Journal of the Korean Ceramic Society
Vol. 41, No. 12, pp. 873~879, 2004.

A Fuzzy Modeling Approach for a Spray Drying Production Process

Hani Mohammad A. Aburas†

Department of Industrial Engineering, Faculty of Engineering, King Abdul Aziz University, Jeddah 21589, Saudi Arabia
(Received June 23, 2004; Accepted November 10, 2004)

ABSTRACT

In all major industries ranging from powder industries and advanced ceramics, to the food and pharmaceutical manufacture powder industries, the main production process is the spray dryers. In this paper, a systematic approach is used and six rules are obtained for the basis of the fuzzy model. A fuzzy model is based on the past behavior of the target system and expected to be able to reproduce the behavior of the target system. The output of the developed fuzzy model shows, graphically and statistically, a high level of face validity. Therefore, it is concluded that the developed fuzzy model mimics the actual process and can be considered, with confidence, as a reliable model to study, analyze, and improve the existing process.

Key words : Fuzzy modeling, Spray dryer granulation, Fuzzy inference system

1. Introduction

There are many production processes that can not be modeled mathematically because their mathematical-model based approaches are too complex to be used practically. However, such processes can often be controlled by operators because of their ability to interpret linguistic statements about the system parameters and their past experiences about the process. System operators do not need mathematical equations to control the production processes. Therefore, if we have a certain fuzzy model of a process, we may design fuzzy controller in a more sophisticated way. By fuzzy modeling, we mean representing the characteristics of a given process by a set of its fuzzy behaviors that can be expressed by using fuzzy implications concerned with inputs, state variables and outputs.

Spray dryers are complex production systems, their system parameters are controlled by human operators, without using any mathematical equation. In general, a fuzzy system model is based on past behavior of target system. The fuzzy model is then expected to reproduce the behavior of the target system. Therefore, the experience and qualification of the system operator becomes crucial. Fuzzy modeling approach takes the advantages of domain experts whose knowledge cannot be easily or directly employed in other modeling techniques. Fuzzy sets use the past experience and the qualification of domain experts to identify and model the production system. Hence, fuzzy set theory is applied to the modeling of spray dryers.

†Corresponding author : Hani Mohammad A. Aburas
E-mail : haburas@kaau.edu.sa
Tel : 966(2)640-2000 (# 68470) Fax : 966(2)695-2486

2. The Basic of Spray Drying Process

Spray drying is the most common granulation technique for producing ceramic press powders. It is a continuous operation that produces free flowing particles with uniform and repeatable properties. The feed for the spray dryer is usually a water-based suspension called slurry. This slurry is fed into a warm drying medium to produce nearly spherical particles that are relatively homogeneous. The pressing operation and the microstructure of the pressed ware depend to a large extent upon particle properties (size, shape, etc.), the characteristics of the particle agglomerates (shape, size, distribution, etc.) and the pressing additions (moisture, binders, etc.).

The powder must have good flowability. This depends upon the friction between particles which again depends on granule characteristics such as shape, size distribution, density, deformability as well as outside variables such as moisture content of granules, pressure, inlet and outlet temperature of process, and chemical additives.[1]

The smallest granule size fractions, below 125 μm, have low flowability although they are partially made up of spherical granules, owing to the notable amount of non-agglomerated particles. The fractions sized 125−500 μm exhibit the highest flowability due to their spherical shape and smooth surface. However, the granule fractions larger than 500 μm flow worse than the particles between 125−500 μm range because they have been mainly formed by the flattened sized granules.

A well designed slurry formulation and consistency in slurry performance over time are required. Variability in the slurry composition or properties is a common cause of variability in the character and pressing performance of granules. Less water in the slurry reduces the drying cost and also has an influence on the character of the granules. A slurry with a high level of solid content is desirable, but it should be free of air because air bubbles reduce the density of both the granules and porcelain products.

Consistent production of granules depends on tight control of starting materials, batching slurry preparation and spray dryer conditions. The quality of product directly depends on the granule pressibility enabling production of satisfactory product that meets customers requirements. To rise the flowability, two variables in spray drying processes must be commonly and carefully monitored. Theses variables are the temperature and the moisture content.

