



TRANSFORMING INDUSTRIAL SUPERVISION SYSTEMS: A COMPREHENSIVE APPROACH INTEGRATING MACHINE LEARNING TECHNIQUES AND FUZZY LOGIC

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Abstract *In addressing the mounting challenges of industrial supervision systems grappling with intricate processes, this study pioneers a transformative paradigm centered on the SCIMAT cement factory. By seamlessly integrating Machine Learning and Fuzzy Logic, the primary aim is to revolutionize real-time control systems, with a keen focus on cement production. SVM integration into the supervision system, coupled with connectivity to a Programmable Logic Controller (PLC), is complemented by fuzzy real-time controllers' regression analysis. Rigorous testing and evaluation validate the proposed approach's reliability, showcasing its effectiveness in discerning optimal system functioning. The system's practical application within a PLC environment underscores its prowess in issuing commands to industrial equipment, thereby enhancing operational efficiency. Going beyond conventional methodologies, our approach amalgamates SVM classification, fuzzy controllers, and real-time regression analysis, delivering a multifaceted solution for industrial supervision. The system's standout achievement is an SVM classification accuracy surpassing 94% compared to other classifiers. The K-Nearest Neighbors (K-NN) model demonstrated an accuracy rate of approximately 93.83%. The decision tree model attained an accuracy of around 83.73%. The logistic regression model achieved an accuracy of 80.25%. These models are not only adept at distinguishing optimal functioning from faults but also adept at preserving the linguistic language used by operators. The study's novelty lies in the holistic integration of SVM and Fuzzy Logic, offering a practical and adaptable solution that not only advances classification accuracy but also significantly reduces maintenance costs, marking a substantial improvement over the traditional methods. This transformative model, validated through SVM classification and practical application, establishes a new standard for flexibility, cost reduction, and overall productivity enhancement in industrial processes.*

Keywords: Intelligent Systems; Knowledge Exploitation; Cement Industry; Fuzzy Control; Machine Learning; Support Vector Machine; Real-Time Control; Predictive Analysis; Industrial Optimization; Process Efficiency.

1. INTRODUCTION

Cement production, known for its significant industrial role, reflects a capital-intensive nature and profound impact on economic prosperity. Within the building materials industry, cement manufacturing is intricately woven into the fabric of global economic growth, with projections indicating a doubling of demand by 2050. Beyond addressing the needs of a growing population, the cement sector faces the challenge of embracing scientific

and technological advancements to ensure sustainability and reduce operational costs. Controlling operations such as cement kilns poses perennial challenges for plant operators, necessitating the evolution from a convenient computer-based pyro control system to an absolute necessity.

Deviations in the pyro process, such as off-spec clinker and faulty operating conditions, underscore the importance of an automated control system. Effective implementation extends beyond technology adoption, requiring a stringent management policy that integrates the latest equipment technology, judicious resource utilization, and innovative materials. This approach not only meets present demands but also lays the foundation for a sustainable future. The complexity of cement manufacturing's operation stems from a lack of detailed structural knowledge, leading to a paradigm shift towards interconnecting users and machines through Artificial Intelligence (AI) and the developed models of machine learning techniques [1].

In the mid-20th century, the term Artificial Intelligence (AI) gained new meaning, representing a brain or memory capable of tasks like learning and thinking when human cognition is limited [2,3]. As a branch of AI, Machine learning (ML) emerged, enabling machines to learn and reason in situations where human cognition faces limitations. Intelligent systems, while potent, encounter limitations in capturing the subtleties of complex industrial systems. The integration of AI, particularly machine learning models, emerges as a solution to navigate intricacies, transcending traditional methodologies.

The deluge of information surpasses the cognitive capacity of the human brain every eighteen hours. Acknowledging this limitation, the concept of driving machines to learn and think offers the potential to accelerate knowledge development. This symbiotic relationship between human cognition and machine learning enhances our ability to comprehend complex phenomena, propelling us toward knowledge frontiers at an unprecedented pace. In this knowledge exchange, machines engage in the learning process, requiring a structured conduit between data and the machine itself, termed "training." This guides machines to assimilate and

synthesize data, allowing them to learn and predict outcomes. As industries move toward intelligent automation, the imperative is clear: augmenting productivity while reducing costs and enhancing reliability, availability, and overall product quality. However, this pursuit introduces a challenge—amplifying the complexity associated with the development of supervision systems. Data and knowledge underpinning these systems often come from experts relying on common sense, introducing vagueness and ambiguity. It is within this juxtaposition of human intuition and machine precision that the promise of intelligent automation unfolds.

In the context of contemporary industrial environments, where intricate processes, especially within cement manufacturing, pose formidable challenges, there exists a notable research gap. This gap stems from the limited understanding of the intricate behaviors of these processes, resulting in the inadequacy of traditional control theories and intelligent systems. The research aims to bridge this gap and addresses the two following goals. Firstly, the primary research gap resides in the insufficiency of current control methodologies to effectively address the complexities inherent in cement manufacturing processes. Traditional approaches lack the necessary granularity in understanding structural details, hindering their practical application in the industry. By explicitly recognizing and addressing this gap, the research aims to contribute to the advancement of control systems tailored to the specific intricacies of the cement manufacturing domain.

The second gap is based on the goal of sustainable industrial practices. The cement industry, characterized by its substantial energy and raw material consumption, faces the dual challenge of meeting escalating product demand while embracing sustainable practices. The research aims to align industrial control systems with this overarching goal by proposing innovative solutions that balance production needs with environmental responsibilities. Through the development of an intelligent control system, the research seeks to contribute to the conservation of natural resources and the mitigation of environmental impact, reinforcing the industry's pursuit of longevity and relevance. Endowing computers with an understanding akin to a knowledge engineer remains a formidable challenge.

Advanced technologies like Machine Learning and Fuzzy Logic are fundamental to modern intelligence augmentation, bridging the gap between human-derived knowledge and machine-driven insights. Fuzzy Logic, announced by Zadeh in 1965 [4], delivers a nuanced framework for handling imprecise and vague information—an inherent characteristic of human-derived knowledge [5]. Complementing Fuzzy Logic is the expansive domain of Machine Learning, offering diverse techniques aimed at imparting the ability to learn and predict from data. A

standout technique within Machine Learning well known techniques is the Support Vector Machine (SVM).

Acknowledged in the work of Awad and Cristianini & Schölkopf [6,7], SVM offers a robust foundation for classification and regression tasks, emerging as a linchpin in predicting the position of new data within the evolving knowledge landscape. These scientific endeavors find application in the heart of the industry, focusing on addressing control challenges inherent in pyro-processes. By utilizing the most advanced applied technologies, the objective is to develop an intelligent model that surpasses traditional operator supervision. This model not only monitors industrial processes but, crucially, enhances and optimizes existing supervision systems. This work signifies a paradigm shift in industrial control, ushering in a new era of efficiency and adaptability through the synergy of theoretical foundations and practical implementations in the realm of machine learning. The research contributions are twofold, the first one is the Intelligent Control System Development. This study pioneers the conceptualization, design, and implementation of an intelligent control system tailored to the complexities of cement manufacturing.

By leveraging Fuzzy Logic and SVM techniques, the system aims to enhance decision-making processes within PLCs in real-time, marking a paradigm shift in industrial automation. The second is the convergence of Theoretical Insights and Practical Applications. The research uniquely contributes to bridging the gap between theoretical foundations, specifically in machine learning and artificial intelligence, and their pragmatic application in industrial settings. This convergence represents a significant stride towards achieving heightened efficiency and adaptability within the realm of industrial control paradigms.

