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Original Article

Use of Defuzzification Methods for a Dry Cement Rotary Kiln

Brayham Smit Tunco Quispe[1], Luciano Gabriel Cuayla Flores[2], German Alberto Echaiz Espinoza[3], Pedro Alberto Mamani Apaza[4], Fernando Echaiz Espinoza[5]

[1,2]*School of Professional Electronic Engineering, National University of San Agustín of Arequipa, Arequipa, Perú.*
[3]*Academic Department of Electronic Engineering, National University of San Agustín of Arequipa, Arequipa, Perú.*
[4]*Academic Department of Mathematics, National University of San Agustín of Arequipa, Arequipa, Perú.*
[5]*Institute of Mathematics, Federal University of Alagoas, Alagoas, Brazil.*

[3]*Corresponding Author : gechaiz@unsa.edu.pe*

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Abstract - *Controlling nonlinear thermal systems like rotary cement kilns is a long-standing problem in industrial automation since they are dynamic and hard to predict. Fuzzy Logic Controllers (FLCs) present a strong alternative; nonetheless, the essential defuzzification phase - responsible for transforming fuzzy outputs into actionable values - has been inadequately examined in comparative analyses. This project creates a Mamdani-type FLC with 88 rules based on experts and four main inputs: combustion temperature, furnace torque, CO percentage, and preheater temperature. It will be used to control a high-capacity rotary kiln. We comprehensively examine five defuzzification methods: centroid, bisector, Smallest of Maximum (SOM), Middle of Maximum (MOM), and Largest of Maximum (LOM), using simulations generated in MATLAB's Fuzzy Logic Toolbox. The results reveal that the output is generally consistent among approaches, except for the kiln feed rate, which is quite sensitive. The research illustrates that the selection of defuzzification strategy significantly influences control performance, with maxima-based approaches providing enhanced stability. These results provide practical advice for developing strong fuzzy controllers for complicated industrial processes.*

Keywords - *Defuzzification techniques, Fuzzy Logic Controller, Mamdani inference, Nonlinear process control, Rotary kiln automation.*

1. Introduction

The control of nonlinear thermal processes, such as dry cement rotary kilns, remains a significant challenge in industrial automation due to their high dynamic complexity, strong coupling among variables, and inherent operational uncertainty. Conventional control methods, such as PID controllers, frequently encounter difficulties under these circumstances, prompting the use of intelligent control strategies. Fuzzy Logic Controllers (FLCs) have become a strong and adaptable option that allows for the use of expert knowledge and can handle behavior that is not always predictable [1, 2]. The defuzzification stage, which changes vague, linguistic findings into exact numerical control actions, is a very important part of FLC design that is often ignored. There are other ways to defuzzify, such as the centroid, bisector, Smallest of Maximum (SOM), Middle of Maximum (MOM), and Biggest of Maximum (LOM). However, most commercial applications choose the centroid technique without a strong technical reason [3]. This approach presupposes a negligible impact of defuzzification on system behavior, although data indicate its potential effects on control sensitivity, stability, and responsiveness, especially in systems characterized by asymmetric or multimodal membership functions [4]. Recent studies on Fuzzy Logic Controllers (FLCs) in rotary kiln applications have focused on optimizing controllers or comparing them to traditional approaches, mainly neglecting a thorough examination of defuzzification procedures [5, 6].

Even studies that employ more complex models, such as neuro-fuzzy or type-2 systems, sometimes skip the defuzzification stage altogether, especially when Sugeno-type structures are used. Consequently, the effects of defuzzification on essential variables, including fuel flow, rotation speed, and feed rate, remain little examined. This paper seeks to fill this methodological need by comparing five prevalent defuzzification approaches utilized in a Mamdani-type fuzzy controller for rotary kiln operation. There are 88 expert-defined rules and triangle membership functions in the controller. It was made in MATLAB using the Fuzzy Logic Toolbox. The system's performance is evaluated in typical operating circumstances, with performance

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measures concentrating on essential output variables associated with clinker quality and energy efficiency. This paper offers empirical information about the impact of defuzzification approaches, serving as a technical decision-making guide for FLC designers and reinforcing the framework for repeatable, scalable, and resilient fuzzy control in intricate industrial settings.

2. State of the Art

In recent decades, the automation and management of rotary cement kilns have progressed, integrating sophisticated methods such as fuzzy logic, expert systems, neuro-fuzzy models, and explainable artificial intelligence. Even though these advances have been made, one important part has always been overlooked: the defuzzification process, which turns linguistic deductions into exact control actions. The next section looks at five important studies that show how things are now in this field of knowledge.

2.1. Specialized Systems are used for the Control of Rotary Kilns

In a long study about the use of specialized systems for managing cement kilns, many applications of methods based on logical rules, Mamdani-type fuzzy logic, and artificial intelligence algorithms stand out as ways to improve thermal efficiency, operational stability, and product quality [1]. The research shows how expert systems help make faster and more effective decisions when procedural conditions change, surpassing conventional PID-based models. However, the article does not delve into the defuzzification phase, considering it an implicit component of the system without examining how the selection of the method can influence the controller's accuracy, stability, or sensitivity. This gap is important because many of the systems mentioned are based on logic that is not clear, and this is the exact point where the transition from symbolic deductions to numerical results happens.

2.2. Evaluation of Temperature Parameters through Fuzzy Inference

A study of the process of making sponge iron uses Mamdani-style fuzzy logic to evaluate the metallization and the formation of crusts (accretion) in the rotary furnace, considering factors like the fire temperature, the residence time, and the rotation speed [7]. Triangular membership functions are established, and rules based on operational experience are implemented, facilitating the real-time detection of the furnace's behavior. The system can model uncertainty and improve the understanding of the incoming data. However, only the centroid defuzzification procedure is chosen, without providing technical reasons or considering other options that could respond more effectively to asymmetric or multimodal membership functions. This one-of-a-kind choice puts the system's growth at risk and misses out on the chance to perform better under a variety of procedures.

2.3. Experimentation under Noise with Type-2 Neuro-Fuzzy Systems

From a more advanced perspective, a type-2 Takagi-Sugeno system is proposed to determine the dynamic behavior of a rotary kiln under noisy conditions [8]. This proposal is unique because it can adapt and handle uncertainty through an improved neuro-fuzzy system with genetic algorithms. The model uses type-2 membership functions in the antecedents and linear functions in the consequents. This helps it achieve a lower Mean Squared Error (MSE) than type 1 systems. However, when using a Sugeno architecture, the output is determined directly without the need for defuzzification, which means this crucial phase is neither considered nor examined, maintaining its utility in industrial Mamdani systems where this phase is essential.

2.4. Modeling Operational Variables through Explainable Artificial Intelligence

Recent research suggests the use of Explainable Artificial Intelligence (XAI) methods to simulate the operation of furnace operational variables, such as feed rate, furnace torque, and fan current [2]. Using XGBoost and SHAP, we can accurately predict these variables (R2 > 0.96) and see how important each input is compared to the others. This makes it easier to make decisions in the plant. Although the method allows for a detailed and visual interpretation of the data, fuzzy logic is not applied, nor are defuzzification methods considered, which limits its ability to convert symbolic expert knowledge into real-time numerical decisions. The model is easy to understand, but cannot be changed from a fuzzy point of view.

2.5. Critical Evaluation of Conservation using Fuzzy Logic

In a setting that focuses more on knowledge management, a diffuse system is suggested to assess the importance of maintenance tasks in cement kilns, considering factors such as frequency, cost of interruption, and the consequences of a failure [5]. A Mamdani system is set up using MATLAB and the Fuzzy Logic toolbox, which makes it easier to show uncertainty in the order of tasks. The method has practical value, but the system only uses the centroid method as the defuzzification method and does not consider other options that could change the priorities of the tasks. This technical restriction makes it impossible to assess how vulnerable the system is to the choice of exit method, which is important in systems where the relative importance of decisions may be low.

2.6. Overall Conclusion on the State of the Art

Although fuzzy logic is widely used to control rotary kilns, the literature review shows that the defuzzification phase has been considered a secondary decision, restricted to the centroid method, or completely ignored in Sugeno-type systems [1, 5]. None of the studies looked at a comparative study or looked at how choosing the defuzzification method might affect the system's accuracy, stability, or sensitivity.

This methodological gap is important because defuzzification turns symbolic deductions into real actions; an incorrect choice can negatively affect thermal efficiency, clinker quality, or the system's overall performance. This study suggests a comparative study of five defuzzification techniques: centroid, bisector, SOM, MOM, and LOM, used in a Mamdani controller with eighty-eight rules and triangular membership functions. The system is simulated in MATLAB using the Fuzzy Logic toolbox, and its performance is evaluated based on key variables such as the flow of the furnace, the speed of rotation, and the fuel consumption. This analysis provides a technical guide for choosing the best defuzzification method, which helps create more accurate, robust, and reproducible fuzzy controllers in industrial situations. The logical structure of the present study shows the identified gap in fuzzy controller design and the proposed comparative analysis of defuzzification methods.

