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ADVANCED PROCESS CONTROL FOR FLUIDIZED BED AGGLOMERATION

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Abstract. Fluidized bed agglomeration is an advanced technology to produce spherical coarse-grained material of uniform size ready for sale without any need for post-treatment. This study discusses the possibilities and appropriateness of an intelligent control method such as a fuzzy logic controller in simulating and controlling fluidized bed agglomeration performance. Modeling and simulation was performed on the basis of data collected from several experiments. The resulting fuzzy controller is a knowledge-based system that performs closed-loop operations autonomously either by supervising or replacing conventional algorithms.

Keywords: fuzzy control, process control, fluidized bed agglomeration.

1. Introduction

The granulation (also known as agglomeration) of powders to produce chemical and pharmaceutical solid dosage forms is an essential operation, and the use of fluidized bed technology provides a rapid and cost-effective means of performing this process. More than 70% of the global industry's granulation systems use wet agglomeration [1]. The process is, however, extremely complex and many factors contribute to its overall success.

In the search for an easy, efficient, cost-effective control design and development technique, fuzzy logic (FL) seems to provide a method of reducing system complexity while increasing control performance [2]. Fuzzy set theory was originally investigated by Lukasiewicz and Knuth. However it was only formalized by Zadeh in 1965. Since then, many researchers have used fuzzy logic techniques to solve different types of control problems [2]. The ability to model problems in a simple and human-oriented way, and the ability to produce smooth control actions around the set points of relevance make fuzzy logic an especially suitable candidate for use in fluidized bed agglomeration control.

Today, plant operators are faced with ever-increasing pressure to improve efficiency, quality and productivity. Without making fundamental changes to their production processes, improvements can usually be made by applying advanced control technologies. Using modern computer hardware, software and innovative techniques, application engineers can collect both real time and historical data. Data analysis, modeling and simulation provide a better understanding of the dynamics of process behavior. Once the process characteristics have been accurately identified, the options for applying suitable control methodologies are no longer limited to conventional control techniques.

This study discusses the possibilities and appropriateness of an intelligent control method such as FL in simulating and controlling fluidized bed agglomeration performance. The resulting fuzzy controller is a knowledge-based system that performs the closed loop operations autonomously either by supervising or replacing the conventional algorithms. It allows the representation of plant uncertainties, takes into account system nonlinearities, and generates smooth control actions. The experiments described later in this paper aim to investigate and quantify the factors that influence performance, limited to the following process variables: inlet air volume, inlet air temperature, outlet air temperature, outlet air humidity, throughput of solids and fluid volume. These variables allow users to determine both process state and control system actions.

2. Related work

Fuzzy Logic Control (FLC) has been successfully used for resolving control issues in situations where operators' process expertise can be transformed into automation. Real-life control actuators are often non-linear because their dynamics change with operating point, or otherwise express non-linearities that are associated with the fluidized bed agglomeration process. However, in the research literature [3-5], we have only been able to identify a few examples of fuzzy logic applications in the realm of fluidized bed granulation. According to [5], fuzzy control systems are implemented through the use of production rules that are determined by considering the degree of influence of three factors known to strongly impact granule quality. The ideal pattern of humidity regulation for a stable fluidization scenario that produces granules of a narrow range of sizes was successfully derived by using the established system. This derivation held true even under difficult granulation conditions supervised using conventional control methods. Juuso in [4] describes fuzzy linguistic equation (LE) modeling possibilities for fluidized bed granulators that are used in the production of pharmaceuticals. His modeling approach aims to dynamically estimate granule size during processing since the results of analyzing samples are not immediately available online.

