Available online at www.sciencedirect.com

ScienceDirect

IFAC PapersOnLine 51-11 (2018) 1542–1547

A Fuzzy Logic Control application to the Cement Industry

Miguel A. Sellitto*. Elia Balugani**.
Rita Gamberini***. Bianca Rimini****

*Production and Systems Engineering Graduate Program, Universidade do Vale do Rio dos Sinos, São Leopoldo, RS 93022750, Brazil (Tel: 55 51 35911122; e-mail: sellitto@ unisinos.br)
** Department of Sciences and Methods for Engineering, University of Modena and Reggio Emilia, Via Amendola 2, Padiglione Morselli, 42122 Reggio Emilia, Italy (e-mail: elia.balugani@unimore.it)
*** Department of Sciences and Methods for Engineering, University of Modena and Reggio Emilia, Via Amendola 2, Padiglione Morselli, 42122 Reggio Emilia, Italy (e-mail: rita.gamberini@unimore.it)
**** Department of Sciences and Methods for Engineering, University of Modena and Reggio Emilia, Via Amendola 2, Padiglione Morselli, 42122 Reggio Emilia, Italy (e-mail: bianca.rimini@unimore.it)

Abstract: A case study on continuous process control based on fuzzy logic and supported by expert knowledge is proposed. The aim is to control the coal-grinding operations in a cement manufacturing plant. Fuzzy logic is based on linguistic variables that emulate human judgment and can solve complex modeling problems subject to uncertainty or incomplete information. Fuzzy controllers can handle control problems when an accurate model of the process is unavailable, ill-defined, or subject to excessive parameter variations. The system implementation resulted in productivity gains and energy consumption reductions of 3% and 5% respectively, in line with the literature related to similar applications.

Keywords: Fuzzy Logic Controllers, Process Control, Artificial Intelligence, Machine Learning.

1. INTRODUCTION

The process industry operates with continuous materials. It mixes, separates, and transforms gases, liquids, fibers, and powdery raw materials by granulometric transformation or chemical reactions (Dennis and Meredith, 2000). The materials involved originate from mining, agriculture, forestry, or other process industries (e.g. the chemical industry). The processes themselves can be continuous, batch-wise, or a mixture of the two (Fransoo and Rutten, 1994). Continuous processes operate in long cycles, with negligible interruptions and infinite lot sizes, while batch processes deliver discrete products in short cycles, managing ordered lots (Vogel-Heuser et al., 2015). A strategic element in the continuous process industry is the construction and management of supporting knowledge to control the industrial process (Marin-Garcia and Bonavia, 2015).

In this context expert, human operators exercise manual control requiring immediate decisions supported by previously acquired knowledge. The knowledge itself is stored in a mental database containing possible actions and expected consequences (Vogel-Heuser et al., 2015). An expert operator builds such knowledge after years of observation and practice in manual control (Holmblad and Østergaard, 1981). Skilled operators are able to factor in their mental cause/effect database parameters such as the intensity of the proposed action (Nazir et al., 2015). This ability is more visible and explicable in regular and predictable processes (Ale et al., 2014), however not all industrial continuous processes are predictable. In emergencies and start-up procedures, operators need both experience and self-confidence to evaluate alternatives and to take action under uncertainty and incomplete information (Ale et al., 2014).

Artificial intelligence provides valuable decision support and control techniques in these uncertain environments. Two common techniques used in this field are artificial neural networks (Haber and Alique, 2003; Lolli et al., 2017) and fuzzy logic. Fuzzy logic is especially useful for processes that are difficult to control by conventional or discrete methods due to the lack of knowledge of quantitative relations between the inputs and outputs. Controls based on fuzzy logic employ a close-to-human language to describe the input-output relationships of the controlled process. The controller converts an expert knowledge-based control strategy into an automatic control strategy imposed on the process (Agrawal et al., 2015).