The integration of Machine Learning algorithms into industrial supervision systems represents a pivotal advancement in optimizing production processes and enhancing operational efficiency. In this study, we aim to develop an intelligent control system for cement manufacturing processes, leveraging SVM and Fuzzy Logic techniques. Specifically, our objectives include, achieving a good accuracy rate in fault detection within the raw mill workshop, decreasing energy consumption by at least 10% through optimized process parameter prediction, reducing manual intervention through automated decision-making using SVM and fuzzy logic controllers, and improving production line functionality by minimizing downtime and maintenance costs.

2. PROBLEM STATEMENT

In today's industrial environments, managing intricate processes, such as those inherent in cement manufacturing, poses a significant challenge due to a lack of comprehensive comprehension of their intricate dynamics. Traditional control theories and intelligent

systems frequently prove inadequate, especially in addressing specific structural intricacies, impeding their efficacy in the industry. This deficiency in understanding calls for inventive solutions to fill the knowledge gap. The cement manufacturing industry, marked by its high consumption of raw materials and energy, faces the dual challenge of meeting rising product demand while conserving natural resources and protecting the global climate. This dichotomy presents a formidable challenge, prompting the industry to navigate towards sustainable practices that balance production needs with environmental responsibilities.

Conservation of natural resources and the mitigation of environmental impact have become paramount considerations in the industry's quest for longevity and relevance. The innovative aspect lies in the successful fusion of theoretical foundations, discussed comprehensively in machine learning and artificial intelligence. This holistic integration transforms traditional industrial automation into an intelligent, adaptive system, marking a significant stride towards heightened efficiency and adaptability in industrial control paradigms. Thus, this research addresses this challenge by proposing the implementation and development of a smart control system.

Leveraging the power of Fuzzy Logic and SVM techniques, integrated using Python language and Automation Simatic Step 7 code, the system aims to seamlessly process real-time data from industrial environments. The ultimate goal is to revolutionize decision-making within PLCs, offering a transformative approach that not only enhances efficiency and reliability but also signifies a leap forward in the convergence of theoretical insights and practical applications in machine learning for industrial control systems.

3. RELATED WORK

Machine learning encompasses several hundred statistically-based algorithms, necessitating the selection of the appropriate algorithm or combination of algorithms. Various machine learning algorithms include K-nearest neighbor, Support Vector Machine (SVM), and Random Forests. [8], Artificial Neural Networks (CNN) [9], and hybrid neural and fuzzy systems. Recently, machine learning has become increasingly prevalent in research and has been integrated into various fields, including medical and public health [10–12], military applications [13,14], industry domains [15], and so forth; It has a variety of applications, including classification of images [16], text mining [17,18], video recommendation [19,20], and multimedia concept retrieval [21,22].

SVM is one of the strong machine-learning algorithms [23]. SVM exhibits strong generalization capabilities and can balance model complexity and learning performance optimally, particularly when addressing small sample sizes and nonlinear problems [24,25]. SVM is widely used

in classification [26,27] regression models [28], and pattern recognition applications [29]. In a classification problem, the objective is to predict a class label from a predefined set of possibilities. SVM classifiers aim to identify the optimal hyperplane that separates two distinct classes of data, thus creating a model that performs well on new data [30]. SVM achieves this by mapping the learning patterns into a high-dimensional feature space and determining the hyperplane that maximizes the margin between the two classes [31]. Numerous recent case studies and research papers have explored the application of SVM in the cement industry. A study describes the use of SVM for fault diagnosis and classification in a cement mill. The study presents a case study in which SVM is used to detect and classify faults in the cement mill, based on the vibration signals of the mill. The outcomes demonstrate that SVM attained high accuracy and efficiency in fault detection and classification, and outperforms other methods such as neural networks and decision trees [32].

Another study describes the use of SVM for optimizing the performance of a cement plant. The study presents a case study in which SVM is used to predict the quality of the cement produced by the plant, based on process parameters such as pressure, flow rate, and temperature. The findings prove that SVM reached high accuracy and efficiency in predicting the quality of the cement, and helps the plant operators optimize the process parameters to reduce the cost of the cement and improve its quality [33]. Fuzzy logic addresses a critical gap in engineering design methods where purely mathematical approaches (such as linear control design) and purely logic-based methods (like expert systems) fall short in system design, or when applied as fuzzy expert systems for knowledge extraction in monitoring and supervision systems [34].

Fuzzy logic offers several advantages that make it highly suitable for various control problems. It can effectively manage both linear and non-linear systems where deriving a precise mathematical model is challenging or not feasible. Beyond its advantages, fuzzy logic finds applications in diverse domains, including in-process control and decision-making [35,36], as well as in failure mode and effect analysis [37] and the detection of structural breaks in time series data [38]. As possibly fuzzy remote control using the Internet and web services [39,40]. Both Fuzzy logic and machine learning techniques were applied in different fields, including financial performance predictions [41], and data mining [42].

Certainly, various studies have integrated fuzzy logic and machine learning to address diverse requirements. This integration has led to the emergence of the field known as fuzzy machine learning several years ago [36,42]. The integration of both techniques is also applied in support of vector learning for fuzzy rule-based classification systems. Authors [43,44] have applied fuzzy membership to each input point and restructured SVMs so that various

input points can contribute differently to the learning of the decision surface. They termed this approach fuzzy SVMs (FSVMs).

Different works improved the power of this combination [45,46]. The supervision system can learn from uncertain data how to manage altogether situations, either in a good or in a case of bad functioning, which means when an alarm has occurred. However, different cited works that used SVM or fuzzy SVM did not deal with control/command tasks, especially in complex industrial supervision systems [47].

4. MATERIALS

4.1 Industrial Process

This detailed overview emphasizes the meticulous nature of the SCIMAT factory's materials processing and production procedures, providing a comprehensive understanding of the complexities involved in cement manufacturing. Each workshop in the factory contributes a specific function, underscoring the meticulous nature of cement manufacturing. The limestone, the primary raw materials, and the clay are extracted from quarries owned by the company and undergo a meticulous pre-blending process to achieve the desired chemical composition. After the initial processing, the composition is refined by incorporating corrective materials such as sand, iron ore, bauxite, or industrial waste into the raw mill to ensure accuracy in the raw material mixture. The finely ground raw meal is then stored and homogenized in the raw meal silo, readying it for the subsequent production stages.

The kiln, a pivotal component, includes a static preheating system equipped with pre-calcining and cyclone stages. The kiln feed, considered the raw meal, undergoes heating up to 1000 °C, initiating the calcination process. As the material progresses through the rotary kiln, it reaches temperatures of 1450 °C, resulting in the formation of Portland cement clinker. Clinker, known for its hydraulic properties, is a combination of four synthetic minerals that solidify upon contact with water. The rapid cooling and solidification of these minerals take place in the clinker cooler, which constitutes the third component of the cement kiln system. A crucial aspect of this mineral transformation involves the use of diverse fuels. Traditionally, oil and gas were prevalent, followed by coal and petcock, and in recent decades, alternative fuels have gained traction for heating purposes since the 1980s.