Process control requires checking several parameters of the slurry, the drying process, and the granules. A careful control of the slurry preparation and spray drying parameters may enable the production of the improved granules, so can improve the performance of overall process. The pressing operation and the microstructure of the pressed ware depend on particle properties, the characteristics of the particle agglomerates, and moisture content. To effectively carry out the pressing operation in the die box, a uniformly distributed granular powder bed is required for porcelain production. Thus, powder must have good flowability.[2)]

Granule size increases as the fraction of bed exposed to reduced binding liquid. There is an upper limit on granule size because of the tendency of the powder bed to de-fluidize. However, spray granulation can form larger granules by spray drying due to longer residence times. Modern industrial powder pressing requires a well designed and controlled granulated feed powder. Many variables of the slurry composition and its preparation and spray drying process influence the characteristics and performance of the granulated powder. Granules that are larger and denser and contain more or less deformable binder are more resistant to deformation; however, they may transmit pressure better. Narrowing the range of granule sizes reduces the size of pore heterogeneity and improves the quality of the final product. The granule and fill density will be lower for granules produced from slurries containing more liquid and air bubbles. Granules with larger internal pores are not collapsed in the industrial pressing die boxes and pores craters appear in the sintered compact.

The spray dried granules have to meet certain characteristics before it can be used for shaping in dies. The residual moisture has an influence on the plastic behavior of the body and binder, and on the deformation properties of the grain. For this reason the spray dried granules should have relatively constant residual moisture.

3. A Design Methodology of Fuzzy Control System

A fuzzy logic control includes the following design principles: defining input and output variables, deciding on the fuzzy partition of the input and output spaces and choosing the membership functions for the input and output linguistic variables, deciding on the types of the derivation of fuzzy control rules, designing the inference mechanism, which includes choosing a fuzzy implication and a compositional operator, and choosing a defuzzification operator.

The first two design principles indicate that in the design of a fuzzy logic control system, one has to identify the state and control variables and determine the term set. For example, a six fuzzy term set such as very low, low, moderate, slightly high, high, and very high is satisfactory to express the domain.[1)]

In this process, the number of fuzzy partition, the base of the linguistic terms of input-output spaces, is found to be six. After long iteration of application of Fuzzy C-means clustering algorithm, it has been found that this number has an essential effect on how fine a system control can be achieved. Trapezoidal and Triangular membership functions are used for each linguistic variable.

In this approach, fuzzy control rules are developed based on the behavior analysis and the data taken from the process. By fuzzy modeling, we mean representing the dynamic characteristics of the process by a set of fuzzy implications with inputs, state variables, and output.[2)]

4. Fuzzy Sets and Fuzzy If-Then Rules

Fuzzy theory and methodology has provided us with an effective and realistic technique to code linguistic statements together with imprecise and uncertain information and knowledge into numerical framework. A Fuzzy model consists of many logical rules and is based on human qualitative knowledge.

Although probabilistic, statistic and other mathematical-approach based modeling techniques are very well developed, there are still a number of manufacturing processes that cannot be described mathematically, or their math-model based descriptions are too complex to be done practically. Such processes are often satisfactorily controlled by human beings because of their ability to interpret linguistic statements about the process under control.

By fuzzy modeling we mean to represent the characteristics of these complex processes by a set of fuzzy behaviors (fuzzy rules) which are also expressed by using fuzzy implications concerned with inputs, state variables and outputs. A fuzzy model has series of if-then rules for modeling. These rules are mathematical relationships mapping the inputs to outputs relations. As was pointed by Zadeh,[3)] conventional techniques for system analysis are unsuited for dealing with humanistic systems, whose behaviors are strongly influenced by human judgment, perception, and emotions. Because of this belief, the concept of linguistic variables is used as an alternative approach to model human thinking. For example, if the input temperature is very high then the moisture content should be low and the flowability is 'moderate' in a fuzzy system modeling. These fuzzy rules are used to form the knowledge base. For example, if the input temperature is moderate then the moisture content may be good to a certain degree. One of the most widely known fuzzy modeling algorithm is that of Mamdani approach.[4)]

Fuzzy set is a way to represent vagueness in linguistics. It can be considered a generalization of classical set theory. In a classical set theory, an element of the universe either belongs or does not belong to the set. That is, if the membership of an element is crisp, it is either in the set or not in the set. A fuzzy set is a generalization of an ordinary set in that it allows the degree of membership for each element to range over the unit interval [0, 1]. One of the main differences between the crisp and fuzzy sets is that crisp sets always have unique membership.