This article presents a case study on a continuous process control based on fuzzy logic and supported by expert knowledge in the continuous process industry. The aim of this study is to control the coal-grinding operations in a cement manufacturing plant, the cement industry being a promising field for advanced process control techniques (King, 1988). Cement is a fine powdery grey inorganic substance with hydraulic binding properties. Mixed with water it forms concrete, a key material for building applications. The main research technique was participant observation and the main contribution of this article is the case report. The findings should not be generalized to other continuous processing industries.

The remainder of the article is organized as follows. Section 2 presents a brief literature review of the main grounding

Peer review under responsibility of International Federation of Automatic Control.
10.1016/j.ifacol.2018.08.277

concepts involved in the study. Section 3 presents the case study, which involves a description of the cement manufacturing process, the coal grinding process, the fuzzy logic control, and a discussion on the results. Finally, Section 4 presents some relevant conclusions of the study.

2. LITERATURE REVIEW

According to Legg and Hutter (2007), intelligence is the demonstration of coherent principles used to adapt to a complex environment with verifiable results. It is an individual property that an agent uses to interact with, adapts to, understands, and describes a complex surrounding environment. The opposite of intelligence is determinism. Programmed actions, following previously known steps, cannot be considered intelligence. One of the goals of artificial intelligence (AI) is to understand problems and solve them as human intelligence would. AI uses machines to emulate human thinking (Bose, 1994), providing methods to structure and solve complex decision-making problems (Nikolopoulos, 1997). Among other techniques, AI offers expert systems (ESs), Case-based Reasoning (CBR) and fuzzy logic (FL) for industrial control.

ESs act in a limited area of knowledge learning from experience and solving problems by inferential analysis of random symptoms and intensities. An ES uses a knowledge database with data, facts, rules, and standards, as well as an inference engine and a user interface (Harmon and Sawyer, 1990; Giarratano and Riley, 1998). CBR solves new problems by adapting previously confirmed solutions using the knowledge generated in the past experiences. CBR solves a new problem by the adaptation of the solution of an old case. Each solved problem ads to the database as a new solved case (Olsson et al., 2004).

FL can help solving complex modeling problems, subject to uncertainties or incomplete information, based on linguistic variables that emulate human judgment on a comparative or subjective basis, such as higher or high, lower or low, better or good. FL assigns to each individual a degree of membership to two adjacent sets, according to how far the individual is from the maximum value. As transitions are gradual, an intermediate individual belongs to two sets, according to a common definition. A membership function helps to define the degree of membership of an individual to a given fuzzy set (Larsen, 1980; Lee, 1990; Precup and Hellendoorn, 2011). Figure 1 shows a universe of discourse of five fuzzy sets and the corresponding five linguistic terms for a generic fuzzy variable x (Holmblad and Østergaard, 1995). For instance, if $x = 25\%$, then x = [50% Z + 50% PM].

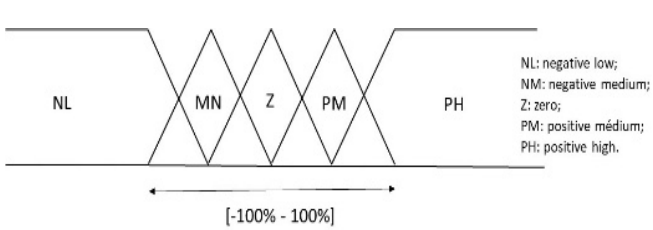

Fig 1. A linguistic variable with five stages.

The use of FL to control industrial processes was first proposed by Mamdani (1974), using fuzzy sets, linguistic terms, conditional sentences, and inference rules. A Mamdani controller relies on the measures of variables and their variations, which implies two universes of discourse: the variable (x) and the gradient (Δx). The inference engine considers the two measures in modifying the control action variation (Δu).

A process control based on FL is called fuzzy control, which embeds the knowledge of human operators, engineers, and designers. Fuzzy controllers have been demonstrated to have an adaptive capacity to handle control problems when an accurate model of the process is unavailable, ill-defined, or subject to excessive parameter variations (Bose, 1994). Additionally, the human experts in control of the process manage to verbalize the control rules they use (Kacprzyk, 1997; Buckley, 1992).