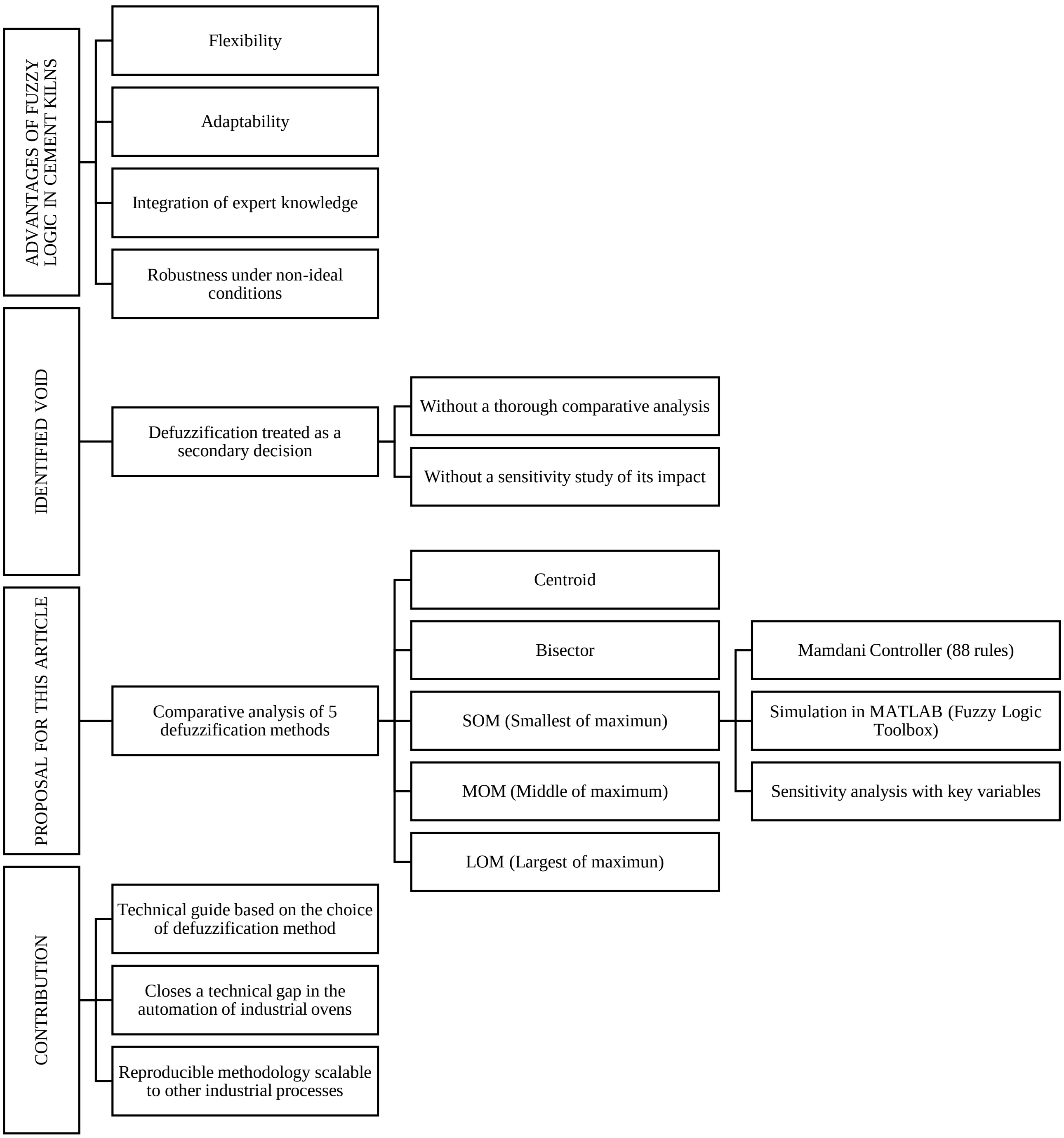


Fig. 1 logical structure of the present study

Table 1. Summary of five common defuzzification methods with their characteristics and expected impact on industrial fuzzy control

Method	Brief Description	Main Advantages	Limitations or considerations	Typical impact on industrial control
Centroid	Calculates the center of gravity of the fuzzy area	Balanced and smooth result; widely used	can be computationally more expensive	Stable control, balanced response
Bisector	Divides the fuzzy area into two equal parts	Maintains balance in asymmetric distributions	less common, less intuitive in some cases	Moderate control, good handling of uncertainty
SOM	Chooses the smallest value with maximum membership	More conservative; avoids aggressive responses	may produce overly rigid control	Conservative results are useful in critical conditions
MOM	Average values with maximum membership	The balance between SOM and LOM is easy to interpret	does not always distinguish multiple maxima well	Control with good balance between aggressiveness and stability
LOM	Selects the largest value with maximum membership	More aggressive responses are useful for quick reactions	may generate unstable or abrupt control	Aggressive control may increase variability

3. Theoretical Framework

3.1. The Fuzzy Controllers

L.A. Zadeh's fuzzy set theory [11] underpins fuzzy control, which subsequently establishes the foundation for an intelligent control system that emulates human cognitive processes. "Diffuse" denotes ambiguous or subjective concepts, with their significance contingent upon the observer's perception and interpretation. We employ ambiguous terms such as "most," "several," "probably," or "not precisely" in all communication. "True," "false," "all," and "none" are specialized terms.

In classical control theory, low-order linear models, such as second-order systems, enable the development of PI or PID controllers using established methodologies. One may employ either pole placement design techniques or frequency domain methodologies for high-order linear systems. You may also suggest controllers that operate by identifying the optimal method to reduce variability or the integral of the quadratic error. The more accurately the model represents the actual process, the more effectively the algorithm-controlled system will respond.

However, complications may arise if the system model is unknown, complex, has significant nonlinearity, or undergoes fast parameter changes. Occasionally, conventional design methodologies become ineffective. Adaptive control systems may modify control actions in real time; however, their practical use is hindered by the complexity of the mathematical apparatus and the extensive computations required.

Fuzzy control is an adaptable method for managing this sort of system, since it converts an operator's expertise and abilities into straightforward, easily comprehensible IF-THEN rules. These criteria facilitate the adaptation of ambiguous specifications into control algorithms suitable for specialized broadcast processors or microcontrollers. The primary advantage is that fuzzy logic establishes a continuum between true and untrue, facilitating the demonstration of the veracity of acts and situations under consideration.

This perspective is effectively exemplified by operating a vehicle. A driver must simultaneously evaluate several inaccurate data points, including other vehicles' distance and speed, to make sound judgments. Internal regulations such as "reduce speed if velocity is excessive" or "apply brakes forcefully if the distance is minimal and speed is high" are not founded on precise metrics but are grounded in common sense. This is ambiguous; yet accidents occur seldom relative to the volume of vehicles on the road [12].

3.2. Defuzzification Methods

Defuzzification is the process of transforming a fuzzified output into a singular, precise value in relation to a fuzzy set. The defuzzied value in a Fuzzy Logic Controller (FLC) signifies the action to be executed in process control.

3.2.1. Centroid Method

The centroid defuzzification method converts the fuzzy output into a numerical value, which corresponds to the coordinate of the center of gravity of the resulting fuzzy set.

$$y_d = \frac{\int_S y \mu_Y \, y(dy)}{\int_S \mu_Y \, y(dy)} \tag{1}$$

In this context, μ_Y Represents the membership function of the output set Y, where the output variable is y and S refers to the domain or range of integration [10].

3.2.2. Bisector Method

The bisection method determines the point that divides the area under the curve of the membership function into two equal areas. That is, we seek the value y_b that satisfies the condition that the accumulated integral from the lower limit to y_b is equal to half of the total area [10].

$$\int_{x_{min}}^{y_b} \mu(x)dx = \frac{1}{2}\int_{x_{min}}^{x_{max}} \mu(x)dx \quad (2)$$

3.2.3. Middle of Maximum Method

The middle of maximum method focuses on the values at which the membership function attains its maximum. The interval of values where the maximum degree of membership occurs is identified, and the midpoint of this interval is calculated [10].

If x_{min}^{*}y x_{max}^{*} Define the limits of the interval where the function $\mu(x)$ is maximum, the defuzzied value y_{mom} is calculated as:

$$y_{mom} = \frac{x_{min}^{*}+x_{max}^{*}}{2} \quad (3)$$

3.2.4. Smallest of the Maximum Method

In the smallest of maximum method, the smallest value within the range of values that reaches the maximum degree of the membership function is selected. It is an alternative that favors a conservative strategy in systems where lower responses are preferable [10]. If x_{min}^{*} The minimum value within the set of points with maximum activation is defined as:

$$y_{som} = x_{min}^{*} \quad (4)$$

3.2.5. Largest of the Maximum Method

In this case, the highest value is selected among those with the maximum activation in the membership function. It is suitable for applications that seek to favor decisions towards the upper end of the interval [10].

Let $\mu(x)$ Be the membership function of the resulting fuzzy set, the maximum degree of membership μ_{max} Is determined, and the set of x values such that:

$$\mu(x) = \mu_{max} \quad (5)$$

3.3. Cement Kiln System

The cement kiln system, which is the subject of this study, is the core of the clinker manufacturing process using the drying method. It is a dry cement rotary furnace that stands out for its compact and modern design, which is optimized for operations with high energy efficiency. Next, we explain how the system is configured and operates:

The furnace is short, with a length of seventy-five meters and a diameter of 4.6 meters. This allows for precise control of the thermal reactions within the process. Its design is aimed at achieving a production capacity of up to 3500 tons per day, meeting the high productivity requirements of contemporary cement plants. To make the most of the residual heat from the exhaust gases, the system includes a double-line preheater organized into four stages.

