.5 R	13.0	16.7	62.4	48.5	95.6	9.6	16.8	84.6	48.7	95.8	48.9	−33.9	95.7
CEM II/A-V 52.5 R	10.6	17.5	74.5	46.0	96.0	16.1	16.7	50.0	48.5	61.0	28.0	−24.1	78.5
CEM II-BM (V-L) 42.5 R	12.2	18.9	65.3	43.5	98.9	12.2	18.8	65.3	43.5	98.9	54.9	−33.5	98.9
CEM IV/A (V) 42.5 R/SR	9.5	10.4	83.5	76.5	92.7	9.2	9.7	86.9	83.7	34.0	7.2	−6.0	63.3
CEM III-A 42.5 SR	23.7	36.8	33.9	22.1	82.3	23.6	36.9	34.2	22.0	87.7	55.9	−35.2	85.0
CEM V-A 32.5 N-SR	29.2	26.5	22.8	30.6	9.6	29.2	26.5	27.8	30.6	9.6	−9.3	21.1	9.6
CEM II/CM (V-L) 32.5 R	13.9	14.8	58.7	55.5	30.6	13.9	14.8	58.7	55.5	30.6	6.6	−5.4	30.6
CEM III/A 42.5 N CE	-	-	-	-	-	-	-	-	-	-	-	-	-

Mill
3

Table 2. Disaggregated operating results for different Mill 5 recipes, with and without the Expert System (ES) activated.

	Previous Month					Current Month					ES Improvement		
	ES Off t/h	ES On t/h	ES Off kWh/t	ES On kWh/t	ES On %	ES Off t/h	ES On t/h	ES Off kWh/t	ES On kWh/t	ES On %	Output %	Energy %	ES On %
CEM I-52.5 R	42.1	45.7	61.8	58.1	91.4	44.0	47.4	58.6	55.9	98.8	8.2	−5.2	95.1
CEM II/A-V 52.5 R	-	-	-	-	-	-	-	-	-	-	-	-	-
CEM II-BM (V-L) 42.5 R	36.2	54.8	71.1	47.9	97.4	50.2	55.4	52.5	47.6	93.5	27.5	−22.7	95.5
CEM IV/A (V) 42.5 R/SR	17.0	25.3	150.6	103.6	65.9	22.3	19.8	115.4	128.7	32.6	14.9	−12.7	49.2
CEM III-A 42.5 SR	39.5	76.5	62.8	33.3	95.8	39.5	76.5	62.8	33.3	95.8	93.9	−47.0	95.8
CEM V-A 32.5 N-SR	41.0	61.2	63.9	44.3	88.9	36.2	63.0	71.9	42.6	81.5	60.8	−36.0	85.2
CEM II/CM (V-L) 32.5 R	38.1	54.0	68.2	47.9	97.9	46.8	56.6	55.1	45.9	87.7	30.2	−23.9	92.8
CEM III/A 42.5 N CE	-	-	-	-	-	-	-	-	-	-	-	-	-

Mill
5

A comparison between the two cement mills further confirms the consistency of the reported results and supports their applicability under different operating conditions. Despite differences in nominal capacity and product mix, both mills exhibited the same general tendency toward higher output and lower specific energy consumption when the Expert System was activated.

Nevertheless, some individual recipes showed limited or negative improvements during specific periods. In industrial practice, such cases may occur when the Expert System is active for only a small fraction of the evaluated time, when strict fineness or quality con-

straints reduce the available optimization margin, or when the process is already operating close to its local optimum. Short production campaigns and temporary disturbances associated with raw material variability, moisture, or maintenance conditions may also influence short-term indicators. These isolated cases do not alter the overall positive trend observed across the dataset but rather reflect the normal variability inherent to full-scale cement grinding processes. This cross-validation under real industrial conditions reinforces the robustness of the proposed methodology and highlights its potential to optimize complex grinding operations while maintaining sustained operational stability.

4.2. Efficiency and Sustainability

The improvements presented not only bring substantial economic benefits and contribute to operational excellence but also play a key role in environmental sustainability. In a typical cement plant that produces 400,000 tons per year, with a typical average consumption of 51 kWh/t of cement, the implementation of the proposed ES to optimize energy consumption generates annual savings of approximately €140,000 compared with manual operation, derived from a 9.3% reduction in electricity consumption.

In addition to the economic benefits, these improvements contribute significantly to the reduction in companies' carbon footprint. It is estimated that the plant saves 474 tons of CO₂ annually, owing to a decrease in electricity consumption, and a carbon emissions factor of 0.25 kg CO₂/kWh.

