

## DESIGN OF A SIMPLE FUZZY LOGIC CONTROL FOR FOOD PROCESSING

A. O. Alghannam

Department of Agriculture Systems Engineering, College of Agricultural and Food Sciences, King Faisal University, P.O. Box 420, Al-Hassa 31982, Saudi Arabia.  
Email:aalghannam@kfu.edu.sa

(Received: Mar. 25 , 2012)

**ABSTRACT:** *In this paper, a simple design of fuzzy logic control for food processing as well as basics for designing fuzzy logic control were introduced. Due to the simplicity and power of the Fuzzy Logic Control (FLC) method for managing complex properties of food the processing operation, three design steps approach are presented as follow: 1) starting with a Proportional Integral Derivative (PID) controller, 2) insertion of an equivalent linear FLC and 3) a gradual conversion of the linear FLC to a nonlinear one for designing a simple FLC that includes the most possible key instrumentations used in food processing.*

**Key words:** *Food processes; Fuzzy logic control; Control; Quality; Food process instrumentation.*

---

### INTRODUCTION

The main objectives of the food process control are to maintain food safety, quality assurance, reduce processing time, and to keep high production at minimum cost (Linko and Linko, 1998). The food industry end-products must achieve a compromise between several properties including; sensory, sanitary and technological properties. From these, sensory and sanitary properties are essential because they influence consumer choice and preference. Computerized control systems in the food industry have been comprehensively discussed (Mittal, 1997). Advanced, intelligent control techniques such as model-based, expert, neuro-fuzzy and hybrid control systems offer particular advantages in food and allied processes (Caro and Morgan, 1991). Investments in automation, robotics and advanced control techniques are likely to result in marked savings in costs, productivity, improved and more consistent product quality, and increased safety (Linko and Linko, 1998). A collection of papers concerning the topic of fuzzy logic and the quality control of the food were written by Perrot *et al.* (2006). Only forty of these papers address the subject of supervision decision help system control. Most of these are classical applications of the Takagi–Sugeno controller such as;

Linko *et al.* (1992) for extrusion cooking, Zhang and Litchfield (1993) for drying, Norback (1994) for cheese-making, Alvarez *et al.* (1999) for controlling isomerizes hop pellet production, Honda *et al.* (1998) for controlling the sake brewing process, and O'Connor *et al.* (2002) for controlling the brewing process. Guillaume *et al.* (2001) optimized a fuzzy rule basis using a genetic algorithm to establish a decision support system for the cheese-making process. Davidson *et al.* (1999) developed a fuzzy control system for continuous cross flow in which he used a fuzzy arithmetic that estimates the browning of peanut roasting. Perrot *et al.* (2000) proposed a fuzzy logic approach to control the quality of the biscuits in an industrial tunnel oven. Voos *et al.* (1998) developed a fuzzy control of a drying process in the sugar industry based on operator experience, and Curt *et al.* (2002) developed five Takagi–Sugeno modules to control the quality of the sausage during ripening. Supervisory tasks were performed by Acosta-Lazo *et al.* (2001) for the supervision of a sugar factory. Perrot *et al.* (2004) developed a decision help system to control the cheese ripening process, integrating the uncertainty of human measurements. Petermeier *et al.* (2002) used a hybrid approach to develop a model of the fouling behavior of an arbitrary heat treatment device for milk. This was

developed by combining deterministic differential equations with cognitive elements for the unknown parts of the knowledge model. These authors emphasized the relevance of this open field of research in the context of food processes and the interest of fuzzy symbolic representation of expert reasoning. Nevertheless, they called into question the optimality of the approaches developed on the basis of imperfect and incomplete expert knowledge. More papers emphasizing the application of control techniques were written by Kupongsak and Tan (2006) who applied fuzzy set and neural network techniques to determine food process control set points for producing products of certain desirable sensory quality. The results demonstrated a great potential of the fuzzy set concept and neural network techniques in sensory quality-based food process control. Soares *et al.* (2010) applied high performance nonlinear fuzzy controllers for a soft real-time operation of a drying machine. All the criteria evaluation used for controller performance analysis for several steps tracking tasks showed much better performance of the fuzzy logic controller. The absolute errors were lower than 8.85% for the fuzzy logic controller and about three times lower than the experimental results. Omid (2011) designed an expert system for sorting pistachio nuts through decision tree and fuzzy logic classifier. The correct classification rate and root mean square error (RMSE) for the training set were 99.52% and 0.07 and for the test set were 95.56% and 0.21, respectively. These encouraging results, as well as the robustness of the fuzzy interface system (FIS) based expert system, makes the approach ideal for automated inspection systems. A prototype-automated system for visual inspection of muffins was developed by Zaid *et al.* (2000). The automated system was able to correctly classify 96% of regarded and 79% of ungraded muffins. The algorithm procedure classified muffins to an accuracy of greater than 88% compared to 20-30% variations in quality decisions amongst inspectors. Podržaj and Jenko (2010) found that temperature control based on fuzzy logic is suitable for processes in