The starting point of a fuzzy control is to extract a collection of IF-THEN type rules from the expert´s knowledge and organize them into a system. Wang (1999) points out that a fuzzy control can be a pure fuzzy system, a Takagi-Sugeno-Kang (TSK) fuzzy system, or a fuzzifier-defuzzifier fuzzy system. A fuzzifier device transforms the current state of a variable into a fuzzy variable and a defuzzifier does the opposite. According to Wang (1999), the fuzzifier-defuzzifier controller is the most suitable for industrial applications, and thus this paper focuses exclusively on this controller. Figure 2 illustrates the fuzzifier-defuzzifier controller.

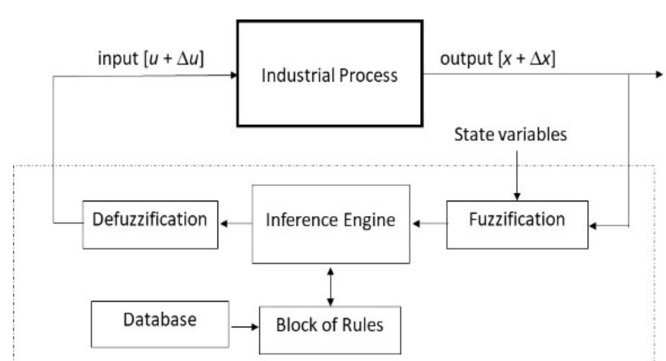

Fig. 2. Fuzzifier-defuzzifier industrial process controller.

The controller feeds back and fuzzifies the output variable and its gradient ($x + \Delta x$) as well as state variables anticipating the behavior of the process. According to a block of rules representing the experts´ knowledge, an inference engine calculates incremental values Δu to impose on the input variable u, achieving an expected result on x according to an established control strategy. According to the membership functions, the controller calculates the fuzzy values used for the inference. The inferred value converted into engineering units by scale factors derived from the database is the variation of the controller setpoint. The construction of the database and the block of rules follow the CBR methodology. Given a certain number of cases certified by practical results, a routine of selection, mixing, and improving the rules provides a new solution that increments the database.

3. THE CASE STUDY

Manufacturing cement involves either a wet or a dry technological process. Of these, only the dry process is relevant for our purposes, given the lower energy efficiency of the wet process. Dry cement manufacturing requires mining and quarrying limestone, chalk, and clay; crushing the limestone; pre-homogenization of the raw material and reclaiming the pre-homogenized raw material; raw grinding in raw mills, producing the raw meal; pre-calcination and calcination of the raw meal, producing the clinker, which requires pulverized coal as fuel; cooling of the clinker, finishing the grinding in cement mills, which requires the addition of gypsum, fly ashes, and secondary additives; packing in individual bags, crates, and pallets; and distribution by truck and train in packs and bulk formats.

Figure 3 shows the technological route of the dry process. Typical cement plants have two configurations, a complete process and a clinker-grinding process, indicated by the dashed line in the figure. In the second case, the plant operation depends on a logistic channel to receive the clinker.

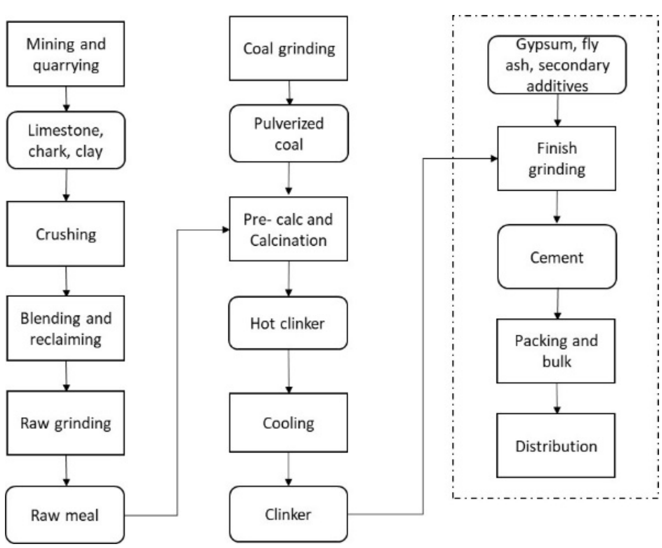

Fig. 3. Dry process of cement manufacturing.