5. Fuzzy System Modeling Approach

In general, a fuzzy modeling system model is based on the past behavior of a target system. The fuzzy system model is then expected to be able to reproduce the behavior of the target system. If the target system is a human operator in charge of a chemical process, then the fuzzy system becomes a fuzzy logic controller that can regulate the control process.[5,6] Fuzzy modeling takes advantages of domain knowledge that might not be easily or directly employed in other modeling techniques, when the input-output data of a target system is available. In other words, the numerical data taken from a production system can play an important role in fuzzy modeling. Fuzzy modeling can be pursued in two stages; the first stage is the identification of the surface structure which includes the following tasks: select the relevant input and output data, choose a specific type of fuzzy inference system, determine the number of if-then rules associated with each input and output variables. Second, the identification and determination of appropriate family of parameterized membership functions by interviewing human experts who is familiar with the target system. We used fuzzy clustering approach to generate objective number of rules that is based on clustering of input-output data. Fuzzy C-means clustering algorithm was used to derive optimal number of rules and the level of fuzziness of clusters and generate membership functions.[7]

5.1. Fuzzy Structure Identification

Structure identification of fuzzy systems is possible by construction of enough rules with appropriate input and output membership functions. This goal can be carried out by two separate stages: rule generation and input selection and membership value assignment. In this method, the number of rules will be usually equal to the number of output clusters regardless of the number of input variables. Input variables will be specified by generating the projection of the output clustered on each input variable, separately.[7] Fuzzy modeling is constituted from fuzzy rules which are generated through fuzzy C-means clustering algorithm. The idea of fuzzy clustering is to divide the output data into fuzzy partitions that overlap with each other. The containment of each data to each cluster is defined by a membership grade in [0, 1]. The target of fuzzy clustering is to find the optimum membership values matrix $U = [u_{ik}]$. The most widely used objective function for fuzzy clustering is the weighted within groups sum of squared errors objective function J_m (Equation 1), which is used to define the constrained optimization problem.[5] $X = \{x_1, x_2 \ldots, x_k\}$ is the data set for assignment of number of clusters (c) to the vector X.

$$\underset{(U,V)}{Min}\left\{ J_m(U,V,X) = \sum_{k=1}^{N}\sum_{i=1}^{c}(u_{ik})^m \| x_k - v_i \|_A^2 \right\} \tag{1}$$

$V = \{v_1, v_2, \ldots, v_c\}$is vector of cluster centers. A is then hxh positive definite matrix that specifies the shape of the cluster. The matrix A is usually selected to be as the identity matrix. The fuzzy C-means clustering algorithm suffers from some difficulties: it is not always possible to assign the number of clusters as priori, there is no theoretical basis for an optimal choice of weighting exponent (m), and the initial guesses of the cluster centers v_i. Now, our aim is to eliminate these difficulties and constitute the fuzzy model step by step.

5.2. Cluster Validity-Specification of The Number of Clusters

As a prerequisite for Fuzzy C-means algorithm, it is required to assign the number of underlying partitions that appear in the data set. In order to find number of clusters from a theoretical point of view, we perform a proper generalization of scattering criteria that are mainly applied for expressing the compactness and separation between the hard clusters. S_B (Equation 2) represents the separation between the fuzzy clusters and S_w (Equation 3) is an expressive index for the compactness of fuzzy clusters.

$$S_B = \sum_{i=1}^{c}\left(\sum_{k=1}^{N}(u_{ik})^m\right)(v_i - \bar{v})(v_i - \bar{v})^T \tag{2}$$

$$S_w = \sum_{i=1}^{c}\sum_{k=1}^{N}(u_{ik})^m (x_k - v_i)(x_k - v_i)^T \tag{3}$$