which a high degree of precision is required. Research conducted by Venayagamoorthy *et al.* (2003) showed that the fuzzy logic controller augmenting the conventional proportional (P) and proportional integral (PI) controller more efficiently controls the industrial food processing plant with respect to set point tracking and disturbance rejection. Tuning a predictive fuzzy logic controller for resin manufacturing the predictive fuzzy logic controller (FLC) scheme was found to be highly useful and satisfactory in controlling an exothermic process (Nagarajan *et al.*, 1998). Perrot *et al.* (2006) and Welte *et al.* (2002) stated that managing the properties of food starting from the input stage with the aim of controlling them is not an easy task for following reasons: 1) there are many parameters in food industry that must be taken into consideration in parallel. A single sensory property like color or texture can be linked individually to several dimensions recorded by the human brain; 2) the food industry works with non-uniform variable raw materials that when processed should be shaped into a product that satisfies a fixed standard; 3) the control processes of foods are highly non-linear and variables are coupled; 4) little data is available in traditional manufacturing plants that produce, for example, sausage or cheese and this situation is applied to most food processing industries; 5) in addition to the temperature changes during a heating or cooling process, there are biochemical (nutrient, color, flavor, etc.) or microbial changes that should be considered; 6) the moisture in food is constantly fluctuating throughout the process which can affect the flavor, texture, nutrients concentration and other properties; 7) other properties of foods such as density, thermal and electrical conductivity, specific heat, viscosity, permeability, and effective moisture diffusivity are often a function of composition, temperature, and moisture content and therefore are in a state of flux during the process; 8) the system is also quite non-homogeneous and such detailed input data are not available; and 9) often irregular shapes are present.

In most process control problems, it is relatively easy to design a proportional integral derivative (PID) controller and to merge fuzzy rules into the system to produce many extra design alternatives. Despite the availability of publications on fuzzy control on food processing, there are few general guidelines for setting the parameters of a simple and practical fuzzy controller. Therefore, the proposed approach is based on a three step design procedure that builds on a PID control suggested by Jantzen (1998). The three steps of the design are: 1) starting with a PID controller, 2) insertion of an equivalent linear fuzzy controller, and 3) gradual conversion of the linear fuzzy controller to a nonlinear one.

### **Three steps design approach of a simple fuzzy logic control for food processing**

#### **1. Starting with a PID controller**

The term control in engineering refers to a discipline whose main interest is to solve problems of regulating and controlling the behaviour of a physical system. In food process, both an open and close-loop control configuration are applied. A bottle washing machine performing a predefined sequence of operations without any information "with no concern" regarding the results of its operation is an example of an open-loop control system. The bottle washing machine mentioned above as an open-loop system would operate in a close-loop mode if it were equipped with a measuring device capable of generating signal related to the degree of cleanness of the bottles being washed. For decades, food process engineers have adopted control strategies that have been introduced by control engineering. Control engineering is based on the foundation of feedback and feed-forward theory and linear system analysis. It is basically an interconnection of components forming a system configuration that will provide a desired system response (Dorf & Bishop, 2010). The feedback control acts when a deviation from the set point occurs.

Kreider and Rabl (1994) reported that the feedback control uses the difference of the controlled variable between the set point and the actual one to control the actuators of the process in the following four modes: 1) two position (on/off), 2) proportional, 3) integral, and 4) derivative. The distinct advantage of the feedback control system is the ability to adjust the transient response and steady-state performance. A schematic diagram of the feedback theory is depicted in Fig.1. The two position control applies to an actuator or a relay that is either fully opened or fully closed. When the controlled variable drops below the minimum decided limit, the actuator opens fully and remains open until the controlled variable reaches the maximum limit. The maximum and minimum limits are sometimes adjustable. The two position control is the least expensive method of automatic control and convenient for use in systems with large time constants (Kreider & Rabl, 1994).

The proportional, integral, and derivative modes are usually used in a variety of combinations with one another to achieve the right control process. The proportional control corrects the controlled variable in proportion to the difference between the controlled (sensed) variable and the set point of the variable. The error is calculated as follows:

$$e = T_{set} - T_{sensed} \quad (1)$$

Where:  $e$  = error  
 $T_{set}$  = controlled (sensed) variable  
 $T_{sensed}$  = set point of the variable

Integral control is often added to proportional control to eliminate the error inherited in proportional-only control. The integral component has the effect of continuing to increase or decrease the output as long as any offset continues to exist (Smith and Corripio, 1997; Kreider and Rabl, 1994). Derivative control is often called the rate action, or pre-act and is used to anticipate where the direction of the process by tracking the time rate of change of the error and its derivative. In other words, it gives the controller the capability to "look