This preheater is configured with several stages of cyclones, with three of them having each stage equipped with two cyclones and stage two equipped with a single cyclone, as the temperature of the preheater, identified as the most sensitive point of the process, is measured in this section. This arrangement makes it possible to improve thermal efficiency by preheating the raw material before it goes into the main oven.

The oven, which is a steel cylinder lined on the inside with refractory material, is tilted a few degrees from the horizontal and rotates around its axis. This movement, along with the injection of fuel (liquid in this case, but natural gas can also be used), creates a combustion that goes in the opposite direction of the flow of the material, making sure that the heat is evenly distributed throughout the process.

3.4. Operational Considerations

3.4.1. Maintain a Constant Temperature in the Combustion Zone

The temperature in the combustion zone must be maintained within an optimal range, as this is what ensures the chemical reaction is completed correctly and a high-quality clinker is formed. Any change outside of this range can have a harmful effect on the sintering process and the final product's quality.

3.4.2. Ensure an Adequate Dwell Time for the Material in the Furnace

The time the material spends in the kiln is important for the sintering and calcination reactions to occur correctly. Ensuring an optimal residence time guarantees that the raw material is treated homogeneously and that the resulting clinker meets the desired specifications.

3.4.3. Limit the CO Percentage for Complete Combustion.

It is important to control and reduce the percentage of Carbon Monoxide (CO) in the process. A low CO level indicates that combustion is being carried out completely, which improves the utilization of the fuel's calorific content and helps reduce pollutant emissions.

3.4.4. Maintain an Adequate and Uniform Temperature in the Preheater

The preheater is important for the pretreatment of the material, and its temperature must be stable and adequate to ensure uniform calcination. A well-controlled temperature at this stage is particularly important for the operational stability of the kiln and, ultimately, for the quality of the clinker.

4. Definition of the Problem

The efficient operation of a dry cement rotary kiln involves managing a series of critical variables that directly impact the quality of the cement and the energy efficiency of the plant. The complexity and non-linear nature of the process, combined with limited sensor availability, make the development of adaptive control strategies indispensable. In this context, two fundamental groups of variables are identified.

4.1. Input Variables

4.1.1. Combustion Zone Temperature (BZ)

This variable indicates the temperature where combustion occurs, which is vital to ensure that the optimal range (around 1400°C) necessary for a complete chemical reaction and clinker formation is reached and maintained. Its precise control directly influences the quality of the final product.

4.1.2. Oven Torque (TOR)

The torque reflects the distribution and movement of the material inside the furnace, indirectly measured through the motor current. An adequate torque value ensures a homogeneous distribution, which is essential for maintaining the stability of the combustion process and the overall operability of the furnace.

4.1.3. CO Percentage in the Preheater

These variables measure the level of CO present at the precooler outlet, an essential indicator of combustion efficiency. Keeping this percentage low is crucial to ensure the fuel burns completely, optimizing thermal performance and reducing energy losses.

4.1.4. Preheater Temperature (PT)

It represents the temperature of the material in the initial calcination stage within the preheater. A controlled temperature (approximately 755°C in the studied case) is essential to ensure a uniform pretreatment of the material, laying the groundwork for the proper development of subsequent calcination and sintering processes.

4.2. Output Variables

4.2.1. Kiln Flow (KF)

This variable quantifies the productivity of the kiln, determining the amount of clinker produced per unit of time. An optimal flow translates into efficient use of the plant and maintenance of production at the desired level, directly impacting the profitability of the process.

4.2.2. Main Burner (MB)

It controls the supply of fuel necessary to raise and maintain the temperature in the combustion zone. Its adjustment is crucial to properly sintering the clinker, allowing for the required thermal balance in the operation of the furnace.

4.2.3. Preheater Fuel (PRE)

This variable refers to the fuel flow intended for the material pre-calcination process. A correct supply ensures that the material reaches the necessary temperature to release carbon dioxide and promote the formation of the essential chemical compounds of the clinker, ensuring an optimal transition to the rotary kiln.

4.2.4. Kiln Speed (KS)

It represents the rotation speed of the kiln, which determines the material retention time. A precise control of this speed is essential to ensure an adequate residence time, promoting a uniform transformation of the material and proper sintering.

4.2.5. Preheater Fan Speed (DS)

It controls the gas flow in the preheater, facilitating thorough combustion and consistent heat dispersion. Its stability is crucial for optimizing heat transfer and, consequently, improving the overall efficiency of the pre-calcination process.

5. Materials and methods

5.1. Design of the Fuzzy Controller

For the design of the fuzzy controller, the approach is based on the general diagram, as shown in Figure 3, which represents the functional structure of the fuzzy controller.

5.2. The Fuzzification Technique

To conduct the analysis of this control technique, a fuzzifier using triangular fuzzy sets is employed, as implemented by default in the fuzzy logic designer environment of MATLAB.

This choice is justified by the quality of the representation that is closest to reality and by the ability to avoid the propagation of system noise, without the need for probabilistic or hybrid fuzzifiers.

Table 2. Input and output ranges

Inputs	**Very Low**	**Low**	**Normal**	**High**	**Very High**
BZ. (°C)	1330	1360	1400	1440	1470
TOR (N · m)	0.08	0.18	0.24	0.3	0.4
CO (%)	-	0	0.15	0.22	0.3
P.T (°C)	735	745	755	765	775
Outputs					
KF (t/h)	244	247	250	253	256
MB (lit/h)	6250	6300	6350	6400	6450
PRE (lit/h)	8800	8900	9000	9100	9200
KS (r.p.m)	2.6	2.7	2.8	2.9	3
DS (r.p.m)	900	910	920	930	940

5.3. Assignment of Membership Functions

Each input variable will have five membership functions: "very low," "low," "normal," "high," and "very high." Except for the CO percentage in the preheater, which only has four membership functions: "low," "normal," "high," and "very high." For the outputs, each variable will use five membership functions of the same classification: "very low," "low," "normal," "high," and "very high."

Triangular functions were chosen as they adequately represent the variables of the real environment, in addition to being computationally efficient.

Table 2 shows the ranges of the outputs and inputs that must be considered in the triangular functions of our Fuzzy controller according to Figure 2.

5.4. The Fuzzy Rule Base

Appendix 2] is composed of 88 IF-THEN (Mamdani) rules, which were obtained from the knowledge of experts from the ASEC company in Egypt. These rules cover all scenarios that can occur during the normal operation of the furnace, excluding extreme events such as electrical failures or disasters. It is important to note that additional combinations were discarded to represent unrealistic conditions in the operation of the system.