Where, the fuzzy total mean vector $\bar{v}$ (Equation 4) is a weighted mean of data considering their belongness to each of the clusters in fuzzy partition is defined as

$$\bar{v} = \frac{1}{\sum_{i=1}^{c}\sum_{k=1}^{N}(u_{ik})^m}\sum_{i=1}^{c}\sum_{k=1}^{N}(u_{ik})^m x_k \tag{4}$$

and v_i (Equation 5) is the fuzzy cluster centers;

$$v_i = \frac{1}{\sum_{k=1}^{N}(u_{ik})^m}\sum_{k=1}^{N}(u_{ik})^m x_k \tag{5}$$

Hence, in attempt to derive the best clusters, we minimize $tr(S_w)$ to increase the compactness of clusters and maximize

$tr(S_B)$ to increase the separation between clusters. So, the cluster validity index S_{CS} (Equation 6) can be determined as (m) approaches its extremes.

$$S_{CS}(U, V, X) = tr(S_w) - tr(S_B) = tr(S_w - S_B) \quad (6)$$

Where tr is the trace of matrix. The difference is significant for large values of weighting exponent (m) in Fuzzy C-means clustering algorithm.[5,7]

5.3. Selection of Weighting Exponent

The weighting exponent (m) controls the extent of membership sharing between fuzzy clusters in the data set. Therefore, in the range of $(1,\infty)$ the larger (m) is the fuzzier, are the membership assignment to each data point. In order to select (m) we consider the cluster validity criterion S_{sc}. So, first we examined the behavior of S_{sc} as (m) approaches its extremes, one, and infinity. In order to have a reliable index for cluster validity S_{sc}, the weighting exponent (m) should be far from its both extremes. To specify this condition, the extremes should be clearly defined. The extreme one is clear enough, but the infinity mainly depends on the data of the production system.[5,7] Then we defined fuzzy total scatter matrix S_T as the sum of fuzzy within-cluster and fuzzy between scatter matrices.

$$S_T = S_w + S_B = \sum_{k=1}^{N}\left(\sum_{k=1}^{c}(u_{ik})^m\right)(x_k-\bar{v})(x_k-\bar{v})^T \quad (7)$$

The trace of S_T (Equation 7) decreases monotonically from a constant value to zero, as (m) varies from one to infinity. Therefore, the method of determining (m) is that for each input parameter data set the output data will be clustered. K (Equation 8) is calculated from data set to be clustered and it depends only on the data set.

$$K = \left(\sum_{k=1}^{n}\left(\left(x_k - \frac{1}{N}\sum_{k=1}^{N}x_k\right)\cdot\left(x_k - \frac{1}{N}\sum_{k=1}^{N}x_k\right)^T\right)\right) \quad (8)$$

An appropriate value for (m) is what holds $tr(S_T)$ somewhere in the middle of its domain $[K, 0]$. Since $tr(S_T)$ is a function of number of clusters (c) and (m), the process of choosing (m) and (c) is performed by a few iterations. We started with a suitable selection of (m), then derive S_{sc} for several (c)'s and find optimum (c). Then we checked if for this (c) and (m), $tr(S_T)$ is satisfactorily far from its extremes. The number of (c) starting with 2, so after number 11, no changes were found in the trace of scatter matrix and weighting exponent, so, we stopped the iteration and search the reliable region for (m) on $K/2$, see Fig. 1.

As a result of all these calculations and computer iterations, optimum weighting exponents (m) was found to be 1.87 (see Fig. 1), and optimum number of cluster center was found to be 6 (see Fig. 2).

5.4. Initial Guesses and Optimality in Fuzzy C-means Algorithm

The last problem in Fuzzy C-means clustering algorithm is that the algorithm may produce only local minimum or partially optimal points. Therefore, random initial guesses for mean vectors v_i may lead to different optimum results.[5,7] This affects the cluster validity and analysis. In order to effectively obtain a preference for initial locations for clusters, we implemented Agglomerative Hierarchical Clustering algorithm d_{ij} (Equation 9). This algorithm gives suitable guesses for the initial locations of cluster prototypes for the Fuzzy C-means algorithm. The matrix of dissimilarities is based on distance as follows.[5]

$$d_{ij} = d(X_i - X_j) = \sqrt{\frac{2n_i n_j}{n_i + n_j}}|v_{ki} - v_{kj}| \quad (9)$$

Where, v_{ki} and v_{kj} are the mean vectors of the clusters X_i and X_j. In Fig. 3, the cluster centers and the number of clusters for the input temperature (X) and for the moisture content (Y) of the production system is given.