A notable aspect is the complete incorporation of fuel ash into the clinker, contributing to the final clinker composition. Clinker, serving as a critical intermediate product, is not only essential for cement manufacturing but is also a globally traded commodity among cement producers. The cement production process involves the mixing and fine-grinding of clinker, gypsum, and mineral components in cement mills.

The final product is stored in dedicated facilities, ensuring proper inventory management, and safeguarding the quality of the cement. Workshops in this phase are designed for the efficient transportation and distribution of cement to various destinations, contributing to the seamless flow of the final product to the market. From raw material extraction and processing to the final stages of cement production and distribution, the integrated approach ensures efficiency, precision, and production of high-quality cement products.

In this research, the focus is directed on the raw mill workshop, which is chosen as the primary case study. This workshop constitutes a dedicated production line where the product undergoes a sequence of operations facilitated by an array of electric, mechanical, and automated equipment. These components collectively ensure the smooth processing of the operation and maintain optimal functionality as dictated by the system's requirements. The raw mill is employed to grind raw materials into a "raw mix" during the cement manufacturing process. This raw mix is subsequently fed into a cement kiln, where it transforms into clinker, which is further ground to produce cement.

The raw mill workshop is a critical part of the cement manufacturing process, as it determines the quality and quantity of the raw mix, and affects the efficiency and cost of the cement production. By focusing on the raw mill workshop, the study aims to develop a novel approach to fault detection and optimization of cement processes, based on the integration of SVM and Fuzzy Logic techniques into the supervision system of a cement workshop. The intricacies of the cement mill workshop's process are visually represented in Figure 1, providing a comprehensive illustration of the workflow and the interplay of various elements within this crucial segment of the cement manufacturing journey.

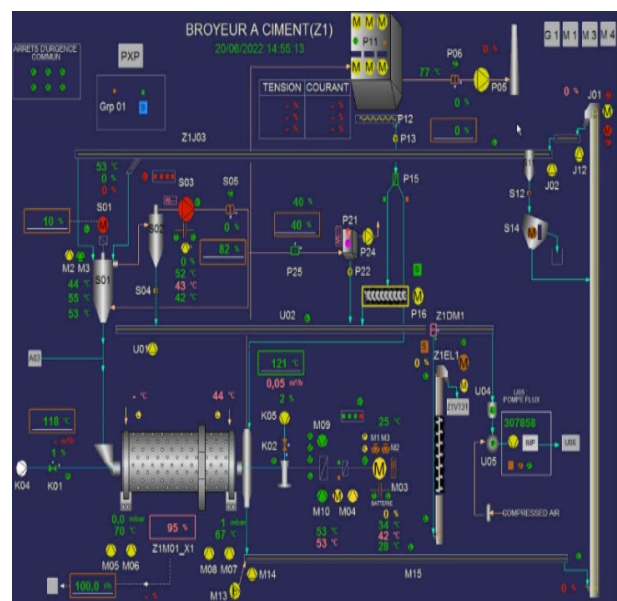


Figure 1. The raw mill workshop process.

4.2 Data Analysis

The dataset utilized in this study is sourced from the cement factory SCIMAT in Ain-Touta (Batna), Eastern Algeria. It encompasses 21 parameters, with one designated class indicating the state of the production line—either functioning well (class "state = 1") or experiencing a malfunction (class "state = 0"). The dataset consists of more than 38,000 instances gathered over six trimesters in 2018/2019 from the production line. The classes indicate whether a detected fault, signaled by an alarm, is present or absent. The industrial system's sensors are configured with specific settings, facilitating their incorporation into the training of the developed machine learning models.

The production line exhibits a predominance of good functioning, with 77% of instances falling into this category. However, approximately 23% of instances indicate a state of malfunction, potentially posing adverse effects on the economic development of the enterprise. The production line, as previously noted, experiences a 23.06% incidence of suboptimal functioning, posing a significant risk to the economic prosperity of the enterprise. Each component of the equipment is endowed with a distinct set of parameters essential for the manufacturing system to commence, halt, and regulate operations, steering it toward optimal performance. The graphical representation in Figure 2 elucidates the spreading of all scrutinized features relative to the system's operational states.

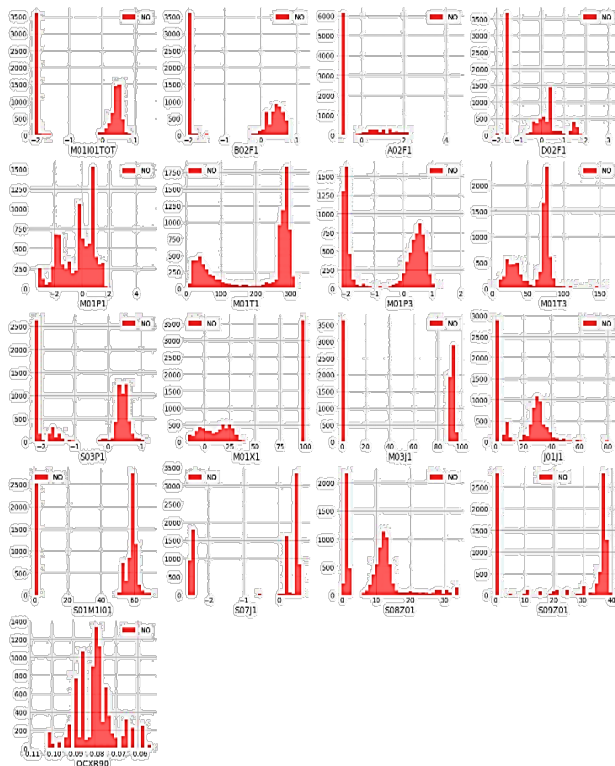


Figure 2. The features spread based on class 0 (malfunction).

The system relies on various features as associated factors, with particular emphasis on key parameters that exert a significant impact on the supervision system. Significant among these influential factors are Transporter Tape flow M01I01 (the aggregate quantity from workshop feeders A02, D02, and E02) and other sensors. Table 1 provides a detailed account of the parameter settings (features) associated with these critical elements.

Table 1. The workshop's sensors.

Sensors	Value range and unit	Designation
M01X1	[0-50] (%)	Acoustic equipment of the Crusher
M01I01	[100-150] (t/h)	Crusher Total feed's rate
J01J1	[0-60] (%)	Elevator's power
E02F1	[0-5] (t/h)	Flow rate of the Feed Transporter E02
QCXR90	[0.9-18] (%)	Operator sp02
QCXH2O	[0.8-15.8] (%)	Operator sp03
M01P3	[17-24] (mbar)	Pressure Crusher's output
M01P1	[1-2.1] (mbar)	Pressure in Crusher's input
S08Z01	[0-95] (%)	Separator Butterfly register's position
S09Z01	[0-50] (%)	Separator Butterfly register's position
S07J1	[0-94] (%)	Separator Fan's power
S01M1I01	[0-120] (%)	Separator's Current
S03P1	[0-60] (mbar)	Separator's Pressure
M01T1	[220-400] (C°)	Temperature Crusher's input
M01T3	[70-120] (C°)	Temperature Crusher's output
M03J1	[0-92] (%)	The Crusher Engine's power
A02F1	[0-24] (t/h)	The flow rate of the Feed Transporter A02
B02F1	[100-150] (t/h)	The flow rate of the Feed Transporter B02
D02F1	[0-3] (t/h)	The flow rate of the Feed Transporter D02

4.3 Feature Selection

To ensure that the selected features align with the specific requirements of the industrial setting, contributing to the robustness and scientific validity of the intelligent industrial supervision system. The feature selection process involved a meticulous evaluation of the industrial system's critical components and parameters. Key considerations included the potential impact of each sensor value on the overall functioning of the system, its relevance to the specific context of cement manufacturing, and its ability to capture variations indicative of optimal or suboptimal performance. The following steps outline our methodology. We conducted an extensive literature review and engaged in consultations with domain experts to identify features commonly associated with the efficient operation of cement manufacturing processes.