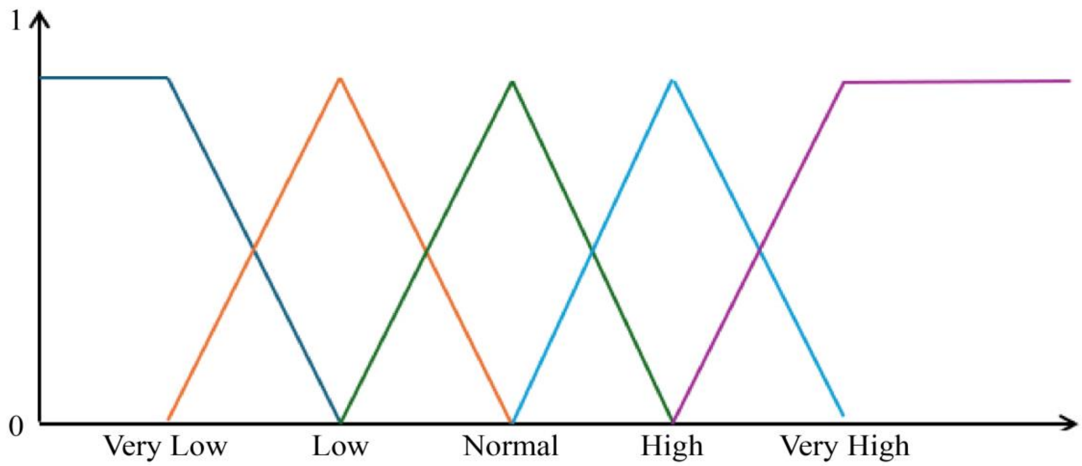


Fig. 2 Membership function of inputs and outputs

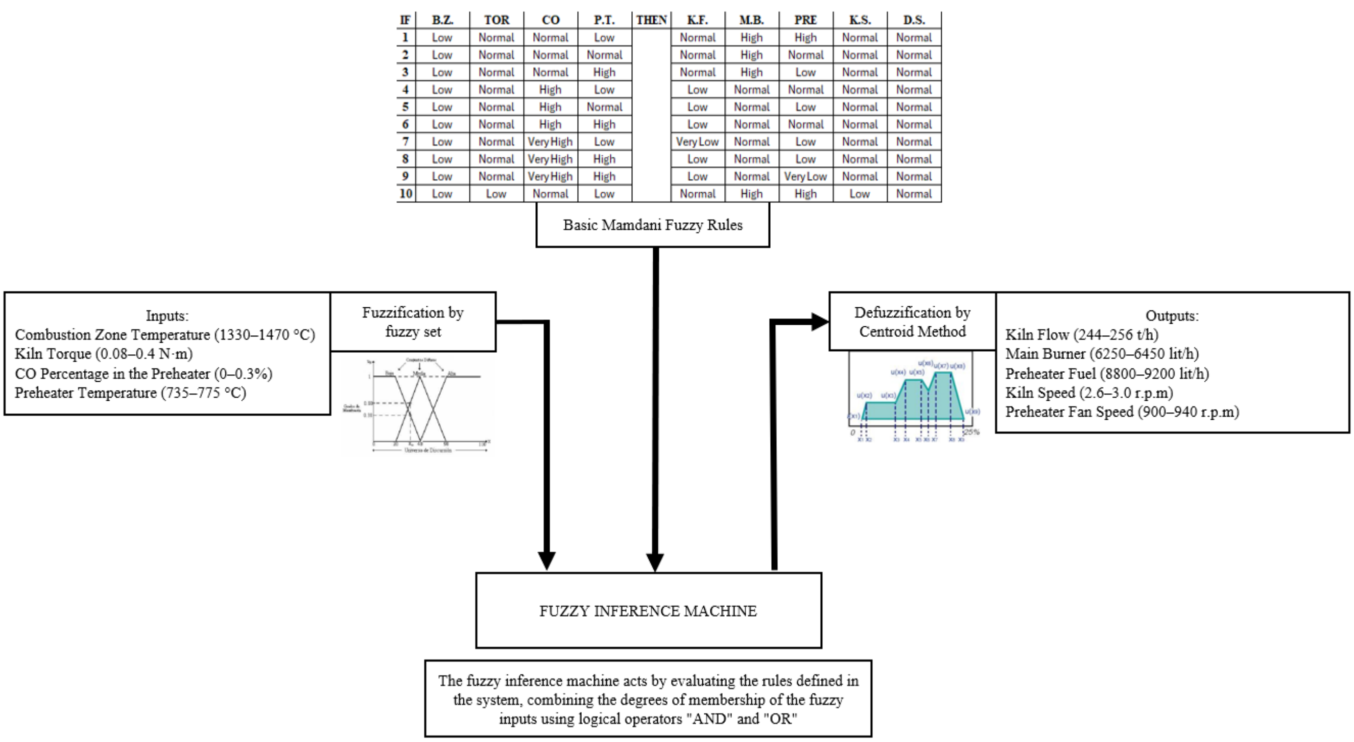


Fig. 3 General diagram of a fuzzy controller

5.5. Designed a Fuzzy Controller

The result can be found in Appendix 4, which contains the code that represents the program of this fuzzy controller.

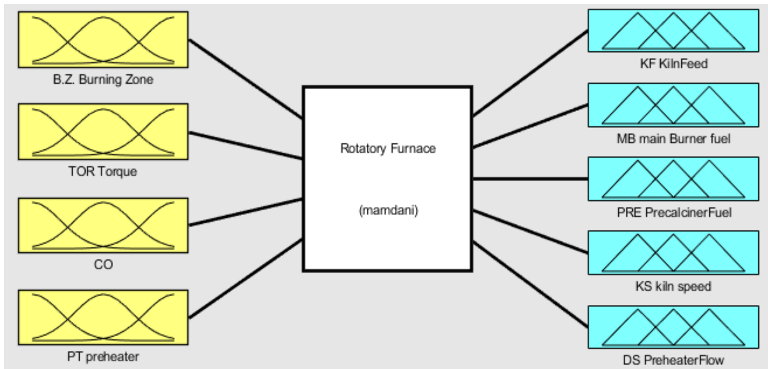
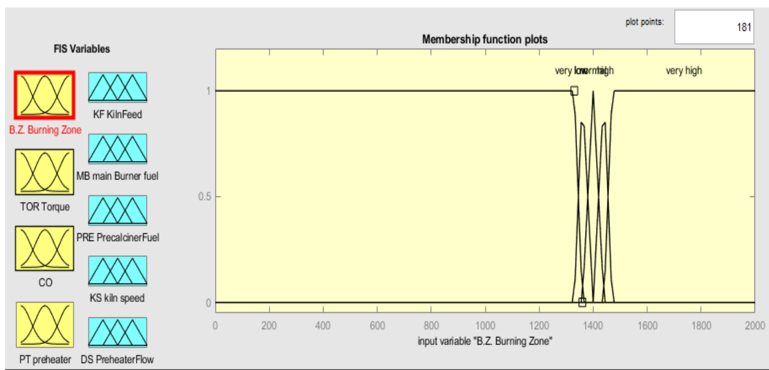
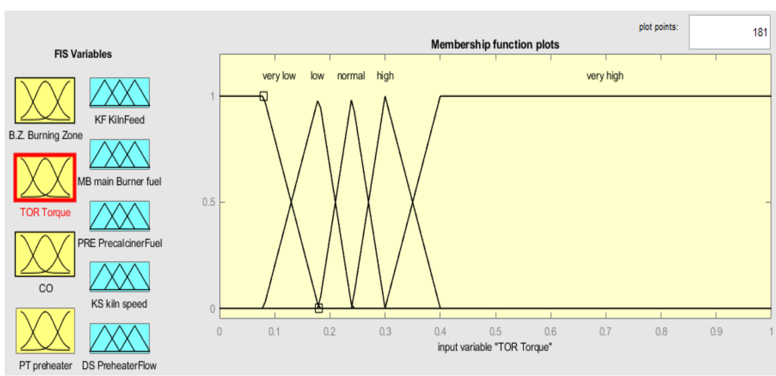


Fig. 4 General diagram of the fuzzy controller - MATLAB



(i)



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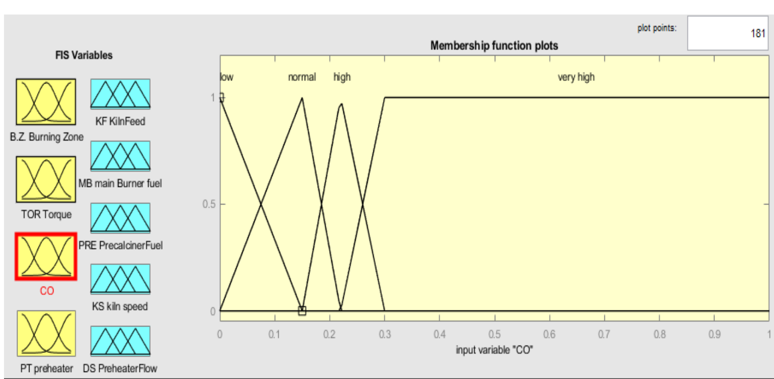

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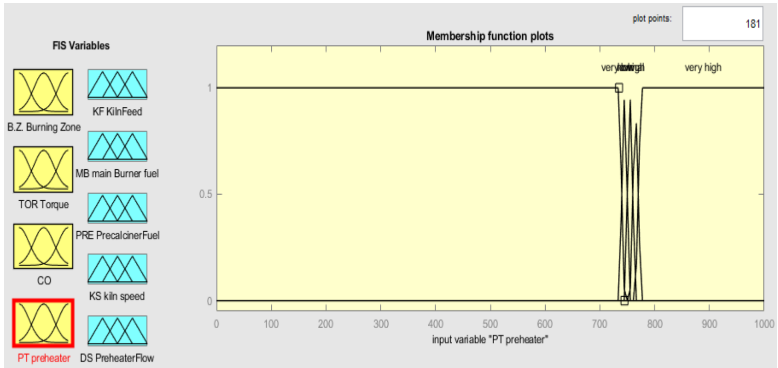
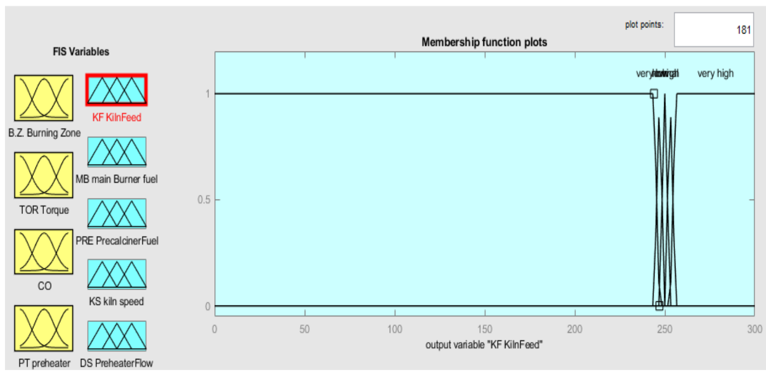


(iv)

Fig. 5 Membership functions (i) BZ, (ii) TOR, (iii) CO, and (iv) P.T.