The input parameter is input temperature of spray dryer (X); the output parameter is the moisture content of granules (Y). The input and output parameters match was done for all the input-output parameters of the production system.

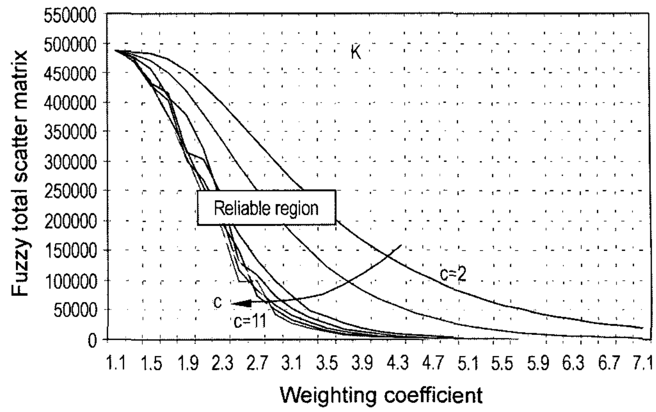

Fig. 1. Trace of fuzzy total scatter matrix.

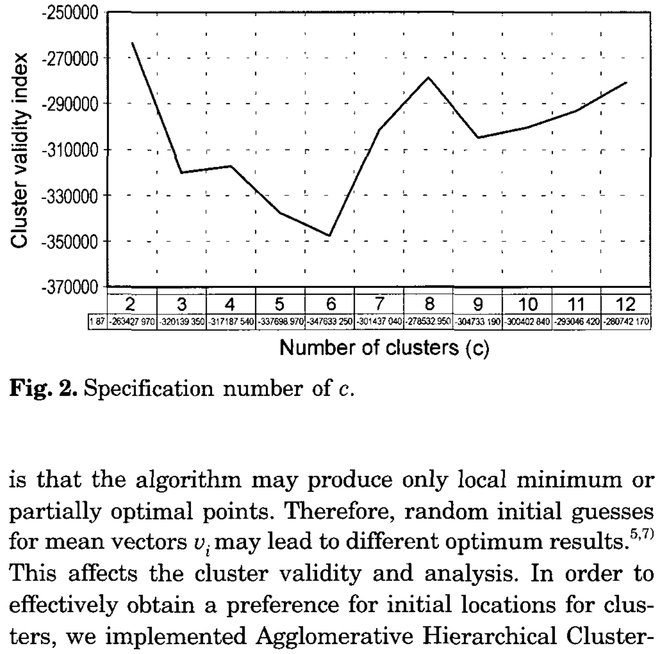

Fig. 2. Specification number of c.

5.5. Membership Functions Formation

In this fuzzy modeling approach, the output sample data are assorted in several fuzzy clusters. In order to extend the

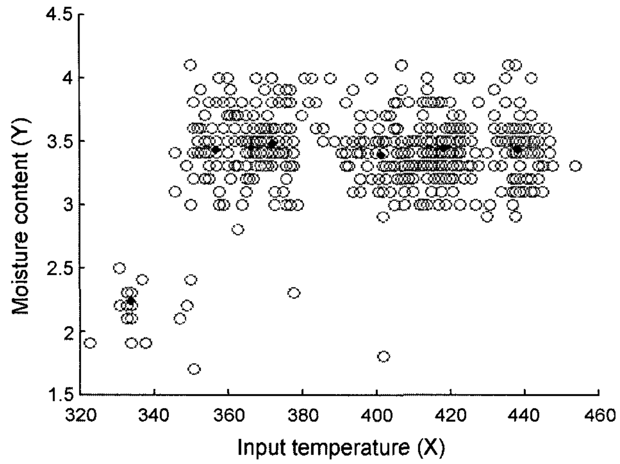

Fig. 3. The cluster centers and number of clusters.

assigned fuzzy clusters to the entire output space, classification process is required. In the clustering process, we make a suitable partitioning of the data set for the system parameters, but in classification, every data point in the entire space has to be labeled. Therefore, the problem of membership function formation for the entire output space is considered as classification problem.[5] After assignment of the data in the entire space to the fuzzy partitioning, we obtained simple membership functions that are approximated by triangular and trapezoidal functions, see Fig. 4.