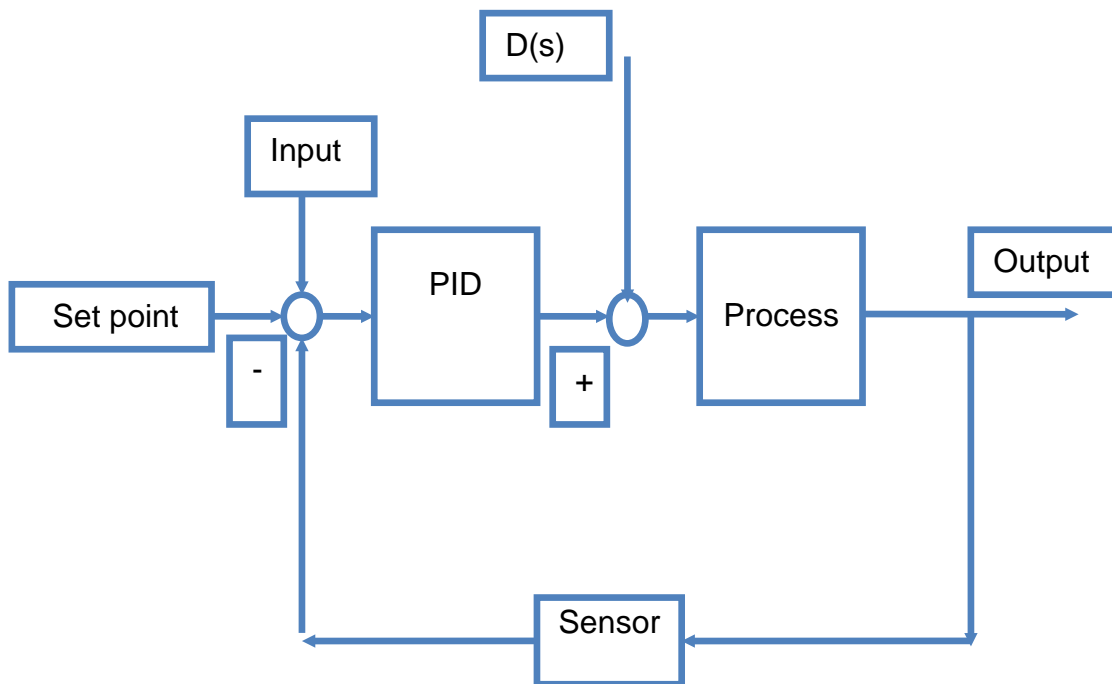


Fig.1. A schematic drawing of PID control system

ahead" by calculating the derivative of the error (Smith and Corripio, 1997). The use of advanced instrumentation and sensors in the food industry has led to continuing improvement in food quality control, safety and process optimization. Some of the basic measurement devices used in process control of foods are; pressure, temperature, level and flow sensors. Other measurement devices are used such as color vision, speed of sound, viscometers texture sensors, chemo-sensors, biosensors, immune-sensors, electronic noses and tongues, sensors for food flavor and freshness: electric noses, tongues and testers in situ freshness monitor of frying oil (resonant viscosity probe) , knife-type meat freshness tester (glucose profiling biosensor). Fig.2. shows an overall diagram of food process control systems that illustrates some of the possible variables, parameters, actuators and sensors. (Kress-Rogers and Brimelow, 2002). In most food process control applications, standard "off-the-shelf" devices are used to obtain the desired system

performance. These devices are commonly called industrial controllers. The manner in which the controller produces the control signal in response to the controller error is referred to as a control algorithm or control law. The most common control algorithms implemented in industrial controllers are the two position or on/off control, the proportional integral derivative control (PID), and the fuzzy logic control. PID controllers are affordable, robust, fairly easy to use, tune and maintain, and are generally commercially available.

Fuzzy logic deals with uncertainty. This technique which uses the mathematical theory of fuzzy sets simulates the process of normal human reasoning by allowing computer to behave less precisely and logically than conventional computers do. Some of the drawback, however, of the on/off switching system used in food process engineering are that they are incapable to maintain a set point temperatures accurately due to the non-linearity of this system, and it is difficult to design a controller to maintain a