Features were categorized based on their known influence on industrial system performance, with a focus on parameters affecting the raw mill workshop within the cement production process. Each identified feature underwent a relevance assessment, considering its potential to provide unique and significant information about the system's status. Features were evaluated based on their sensitivity to deviations from optimal conditions, ensuring that selected features could effectively capture variations requiring attention. Features were further categorized into specific ranges defined by setpoint intervals: "High range" for values superior to the setpoint, "Medium range" for values within the range of high and low setpoints, and "Low range" for values inferior to the setpoint. This categorization strategy was designed to facilitate the SVM classification process and enhance the interpretability of results.

A correlation analysis was conducted to identify relationships and dependencies among features. This step aimed to ensure that the selected features were not redundant and collectively provided diverse information. The dataset showcases a noteworthy lack of strong correlations among its characteristics, underscoring the thorough consideration of all features within the scope of the study. This suggests that each feature contributes unique and independent information to the analysis. To elucidate the intricate interplay between the different features, a heatmap in Figure 3 vividly portrays the correlations within the selected dataset. The heatmap provides a nuanced depiction of how each feature relates to others, offering insights into potential patterns or dependencies that may influence the overall functioning of the industrial system.

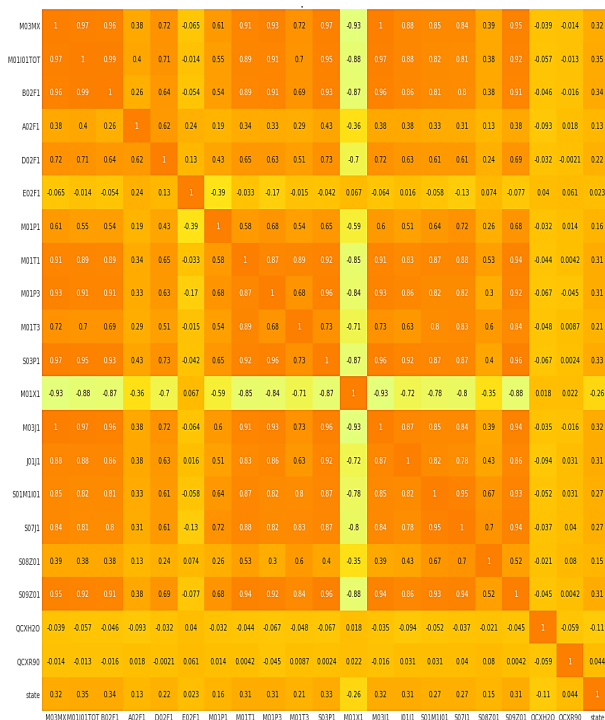


Figure 3. The correlations between features.

5. METHODS

Machine learning, a branch of artificial intelligence, focuses on developing algorithms and models capable of learning from data to make predictions or decisions based on learned patterns. There are three main categories of machine learning algorithms: supervised learning, unsupervised learning, and reinforcement learning. Supervised learning algorithms learn from labeled data, where input-output pairs are provided, and then apply this knowledge to new data. Unsupervised learning algorithms, on the other hand, learn from unlabeled data, identifying hidden patterns or structures within the data. Reinforcement learning algorithms learn through interaction with an environment, receiving rewards or penalties based on actions taken, and aim to maximize cumulative rewards over time. Two prominent and effective machine learning algorithms are Support Vector Machines (SVM) and Fuzzy Logic. SVMs, a supervised learning technique, excel in handling non-linear and high-dimensional data, offering generalization and regularization in model training [48].

The Fuzzy Logic and SVM methods are applied to real-world scenarios within cement manufacturing, such as fault detection and optimization of cement processes. We use the dataset from the SCIMAT cement factory to train and test the models, and then apply the models to the real-time data to detect and classify the faults, predict the optimal process parameters, and reduce the energy consumption. The application of our approach to real-world scenarios can prove the efficiency and the pertinence of the Fuzzy Logic and SVM methods in industrial control systems, and provide some insights and recommendations for future research or practice. A dataset from the SCIMAT cement factory was used to evaluate the developed models, and then compare the findings with the existing methods. The comparison of our approach with existing methods can reveal the disadvantages and advantages of the Fuzzy Logic and SVM methods, and provide some guidelines and recommendations for choosing and optimizing the methods in industrial control systems.

In this study, we propose an original approach to fault detection and optimization of cement processes, based on the integration of Fuzzy Logic and SVM into the supervision system of a cement factory. Our approach aims to report the boundaries and challenges of current approaches, such as rule-based systems, expert systems, or neural networks, and provide flexibility, accuracy, and efficiency in decision-making.

Figure 4 illustrates the architecture of this transformative contribution, marking a significant advancement in the realm of industrial supervision and automation. This methodology leverages advanced computational techniques to analyze and interpret data patterns, enabling the development of models capable of predicting outcomes or making informed decisions within the

manufacturing context. The subsequent sections investigate the specific techniques utilized, including SVM and Fuzzy Logic, detailing their application to optimize production line functionality and fault detection.

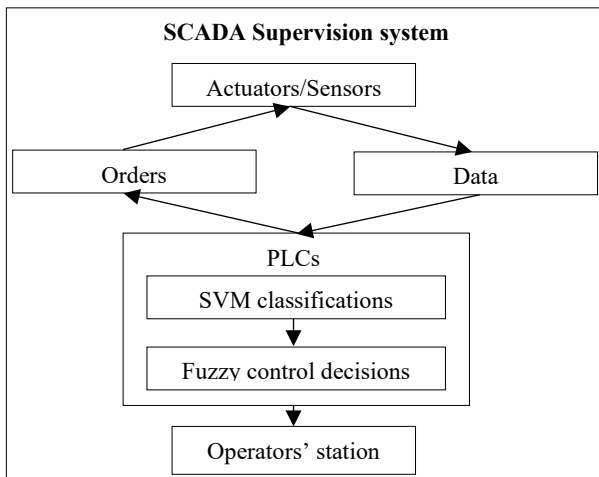


Figure 4. The proposed architecture.

5.1 Fuzzy Logic

In the domain of intelligent systems, where continuous evolution and enhancement are crucial, particularly through user interactions, Fuzzy Logic emerges as a potent technique. In industrial processes, human operators often rely on imprecise and fuzzy measurements of the process state, drawing from their extensive experience. Fuzzy Logic, extending beyond conventional logic, adeptly handles such scenarios by accommodating partial truths. This approach has proven highly effective in developing sophisticated control systems. Fuzzy Logic mimics human cognitive processes, aiming to model our understanding of concepts, decision-making, and common sense.