6. Fuzzy Inference System

The fuzzy inference system is a computing framework based on the concepts of fuzzy set theory and fuzzy reasoning. It has successful applications in a wide range of fields, such as automatic control, decision analysis, robotics, and etc. The basic of our fuzzy inference system consists of three conceptual components: the rule base, the database, and the reasoning mechanism. Most fuzzy system parameters have been designed by referring to human operator's experience and control engineer's knowledge.[5,6] As an operator can play an important role in process control, it is useful to use his/her knowledge in control by interviews and to express knowledge in terms of fuzzy implications. But there are some difficulties of this method. Firstly, an operator cannot well express his/her secrets about the process linguistically. Secondly, it is difficult to write down control rules even from a control engineer's sense if the process is complex. So, it is very difficult to give a general design procedure. In order to select control parameters in system identification, we found that the most dominant input variables that affect the output among all of the input candidates. In our fuzzy modeling approach, we defined all input and output parameters by the help of domain expert and with a deep literature study. We found that the most dominant input variables are Input Temperature (IT), Output Temperature (OT), Pressure (P), Viscosity of slurry (V), Amount of used Chemicals (AC), and Density of Slurry (LA). The output variable is the Moisture Content of granules (MC). The residual moisture has an influence on the plastic behavior of the porcelain products.

For this reason the spray dried granules should have relatively constant residual moisture, and this makes the moisture content of granules one of the most important output parameter for control.

A part of the data concerning input-output parameters and their membership values are given in Table 1. Results show that the basic fuzzy inference system has crisp inputs, however; the outputs it produces are fuzzy numbers, see Table 1. These outputs are then re-converted into crisp val-

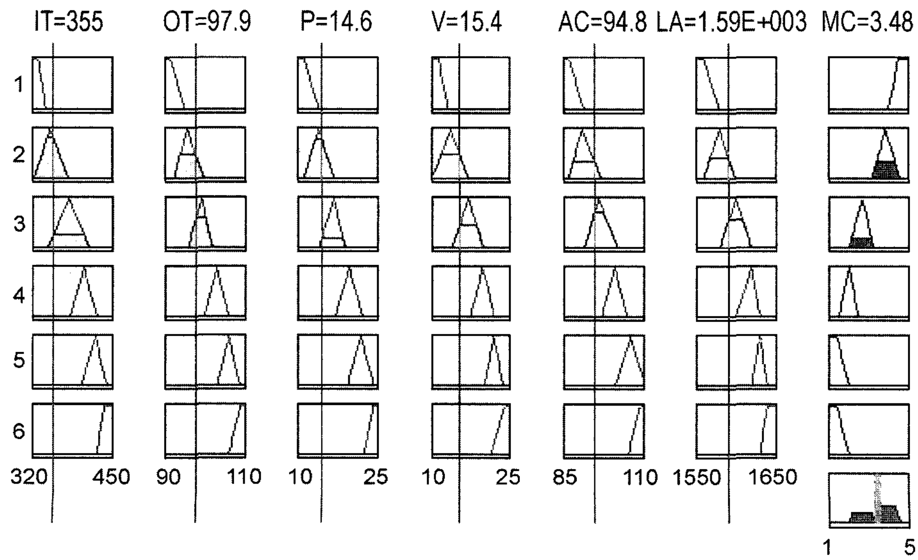

Fig. 4. Fuzzy inference system.