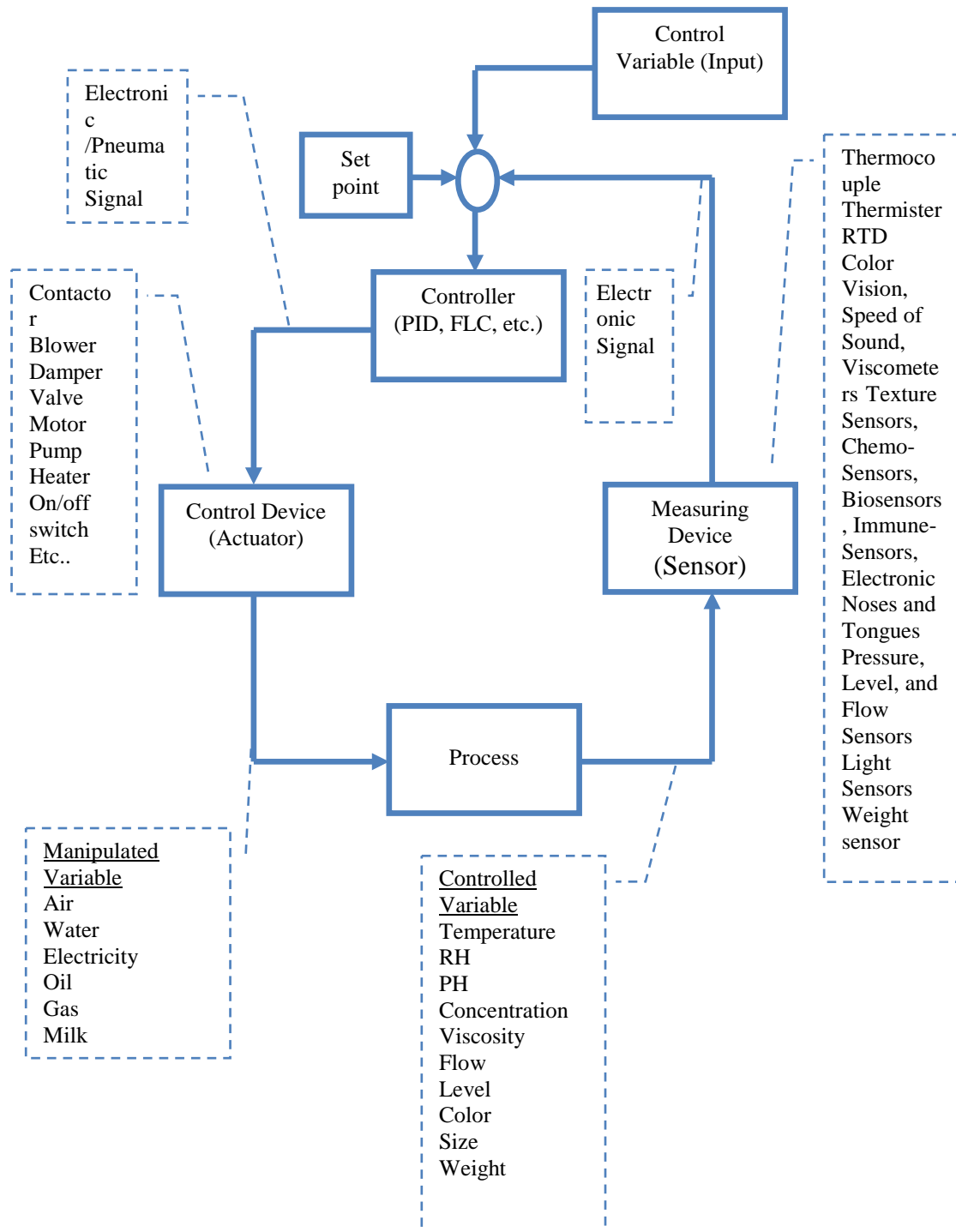


Fig.2. An overall diagram of food process control systems that illustrates some of the possible variables, parameters, actuators and sensors.

fixed process variable; whereas the weakness of the proportional integral derivative (PID) controller is its inability to implement human thinking. Most food related processes are multivariable, time-varying and non-linear. Non-linear processes are difficult to predict with conventional control systems designed for linear processes, but cases involving several process variables have been generally dealt with by multi-loop controllers running several independent PID-loops concurrently (Linko and Linko, 1998). However, the advantages of the fuzzy logic control systems are in its simplicity to use and maintain and its affordability. Fuzzy logic can be used for controlling a process that is too nonlinear or not understood to use in conventional control design. Also, fuzzy logic enables control engineers to easily implement control strategies used by human operators. Other advanced control systems are the hybrid systems that encompass decision trees, neural networks (NN), evolutionary algorithms, and expert systems (Omid, 2011). On the other hand, fuzzy logic is simple to use if incorporated with analog-to-digital (D/A) converters and micro controllers. This can easily be upgraded by changing rules to improve performance or add new features to the system. In many cases, fuzzy control can be used to improve existing controller systems by adding an extra layer of intelligence to the current control method. Although fuzzy logic control systems are still new to food process engineering, applications of fuzzy systems are very broad. Those applications include: pattern recognition and classification, modeling of classification control systems fault diagnosis operation research, and decision support systems (Omid, 2011). Therefore, more precise systems are needed for the many applications in the field. Furthermore, fuzzy logic systems could be used as an alternative controller for most of the food process plants. With the rapidly growing number of computer applications in food engineering, there is a need to test and evaluate more advance controllers to reach the best and most affordable food process control systems. Fuzzy logic is basically a multi-valued logic

that allows transitional values to be between the normal two valued evaluations like Yes/No, True/False, and Black/White. Instead, phrases like "very light" or "pretty heavy" can be formulated mathematically and dealt with by computers. Fuzzy controllers have three transitional steps: an input step, a processing step, and an output step. The input step, which is fuzzy matching, maps sensor output, or the error or other inputs, to the proper membership functions by calculating the degree of membership. The processing step triggers each appropriate rule and produces a result for each then joins the results of the rules together, and, finally, a crisp control value of the result is obtained through the output step (Bauer *et al.* 1998; Yen and Langari, 1999). The control system block from Figure1 is detailed further to include the fuzzy logic control system as shown in Fig.3.

## 2. Insertion of an Equivalent Linear Fuzzy Controller

The fuzzy controller is composed of three elements; 1) a fuzzification interface, which converts controller inputs into information that the inference mechanism can easily use to activate and apply rules. Shapes of membership functions are the triangular, trapezoidal, and bell, but shapes are generally less important than the number of curves and placement. An input triangular fuzzification membership function for error input with 50% overlap is illustrated in Fig. 4. Bauer *et al.* (1998) and Yen and Langari (1999) stated that from 3 to 7 curves are generally enough to cover the intended range of an input value (the "universe of discourse"), 2) a rule-base (a set of If-Then rules), which contains a fuzzy logic quantification of the expert's linguistic description of how to achieve good control. In other words, the rule base is derived from an "inference engine" or "fuzzy inference" module, which emulates the expert's decision making in interpreting and applying knowledge about how best to control the plant. The processing stage is basically a group of logic rules in the form of IF-THEN statements, where IF is called the "antecedent" and THEN is called the "consequent" (Yen and Langari, 1999). For

example the rule of a thermostat works as follows:

IF the temperature is "cold" THEN turn the heater to "high"

This rule basically implements the truth-value of the temperature input, which is "cold" to create a result in the fuzzy set to switch the heater to high. The results of all the rules are joined together using one of the defuzzification methods to finally come up with the crisp composite output. Sometimes membership functions are formulated by "hedges". Examples of hedges include "more", "less", "about", "close to", "approximately", "very", "slightly", "too", "extremely", and "somewhat". These phrases may have precise definitions and mathematical representation. For example, "very" squares membership functions, and, since the membership magnitudes are always below 1, this reduces the membership function (Bauer *et al.* 1998; Yen and Langari, 1999).