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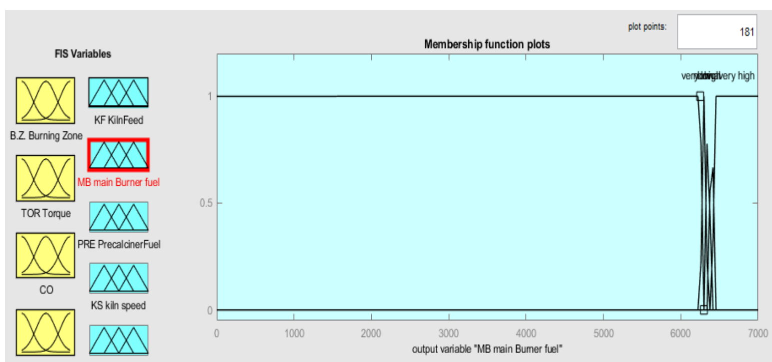

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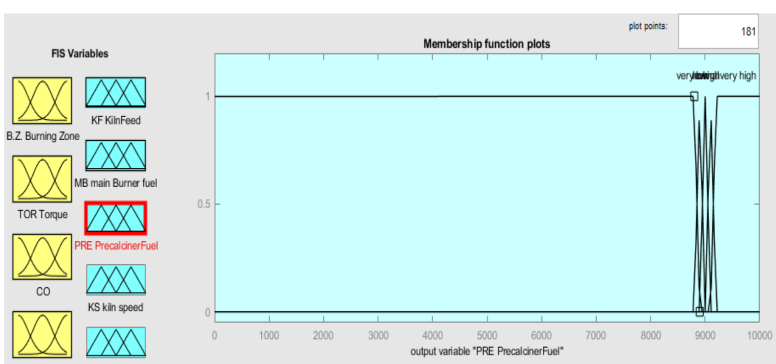

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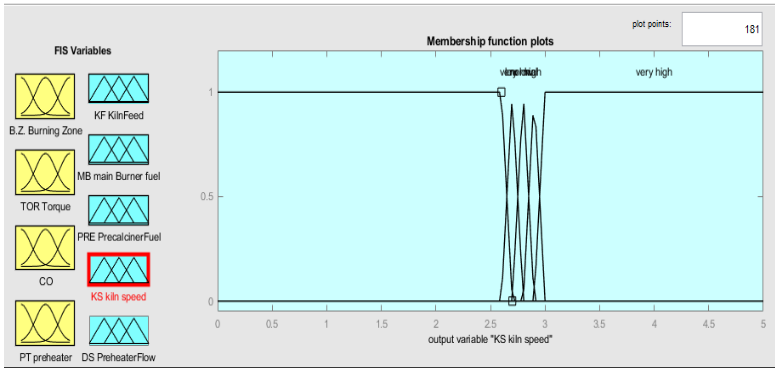

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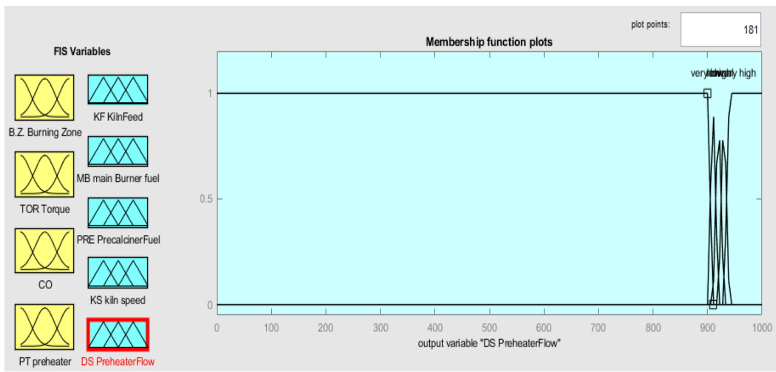


(v)

Fig. 6 Membership functions – outputs (i) KF, (ii) MB, (iii) PRE, (iv) KS, and (v) DS.

Table 3. Rules are evaluated in the controller

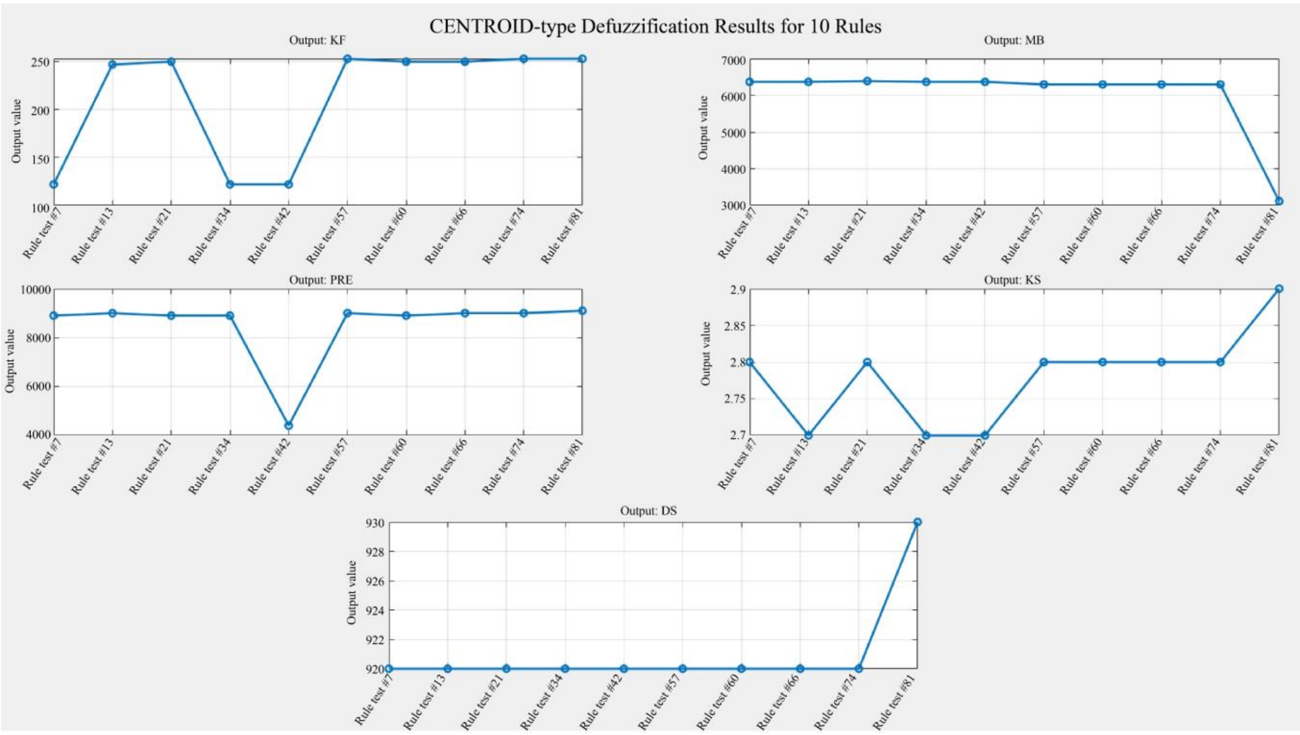
IF	BZ. (°C)	TOR (N · m)	CO (%)	P.T (°C)
7	low	normal	very high	low
13	low	low	high	low
21	low	high	normal	high
34	very low	normal	very high	low
42	very low	low	high	high
57	high	normal	normal	high
60	high	normal	high	high
66	high	low	high	high
74	very high	normal	normal	high
81	very high	high	high	low
IF	**BZ. (°C)**	**TOR (N · m)**	**CO (%)**	**P.T (°C)**
7	1360	0.24	0.3	745
13	1360	0.18	0.22	745
21	1360	0.23	0.15	765
34	1330	0.24	0.3	745
42	1330	0.18	0.22	765
57	1440	0.24	0.15	765
60	1440	0.24	0.22	765
66	1440	0.18	0.22	765
74	1470	0.24	0.15	765
81	1470	0.3	0.22	745

5.6. Defuzzification

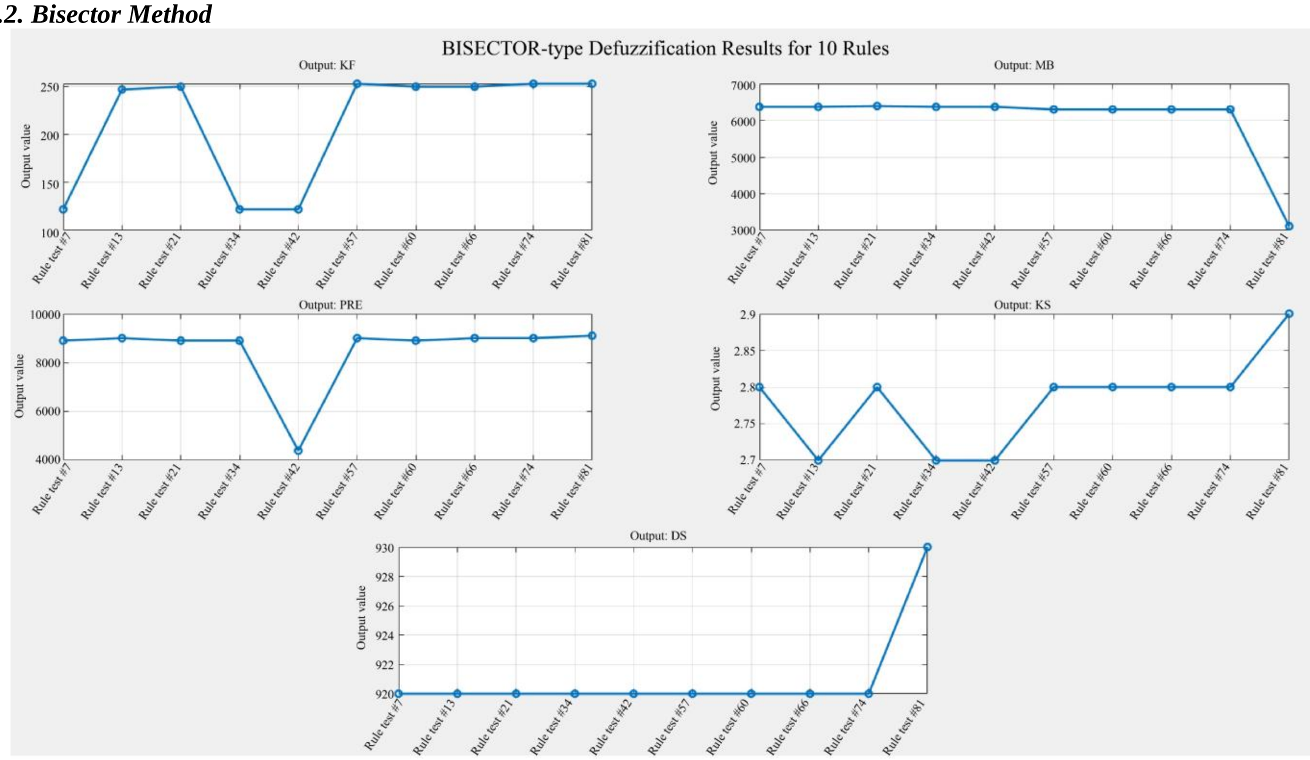
In the present work, the five most common defuzzification methods will be employed: Centroid (center of gravity), Bisector, Average of Maxima (SOM, MOM, and LOM), with the aim of comparing the results obtained in each case. This comparison will allow us to evaluate how the output of the fuzzy system varies depending on the selected method and determine which of them offers the most suitable performance in relation to the posed problem. For this, the following ranges will be considered, corresponding to ten randomly chosen rules (7, 13, 21, 34, 42, 57, 60, 66, 74, 81), with the aim of having a known range to verify the action of each type of defuzzification.For each rule, we will use the following input variables [Appendix 2].