Table 1. Parameters of Actual Production System vs. Fuzzy Model

IT	OT	P	V	AC	LA	Actual System (MC)	Fuzzy Model (MC)
320.00	90.00	10.00	11.30	87.60	1560.00	4.59	4.61
334.00	92.60	11.20	13.00	88.20	1570.00	4.54	4.53
334.00	92.60	11.20	13.00	88.20	1570.00	4.54	4.53
340.00	92.60	12.30	11.60	90.50	1570.00	4.38	4.40
328.00	93.50	13.70	12.00	89.40	1570.00	4.19	4.18
337.00	93.00	12.30	12.30	90.50	1580.00	3.97	3.98
328.00	94.00	14.40	14.50	91.70	1570.00	3.93	3.91
337.00	95.30	14.00	14.10	91.70	1580.00	3.90	3.91
343.00	97.70	15.10	14.50	92.80	1570.00	3.89	3.91
352.00	98.10	13.30	16.30	89.90	1590.00	3.90	3.91
355.00	95.70	13.40	12.80	91.60	1580.00	3.88	3.90
370.00	100.00	16.50	15.90	94.60	1580.00	3.44	3.43
382.00	97.20	17.80	16.30	96.90	1590.00	2.68	2.67
388.00	98.10	19.20	16.60	94.60	1610.00	2.66	2.66
403.00	101.00	18.90	18.00	100.00	1600.00	2.44	2.43
412.00	106.00	21.30	20.50	97.50	1630.00	2.03	2.02
412.00	108.00	23.80	22.70	106.00	1630.00	1.49	1.47
430.00	105.00	21.30	23.00	107.00	1630.00	1.45	1.44

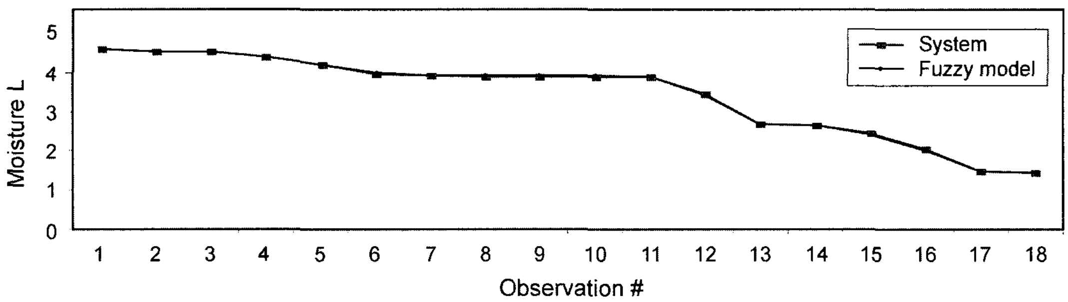

Fig. 5. Graphical comparison between actual system and fuzzy model.

ues by mean of maximum method of de-fuzzification, since the fuzzy inference system has to be used as a controller. We considered Mamdani fuzzy inference system, where the main block indicates the basic of inference system, the last column on the right shows the de-fuzzification block that serves for the purpose of transforming an output fuzzy set into a single crisp value. The fuzzy system identification is based on 470 input-output data of a spray dryer process. The fuzzy model consists of six rules each of which includes suitable functions, see Fig. 4. In this approach, linguistic variable assignment is not needed for the membership functions.

7. Conclusions

In general, a fuzzy model is based on the past behavior of the target system. The fuzzy model is then expected to be able to reproduce the behavior of the target system. Fuzzy system might become a fuzzy logic controller that can regulate and control the process. In modeling of the spray dryer process, a systematic approach was used and six rules were obtained for the basis of the fuzzy model. The nature of the process is fuzzy because the production processes is dynamic and the domain expert usually uses his/her intuition, feelings, and past experiences to judge the magnitude of the process dynamics. The domain expert and the customers always express their quality related decisions about the product in linguistic terms rather than using numerical values. In fuzzy systems, human decisions or control actions are made on the basis of imprecise, incomplete and uncertain system information.

Table 1 shows actual system versus fuzzy model results under the same sets of input variables. Both results were compared graphically and statistically. Graphical comparison, as shown in Fig. 5, shows high level of model validity.

On the other hand, the statistical comparison, at 0.05 level of significance, confirms our previously drawn conclusion and clearly proves that the model output is almost identical to the actual collected observations. Therefore, the developed fuzzy model mimics the actual process and can be considered, with confidence, a reliable model to study, analyze, and improve the existing process.

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