Very:

$$\mu_{\text{very}A}(x) = [\mu_A(x)]^2 \quad (2)$$

"Extremely" cubes the values to give more reduction:

$$\mu_{\text{extremely}A}(x) = [\mu_A(x)]^3 \quad (3)$$

and "somewhat" broadens the function by taking the square root;

$$\mu_{\text{somewhat}A}(x) = \sqrt{\mu_A(x)} \quad (4)$$

Membership functions can be joined together using a number of logical operators. For example, **AND** uses the minimum value of all the antecedents; however, the **OR** and **NOT** use the maximum value and the complementary value, respectively. There are other different operators used to define the result of a rule, but, the most commonly used method to calculate the output is the "max-min" inference method (Yen and Langari, 1999; Bauer *et al.* 1998). Those rules can be implemented using hardware or software. Jantzen (1998) suggested some sources of control rules:

- Expert experience and control engineering knowledge: the most common approach to establishing such a collection of rules of thumb is to question experts or operators using a carefully organized questionnaire.

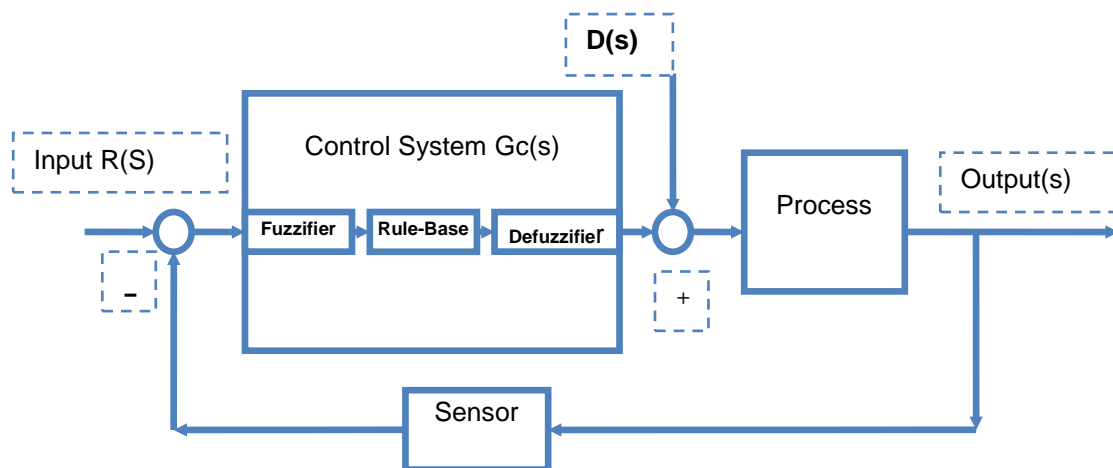


Fig.3. A schematic drawing of feedback control system with fuzzy logic controller

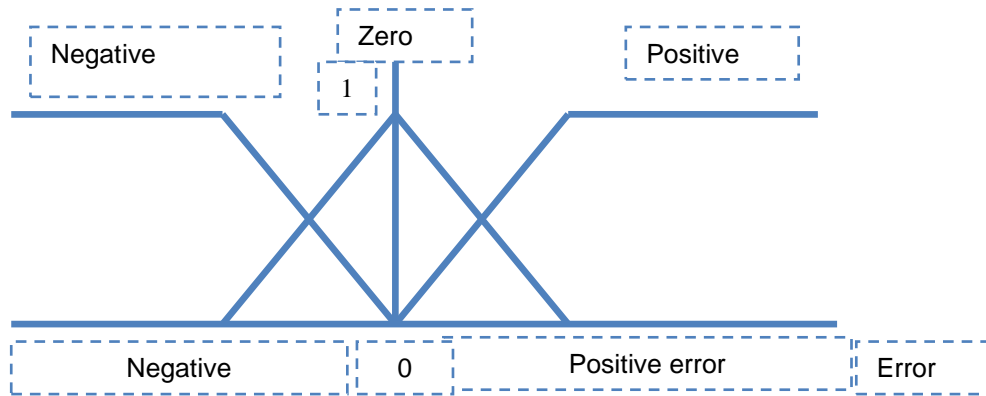


Fig.4. An input triangular fuzzification membership function for error

- *Based on the operator and control action:* fuzzy-if-then rules can be deduced from observations of an operator's control actions or a log book. The rules express input-output relationships.
- *Based on a fuzzy model of the process:* a linguistic rule base may be viewed as an inverse model of the controlled process. Thus the fuzzy control rules might be obtained by inverting a fuzzy model of the process. This method is restricted to relatively low order systems, but it provides an explicit solution assuming that fuzzy models of the open and closed-loop systems are available. Another approach is a fuzzy Identification or fuzzy model-based control.
- *Based on learning:* the self-organizing controller is an example of a controller that finds the rules itself and neural networks is another possibility.

A defuzzification interface converts the conclusions reached by the inference mechanism to the inputs to the plant. In other words, results of the fuzzy rules are defuzzified using one of the defuzzification techniques to give a final crisp value to be sent as the control parameter. An output triangular defuzzification membership function for error input with 50% overlap is illustrated in Fig.5.

Among the defuzzification techniques are (Bauer *et al.* 1998; Yen and Langari, 1999):

**1. Mean of Maximum (MOM) defuzzification:**

Suppose "y is A" is a fuzzy conclusion to be defuzzified, MOM defuzzification

method can be expressed using the following formula

$$MOM(A) = \frac{\sum_{y^* \in P} y^*}{|P|} \quad (5)$$

$$P = \{ Y^* \mid \mu_A(Y^*) = \sup_y \mu_A(Y) \} \dots (6)$$

Where:

P = the set of output values with the highest possibility degree in A.