Another common advanced control method for the granulation process is Model Predictive Control (MPC). MPC is an effective method for controlling processes that involve multiple inputs and multiple outputs [6]. To control multiple outputs by changing the inputs, the controller uses a process model to calculate the influence of input variables on future states of the process. The complex nature of agglomeration makes MPC an obvious choice as has been suggested by Wang and Cameron [7] in their review of modeling and control of continuous drum granulation. However, there are only a few examples in the literature that discuss MPC being applied to granulation. Pottmann et al. [8] used a black box, linear discrete-time model to process their data. They tested plant-model mismatch scenarios by perturbing individual step response gains and time constants and introducing Gaussian measurement noise to the outputs. Gatzke and Doyle [9] introduced soft output constraints and prioritized control objectives to the same MPC setup.

In light of the huge variety of available advanced control methods [10], we have restricted the scope of this paper to fuzzy logic control strategies.

3. Method of development

The proposed fuzzy control application was developed to solve control challenges that an operator may face in the course of routine management of a fluidized bed system. Our process control methodology was developed and implemented in two stages:

Stage 1: In the *model-related* step, the relevant agglomeration kinetics was described through mathematical and physical laws [11-14]; based on these, a fuzzy control simulation was devised [15] to allow for “on-line observations” of the dynamic process.

Stage 2: After investigating the Stage 1 process, the concept was put into practice in a *real*, experimental process. Our fuzzy controller included a functional override mode that allowed the algorithm to assume complete control of the fluidized bed agglomeration process.

Figure 1 shows the process.

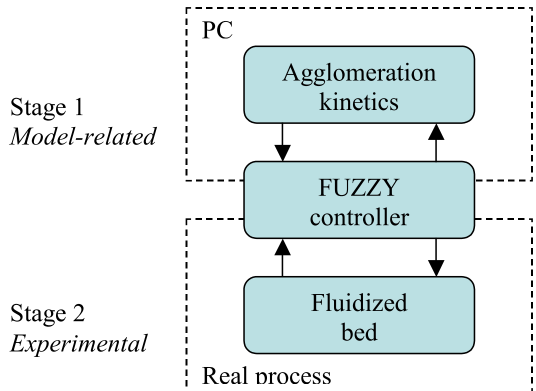


Figure 1. Experimental and model-related approaches (based on Koerfer [16])

Control objectives and structure

The *first step* in designing the fuzzy controller was to summarize all the goals of the control process. For the fluidized bed agglomeration process, three target goal groups were articulated:

- Optimize product quality (constant agglomerate size distribution).
- Minimize the need for manipulative intervention at the operating point (steady state); this results in a steady process behavior with uniform product quality.
- Targeted and rapid start-up plant procedures.

These form the basis for selecting the measurable process variables, manipulated variables and rule structure.

In the *second step*, for actual fluidized bed agglomeration, the following process variables (Table 2) needed to be acquired to clearly describe the intended process conditions.

These variables are also the measured values of the process, which are defined for the first controller design as input variables of the fuzzy controller. Based on these values, the fuzzy controller controls the following setpoints: the mass flow of the powder (DW); the mass flow of the liquid (WP); and the air throughput (AK) (outlet air flap position).

Table 2. Selected process variables for fuzzy control

Process variables	
Fuzzy control - Input	*Fuzzy control - Output*
ZM - air throughput	AK - outlet air flap position
ZT - inlet air temperature	WP – water pump
AF - outlet air humidity	DW – dosing scale
AT - outlet air temperature	
FM - solid mass flow	
X_{50} - agglomerate size	

Figure 2 presents the general scheme of the fuzzy control system used.