This effort not only strengthens the plant's competitive position in the face of demanding global environmental standards but also facilitates compliance with international agreements, such as the Paris Agreement, adopted in December 2015 during COP21. In addition, in line with the most recent commitments of the United Nations Climate Change Conference (COP29), the system contributes to achieving more ambitious sustainability goals such as reducing emissions and transitioning to low-carbon economies. These initiatives consolidate the plant as a model for sustainable modernization and environmental compliance in the cement industry.

In the long term, reductions in CO₂ emissions are critical for mitigating future regulatory risks by aligning with government policies that penalize industries with prominent levels of energy inefficiency. Likewise, commitment to energy efficiency and sustainability contributes to improving the environmental reputation of companies, a factor that is increasingly valued by both consumers and investors in a global context that demands greater environmental responsibility.

4.3. Challenges Encountered

Despite the success achieved by the system, its industrial implementation has revealed several significant challenges that highlight the complexity inherent in integrating advanced technologies into well-established industrial environments. These challenges span the technological, operational, human, and organizational dimensions, highlighting the importance of adopting a comprehensive approach that ensures an effective transition to more efficient, automated, and sustainable operations.

From a technological perspective, the integration of an ES with pre-existing infrastructure is one of the most complex challenges of a project. Considerable effort is required in development to ensure the correct interaction between the new algorithms and the plant's control system. This process involved adjustments to both hardware and software, with particular attention paid to actuator timing and real-time processing demands.

Careful selection of programming tools, in collaboration with the plant operating staff, was also critical to ensure that the algorithms were properly tailored to the specific needs of the industrial environment. This joint work made it possible to identify the best techno-

logical solutions for optimizing the performance of the system without compromising the operation of the plant.

Reliability in the measurement of critical devices is a key factor that directly affects the installation performance. A prominent example is the calibration of an electronic ear, which is used to measure the fill level in the first chamber of the mill. Essential for accurate process monitoring under normal operating conditions, this device is overly sensitive to variations in mill ball loading, material moisture content, and specific requirements of each cement recipe. Additionally, different production needs, such as adjustments to product fineness and clinker content, add an additional level of complexity. To address these challenges, the design of the self-adaptive ES integrates dynamic adjustment mechanisms capable of making corrections in real time, adapting not only to operational fluctuations but also to the specific demands of each recipe and production scenario.

The implementation of the ES also presents human challenges, especially in terms of training and cultural acceptance. Training operators was essential to ensure a proper understanding of the system and minimize errors during the transition to an automated model. The initial resistance, motivated by the reduction in direct intervention in favour of data-driven supervision, was addressed through the collaborative development of an intuitive interface that would facilitate the monitoring of the process and understanding of the decisions made by the ES. Not only did this approach help overcome cultural barriers, but it also highlighted the benefits in terms of efficiency and reduction in repetitive tasks. Consequently, operational roles were optimized, allowing operators to focus on strategic decisions within a highly automated and efficient environment.

Finally, to evaluate the scalability of the system, it was implemented in two cement mills at the same factory. Despite the operational differences between the two facilities, the implementation was conducted in a straightforward manner, replicating the application and adjusting only nominal reference parameters, such as the power of the motors.

Despite these challenges, the system's ability to manage varying conditions and adjust to diverse production needs cemented its position as an indispensable tool for dynamic operations, laying a solid foundation for future optimization and expansion.

4.4. Strategic Relevance

The strategic implications of this self-adaptive ES transcend immediate operational benefits, positioning it as an essential component of the transition to a more sustainable and competitive industry. Its ability to improve energy efficiency and significantly reduce CO₂ emissions reinforces its contribution in meeting global climate goals and strict environmental regulations, promoting industrial practices aligned with long-term sustainability.

In addition, optimizing industrial processes not only reduces operating costs but also provides plants with a key competitive advantage in an increasingly demanding market environment.

The successful integration of the system with the existing infrastructure has not only benefited the facilities where it was implemented but has also represented a milestone in the digital transformation of the cement industry. Thanks to its open, scalable, and modular design, the solution can be adapted to a wide range of plant configurations, enabling straightforward deployment across diverse operating environments.

Compared with standalone approaches such as conventional PID loops, isolated MPC schemes, or rule-based expert systems, the proposed architecture delivers superior operational performance by combining the strengths of these methods within a single framework. PID modules provide fast and reliable regulatory control, advanced routines continuously optimize key performance indicators, and the expert supervisory layer applies process knowledge through adaptive decision-making. Fully embedded as an extension

of the plant control system, this unified solution offers greater robustness, adaptability, and sustained long-term performance than any individual control technology operating alone. Furthermore, its modular nature allows the future incorporation of emerging techniques, such as ANNs and genetic algorithms, thereby expanding its predictive and optimization capabilities.