6. Results and Discussion

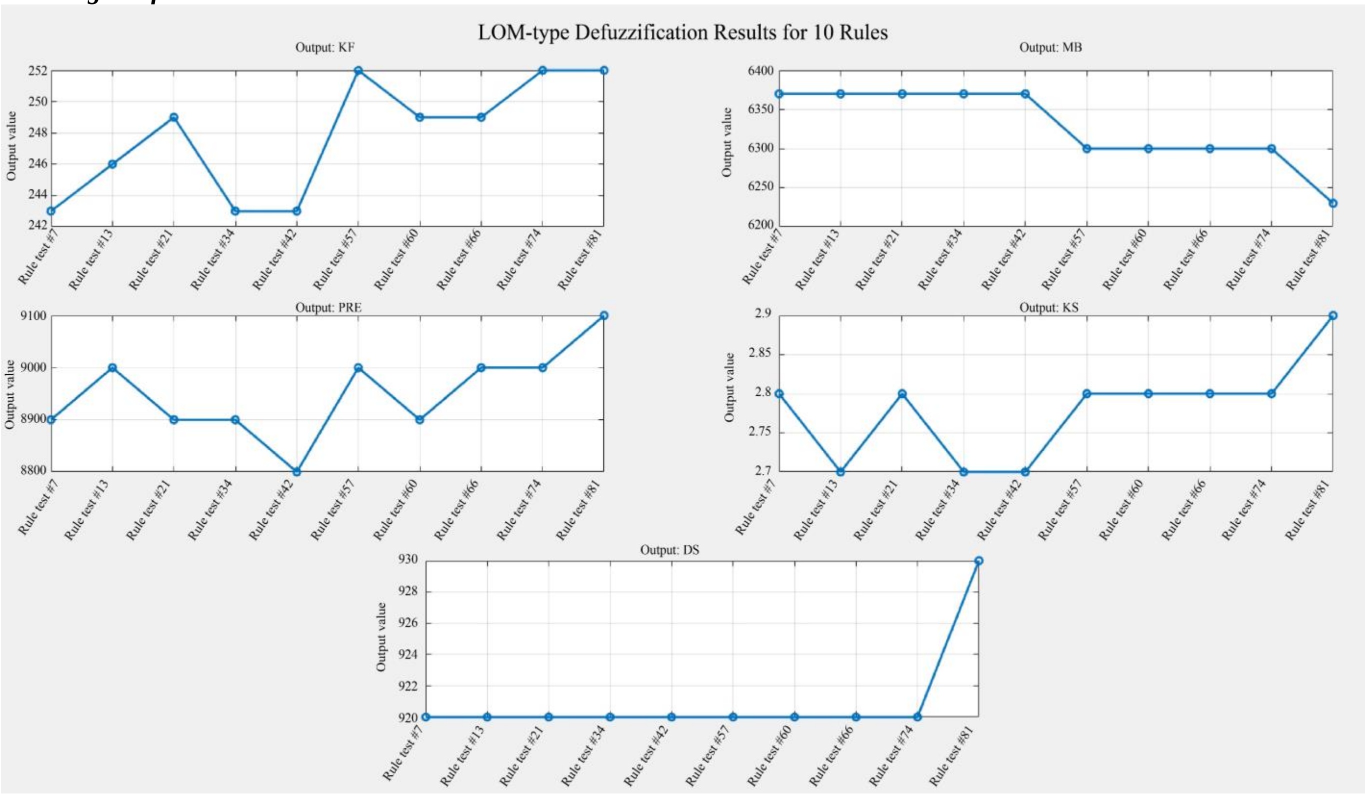
6.1. Centroid Method



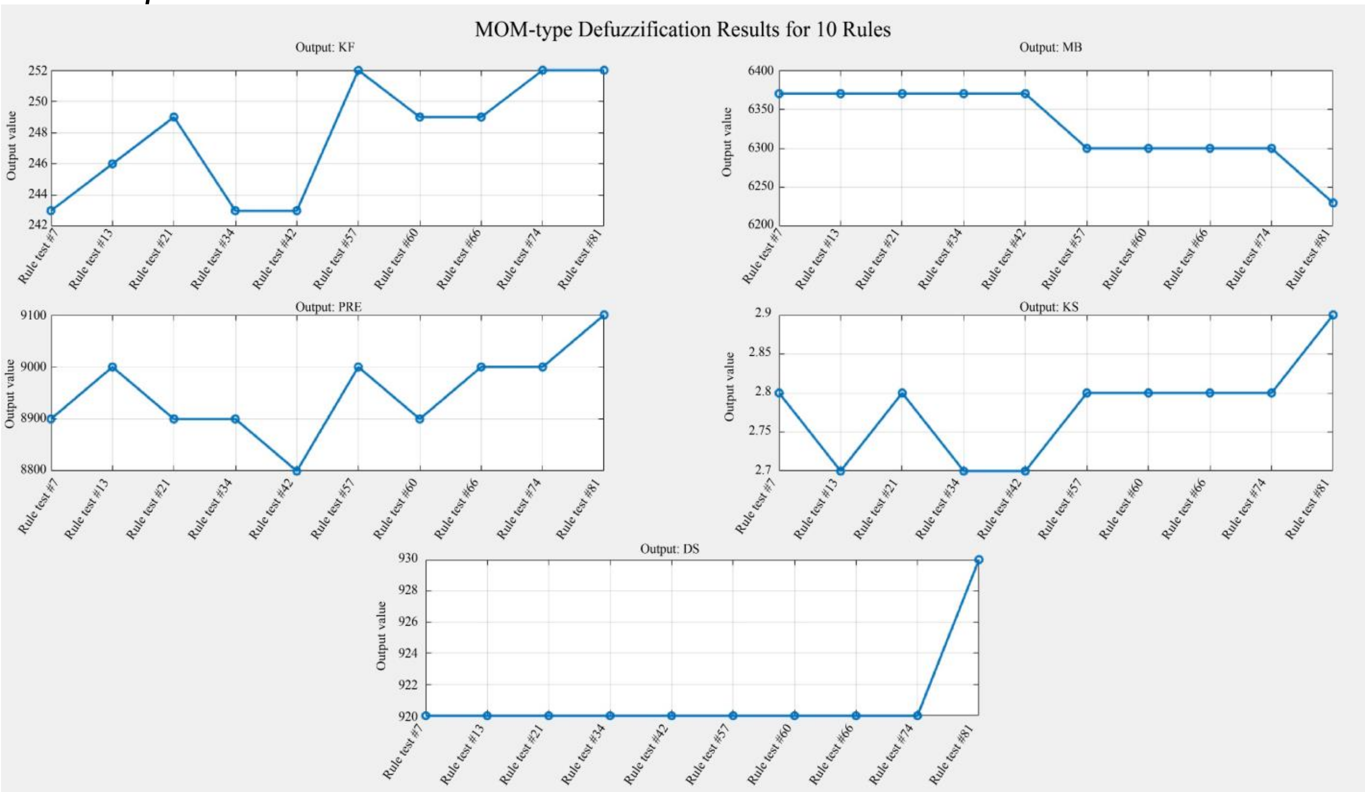
6.2. Bisector Method



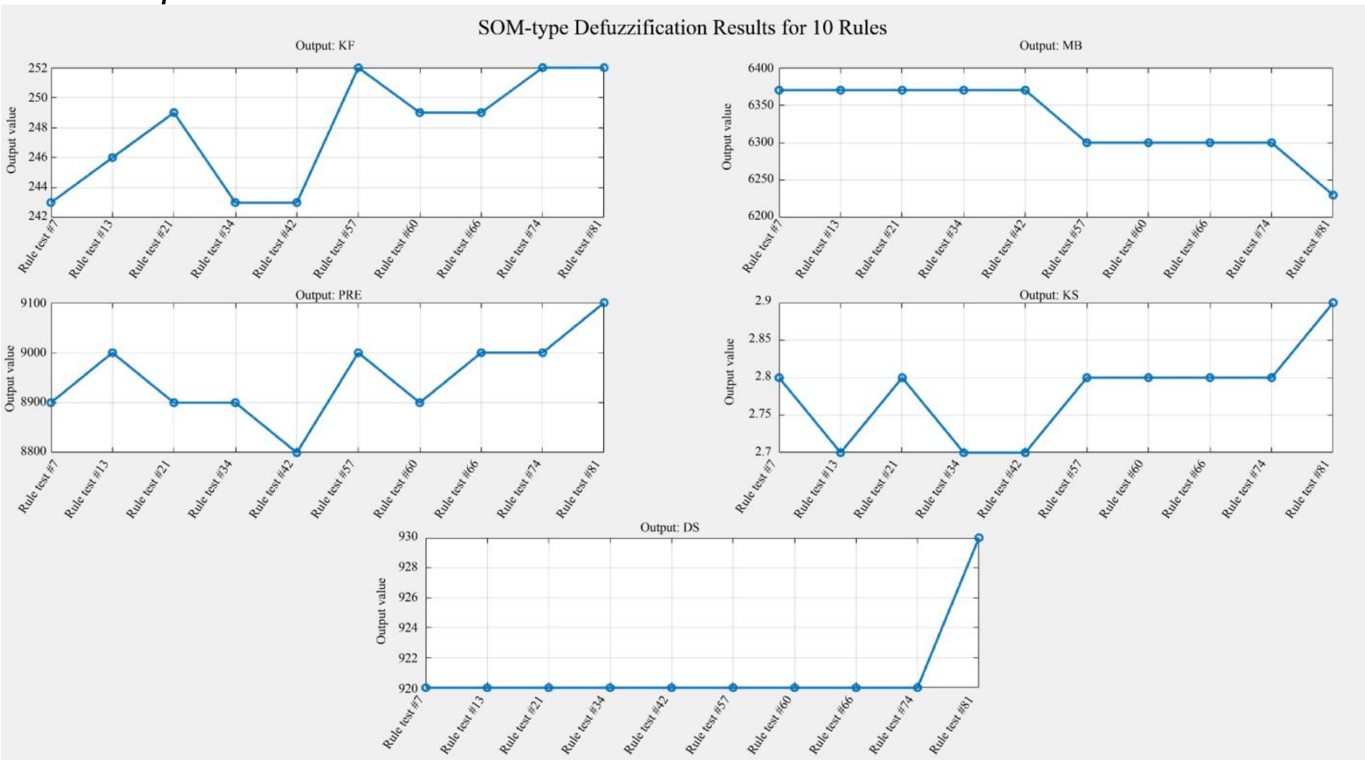
6.3. Largest of the Maximum Method



6.4. Middle of Maximum Method



6.5. Smallest of the Maximum Method



The analysis of the results obtained from the fuzzy controller for different inputs shows a clear consistency in most of the output variables, regardless of the defuzzification method applied.

As can be seen in Annex 3: Summary of the fuzzy controller responses for different inputs, the variables of the Main Burner (MB), Pre Calciner (PRE), Kiln Speed (KS), and Preheater Flow (DS) show consistent values for all inputs, indicating low sensitivity to the defuzzification methods (Centroid, Bisector, LOM, SOM, MOM).

On the contrary, the variable "furnace feed" (KF) shows notable variations between methods, especially between the Centroid/Bisector methods and the LOM, SOM, and MOM methods. For example, for multiple inputs such as #1, #5, #6, #8, and #9, the Centroid method yields values of 122, while LOM, SOM, and MOM result in 243.

This behavior suggests that the furnace feed is the variable most affected by the choice of defuzzification method, reflecting the differences in how each technique interprets the distribution of the membership function.

According to the analysis conducted on the methods, the following comparison is made between the centroid method and the middle of maximum method, as these are where the most notable differences in the outputs are observed.

- Fuzzy controller stability with Centroid [Appendix. 4]
- Fuzzy controller stability with MOM [Appendix. 4]

Detailed investigation of the furnace Energy Flow (KF) reaction to different desulfurization methods shows that this variable is the most essential element for system stability. In the simulations performed (see additional videos), minimal fluctuations in the maximum-based methods (LOM, MOM, and SOM) generate more cautious and stable responses.

On the other hand, the centroid technique produces longer oscillations, which show a more significant effect on the global distribution of the membership function. This sensitivity indicates that choosing an incorrect method could cause problems in the furnace feed, which would affect the uniformity of clinkerization and heat efficiency.

In contrast to advanced predictive control techniques or adaptive strategies mentioned in the literature, the proposed fuzzy approach provides optimal performance, as it achieves feed stabilization without requiring complex modeling or a considerable computational load. However, a drawback has been detected: the fuzzy methodology is based on the proper determination of membership functions and the rules of the specialists. Therefore, future improvements could include combined strategies that amalgamate fuzzy logic with automatic optimization techniques or supervised learning to decrease this sensitivity.

7. Conclusion

- This study shows that variables such as preheater flow rate, kiln speed, and pre-firing energy are constant regardless of defuzzification. This indicates that the method has no significant effect on the outcomes..
- On the other hand, the Kiln Feed rate (KF) varies depending on the defuzzification method selected. This is crucial in ensuring the fine-tuning and control system works properly.
- The results of the centroid method differ significantly from those of the LOM, SOM, and MOM methods. This shows that the centroid method is more sensitive to the distribution of member functions. Therefore, when used for the same industrial purpose, using maximum value-based methods to obtain more reliable and predictable results would be appropriate.
- Most variables remain constant in most cases, but using an inappropriate defuzzification method can cause significant fluctuations in important variables such as the furnace's fuel feed. This can make the clinker production process unstable and inefficient.