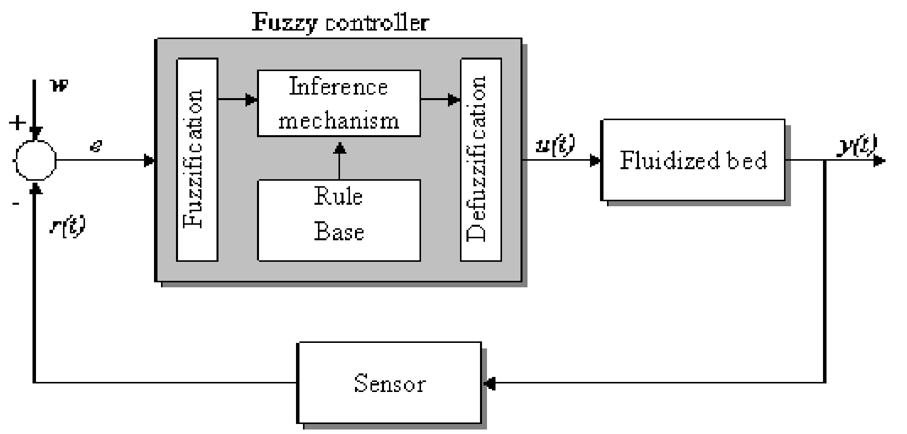


Figure 2. Fuzzy closed-loop control system. *w* – setpoint, *e* – error, *r(t)* – measured value, *u(t)* – control action, *y(t)* – process output

Development of the data base

After determining the linguistic variables, we began by converting an expert's knowledge of the system into IF-THEN rules. Combinations of different linguistic terms in the context of the six input variables colloquially described different operational states of fluidized bed agglomeration. The linguistic terms, that appeared in the rules, specified the control instructions in the form of reactions to relevant process conditions. Our approach was to start with a small number of rules and then to add rules in stages as needed. The resulting rules were modified until a desired minimum rule quality was secured. In the case of our agglomeration process, a total of 25 rules were formulated. For example, a rule for the water pump regulation reads:

IF air throughput is *adequate*

AND x_{50} value is *small*

AND exhaust humidity is *above normal*

AND inlet air temperature is *medium*

THEN water pump should transfer fluid *moderately*.

The inference method applied here is a standard inference strategy (Max-Min inference). As in defuzzification methods, the priority method for singletons is used. This method is advantageous as compared with the general priority method for simpler calculations. This was very important for the hardware implementation

Implementation of expert knowledge in the fuzzy application

To incorporate expert knowledge, the Fuzzy Control Manager (FCM) developed by TransferTech GmbH was selected. The FCM-PLC version of the graphical development platform was chosen, with dedicated hardware support for the FP-3000 fuzzy co-processor (OMRON), which was to be used subsequently for controlling the plant. This development platform also allows integration of the fuzzy controller (FZ001, OMRON) with a simulation. This permits computer-based control of dynamic behavior.

Rules for control of fluidized bed agglomeration were selected and implemented using experience gained from the experiments [11] after evaluation of the theoretical (Stage 1) principles behind the process-based behavior of fluidized bed agglomeration. Of special significance was how we investigated primary influencing factors and their sensitivity in agglomeration performance. In the course of our experiments, the rules were improved upon and supplemented.

4. Experimental setup

Fluidized bed agglomeration

It is a fact that fluidized bed agglomeration is a very complex process that can be difficult to control due to the numerous and sometimes unknown factors that can affect the process and hence the product properties. Factors of relevance can be specific to the apparatus, process and product (Table 3).

Table 1. Factors influencing fluidized bed agglomeration

Factors influencing the apparatus	Factors influencing the process	Influencing factors specific to solid
Stream-in floor	In- and outlet air mass volume	Fluidizing characteristics
Nozzle type	In- and outlet air temperature	Moistening factor
Nozzle alignment	In- and outlet air humidity	Type of solid
Nozzle fixtures in the bed	Fluid feed volume	Type of fluid
External shape	Nozzle operating parameters	Type of binder
Internal structure	Drip size distribution	Binder concentration
Load	Humidity in the fluidized bed	Feed volume per time
Service life (cleaning)		Particle size distribution

Traditionally, the control of fluidized bed agglomeration is based on indirect measurements. These control methods use process air properties [17-19]. However, the airflow rate, temperature and humidity of the inlet air and the addition rate and droplet size of the granulating liquid are critical input variables [11, 20]. Temperature and humidity measurements related to the process air are the most important parameters for monitoring both heat and mass transfer. However, the inlet air humidity cannot usually be accurately specified because seasonal variations in humidity are difficult to control entirely.