By doing so, it facilitates the creation of more human-like intelligent systems. In the quest to improve the reliability and availability of control systems, a supervisory system has been devised, implementing various solutions and employing different strategies to implement fuzzy control effectively [49]. The roots of fuzzy set theory, formalized by Lotfi Zadeh in 1965 [4,50] and further expounded upon in subsequent years, lay the foundation for understanding the generality and ambiguity inherent in human comprehension of complex systems. This can help traders make more informed and accurate decisions based on the available data. Moreover, a study describes the use of fuzzy logic for fault detection and diagnosis in a cement kiln. The study presents a case study to detect and diagnose faults in the cement kiln, based on the temperature and pressure signals of the kiln [51].

5.2 Support Vector Machines (SVM)

Support Vector Machine (SVM) is a supervised machine-learning algorithm introduced by Vapnik [52,53]. SVM

constructs decision planes or hyperplanes in two or multidimensional spaces to establish decision boundaries that separate instances belonging to different classes. It is renowned for its robust theoretical underpinnings and has demonstrated exceptional empirical performance. SVM has firmly established itself as a powerful tool in machine learning. SVM has garnered attention for its superior performance in comparison to traditional learning machines, establishing itself as a robust tool for tackling classification problems. While SVM offers compelling advantages, it is essential to admit certain boundaries associated with its application. SVMs can be sensitive to outliers, anomalies, or noise in the data. Outliers may influence the positioning of the decision boundary, potentially impacting the overall performance of the classification.

Training an SVM model can be computationally intensive, especially with large datasets. The algorithm's complexity may result in extended learning times, making it less suitable for real-time applications with stringent time constraints. SVMs are effective in high-dimensional spaces, but in certain cases, they may end up with a large number of support vectors. This flexibility makes SVMs a robust choice for diverse classification problems, offering adaptability to the inherent complexity of real-world datasets. SVMs provide a powerful framework for discerning between good and malfunctioning states in the production line, showcasing their utility across varied classification scenarios [24]. In multiclass classification, commonly used voting schemes such as one-against-one and one-against-all are employed. SVMs focus on achieving accurate categorization of new test instances based on training instances. This process, known as optimal separation, is fundamental to SVM's classification capabilities.

The accuracy and effectiveness of the machine learning algorithms depend on the relevance and representativeness of the data, as well as the choice and optimization of the algorithms. Fuzzy Logic and SVM were specifically chosen over other techniques within the realm of industrial control systems, based on their relevance and efficacy. Fuzzy Logic is a type of rule-based system that can handle uncertainty and imprecision in the data, and provide some flexibility and adaptability in the decision-making process. Fuzzy Logic uses linguistic variables and fuzzy sets to represent the data and then applies fuzzy inference and defuzzification to generate the output. Compared to other rule-based systems such as expert systems or decision trees, Fuzzy Logic can handle more complex and dynamic systems, and provide more accurate and robust results [48].

Fuzzy Logic and SVM are two of the most popular and effective methods for industrial control systems, due to their versatility, accuracy, and efficiency. Fuzzy Logic can handle uncertainty and imprecision in the data, and provide some flexibility and adaptability in the decision-making process. SVM excels in handling non-linear and

high-dimensional data while offering generalization and regularization in the model. Compared to other methods like decision trees, random forests, or k-nearest neighbors, both Fuzzy Logic and SVM can yield more accurate and robust results while demanding less training data and computational resources. This study also seeks to illustrate the effectiveness and applicability of Fuzzy Logic and SVM in industrial control systems, aiming to offer insights and recommendations for future research and practical applications.

6. RESULTS AND DISCUSSION

The dataset obtained from the SCIMAT factory informs the choice and optimization of machine learning algorithms for fault detection or production line optimization. Some specific examples of how the dataset is used in real-world scenarios within cement manufacturing, including, fault detection. The dataset includes the vibration signals of the mill, as well as the parameters and classes of the mill operation. Machine learning algorithms leverage this data to detect and classify faults in the mill, such as bearing wear, gear damage, or motor failure.

The effectiveness and efficiency of these algorithms hinge on the quality and quantity of the data, along with the selection and optimization of the algorithms themselves. In the context of optimizing cement plant performance, the dataset from the SCIMAT factory serves to predict the plant's operational class based on process parameters. This dataset comprises historical operational data of the plant, including both the process parameters and the corresponding classes of cement production.

6.1 Model Architecture

The integration of machine learning techniques, mainly SVM, into industrial supervision systems for intelligent automation has witnessed a paradigm shift. In this study, SVM proves to be a robust algorithm employed to classify diverse data and measurements originating from sensors, effectively discerning whether the industrial process is in a state of optimal functioning or degradation. The developed application features a precise classification of features, categorized into distinct ranges based on predefined setpoint intervals: "High range" for values exceeding the setpoint, "Medium range" for values falling between the high and low setpoints, and "Low range" for values below the setpoint. SVM plays a central role in analyzing these datasets, employing both classification and regression functions tailored to handle various types of data effectively.

The SVM technique meticulously undergoes training, testing, and validation processes, classifying datasets according to predefined criteria. This not only empowers the system to predict but also enables the assignment of new data to its appropriate class. The utilization of an RBF kernel, known for its superior performance, underscores

the efficiency of SVM as a high-performance classification technology, garnering attention across diverse fields. The integration of fuzzy logic further enhances the model's adaptability to the vagueness, imprecision, and uncertainty inherent in industrial processes.

Fuzzy controllers, fueled by SVM classification results, are employed to command different equipment and machines, illustrating a holistic approach to intelligent automation in industrial settings. Expert knowledge, extracted through operator interviews and technical manuals, contributes to the creation of the supervision system. The SVM classification algorithm and fuzzy control are integrated into the available PLC, with classes (low, medium, and high) serving as inputs to the fuzzy controllers. This innovative approach, replaces traditional supervision systems, minimizing operator tasks in the main control room.

The developed Python code under v3.9 enables communication effectively with the Simatic Step 7 PLC code using the Snap 7 library and facilitates real-time prediction and classification from the industrial system. This seamless connection allows the program to access system parameters and automate control, eliminating the need for constant manual intervention. The architecture of this contribution is characterized by flexibility in control and efficient data processing, ultimately improving productivity and reducing maintenance costs. Moreover, this collaborative approach proves instrumental in the development of the predictive model, marrying the capabilities of both languages for enhanced efficiency and adaptability.

6.2 Model Construction and Results

The construction of the SVM predictive model involves a systematic process to ensure its effectiveness in industrial supervision. Begin by comprehensively assessing and cleaning the dataset, addressing any data anomalies, or missing values. Identifying feature selections based on their relevance to the system's performance. The dataset is partitioned into training (70%) and test sets (30%) for model training and evaluation. Before training, features are normalized to ensure uniform scales across the dataset. All hyperparameters were optimized through experimentations. The SVM model was trained by selecting an RBF kernel function. The flowchart of the construction of the model is illustrated in Figure 5.

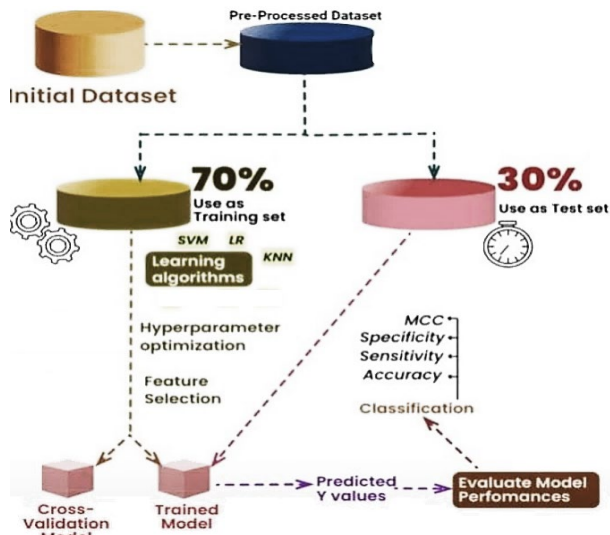


Figure 5. The model construction phases.