Typical applications of fuzzy control in the cement industry occur in the raw grinding, clinker calcination, cooling, coal grinding, and finish grinding systems. In 1978, Holmblad and Østergaard (1981) conducted the first successful application of FL in the cement industry in the kiln of F.L. Smidth in Denmark. The FL controller had four state variables and two outputs and showed a slight improvement compared to the results of human operators.

3.1 Coal grinding mill control

The process under analysis combines CBR and FL. A database of certified rules of inference and defuzzification derived from over 50 plants forms the set of original cases. The experts then enrich the most similar cases, resulting in a new case. When equipping a plant, the manufacturer accesses the database and, based on parameters such as the raw material, final product, type of kiln, and production capacity, retrieves similar cases. Expert operators and engineers, supported by the provider of the technology, adapt them to the new case. In this stage of the project, the team defined the number of fuzzy sets, the type of membership functions and the inference rules. In particular, experience gained through years of manual control of the process support the rules.

Although the system runs continuously to avoid instability, updates input and output data every minute and transfers the updates to the field equipment every five minutes, the experts can change these periods. Given the typical inertia of industrial systems, there is a time lag between a change in the setpoints and a change in the feedback, and the system also smooths the field signals to avoid noise.

In this study, we present the control of coal grinding. The process is difficult to model and can be satisfactorily controlled by human operators who are able to explain their rules, which satisfies the requirements imposed by Mamdani (1974) for the use of fuzzy controls. The control logic resides in an electronic controller based on FL, the state variables are the electric current of the main motor (*amps*) and the mill temperature (*temp*), whose engineering units are amperes (A) and Celsius degrees (ºC), respectively. The output variables are the raw coal flow (*feed*) and the airflow (*fan*), whose engineering units are tonnes per hour (t/h) and normal cubic meters per hour (Nm^3/h), respectively. Figure 4 presents a typical coal roll mill and its auxiliary equipment.

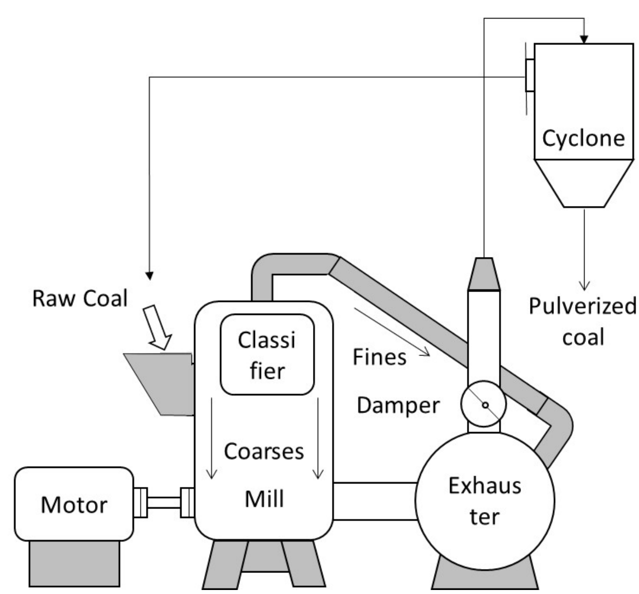

Fig. 4. The coal grinding mill system.