The following explains the practical implementation of fuzzy control in fluidized bed agglomeration (Figure 3). All of our agglomeration experiments were performed in a fluid bed granulator (Glatt WSG, Glatt GmbH, Binzen, Germany) by using a powdered raw product (skimmed milk powder). The experimental apparatus operated according to the scheme shown in Figure 3.

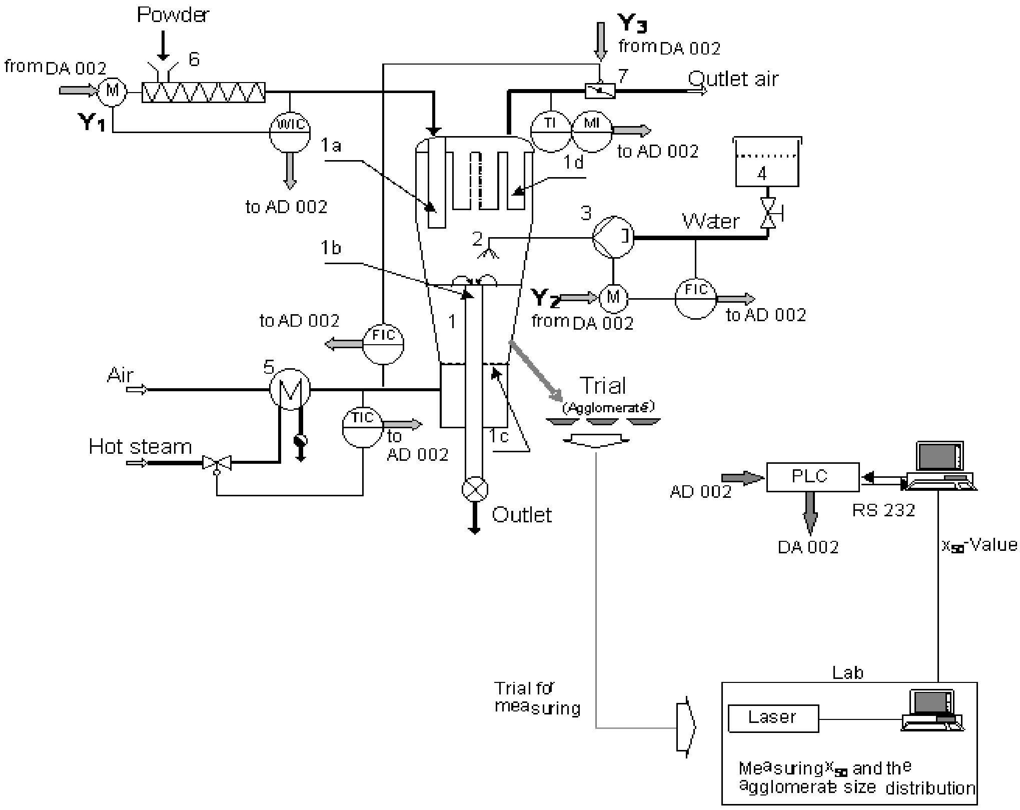


Figure 3. Experimental setup used for fluidized bed agglomeration: *1* – apparatus tower, *1a* – down-pipe, *1b* – stand-pipe, *1c* – sieve, *1d* – single-chamber shacking filter, *2* – spray nozzle, *3* – spray pump, *4* – spray solution, *5* – heater, *6* – differential dosing scale with a rotary valve, *7* – air outlet flap, Y_1 - powder mass flow (kg/h), Y_2 - fluid volume (ml/min), Y_3 - outlet air flap (%), *AD002* – A/D converter, *DA002* – D/A converter

In Figure 3, the conical fluidizing chamber (1) (diameter 230–500 mm, height 1210 mm) forms the central apparatus. The solid is fed through a differential dosing scale (6) of type K-Tron (1.2–30 kg/h), and the product enters the fluidized bed through a down-pipe (1a) (∅ 50 mm) submerged in the fluidized bed. The solid is drawn from a 20 kg capacity storage container above the experimental apparatus automatically by the differential dosing scale and transferred onto the fluidized bed through a rotary valve (6).