5. Conclusions

The self-adaptive ES implemented in cement grinding has proven to be an effective tool for improving key performance indicators. Production increased by an average of 11% in the most representative cement, whereas specific electricity consumption decreased by 9.3%, reflecting its ability to adapt to operational variations. In addition, real-time analysis of operational data made it possible to identify significant improvements in process stability and overall efficiency, consolidating its effectiveness in different industrial environments.

The results, validated through a comparative analysis between the two cement mills, highlighted the consistency of the system, confirming its applicability in diverse industrial scenarios. These improvements not only bring economic benefits, with an estimated annual savings of €140,000 in electricity consumption but also contribute to environmental commitment by reducing CO₂ emissions by 474 tons each year. In this context, the system is positioned as a comprehensive solution for addressing the energy and environmental challenges of the cement industry.

Developed using symbolic Artificial Intelligence (AI) and advanced control algorithms, this system dynamically adapts to changing process conditions and operational demands. Its ability to adjust key parameters such as mill fill rate, recirculation factor, and feed in real time ensures stable and efficient operation, even in the face of variations in material quality or production targets. Its interpretable and manageable design compensates for the absence of machine learning, facilitates its implementation in environments with limited technical resources, promotes the participation of technical staff, and simplifies the resolution of new challenges.

The integration of advanced algorithms with intuitive interfaces is crucial to ensure wide acceptance of the system by operational personnel. These interfaces, designed to display the status of the system in real time, allow informed decisions to be made and the resistance to change to be minimized. On the other hand, the modular design of the system not only favors its adaptation to variable operating conditions but also facilitates the incorporation of emerging technologies such as IoT and cloud analytics, expanding its scope and functionality. This approach optimizes resources, reduces reliance on constant monitoring, and reinforces the consistency of results.

Three strategic areas are proposed for future research to maximize the potential of the system. First, it is proposed to incorporate advanced subsymbolic AI techniques, such as deep Artificial Neuronal Networks (ANNs) and genetic algorithms, with the aim of complementing the current capabilities and improving their adaptability to complex and dynamic conditions. This would increase the precision and efficiency of industrial process management. Second, it seeks to expand its application to other energy-intensive industries such as metallurgy and chemicals through specific adaptations. The integration of hybrid models based on neurosymbolic computing would be particularly effective in these sectors, managing complex interdependencies and improving operational efficiency. Finally, the development of scalable architectures based on cloud computing is proposed, which facilitates their implementation in plants with assorted sizes and configurations. This approach would also allow for remote analysis, continuous upgrades, and reduced operating costs, thus strengthening its sustainability in a global context.

The self-adaptive ES represents a significant advancement in process engineering, offering an innovative and sustainable solution to the energy and operational challenges of cement grinding. Its success transcends its immediate scope, opening new opportunities for the design of intelligent systems in other industrial sectors. This achievement reaffirms the transformative potential of symbolic AI in the optimization of complex processes, contributing significantly to the sustainability, efficiency, and competitiveness of the cement industry.

Author Contributions: R.F.G. contributed to the conceptualization and methodology of the study; carried out the data curation, and formal analysis; developed the software and visualizations; and drafted the original manuscript. L.S.H. contributed to conceptualization and methodology, provided resources and project administration, supervised the research, and contributed to manuscript review and editing. J.M.C.-N. contributed to conceptualization and methodology, participated in validation, provided supervision, and contributed to manuscript review and editing. All authors have read and agreed to the published version of the manuscript.

Funding: Funding for open access charge: Universidad de Málaga, CBU. Heidelberg Materials.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Informed consent was obtained from all authors included in the study.

Data Availability Statement: The data supporting the findings of this study are presented in the article. The underlying operational datasets contain confidential and commercially sensitive information from an industrial cement plant and are therefore not publicly available. Additional information may be obtained from the corresponding author upon reasonable request and subject to permission from the data owner.

Acknowledgments: We are deeply grateful to Heidelberg Materials for their significant contributions and for providing the essential industrial resources for validating the proposed system. We also extend our heartfelt gratitude to the Universidad de Málaga-Campus de Excelencia Internacional Andalucía Tech for invaluable support and collaboration. Their combined efforts were instrumental to the success of this study.

Conflicts of Interest: The authors declare no competing financial interests or personal relationships that could influence the work reported in this study.