- In the future, by combining fuzzy control with optimization and adaptive learning approaches, it will be possible further to reduce the sensitivity of industrial furnaces to important parameters, stabilize the process, and reduce energy consumption.

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Appendix 1. Justification for the Selection of Eighty-Eight Fuzzy Rules

As we mentioned, we would have five fuzzy labels for each of the 4 inputs (BZ, TOR, CO, P.T.), so there would be 625 possible antecedent combinations "IF ... THEN ...". However, in practice, only eighty-eight rules are implemented, selected according to the following criteria:

i) Operational Relevance

- Definition: Only the combinations of process conditions that occur in a cement rotary kiln during normal operation or in typical variation situations (changes in raw materials, partial blockages, degradation of linings, etc.) are considered.
- Example:
  Discarded rule: IF BZ is Very Low AND TOR is Very High AND CO is Very Low AND P.T is Very Low, so why is it not used? An extremely low combustion temperature (BZ "Very Low") with very high torque implies that the furnace

is cold but loaded with material, a condition that never occurs; either the furnace stops (manually), or the torque drops as it cools down.

ii) Physical Plausibility

- Definition: Contradictory or physically impossible combinations are eliminated, for example, very low CO levels (very complete combustion) when the combustion zone temperature is "Very Low.
- Example:
- Discarded rule: IF BZ is Very Low AND CO is Very Low AND P.T is Very High AND TOR is Low, so,
- Why is it not used? There cannot be a minimum CO (perfect combustion) while the temperature of the combustion zone falls below the minimum threshold.

iii) Expert Knowledge and Operational Tests in a Real Plant

- The eighty-eight implemented rules are not generated arbitrarily or theoretically but were constructed based on the empirical knowledge of operators and engineers from ASEC Cement (Egypt), a company recognized for its expertise in handling high-capacity cement rotary kilns.
- The eighty-eight implemented rules are not generated arbitrarily or theoretically but were constructed based on the empirical knowledge of operators and engineers from ASEC Cement (Egypt), a company recognized for its expertise in handling high-capacity rotary cement kilns.
- These rules were designed after multiple tests in real industrial environments, where the most frequent operating ranges, critical process points, and combinations requiring automatic adjustments were identified. These rules were designed after multiple tests in real industrial environments, where the most frequent operating ranges, critical process points, and combinations requiring automatic adjustments were identified.
- Therefore, the rule base faithfully represents the operational reality of the furnace, incorporating the accumulated experience of normal events and controlled variability situations. Extreme or infrequent conditions resolved manually or by stopping the system were not considered within the automatic control.

iv) Reduction of Redundancies

- Definition: Many adjacent combinations (for example, "Low" vs. "Very Low" in BZ with identical conditions in TOR, CO, and P.T.) produce similar adjustments in the outputs. These are grouped under a representative rule to smooth the control surface without sacrificing resolution.

v) Unimplemented Rules

Next, we explain two theories within our total rule map, but that were not used:

- Theoretical rule 1: IF BZ is Very High AND TOR is High AND CO is Very Low AND P.T is Very High THEN…Reason for rejection: A "Very High" BZ (>1470 °C) and "Very High" P.T (~775 °C) would generate high CO due to incomplete combustion, not "Very Low". This combination contradicts the physics of combustion and never occurs in actual operation.
- Theoretical rule 2: IF BZ is Normal AND TOR is Very Low AND CO is Very High AND P.T is Low THEN…
- Reason for discard: A "Very Low" torque would imply little material in the combustion zone (high overheating), which does not coincide with a "Very High" CO (poor combustion). This situation would correspond to a catastrophic failure that is managed manually, not with the FLC.