The agglomerates are delivered by overflowing from the fluidized bed (this ensures a nearly constant fluidized bed volume); the stand-pipe (1b) is approximately 300 mm long with a 50 mm diameter. Turbulence is created on a 0.75 thick sieve (1c) base with a fine perforation of 0.15 mm. For the agglomeration fluid, water was sprayed without adding any binding agents at 20 °C (room temperature) using a two-component nozzle (2) Model 970, manufactured by Schlick, by means of a hexagon head peristaltic pump (3), manufactured by Meredos, and compressed air. The two-component nozzle was positioned centrally over the fluidized bed to spray in the downward direction. The clearance to the bed surface was approximately 200 mm.

The turbulence gas used was dry compressed air from a network, which was first decompressed and buffered in two tanks. This enabled the avoidance of high expenditure for air conditioning. The air flowing through the fluidized bed was led through an electrical heating element (5) and heated to the desired temperature. Temperature sensors were used in the pneumatic manifold chamber to regulate and measure the air temperature. The temperature was set by the temperature controller integrated in the switchgear cabinet. An air flap (7) integrated in the ventilating outlet accurately regulated the inlet air volume. As described in [11], since no real-time particle size measurement was available, the trials were analyzed using laser diffraction with a Helos measuring device manufactured by Sympatec GmbH at intervals of 10 min. These data were made available to the PLC (OMRON) through an RS-232 interface.

The fluid volume (Y_2) and product mass flow (Y_1) change the retention time of the powder and the particle size distribution in the apparatus and influence directly the process velocity. The outlet air flap (Y_3) is a control element by which the air current is set for the entire apparatus. By changing the air and product feed as well as by varying the fluid transfer rate, the present agglomeration process can be characteristically influenced and, thus, influences the product (e.g. average agglomerate size).

5. Results

In order to illustrate the dynamic behavior of fluidized bed agglomeration and – in particular – the quality of the fuzzy controller for certain important situations, we simulated the fuzzy control model. Our goal was to test a controller that exhibits good characteristics for all states of the agglomeration processes.

For all standard trials and for their variations, the following reference conditions were selected:

Process variable	Setting value
Solid throughput	4 kg/h
Solid material in the bed	4 kg
Inlet air volume	28 m^3/h
Inlet air temperature	40° C
Inlet air humidity	0 %
Agglomeration fluid volume	12 ml/min
Fluid temperature	20 °C

We examined two scenarios involving modification of the water feed, inlet air volume and average agglomerate size (x_{50}):

Scenario 1	Controlling for a certain new setpoint for the target variable x_{50}.
Scenario 2	Adjusting to the disturbances.

Simulations that controlled the behavior of practical experiments were compared with the results of our model-related simulations.

Scenario 1: The fuzzy controller tried to reach a new setpoint starting from a steady state by manipulating variables like volume of water, position of the outlet air flap and solid dosing as specified by the fuzzy rules. Time-related controller behavior was monitored until a new steady state could be reached. Figures 4-6 show the progression of the target variable x_{50} and the initial system variables during the experiment.

For a constant inlet air temperature, the controller used fuzzy rules to maintain a given strategy. In the diagram (Figure 4, curves 2-4), while x_{50} increases from 380 µm to 400 µm the volume of inlet air is first reduced (Figure 5, curves 2-4) while the volume of water increases (Figure 6, curves 2-4). A similar strategy is also used for major setpoint changes. In reducing the x_{50} setpoint (Figure 4, curve 1) the actions are inverted, i.e., the volume of water is lowered (Figure 6, curve 1) and the volume of inlet air increases (Figure 5, curve 1). It is evident that the reduction in x_{50} value is primarily effected by an obvious change in the volume of inlet air, whereas an increase in x_{50} is achieved mainly by changing the volume of water. By doing so, the practical controller reaches the target x_{50} value after 1.5 retention periods and with an accuracy that is adequate for practical purposes.