References

1. Guo, Y.; Luo, L.; Liu, T.; Hao, L.; Li, Y.; Liu, P.; Zhu, T. A review of low-carbon technologies and projects for the global cement industry. *J. Environ. Sci.* **2024**, *136*, 682–697. [CrossRef] [PubMed]
2. Alsop, P.A.; Chen, H.; Chin-Fatt, A.L.; Jackura, A.J.; McCabe, M.I.; Tseng, H.H. *The Cement Plant Operations Handbook*, 7th ed.; Tradeship Publications Ltd.: Dorking, UK, 2019.
3. Parejo Guzmán, M.; Navarrete Rubia, B.; Mora Peris, P.; Alfalla-Luque, R. Methodological development for the optimisation of electricity cost in cement factories: The use of artificial intelligence in process variables. *Electr. Eng.* **2022**, *104*, 1681–1696. [CrossRef]
4. European Cement Research Academy and Cement Sustainability Initiative. Development of State of the Art-Techniques in Cement Manufacturing: Trying to Look Ahead. 2017. Available online: https://docs.wbcsd.org/2017/06/CSI_ECRA_Technology_Papers_2017.pdf (accessed on 26 July 2026).
5. Ghalandari, V.; Iranmanesh, A. Energy and exergy analyses for a cement ball mill of a new generation cement plant and optimizing grinding process: A case study. *Adv. Powder Technol.* **2020**, *31*, 1796–1810. [CrossRef]
6. Fleiger, P.; Hoenig, V.; Komorek, D.; Schneider, M.; Treibe, K. *Future Grinding Technologies—Report about Phase 1: Evaluation of Roundtable Event*; European Cement Research Academy: Düsseldorf, Germany, 2015. Available online: www.ecra-online.org (accessed on 4 December 2025).
7. Holmblad, L.P.; Ostergaard, J.-J. Control of a cement kiln by fuzzy logic techniques. *IFAC Control Sci. Technol.* **1981**, *14*, 809–814. [CrossRef]