SUP= an operator that returns the maximum value of a continuous function.

**2. Center of Area (COA) or Centroid:**

The centroid defuzzification method calculates the weighted average of a fuzzy set. The result of applying COA defuzzification to a fuzzy conclusion "y is A" can be expressed using the following formula:

$$COA(A) = \frac{\sum_x \mu_A(x) \times x}{\sum_x \mu_A(x)} \dots \dots \dots (7)$$

$\mu_A(x)$  = Weight for value x.

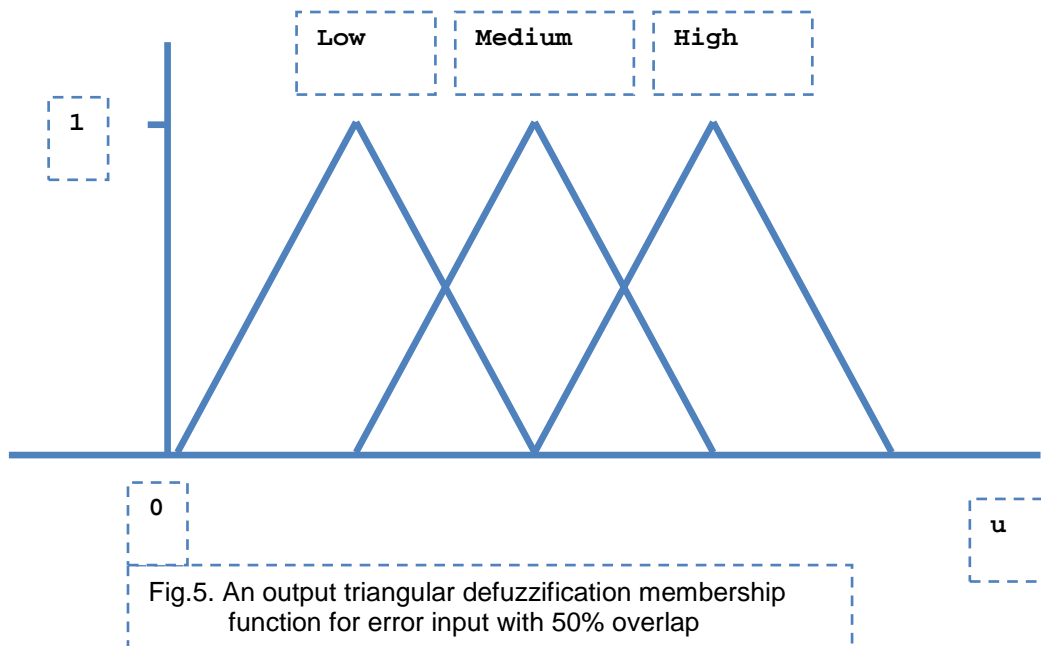
**3. Center of gravity method for singleton (COGS)**

$$Y = \frac{\sum_{k=1}^m C_k w_k}{\sum_{k=1}^m w_k} \dots \dots \dots (8)$$

$C_k$  = The center of gravity

$w_k$  = The degree of match with the input data





### Optimization in food process control

In recent years, many efforts have been directed to the optimization and efficient control of food processing. Most bioprocesses have highly nonlinear dynamics and constraints are frequently present on both the state and the control variables. Thus, efficient and robust dynamic optimization methods are needed in order to successfully obtain their optimal operating policies (Balsa *et al.*, 1998). Optimization can be defined as the process of finding the conditions that give the optimum (maximum or minimum) value of a function of certain decision variables subject to restrictions or constraints that are imposed (Edgar and Himmelblau, 1989).

Optimization may be the process of maximizing a desired quantity or minimizing an undesired one. The conditions (values of the processing variables) that produce the desired optimum value are called optimum conditions, while the best of all feasible designs is called "optimal design". In its most general meaning, optimization is the effort and process of making a decision, a design, or a system as perfect, effective, or functional as possible. Optimization for a system may mean the design of system

parameters or the modification of its structure to minimize the total cost of the system's products under boundary conditions associated with available materials, financial resources, protection of the environment, and governmental regulation, taking into account the safety, operability, reliability, availability, and maintainability of the system. Optimizers or decision makers use optimization in the design of systems and processes, in the production, and in systems operation. Some examples of the optimization use are selection of processes or size of equipment, equipment items and their arrangement, operation conditions (temperature, pressure, flow rate, and chemical composition of each stream in the system), and equipment combination in specific processes to increase the overall system availability (Tzia and Liadakis, 2003).

### Performance Indices:

In order to determine the control parameters, whether PID or fuzzy logic parameters, a method of optimization should be applied to shorten time and get the best output (Edwards and Choi, 1997). Some simple tuning methods have been used for

this optimization, such as, Ziegler-Nichols method which uses small amount of information about the process to tune the system (Chipperfield and Fleming, 1993). Several general performance indices exist in the literature that use the error as an indicator of the system deviation. The system is considered to have achieved the optimum output when these indices reach the minimum value (Dorf and Bishop, 2010).

**General indices:  
Integral of square of error (ISE):**

$$ISE = \int_0^t e^2(\tau) d\tau \dots \dots \dots (9)$$

t = Settling time, or could be an arbitrary steady state time

Another performance index is the integral of absolute error (IAE):

$$IAE = \int_0^t |e| d\tau \dots \dots \dots (10)$$

This criterion is suitable for computer simulation.