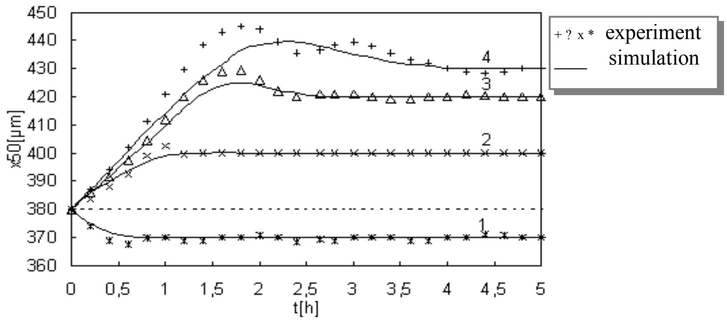


Figure 4. x_{50} over time for different setpoint defaults: comparison of real process with simulated control system; (1) $x_{50} = 370\mu m$, (2) $x_{50} = 400\mu m$, (3) $x_{50} = 420\mu m$, (4) $x_{50} = 430\mu m$

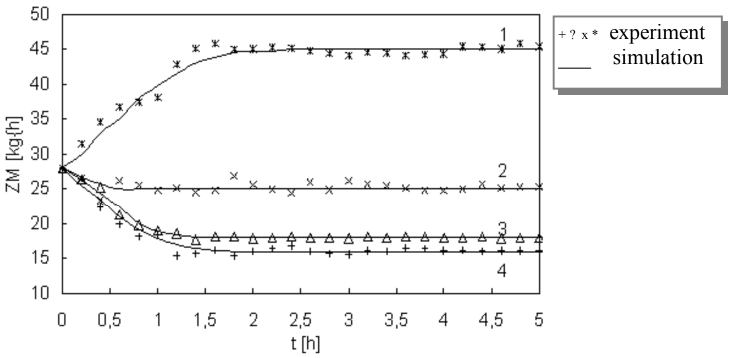


Figure 5. Volume of inlet air (ZM) over time to reach the setpoint x_{50} : comparison of real process with the simulated control system; (1) $x_{50} = 370\mu m$, (2) $x_{50} = 400\mu m$, (3) $x_{50} = 420\mu m$, (4) $x_{50} = 430\mu m$

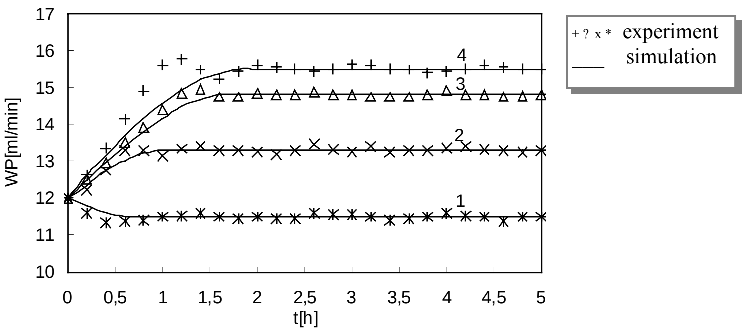


Figure 6. Volume of water feed (WP) over time required to reach the setpoint x_{50} : comparison of real process with the simulated control system; (1) $x_{50} = 370\mu m$, (2) $x_{50} = 400\mu m$, (3) $x_{50} = 420\mu m$, (4) $x_{50} = 430\mu m$

In all cases, a slight transient oscillation towards the setpoint is the result when the setpoint changes by more than 10%. The overshoot is, however, less than approx. 2.5% and fades out at the most after 4 retention periods. Figures 4 to 6 illustrate smaller discrepancies between the simulation and experiment. This is due to various factors of relevance that are not yet recorded in the simulation model, the underlying dynamics of the practical process and also the “discontinuous feedback” provided by the control loop during the simulation. In addition, manual analysis of the trials indicates that there are several statistical errors in the data. These impact the results strongly because they resulted in smaller values being passed into the control process.