A belt weightier, a rotary feeder, and a hopper feed the mill with the raw coal, transported to the internal grinding table. After grinding, the airflow drags the material through a classifier that separates the fine and coarse materials. The coarse portion returns to the mill until it reaches the required granulometry. The fine portion goes to a cyclone and then to the final selection. The coarse part discarded by the cyclone returns to the mill, while the fine routes to a fuel silo to feed the clinker kiln torch. The electric current of the motor and the mill temperature represent the load and temperature of the system, respectively. A higher than normal current indicates an overload and requires a reduction in the speed of the rotary feeder. A higher than normal temperature indicates that the air from the clinker is not cooling efficiently, thus requiring the inlet air damper to be closed. Lower than normal inputs indicate the opposite and require the opposite solution, while intermediate values represent intermediate situations. The state variable *amps* is a combination of the running average (50%) and the gradient (50%) of the instantaneous electric current of the mill motor. The state variable *temp* is a combination of the running average (38.5%), gradient (38.5%) of the air outlet temperature, and the gradient (23%) of the air inlet temperature. The relationship between the mill load and amps is linear. According to its position, the slope of the relationship between the temperature and damper position changes, and the controller emulates the non-linear relationship between the variables.

There are rules for stable operation, unstable operation, and emergency situations. Three blocks encompass the rules for stable operation. A general block increases the feed up to the setpoint required by the kiln and then balances the feed and fan. A second block holds the feed at a sufficient level, reduces the fan, and loads the mill. A third block holds the fan at 100% and controls the feed to unload the mill. The system starts increasing the feed up to the required setpoint. If the system reaches a balanced point, the control strategy attempts to maintain equilibrium by reacting with small changes in the natural variations of the process. If the system finds a boundary condition, it changes the rule block accordingly.

The rules for unstable operation require caution and involve other variables, such as the speed of the classifier and the pressure of the airflow. Unstable operation requires intensive reactions to situations far the equilibrium. Changes to the angular speed and pressure modify the granulometry of the pulverized coal and can cause severe instability to the flame.

We focus on the general block of stable operation. All the fuzzy sets and membership functions derived from past, consolidated experience, gained after more than 50 applications worldwide. The original definitions could modify if required by the current experience. Anyway, this was not the case and the implementation of the system and the running data gathered over time reinforced the original choice of the fuzzy sets as well as the membership functions.

One example of a rule is: if [*amps*, *temp*] = [OK, OK], then modify [*feed*, *fan*] by [0%, 0%] of [Δ *feed%*, Δ *fan%*]. Another example is: if [*amps*, *temp*] = [H, OK], then modify [feed, fan] by [-120%, 0%] of [Δ *feed%*, Δ *Fan%*]. In the block, Δ *feed%* = 0.05 t/h and Δ *fan%* = 50 Nm^3/h.

The control operates with seven fuzzy sets (very very high VVH, very high VH, high H, OK, low L, very low VL, very very low VVL) and adopts direct relationships among state and output variables. Therefore, there are fourteen original rules. The fuzzy sets have uniform distribution along the range of variables and the membership functions are linear. The fuzzification process grants equal importance to the instant value and gradient of the variables, which is a modifiable condition upon demand. The defuzzification process may follow three schemes, plausible respectively for membership functions whose integrals are easy to obtain (center of gravity), for simple membership functions as triangular or uniform functions (center average), and discontinuous or disjoint membership functions (mean of maxima) (Wang, 1999).

Figure 5 shows the fuzzy sets and the membership functions.

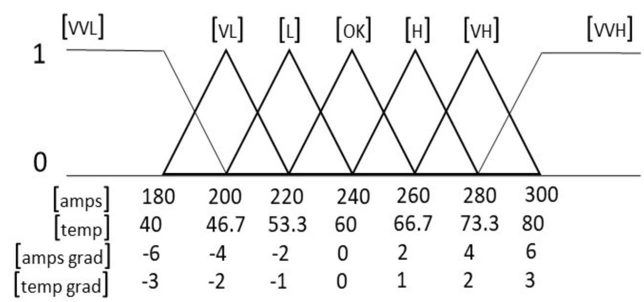

Fig. 5. Fuzzy sets and membership functions.