Other general performance indices are also used for optimization such as ITAE and ITSE (Dorf and Bishop, 2010). During pistachio classification, Omid (2011) compared the root mean square error (RMSE), the mean absolute error (MAE), the relative absolute error (RAE), and the correct classification rate (CCR) as performance indices. Balsa *et al.* (1998) evaluated and compared the solution of the dynamic optimization of three Bioprocesses, including a hybrid stochastic deterministic method, where they found a significant advantage over other approaches.

**2.3 Gradual conversion of the linear fuzzy controller to nonlinear one**

Linear processes have the important property of superposition whereas nonlinear models do not. Superposition means that

the response of the system to a sum of inputs is the same as the sum of responses to the individual inputs. These properties do not hold for nonlinear models. In this respect, it is important to recognize the fact that most food process systems are nonlinear.

There are three sources of nonlinearity in a fuzzy controller.

- I. The Rule Base: The position, shape, and number of fuzzy sets, as well as nonlinear input scaling, cause nonlinear transformations. The rules often express a nonlinear control strategy.
- II. The inference engine: If the connectives AND and OR are implemented, as for example MIN and MAX respectively, they are nonlinear.
- III. The defuzzification: Several defuzzification methods are nonlinear.

With these design choices, the control surface degenerates to a diagonal plane and a flexible fuzzy controller that allows the two controllers to be combined into one entity. When it is linear, it possesses the transfer function and the usual methods regarding tuning and stability of the closed-loop system will apply.

It is possible to construct a rule base with linear input-output mapping. (Siler & Ying, 1989; Mizumoto, 1992; Qiao & Mizumoto; 1996). The following checklist summarizes the general design choices for achieving a fuzzy rule base:

- Use triangular input sets that cross at  $\mu=0.5$ .
- Use the algebraic product (\*) for the end connective.
- The rule base must be the complete and combination of all input families.
- Use output singletons; positions determined by the sum of the peak positions of the input sets.
- Use the (COGS) defuzzification.

**REFERENCES**

- Acosta-Lazo, G.G., C.J. Alonso-Gonzales and B. Pulido-Junquera (2001). Knowledge based diagnosis of a sugar process with teknolid. *International Sugar Journal*:103:44–51.
- Alvarez, E., M.A. Cancela, J.M. Correa, J.M. Navaza and C. Riverol (1999). Fuzzy logic control for the isomerized hop pellets production. *Journal Food Engineering*: 39:145–150.
- Balsa-Canto, E., A. A. Alonso and J. R. Banga (1998). Dynamic optimization of bioprocesses: deterministic and stochastic strategies. *ACoFoP IV (Automatic Control of Food & Biological Processes)*, Göteborg, Sweden, 21-23 September 1998.
- Bauer, P., S. Nouak and R Winkler (1998). Introduction to the Fuzzy Logic Course. An internet source document. <http://www.fill.uniLinz.ac.at/pdw/fuzzy/introduction.html>
- Caro, R. H. and W. E. Morgan (1991). Trends in process control and instrumentation, *Food Technology*, 45(7) 62-66.
- Chipperfield, A.J. and P. J. Fleming (1993). MATLAB toolbox and applications for control. Peter Peregrinus Ltd. Six Hills Way, Stevenage, Herts. SG1 2AY, UK.
- Curt, C., J. Hossenlopp, N. Perrot and G. Trystram (2002). Dry sausage ripening control and integration of sensory related properties, *Food Control*,13:151–159.
- Davidson, V.J., R.B. Brown and J.J. Landman (1999). Fuzzy control system for peanut roasting. *Journal of Food Engineering*,41:141–146.
- Dorf, R. C. and R. H. Bishop (2010). *Modern control systems*. eighth edition. Addison Wesley Longman. Inc.,CA, USA.
- Edgar, T.F. and D.M. Himmelblau (1989). *Optimization of vemical pocesses*. Singapore. Mc- Graw-Hill Book Co., Chapters 1–9, p. 3–438.
- Edwards, D. and H. T. Choi (1997). Use of Fuzzy logic to calculate the statistical properties of strange attractors in chaotic systems. *Fuzzy Sets and Systems*,88:205-217.
- Guillaume, S. and B. Charnomordic (2001). Knowledge discovery for control purposes in food industry databases. *Fuzzy Sets and Systems*,122:487–497.
- Honda, H., T. Hanai, A. Katayama and T.H.T. Kobayashi (1998). Temperature control of Ginjo sake mashing process by automatic fuzzy modeling using fuzzy neural networks, *Journal of Fermentation Bioengineering*,85:107–112.
- Jantzen, J. (1998). Design of fuzzy controllers. Technical University of Denmark, Department of Automation, Tech. report No. 98-E 864 (design), 19 Aug 1998.
- Kreider, J. and A. Rabl (1994). Heating and cooling buildings. McGraw-Hill, Inc. Princeton, USA.
- Kress-Rogers, E. and C.J.B. Brimelow (2002). *Instrumentation and Sensors for the Food Industry (2nd Edition)*. Woodhead Publishing, Cambridge, England .
- Kupongsak, S. and J. Tan (2006). Application of fuzzy set and neural network techniques in determining food process control set points. *Fuzzy Sets and Systems*,157:1169 – 1178.
- Linko, S. and P. Linko (1998). Developments in monitoring and control of food processes. *Transactions of Chemical Engineering*, Vol 76, Part C.
- Linko, P., K. Uemura, Y. Zhu and T. Eerikainen (1992). Application of neural modeling in fuzzy extrusion control, *Transactions of Chemical Engineering*,70:131–137.
- Mittal, G. S. (1997). *Computerized control systems in the food industry*. Marcel Dekker, Inc., NY, USA.
- Mizumoto, M. (1992). Realization of PID controls by fuzzy control methods, *The Institute of Electrical and Electronics Engineers, Inc, San Diego*, pp. 709–715.
- Nagarajan, R., R. N. Kumar, R. A. Halim and A. Rosli (1998). A predictive fuzzy logic controller for resin manufacturing computers, *Industrial Engineering*, 34(2):493-500.
- Norback, J.P. (1994). Natural language computer control of crucial steps in cheese making, *Artificial Neural Networks. Dairy Industry*, 49(2):119–122.