The evaluation of the predictive model's performance is based on a selection of key metrics designed to provide a comprehensive understanding of its capabilities. The chosen metrics, including, Sensitivity, Specificity, Accuracy, Testing Accuracy, and, Training Accuracy, have been carefully considered for their suitability in the context of industrial automation, especially in real-time scenarios (see Table 2). The Accuracy serves as a fundamental measure of overall predictive performance. In industrial settings, accurately predicting the system's state, whether optimal or degraded, is critical for timely decision-making and intervention. A high accuracy score, as demonstrated in our results (94.18%), signifies the model's proficiency in correctly classifying instances, contributing to the reliability of the industrial supervision system.

The Training Accuracy measures the model's performance on the training dataset, while Testing Accuracy assesses its generalization to new, unseen data. The utilized metrics assess the model's capacity to learn from training data and make precise predictions on new instances. High values for training and testing accuracy (98.88% and 94.18%, respectively) validate the model's resilience and its ability to generalize effectively to real-world situations.

In industrial automation, sensitivity (true positive rate) and specificity (true negative rate) are especially critical because false positives or false negatives can have substantial consequences. Sensitivity highlights the model's accuracy in identifying instances of suboptimal performance, while specificity underscores its proficiency in recognizing optimal conditions. The balance between Sensitivity (92.46%) and Specificity (94.59%) ensures a well-rounded evaluation, indicating the model's effectiveness in both detecting degradation and confirming optimal states.

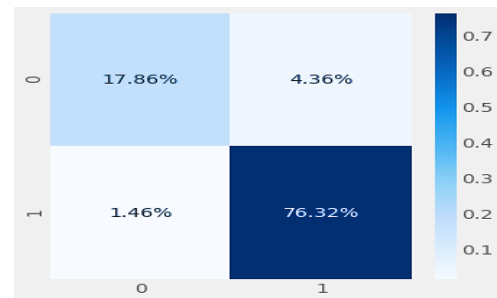
Table 2. The evaluation of the model.

Metrics	Values (%)
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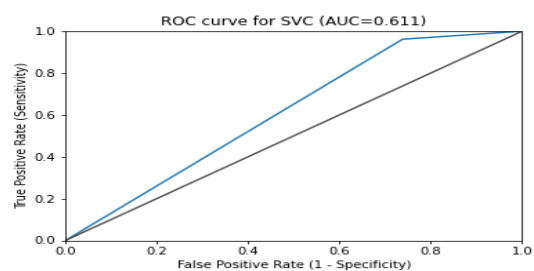
Accuracy score	94.18
Sensitivity	92.46
Specificity	94.59
Testing	94.18
Training	98.88

A cross-validation strategy was implemented to bolster the model's robustness. To gain deeper insights into its performance, we employed a confusion matrix and Receiver Operating Characteristic (ROC) curve. The confusion matrix offers a detailed breakdown of true positives, true negatives, false positives, and false negatives, providing a clear view of the model's predictive accuracy. Concurrently, the ROC curve visualizes the trade-off between sensitivity and specificity across varying threshold settings. Furthermore, the confusion matrix presents both actual values and prediction percentages, serving as a fundamental tool for evaluating the SVM classification model's performance. It provides a comprehensive summary by comparing predicted and actual class labels in the testing dataset.

The Area Under the Curve (AUC) derived from the ROC curve quantifies the model's overall performance, where a higher AUC signifies better accuracy. Analyzing the confusion matrix aids in fine-tuning the model for optimized performance in industrial supervision applications. Similarly, interpreting the ROC curve assists in selecting an optimal threshold, balancing sensitivity, and specificity. It offers critical insights into the model's ability to distinguish between classes and is essential for assessing classification models in industrial supervision systems. Figure 6 illustrates the obtained confusion matrix (a) and ROC curve (b).



(a) The confusion Matrix.



(b) The ROC curves.

Figure 6. Confusion Matrix and ROC curve.

These metrics provide valuable insights into the model's performance in correctly classifying instances, minimizing false positives and negatives, and its overall effectiveness across various classes. The evaluation metrics of the model are summarized in Table 3.

Table 3. Model's evaluation metrics.

	Recall (%)	Precision (%)	f1-score (%)	support
Class "1"	98	95	96	9769
Class "0"	80	92	86	2792
Accuracy			94	12561
Weighted avg	94	94	94	12561
Macro avg	89	94	91	12561

In comparison to accuracies obtained from experiments using other classifiers, the SVM model achieves an accuracy of 94.18%. The K-Nearest Neighbors (K-NN) model achieved approximately 93.83% accuracy. The decision tree model achieved about 83.73% accuracy. The logistic regression model achieved an accuracy of 80.25%. Connecting Python to Simatic Step 7 using NetToPICSim and the Snap7 library is a crucial step in integrating the developed SVM predictive model into the industrial supervision system. NetToPICSim functions as a bridge facilitating communication between Python and the Simatic PICSim environment. This connection is ensured by configuring network IP addresses for the computer, Rack/Slot, and Simatic PICSim. The Snap7 library plays a pivotal role in enabling data exchange between both, Python and Simatic Step 7 codes.

Once the configuration is set, the running of NetToPICSim allows for the seamless execution of any automatic code developed in Python. This setup ensures that the predictive model, implemented in Python, can cooperate with the Simatic Step 7 environment, enabling real-time monitoring and control of the industrial process. The accessibility provided by NetToPICSim and Snap7 is illustrated in Figure 8, showcasing the interconnected network architecture that facilitates the flow of data between Python and Simatic Step 7. In the scenario of acquiring new values in real-time, the dynamic movement of curves and changes in classes is indicative of variations in the feature measurements. This dynamic behavior serves as the real-time feedback mechanism, enabling operators to discern when the system deviates from the expected range.

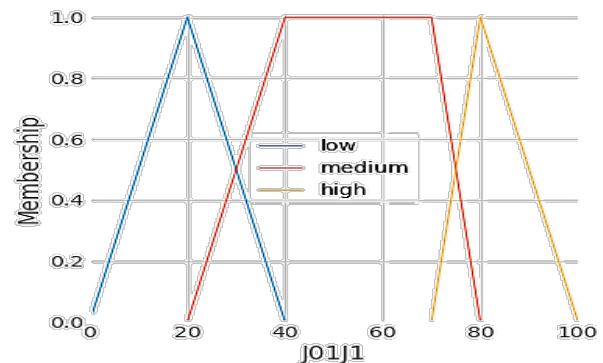
The complexity of data exchange was alleviated by establishing a systematic protocol, emphasizing the importance of consistent scales and normalized features for effective communication. An aspect that deserves explicit attention is network security. While our integration focused on functionality, future implementations should prioritize the incorporation of robust security measures, safeguarding industrial systems against potential vulnerabilities associated with external connections. Our work showcased the real-time

monitoring capabilities of the integrated system, emphasizing its significance in anomaly detection. However, an aspect that merits further discussion is the system's responsiveness to anomalies. Detailed analysis of response times, encompassing the speed and accuracy of the system's reactions to deviations, is crucial for understanding its practical implications in industrial operations.