Table 1 shows the rules. The defuzzifier scheme is center average, which is embedded in the Δ Feed % and Δ Fan % data.

Table 1. Block of application rules

amps fuzzy	Δ Feed %	temp fuzzy	Δ Fan %
VVH	-150	VVH	-500
VH	-100	VH	-240
H	-75	H	-120
OK	0	OK	0
L	50	L	40
VL	200	VL	80
VVL	300	VVL	120

Table 2 shows the ranges of variables and gradients.

Table 1: Ranges of variables

	range	
tag	variable	gradient
amps	180 - 300 A	-6% a +6%
temp	40 - 80 ºC	-3% a +3%
feed	3 - 5 t/h	
fan	3,000 - 5,000 Nm3/h	

Let us assume that in a given five-minute interval, the running average of the instantaneous value of *amps* is 262 A. Referring to Fig. 5, the fuzzified value is *amps inst* = [18/20 OK + 2/20 H]. Let us also assume that the gradient of *amps* is 2.4% and consequently the fuzzified value is *amps grad* = [16/20 H + 4/20 VH]. The total fuzzified value, according to the rule of equal importance for instantaneous values and gradients is *amps f* = 0.5*[18/20 OK + 2/20 H] + 0.5*[16/20 H + 4/20 VH] = [9/20 OK + 9/20 H + 2/20 VH].

Consulting Table 1, Δ *feed* = [(0*9/20) + (-0.75*9/20) + (-1*2/20)] * 0.05 t/h = (- 0.4375 * 0.05) t/h = - 0.022 t/h. If the current value setpoint for the raw coal flow is 4.5 t/h, for the next five minutes the setpoint will be (4.5 – 0.022) t/h = 4.478 t/h. The benefit of such a slight variation would be barely discernible by a human operator.

Regarding *temp*, let us assume that the instantaneous value and the gradient are 60ºC and 1.5%, respectively. The fuzzified values are *temp inst* = [1 OK] and *temp grad* = [5/10 H + 5/10 VH]. The total fuzzified value is *temp f* = 0.5*[OK] + 0.5*[5/10 H + 5/10 VH] = [10/20 OK + 5/20 H + 4/20 VH]. Therefore, Δ *fan* = [(0*5/10) + (-1.2*5/20) + (-2.4*5/20)] * 50 Nm^3/h = (- 0.9 * 50) Nm^3/h = - 45 Nm^3/h. If the current value for the airflow is 4,100 Nm^3/h, the next setpoint is (4,100 – 45) Nm^3/h = 4,055 Nm^3/h. As in the first case, a skilled human operator would barely perceive the benefit of such a smooth variation at the setpoint of the controller.

Figure 6 summarizes the processing of variables and the calculations from the data acquisition up to the imposition of a new setpoint.

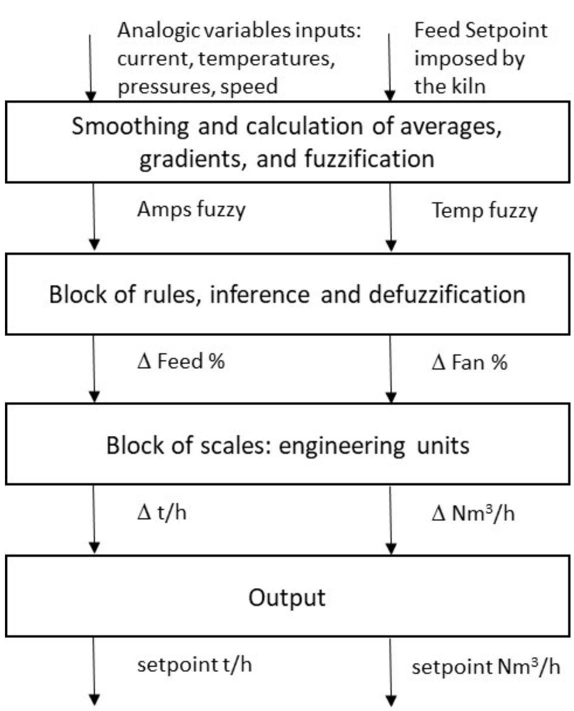

Figure 6. Data processing and calculations.