8. Marin-Garcia, J.A.; Bonavia, T. Relationship between employee involvement and lean manufacturing and its effect on performance in a rigid continuous process industry. *Int. J. Prod. Res.* **2015**, *53*, 3260–3275. [\[CrossRef\]](#)
9. Ale, B.; Van Gulijk, C.; Hanea, A.; Hanea, D.; Hudson, P.; Lin, P.H.; Sillem, S. Towards BBN based risk modelling of process plants. *Saf. Sci.* **2014**, *69*, 48–56. [\[CrossRef\]](#)
10. King, R.E. The intelligent control in the cement industry. *IFAC Proc. Vol.* **1988**, *21*, 303–307. [\[CrossRef\]](#)
11. Russell, S.; Norvig, P. *Artificial Intelligence. A Modern Approach*, 4th ed.; Pearson: Hoboken, NJ, USA, 2021.
12. Kempf, J. Advanced process control boosts energy efficiency and product quality at a cement plant. *Process Worldwide*. 2011. Available online: <https://www.process-worldwide.com/advanced-process-control-boosts-energy-efficiency-and-product-quality-at-a-cement-plant-a-319657> (accessed on 4 December 2025).
13. Ilkou, E.; Koutraki, M. Symbolic vs sub-symbolic AI methods: Friends or enemies? In *CEUR Workshop Proceedings*; CEUR-WS.org: Aachen, Germany, 2020; Volume 2699. Available online: <http://ceur-ws.org> (accessed on 4 December 2025).
14. Lederberg, J. *DENDRAL-64: A System for Computer Construction, Enumeration and Notation of Organic Molecules as Tree Structures and Cyclic Graphs. Part I—Notational Algorithm for Tree Structures*; NASA-CR-57029; National Aeronautics and Space Administration: Washington, DC, USA, 1964. Available online: <https://ntrs.nasa.gov/citations/19650003557> (accessed on 26 July 2026).
15. Van Melle, W. MYCIN: A knowledge-based consultation program for infectious disease diagnosis. *Int. J. Man. Mach. Stud.* **1978**, *10*, 313–322. [\[CrossRef\]](#)
16. Turban, E. *Decision Support and Expert Systems: Management Support Systems*, 4th ed.; Prentice-Hall, Inc.: Englewood Cliffs, NJ, USA, 1995.
17. Kline, J. Getting the most from expert control systems. In *IEEE-IAS/PCA Cement Industry Conference (IAS/PCA)*; IEEE: St. Louis, MO, USA, 2019; pp. 1–11. [\[CrossRef\]](#)
18. Simmons, A.; Sarao, G.; Campain, D. A cement mill upgrade story reboot. In *IEEE-IAS/PCA Cement Industry Conference (IAS/PCA)*; IEEE: New York, NY, USA, 2019. [\[CrossRef\]](#)
19. Minchala, L.I.; Zhang, Y.; Garza-Castanon, L. Predictive control of a closed grinding circuit system in cement industry. In *IEEE Transactions on Industrial Electronics*; IEEE: New York, NY, USA, 2018; Volume 65, pp. 4070–4079. [\[CrossRef\]](#)
20. Vanderstichelen, J. Expert system prototype for process diagnosis in the clinker grinding circuit of a cement factory. In *Proceedings of the CANMET Symposium on Expert Systems in the Minerals Industry*; Laguitton, D., Ed.; CANMET Special Publication SP87-4E; Canada Centre for Mineral and Energy Technology: Ottawa, ON, Canada, 1987.
21. Keviczky, L.; Banyasz, C.; Haber, R.; Hilger, M. Cemexpert—An expert system for the cement grinding process. *IFAC Proc. Vol.* **1987**, *20*, 157–162. [\[CrossRef\]](#)
22. Liao, S.H. Expert system methodologies and applications—a decade review from 1995 to 2004. *Expert Syst. Appl.* **2005**, *28*, 93–103. [\[CrossRef\]](#)
23. Jabbar, H.K.; Khan, R.Z. Development of expert systems methodologies and applications. *Int. J. Inf. Technol. Manag. Inf. Syst.* **2015**, *6*, 49–59. Available online: <https://iaeme.com> (accessed on 4 December 2025).
24. Magnini, M.; Ciatto, G.; Omicini, A. Bridging symbolic and sub-symbolic AI towards cooperative transfer learning in multi-agent systems. In *CEUR Workshop Proceedings*; CEUR-WS.org: Aachen, Germany, 2023; Volume 3419, pp. 12–22. Available online: <https://ceur-ws.org/Vol-3419/paper2.pdf> (accessed on 4 December 2025).
25. Leijnen, S.; van Veen, F. The neural network zoo. *Proceedings* **2020**, *47*, 9. [\[CrossRef\]](#)
26. McCulloch, W.S.; Pitts, W. A logical calculus of the ideas immanent in nervous activity. *Bull. Math. Biophys.* **1943**, *5*, 115–133. [\[CrossRef\]](#)
27. Holland, J.H. *Adaptation in Natural and Artificial Systems: An Introductory Analysis with Applications to Biology, Control, and Artificial Intelligence*; The MIT Press: Cambridge, MA, USA, 1992. [\[CrossRef\]](#)
28. Singh, V.; Banerjee, P.K.; Tripathy, S.K.; Saxena, V.K.; Venugopal, R. Artificial neural network modeling of ball mill grinding process. *J. Powder Metall. Min.* **2013**, *2*, 1000106. [\[CrossRef\]](#)
29. Kunapareddy, A.; Allaka, G. An improved genetic algorithm for production planning and scheduling optimization problem. In *Intelligent Manufacturing and Energy Sustainability. Proceedings of ICIMES 2019*; Springer: Singapore, 2020; pp. 157–171. [\[CrossRef\]](#)
30. Pisano, G.; Ciatto, G.; Calegari, R.; Omicini, A. Neuro-symbolic computation for XAI: Towards a unified model. In *CEUR Workshop Proceedings*; CEUR-WS.org: Aachen, Germany, 2020; Volume 2706, pp. 101–117. Available online: <https://ceur-ws.org/Vol-2706/paper18.pdf> (accessed on 4 December 2025).
31. Garcez, A.D.A.; Lamb, L.C. Neurosymbolic AI: The 3rd wave. *Artif. Intell. Rev.* **2023**, *56*, 12387–12406. [\[CrossRef\]](#)
32. Oguntola, O.; Boakye, K.; Simske, S. Towards leveraging artificial intelligence for sustainable cement manufacturing: A systematic review of AI applications in electrical energy consumption optimization. *Sustainability* **2024**, *16*, 4798. [\[CrossRef\]](#)
33. Fleiger, P.M. *Herausforderungen in der Zementmahlung: Energie- und Ressourcen-Effiziente Produktion*; ProcessNet: Frankfurt am Main, Germany, 2014.

34. Liu, C.; Chen, Z.; Mao, Y.; Yao, Z.; Zhang, W.; Ye, W.; Duan, Y.; Xie, Q. Analysis and optimization of grinding performance of vertical roller mill based on experimental method. *Minerals* **2022**, *12*, 133. [[CrossRef](#)]
35. Pawus, D.; Paszkiel, S. Identification and expert approach to controlling the cement grinding process using artificial neural networks and other non-linear models. *IEEE Access* **2024**, *12*, 26364–26383. [[CrossRef](#)]

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.