Scenario 2: In order to verify control behavior under changing conditions, further experimental simulations were conducted. Under this scenario, the controller had to adjust the setpoint deviation of the target variable back to its previous setpoint (in this case $x_{50} = 380\ \mu m$). Two conditions were consequently changed: (1) the input variable for the volume of water feed, and (2) the inlet air volume. Changes in the process variables were monitored over time and are illustrated in Figures 7-8.

(1) Starting from steady state, a simulated steep increase in the volume of water from 13.5 to 15 ml/min positively impacted the volume of inlet air as well as the volume of solids input to the system (Figure 7).

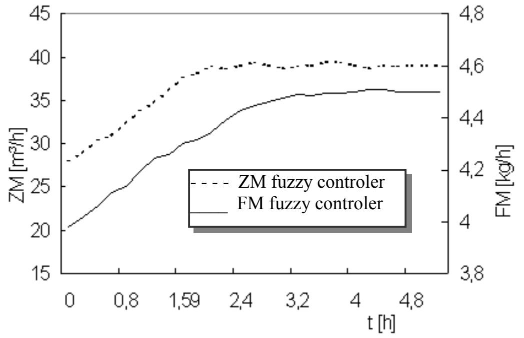


Figure 7. Changes in volume of inlet air (ZM) and volume of solid material (FM) following an initial jump in the water feed volume

In physical terms, this approach provides extra energy (to evaporate the water being fed to the system) by raising the volume of warm inlet air (ZM) and also by intensifying the turbulence so as to maintain the small particle size. Increasing the solid feed (FM) ensures more agglomeration nuclei, more agglomeration surface area and thus a better uniformity in the x_{50} value. We recognize that the control system activates only following the increase of x_{50} to 390 µm. Subsequently, the system counteracts with the actions:

IF FM above normal *AND* x_{50} large *AND* ZT high *AND* AF medium *THEN* WP moderate

IF FM normal *AND* x_{50} large *AND* ZT low *AND* AF high *THEN* WP moderate

IF AF high *AND* x_{50} large *AND* ZM high *THEN* WP moderate

IF AF high *AND* ZM adequate *THEN* WP moderate.

and returns the system to the original steady value without any significant transient oscillations after about 3 retention periods. Figure 8 shows the resulting scenario, comparing experimental results with the model-related simulation.

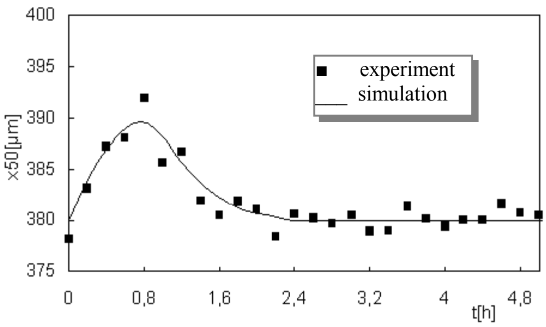
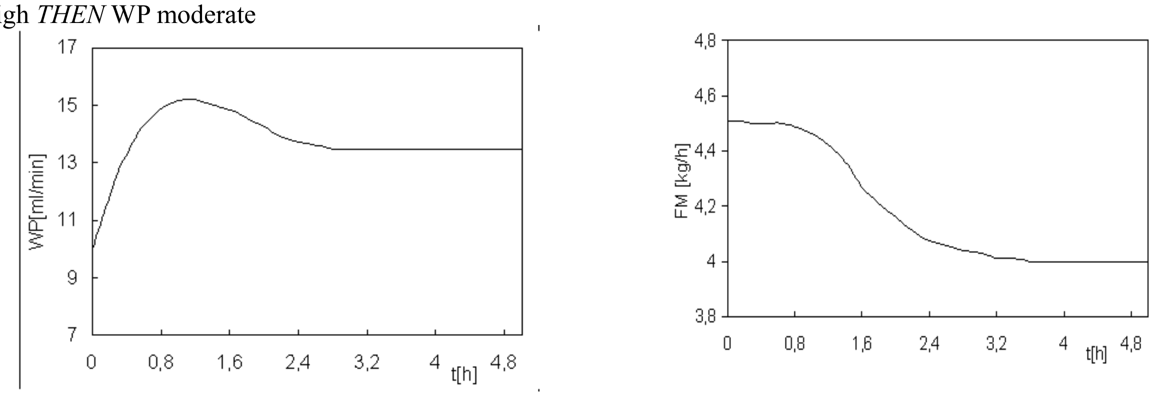