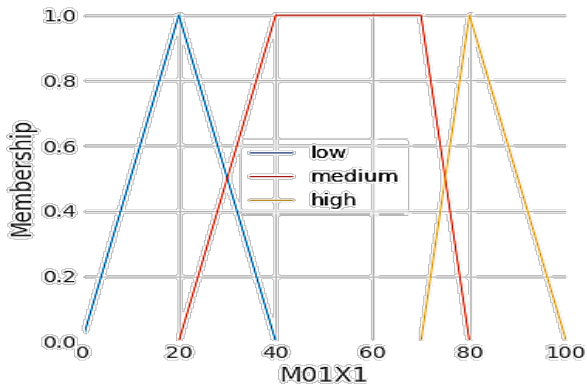
6.3 Fuzzy Control of the Industrial Process

The fuzzy controllers play a crucial role in the intelligent industrial supervision system by establishing fuzzy inferences between inputs and outputs. These controllers serve as a diagnostic tool, offering preventive, identification, and recovery capabilities for abnormal operations or failures within the workshop. Among the diverse controllers developed for workshop control, a noteworthy example is the fuzzy controller designed to monitor material levels in the feeder and elevator and to initiate material transportation to the raw mill. This controller utilizes acoustic equipment to measure material levels within the raw mill, enhancing the overall efficiency and accuracy of the control system.

The integration of fuzzy logic controllers enhances the system's adaptability to handle complex and dynamic industrial processes, ensuring optimal performance and response to varying operating conditions. Multiple fuzzy controllers are developed specifically to manage and synchronize the control loop of material feeders and various parameters within the workshop of the cement mill. These controllers serve as a pivotal component in orchestrating the interplay of various factors and ensuring harmonized operations within the workshop. Its functionality extends to optimizing the material feeders' performance and maintaining synchronization with other critical parameters. In a practical demonstration, the first fuzzy controller operates with two inputs and one output. The first input corresponds to the material level in the elevator, denoted by J01J1 = 15%. The second input is derived from acoustic equipment, indicated as M01X1 = 25% (refer to Figure 7).



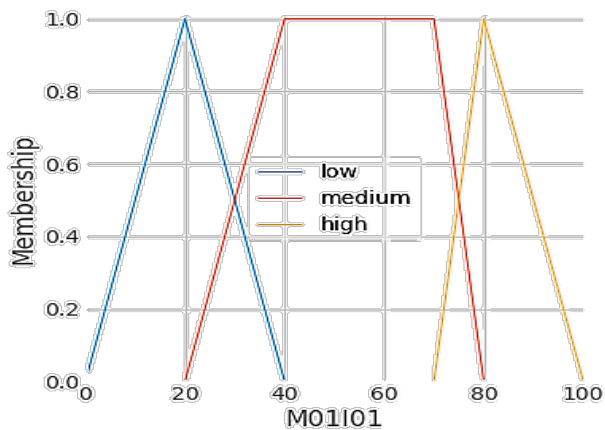
(a) The input J01J1.



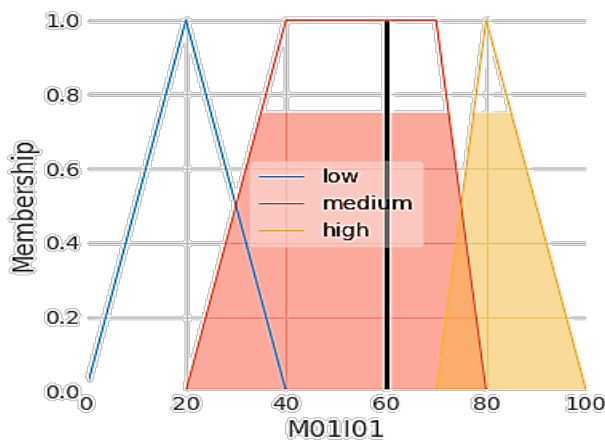
(b) The input M01X1.

Figure 7. The inputs of the fuzzy controller of the Feeder.

As a result, the feeders' amount is determined, with M01I01 equating to 60%. The outcomes of this fuzzy control scenario are visually depicted in Figure 8, offering a graphical representation of the controller's decision-making process based on the specified inputs.



(a) The output M01I01.



(b) The result of the feeder's fuzzy controller.

Figure 8. The output and the outcome of the fuzzy controller for the feeder.

The presented model introduces a comprehensive framework for the fuzzy control of material circulation involving the elevator, raw mill, and feeders within the industrial workshop. The continuous fuzzy control system established by this model is designed to facilitate uninterrupted operations, eliminating the necessity for operator intervention to modify controller setpoints. This continuous control mechanism optimizes the efficiency of material flow and maintains seamless coordination between interconnected components.

This example highlights the controller's ability to integrate multiple inputs, interpret their fuzzy values, and generate a precise output, showcasing the effectiveness of fuzzy logic in managing complex and interconnected industrial processes. This controller implementation underscores its significance in achieving efficient and well-coordinated processes, contributing to the overarching goal of intelligent automation in the industrial setting. By incorporating fuzzy logic into the control system, the proposed model enhances adaptability to dynamic conditions, allowing for real-time adjustments without manual intervention. This automated and intelligent approach contributes to operational stability, reducing the dependency on manual oversight and promoting a more autonomous and responsive industrial process.

6.4 Connecting SVM and Fuzzy Control

To enhance fault detection and provide precise insights into their origin and nature, an interactive human-machine interface has been developed. This interface enables the identification of abnormal conditions such as high pressure or maximum level in the tank. A dedicated table is generated to comprehensively display all alarms, facilitating efficient monitoring and prompt response to deviations from normal operating conditions.

In the development of the HMI, a rigorous usability testing approach was employed, involving operators and relevant stakeholders. This testing aimed to assess the interface's intuitiveness, efficiency, and overall user-friendliness. Participants were given scenarios simulating real-time industrial situations, evaluating how well the interface facilitated their decision-making and response times. Based on the usability testing, iterative refinements were made to the HMI, addressing identified pain points, and incorporating valuable user feedback. The collaborative nature of this process ensured that the interface not only met technical requirements but was also tailored to the cognitive and operational needs of the end-users.

The HMI features a dedicated table that comprehensively displays all alarms, providing operators with a centralized and real-time overview of the system's status. This design choice facilitates efficient monitoring and allows for prompt responses to deviations from normal operating conditions. As an example, the focus is placed on the

changes in the engine temperature input, denoted as M01T1. This particular feature is critical and is characterized by a setpoint range of [220-400] °C. The SVM curve for M01T1 is visually represented in Figure 9, providing a clear and informative depiction of how the SVM classifies the data points associated with this feature. This graphical representation helps operators comprehend the behavior and classification patterns of the SVM model. It aids in interpreting feature measurements and enhances the overall effectiveness of the intelligent industrial supervision system.