4. CONCLUSIONS

Since a human operator acts continuously, asynchronously, and randomly in deciding setpoint changes, two scenarios are possible. In the first one, the operator has inherent difficulties, given his/her human nature, in realizing that smooth variations are desirable. In the second one, the operator may overreact to a situation of natural process variation. In the first case, the reaction is less than optimal, while in the second case it is excessive. An operation based on expert systems can prevent both situations. The execution and transfer of the machine decisions to the process are not instantaneous and the expert system considers the natural inertia of the system it controls. The system also has the ability to discern very small variations, keeping the controlled system balanced for a long period.

Previous implementations of FL control allow expecting relevant performance gains, mainly due to the increased stability of the process. Previous applications suggest that the human influence in the process control is mainly due to the human incapacity to discern very small variations in the operational conditions. As previous applications showed run factors up to 85%-90% of the total time, in the long-term perspective, the operation gains stability (Holmblad and Østergaard, 1995).

The field experience of the study showed productivity gains (t/h) of 3% and energy gains (Kcal/t) of 5% compared to expert operators. In cement milling, the productivity increased by 3.1% and the energy savings were 2.9%. In clinkerization, there were increases from 1% to 3% in the daily production, reductions from 2% to 4% in energy consumption, reductions from 12% to 16% in the variability of clinker quality requirements, and reduction of up to 10% in the variability of the lifetime of the liner. In other clinker kilns, there were from 4% to 5% reduction in fuel consumption, from 80% to 90% decrease in variability and increase from 7% to 8% in productivity.

The technology holder highlighted several other applications with gains from 6% to 10% in productivity and up to 3% in energy efficiency. Many authors (Nussbauer, 1994; Vaas and Krogbeumker, 1994; Sheridan, 1984; Wardana, 2004; Swain and Subudhi, 1996) have reported successful applications. The advantages are mainly due to the better response obtained by an automated system to the process variabilities. This is in contrast to the uncertainties of the behavior of human specialists in emergencies, continuous periods of operation, and due to the pressure created by the demand for higher systemic productivity.

Our research findings are in line with the literature. Control systems based on fuzzy logic are suitable for ill-defined processes in the continuous process industry such as the cement industry (Wang, 1999; Bose, 1994). For future studies, we plan to analyze similar data for the control processes of raw meal grinding, finish cement grinding, and clinker kiln calcination.

REFERENCES

Agrawal, V., Panigrahi, B. and Subbarao, P. (2015). Review of control and fault diagnosis methods applied to coal mills. *Journal of Process Control*, 32, 138-153.

Ale, B., Van Gulijk, C., Hanea, A., Hanea, D., Hudson, P., Lin, P., and Sillem, S. (2014). Towards BBN based risk modelling of process plants. *Safety Science*, 69(1), 48-56

Bose, B. (1994). Expert system, fuzzy logic, and neural network applications in power electronics and motion control. *Proceedings of the IEEE*, 82(8), 1303-1323.

Buckley, J. (1992) Universal fuzzy controlers. *Automatica*, 18(6), 1245-1248.

Dennis, D. and Meredith, J. (2000). An empirical analysis of process industry transformation systems. *Management Science*, 46(8), 1085-1099.

Fransoo, J. and Rutten, W. (1994). A Typology of Production Control Situations in Process Industries. *International Journal of Operations and Production Management*, 14 (1), 47-57.

Giarratano, J. and Riley, G. (1998). *Expert systems*. PWS Publishing Co, Worcester, UK.

Haber, R. and Alique, A. (2003). Intelligent process supervision for predicting tool wear in machining processes. *Mechatronics*, 13(8), 825-849.