Figure 8. Changes in x_{50} following an initial increase in the volume of the water feed (WP) from 13.5 to 15 ml/min

The control algorithms cause the x_{50} diameter to pass through a large range in order to ultimately return to its original value. The reaction of the fuzzy system is appropriate and the error adjusts after approximately 3 solid material retention periods.

(2) Another control challenge is a spontaneous increase in the volume of inlet air from 28m^3/h to 32m^3/h, while the system maintains its setpoint for x_{50}. The system reacts in such a way (cf. Figure 9 -10) that first the volume of solid feed is decreased (Figure 9, (a)) and subsequently the volume of the water feed is increased (Figure 9, (b)).



a) b)

Figure 9. a) change in volume of solid over time following an initial increase in the volume of inlet air; b) change in volume of water feed over time following an initial increase in the volume of inlet air

The result is a temporary increase in the average agglomerate diameter, which is subsequently lowered when the volume of water input is again reduced. Thereafter, the old x_{50} value results in a final stationary state (Figure 10). In this case, the flow is adjusted to within approx. 2.5 retention periods for the solid material. The oscillation is hardly any bigger than the measured noise range.

A detailed assessment of the results shows that we achieved our goals. Of particular note is that no offsets were evidenced for any of the target variables.

Under the circumstances, control outcomes can be further improved using better adaptation processes and by extending the relevant rules or adjusting membership functions. To date, inertia of the control elements has not been taken into account. Similarly, the inertia following the increase of inlet air temperature in the heater coils plays an important role. Specifically, faster changes in inlet air temperature are not possible because of heat accumulator capacity in the heater coils.

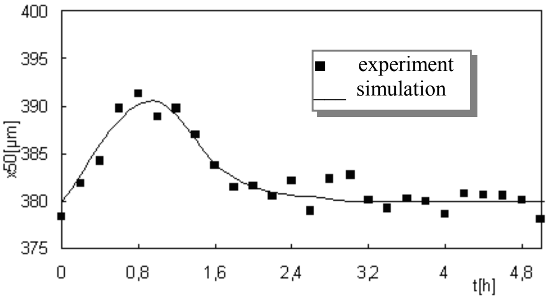


Figure 10. Change in x_{50} following an initial increase in the volume of inlet air: comparison of experiment with model-related simulation

6. Conclusions

The proposed fuzzy control application was developed to address control challenges that operators may encounter during routine operations of a fluidized bed. It showcases approaches for possible future work and offers several requirements for measuring sensors, as well as for control systems and regulation units. Our experiments showed satisfactory performance and various improvements to the automation of the agglomeration process were achieved. We concluded that fuzzy logic is a very appropriate tool to solve fluidized bed agglomeration control challenges.

Our fuzzy control framework can be used: (a) for simulated real-time observations of fluidized bed agglomeration processes; (b) to reduce the number of required operational trials; (c) to simulate various typical control methods such as setpoint changes and input signal errors; (d) to incorporate empirical process know-how; (e) to eliminate “perception-oriented” manual intervention in the process; (f) to improve the quality of process control and for reducing production costs.

Despite our promising results, the reader should remember that fuzzy logic is just one tool that can be used to address process control and process management challenges. Without proper process experience and knowledge to design and tune applications appropriately, advanced artificial intelligence tools like fuzzy logic or neural networks do not bring any better results than conventional systems would.

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