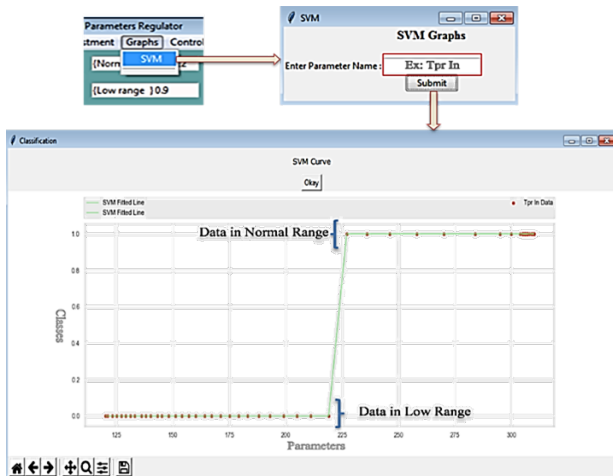


Figure 9. Classification of the state of the system based on the engine temperature input.

The dynamic alteration of parameter ranges based on decisions obtained from the fuzzy controller is visually depicted in Figure 10. This graphical representation illustrates how the fuzzy controller's decisions influence and modify the ranges of parameters within the industrial process. The adaptive nature of the fuzzy control system is evident in its capacity to dynamically adjust parameter values in response to changing conditions, ensuring optimal performance and alignment with specified objectives.

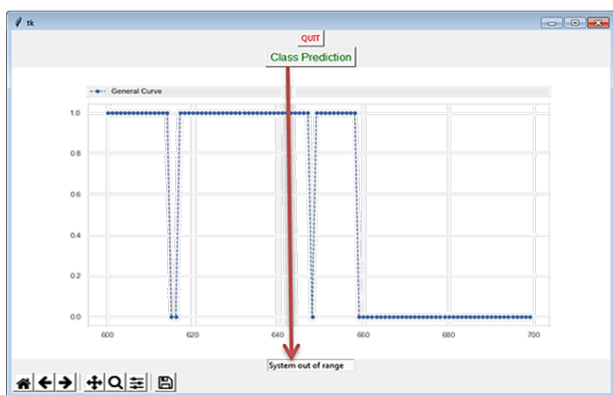


Figure 10. Prediction of the variation of the features.

In acknowledging the complexity of industrial processes, our study thoroughly identifies potential limitations in the

proposed system. These include variations in equipment specifications, dynamic environmental conditions, and the inherent uncertainties within industrial settings. To reinforce the system's robustness, adaptive strategies have been implemented. Machine learning techniques, mainly SVM, are designed to handle diverse datasets with varying characteristics. The system is equipped to dynamically adjust its classification criteria based on the intricacies observed in real-time industrial data. Continuous monitoring mechanisms are incorporated to detect anomalies or shifts in system behavior. Automated calibration routines ensure that the system can adapt to gradual changes or sudden disturbances, maintaining its efficacy over time. The system's architecture is designed with scalability in mind, allowing for seamless integration into different industrial contexts. It is crucial to note that the modular nature of the system permits the addition or modification of components, ensuring adaptability to diverse manufacturing environments. The robustness and scalability of the proposed intelligent industrial supervision system are paramount for its successful deployment in diverse industrial settings.

The scalability of the system has been evaluated across different scales, ranging from pilot studies to larger industrial setups. This comprehensive evaluation provides insights into how the system performs when applied to varying production capacities and complexities. To enhance scalability, the system is engineered for interoperability with existing industrial control and automation systems. This interoperability facilitates the integration of our proposed solution into established frameworks without necessitating a complete overhaul of pre-existing infrastructures. The real-world implementation of the system may encounter challenges stemming from the inherent heterogeneity of industrial setups. Strategies for addressing such challenges include conducting site-specific feasibility studies and developing adaptable modules that can accommodate diverse industrial configurations. As the system scales, user training becomes pivotal. A structured training program ensures that operators and maintenance personnel are well-versed in the nuances of the expanded system, mitigating challenges associated with increased complexity.

The findings of this study hold practical implications that extend beyond cement manufacturing, offering insights applicable to diverse process industries. The successful integration of SVM and fuzzy logic techniques for fault detection and process optimization opens avenues for enhancing production efficiency and resource utilization across sectors such as chemical processing, power generation, and pharmaceutical manufacturing. Moreover, the study lays the groundwork for future research into hybrid Machine Learning models, scalable control systems, and user-friendly interfaces, highlighting opportunities for further innovation in industrial automation. Through ongoing exploration and development, intelligent control systems promise to

revolutionize industrial operations, driving increased productivity, reduced costs, and improved operational flexibility.

7. CONCLUSION

The presented study represents a pioneering endeavor to seamlessly integrate Machine Learning into industrial practices, specifically within the context of a tangible industrial project conducted at SCIMAT Society. Employing the highly accurate SVM algorithm, achieving an impressive accuracy rate exceeding 94%, we have bridged the realms of Python and Simatic Step 7 code to establish a symbiotic link between the industrial supervision system and our cutting-edge code. The resultant automatic controller program, crafted with the intent of emulating operator functionality, places a strong emphasis on the system interface's interactivity, empowering operators with unparalleled control. This endeavor advocates for the pervasive integration of Machine Learning in industrial supervision, envisioning an optimized production system.

The identified potential extends beyond mere data classification, showcasing Machine Learning's transformative prowess in industrial contexts. This not only stands as a viable alternative to human-operated processes but also heralds a paradigm shift towards a more efficient and precise industrial system. The associated costs and time investment are overshadowed by the considerable benefits, including enhanced control, heightened production, consistent quality, operational stability, reduced fuel consumption, minimized standard deviation of free lime, and a remarkably swift return on investment in less than a year.

The paper extensively outlines the numerous advantages of integrating Machine Learning (ML) into industrial settings, showcasing its transformative potential. However, a more nuanced approach is needed to ensure a comprehensive perspective. While recognizing the benefits, it is equally essential to delve into potential drawbacks and challenges associated with the increased reliance on automated systems. Providing an in-depth analysis of the limitations and potential risks will contribute to a more holistic and balanced view, fostering a thorough understanding of the implications of ML integration in industrial contexts.

A reduction of human operators' roles in control rooms is due to the rise in automation. However, to present a more comprehensive and insightful perspective, a deeper exploration of the broader societal and workforce implications is warranted. This entails delving into potential socio-economic consequences, workforce dynamics, and the impact on employment structures. Analyzing the implications of reduced human involvement on job displacement, skill requirements, and potential shifts in labor markets will provide readers with

a more thorough understanding of the societal ramifications of increased automation.

The study presented a significant advancement in industrial automation, showcasing the potential of integrating machine learning algorithms into real-world industrial processes. While the findings demonstrate promising results in fault detection and process optimization, it's crucial to acknowledge the study's limitations. Further validation across diverse industrial contexts and exploration of scalability issues are needed to ensure the applicability of the proposed approach in various settings. Moreover, future research should focus on investigating the broader societal implications of increased automation, including workforce dynamics and socio-economic impacts. By addressing these challenges and continuing to innovate in machine learning techniques and control systems, we can unlock new opportunities for enhancing efficiency and sustainability in industrial operations.

In conclusion, the proposed architecture for integrating machine learning techniques, specifically SVM and GRU algorithms, into the supervision systems of a cement plant demonstrates a significant improvement in the prediction of system faults and process optimization. However, future research must address the scalability of this system across different industrial sectors to broaden its applicability. Additionally, analyzing the broader societal implications of increased automation is crucial to managing the workforce dynamics that accompany such changes. Furthermore, a deeper examination of the system's response times to anomalies will provide insight into the practical challenges and bottlenecks of implementing real-time applications in complex industrial settings. By addressing these aspects, the next generation of predictive and autonomous industrial systems can achieve enhanced productivity, safety, and sustainability.

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