Appendix 2. Fuzzy Rule Bases

BASE OF FUZZY RULES										
IF	**BZ.**	**TOR**	**CO**	**P.T.**	**THEN**	**KF.**	**MB.**	**PRE**	**KS.**	**DS.**
1	low	normal	normal	low		normal	high	high	normal	normal
2	low	normal	normal	normal		normal	high	normal	normal	normal
3	low	normal	normal	high		normal	high	low	normal	normal
4	low	normal	high	low		low	normal	normal	normal	normal
5	low	normal	high	normal		low	normal	low	normal	normal
6	low	normal	high	high		low	normal	low	normal	normal
7	low	normal	very high	low		very low	normal	low	normal	normal
8	low	normal	very high	high		low	normal	low	normal	normal
9	low	normal	very high	high		low	normal	very low	normal	normal

10	low	low	normal	low		normal	high	high	low	normal
11	low	low	normal	normal		normal	high	normal	low	normal
12	low	low	normal	high		normal	high	normal	low	normal
13	low	low	high	low		low	normal	normal	low	normal
14	low	low	high	normal		low	normal	normal	low	normal
15	low	low	high	high		normal	normal	low	low	normal
16	low	low	very high	low		very low	normal	normal	low	normal
17	low	low	very high	normal		very low	normal	low	low	normal
18	low	low	very high	high		low	normal	low	low	normal
19	low	high	normal	low		normal	high	normal	normal	normal
20	low	high	normal	normal		normal	high	normal	normal	normal
21	low	high	normal	high		normal	high	low	normal	normal
22	low	high	high	low		low	normal	normal	normal	normal
23	low	high	high	normal		low	normal	low	normal	normal
24	low	high	high	high		low	normal	very low	normal	normal
25	low	high	very high	low		very low	normal	low	normal	normal
26	low	high	very high	normal		low	normal	low	normal	normal
27	low	high	very high	high		low	normal	very low	normal	normal
28	very low	normal	normal	low		very high	normal	high	low	normal
29	very low	normal	normal	normal		normal	very high	normal	low	normal
30	very low	normal	normal	high		normal	very high	low	low	normal
31	very low	normal	high	low		low	normal	normal	low	normal
32	very low	normal	high	normal		low	normal	low	low	normal
33	very low	normal	high	high		low	normal	very low	low	normal
34	very low	normal	very high	low		very low	normal	low	low	normal
35	very low	normal	very high	normal		very low	normal	very low	low	normal
36	very low	normal	very high	high		low	very low	normal	low	normal
37	very low	low	normal	low		low	very high	normal	low	normal
38	very low	low	normal	normal		low	very high	normal	low	normal
39	very low	low	normal	high		low	very high	low	low	normal
40	very low	low	high	low		very low	normal	low	low	normal
41	very low	low	high	normal		very low	normal	low	low	normal
42	very low	low	high	high		very low	normal	very low	low	normal
43	very low	low	very high	low		very low	normal	low	low	normal
44	very low	low	very high	normal		very low	normal	low	low	normal
45	very low	low	very high	high		very low	normal	very low	normal	normal
46	very low	high	normal	low		normal	very high	normal	normal	normal
47	very low	high	normal	normal		normal	very high	normal	normal	normal
48	very low	high	normal	high		normal	very high	normal	normal	normal
49	very low	high	high	low		low	high	low	normal	normal
50	very low	high	high	normal		low	high	low	normal	normal
51	very low	high	high	high		low	high	low	normal	normal
52	very low	high	very high	low		very low	normal	low	normal	normal
53	very low	high	very high	normal		very low	normal	very low	normal	normal
54	very low	high	very high	normal		low	normal	very low	normal	normal
55	high	normal	normal	low		normal	low	low	normal	normal
56	high	normal	normal	normal		high	low	high	normal	normal
57	high	normal	normal	high		high	low	normal	normal	normal
58	high	normal	high	low		normal	low	high	normal	high
59	high	normal	high	normal		normal	low	normal	normal	high
60	high	normal	high	high		normal	low	low	normal	normal
61	high	low	normal	low		normal	low	high	normal	normal
62	high	low	normal	normal		normal	low	normal	normal	normal

63	high	low	normal	high		normal	low	normal	normal	normal
64	high	low	high	low		normal	normal	high	normal	high
65	high	low	high	normal		normal	low	normal	normal	high
66	high	low	high	high		normal	low	normal	high	normal
67	high	high	normal	low		high	normal	high	high	normal
68	high	high	normal	normal		high	normal	high	normal	normal
69	high	high	high	low		normal	low	normal	normal	high
70	high	high	high	normal		normal	low	normal	normal	high
71	high	high	high	high		high	low	normal	low	high
72	very high	normal	normal	low		high	low	high	normal	low
73	very high	normal	normal	normal		high	low	high	normal	normal
74	very high	normal	normal	high		high	low	normal	normal	normal
75	very high	normal	high	low		high	very low	high	normal	high
76	very high	normal	high	normal		high	very low	high	normal	high
77	very high	normal	high	high		high	very low	normal	high	high
78	very high	high	normal	low		high	very low	high	high	high
79	very high	high	normal	normal		high	very low	high	high	high
80	very high	high	normal	high		high	very low	normal	high	normal
81	very high	high	high	low		high	very low	high	high	high
82	very high	high	high	normal		high	very low	high	high	high
83	very high	high	high	high		high	very low	normal	normal	high
84	normal	normal	normal	low		normal	normal	high	normal	normal
85	normal	normal	normal	high		normal	normal	low	normal	normal
86	normal	normal	high	high		normal	normal	normal	normal	high
87	normal	normal	high	normal		normal	normal	normal	normal	high
88	normal	normal	high	high		normal	normal	low	normal	high

Appendix 3. Summary of fuzzy controller responses to different inputs

	Variable	**Centroid**	**Bisector**	**LOM**	**SOM**	**MOM**
Input #1	KF KilnFeed	122	123	243	243	243
	MB Main Burner	6370	6370	6370	6370	6370
	PRE Precalciner	8900	8900	8900	8900	8900
	KS KilnSpeed	2.8	2.8	2.8	2.8	2.8
	DS PreheaterFlow	920	920	920	920	920
Input #2	KF KilnFeed	247	246	246	246	246
	MB Main Burner	6370	6370	6370	6370	6370
	PRE Precalciner	9000	9000	9000	9000	9000
	KS KilnSpeed	2.7	2.7	2.7	2.7	2.7
	DS PreheaterFlow	920	920	920	920	920
Input #3	KF KilnFeed	247	246	246	246	246
	MB Main Burner	6370	6370	6370	6370	6370
	PRE Precalciner	8900	8900	8900	8900	8900
	KS KilnSpeed	2.7	2.7	2.7	2.7	2.7
	DS PreheaterFlow	920	920	920	920	920
Input #4	KF KilnFeed	247	246	246	246	246
	MB Main Burner	6370	6370	6370	6370	6370
	PRE Precalciner	8900	8900	8900	8900	8900
	KS KilnSpeed	2.6	2.6	2.6	2.6	2.6
	DS PreheaterFlow	920	920	920	920	920
Input #5	KF KilnFeed	122	123	243	243	243

	MB Main Burner	6120	6120	6120	6120	6120
	PRE Precalciner	8900	8900	8900	8900	8900
	KS KilnSpeed	2.5	2.5	2.5	2.5	2.5
	DS PreheaterFlow	920	920	920	920	920
Input #6	KF KilnFeed	122	123	243	243	243
	MB Main Burner	6120	6120	6120	6120	6120
	PRE Precalciner	8900	8900	8900	8900	8900
	KS KilnSpeed	2.5	2.5	2.5	2.5	2.5
	DS PreheaterFlow	920	920	920	920	920
Input #7	KF KilnFeed	247	246	246	246	246
	MB Main Burner	6120	6120	6120	6120	6120
	PRE Precalciner	8900	8900	8900	8900	8900
	KS KilnSpeed	2.6	2.6	2.6	2.6	2.6
	DS PreheaterFlow	920	920	920	920	920
Input #8	KF KilnFeed	122	123	243	243	243
	MB Main Burner	6120	6120	6120	6120	6120
	PRE Precalciner	8900	8900	8900	8900	8900
	KS KilnSpeed	2.7	2.7	2.7	2.7	2.7
	DS PreheaterFlow	920	920	920	920	920
Input #9	KF KilnFeed	122	123	243	243	243
	MB Main Burner	6370	6370	6370	6370	6370
	PRE Precalciner	9000	9000	9000	9000	9000
	KS KilnSpeed	2.7	2.7	2.7	2.7	2.7
	DS PreheaterFlow	920	920	920	920	920
Input #10	KF KilnFeed	247	246	246	246	246
	MB Main Burner	6370	6370	6370	6370	6370
	PRE Precalciner	9000	9000	9000	9000	9000
	KS KilnSpeed	2.8	2.8	2.8	2.8	2.8
	DS PreheaterFlow	920	920	920	920	920

Appendix 4. Database link

- Video of the controller's response using the centroid method.
- Video of the controller's response with the MOM method.
- Source code for the fuzzy controller program.
- Fuzzy test program source code.
- Source code for fuzzy test simulation.

https://data.mendeley.com/preview/9ms8p22chd?a=11ae57b6-3685-4679-a271-696f39735eaf