Harmon, P. and Sawyer, B. (1990). *Creating expert systems for business and industry*. John Wiley & Sons, Inc, Hoboken, USA.

Holmblad, L. and Østergaard, J. (1995). The FLS application of fuzzy logic. *Fuzzy Sets and Systems*, 70(2-3), 135-146.

Holmblad, L. and Ostergaard, J. (1981). Control of a cement kiln by fuzzy logic techniques. *IFAC Proceedings Volumes*, 14(2), 809-814.

Kacprzyk, J. (1997). *Multistage Fuzzy Control.* John Wiley Sons, Chichester, UK.

King, R. (1988). Intelligent control in the cement industry. *IFAC Proceedings Volumes*, 21(19), 303-307.

Larsen, P. (1980). Industrial applications of fuzzy logic control. *International Journal of Man-Machine Studies*, 12(1), 3-10.

Lee, C. (1990). Fuzzy logic in control systems: fuzzy logic controller – Part I. *IEEE Transactions on Systems, Man, and Cybernetics*, 20(2), 404-418.

Legg, S. and Hutter, M. (2007). A collection of definitions of intelligence. *Frontiers in Artificial Intelligence and applications*, 157(1), 17-28.

Lolli, F., Gamberini, R., Regattieri, A., Balugani, E., Gatos, T. and Gucci, S. (2017). Single-hidden layer neural networks for forecasting intermittent demand. *International Journal of Production Economics*, 183, 116-128.

Mamdani, E. (1974). Application of fuzzy algorithms for control of simple dynamic plant. *Proceedings of the IEEE*, 121(12), 1585-1588.

Marin-Garcia, J. and Bonavia, T. (2015). Relationship between employee involvement and lean manufacturing and its effect on performance in a rigid continuous process industry. *International Journal of Production Research*, 53(11), 3260-3275.

Nazir, S., Sorensen, L., Øvergård, K. and Manca, D. (2015). Impact of training methods on Distributed Situation Awareness of industrial operators. *Safety Science*, 73, 136-145.

Nikolopoulos, C. *Expert Systems*. Marcel Dekker, New York, USA, 1997.

Nussbaumer, A. (1994) LINKman II: Experience in the Apasco Group. *Proceedings of the 33rd Technical Meeting/10th Aggregates and Ready-Mixed Concrete Conference*, Basel.

Olsson, E., Funk, P. and Xiong, N. (2004). Fault diagnosis in industry using sensor readings and case-based reasoning. *Journal of Intelligent & Fuzzy Systems*, 15(1), 41-46.

Precup, R. and Hellendoorn, H. (2011). A survey on industrial applications of fuzzy control. *Computers in Industry*, 62(3), 213-226.

Sheridan, S. (1984). Automatic Kiln Control at Oregon Portland Cement Company's Durkee Plant Utilizing Fuzzy Logic. *IEEE Transactions on Industry Applications*, 20(3), 562-568.

Swain, A. and Subudhi, B. (1996). Fuzzy logic Based Cement Kiln Control. *IEEE Journal*, 17(1), 58-61.

Vaas, M. and Krogbeumker, H. (1994) Das mühlenregelungssystem MCE bei Phoenix Zement in Beckum. (The MCE mill control system at Phoenix Cements at Beckum) *ZKG Zement-Kalk-Gips International: Forshung-Herstellung-Verwendung*, 9(1), 12-18.

Vogel-Heuser, B., Schütz, D. and Folmer, J. (2015). Criteria-based alarm flood pattern recognition using historical data from automated production systems (aPS). *Mechatronics*, 31(1), 89-100.

Wang, L. (1999). *A course in fuzzy systems*. Prentice-Hall Press, Upper Saddle River, USA.

Wardana, A. (2004) PID-Fuzzy Controller for Grate Cooler in Cement Plant. *The Proceedings of the 5th Asian Control Conference*, Melbourne.