- O'Connor, B., C. Riverol, P.Kelleher, N. Plant, R. Bevan, E. Hinchy and J. D'Arcy (2002). Integration of fuzzy logic based control procedures in brewing. *Food Control*, 13:23–31.
- Omid, M. (2011). Design of an expert system for sorting pistachio nuts through decision tree and fuzzy logic classifier. *Expert Systems with Applications*, 38:4339–4347.
- Qiao, W. and M. Mizumoto (1996). PID type fuzzy controller and parameters adaptive method. *Journal of Food Engineering*, 17:23–35.
- Perrot, N., L. Agioux, I. Ioannou, G. Mauris, G. Corrieu and G. Trystram (2004). Decision support system design using the operator skill to control cheese ripening—Application of the fuzzy symbolic approach. *Journal of Food Engineering*, 64:321–333.
- Perrot, N., I. Ioannou, I. Allais, C. Curtc, J. Hossenloppc and G. Trystramc (2006). Fuzzy concepts applied to food product quality control: A review. *Fuzzy Sets and Systems*, 157:1145 – 1154.
- Perrot, N., G. Trystram, F. Guely, F. Chevie, N. Schoesettters and E. Dugre (2000). Feed-back quality control in the baking industry using fuzzy sets. *Journal of Food Process Engineering*, 23:249–279.
- Petermeier, H., R. Benning, A. Delgado, U. Kulozik, J. Hinrichs and T. Becker (2002). Hybrid model of the fouling process in tubular heat exchangers for the dairy industry. *Journal of Food Engineering*, 55:9–17.
- Podrzaj, P. and M. Jenko (2010). A fuzzy logic-controlled thermal process for simultaneous pasteurization and cooking of soft-boiled eggs. *Chemo-metrics and Intelligent Laboratory Systems*, 102:1–7.
- Soares, M. P., Nicola C. B., Augusto J. F. and Neto. F. (2010). Nonlinear fuzzy tracking real-time-based control of drying parameters. *World Academy of Science, Engineering and Technology*, 71:187-201.
- Siler, W. and H. Ying (1989). Fuzzy control theory: The linear case. *Journal of Food Engineering*, 17:275–290.
- Smith, C. and A. Corripio. (1997). Principles and practice of automatic process control. Second Edition, John Wiley & Sons Inc., NY, USA.
- Tzia, C. and G. Liadakis (2003). Extraction Optimization in Food Engineering Marcel Dekker, Inc., 270 Madison Avenue, New York, NY 10016, U.S.A.
- Venayagamoorthy, G. K., D. Naidoo and P. Govender (2003). An industrial food processing plant automation using a hybrid of PI and fuzzy logic control. The IEEE International Conference on Fuzzy System, 1059-1062.
- Voos, H., L. Litz and H. Konig (1998). Fuzzy control of a drying process in sugar industry, 6th European Congress Intell. Tech. Soft Comput. EUFIT, vol. 3:1476–1480.
- Welti, J., G. Barbosa-Cánovas and J. A. Miguel (2002). Engineering and food for the 21st Century. CRC Press LLC. 200 N.W. Corporate Blvd., Boca, Raton, Florida, 33431.
- Yen, J. and R. Langari (1999). Fuzzy logic-intelligence, control, and information. Prentice-Hall Inc., NJ, USA.
- Zaid Abdullah, M., S. Abdul Aziz and AM. Dos-Mohamed (2000). Quality inspection of bakery products using a color-based machine vision system. *Journal of Food Quality*, 23 (1):39-50.
- Zhang, Q. and J. Litchfield (1993). Fuzzy logic control for a continuous cross flow grain dryer, *Journal of Food Process Engineering*, 16:59–77.

## تصميم مبسط للتحكم بواسطة المنطق الغامض في التصنيع الغذائي

عبد الرحمن عثمان الغنام

هندسة النظم الزراعية، كلية العلوم الزراعية و الأغبذفة، جامعة الملك ففصل

ص.ب. ٤٢٠ الإحساء ٣١٩٨٢، المملكة العربية السعودية

البرفد الإلكفرونف: aalghannam@kfu.edu.sa

---

### الملخص العربي

فف هذا البفحث تم تقديم تصميم مبسط للتحكم بواسطة المنطق الغامض للتصنيع الغذائي بالإضافة إلى أساسفات التحكم بالمنطق الغامض ونظراً لبساطة وقدره نظام التحكم بالمنطق الغامض (FLC) للأداء والتحكم فف الخواص المعقدة لعملفات التصنيع الغذائي تم عمل ثلاث خطوات للتصميم وهف كالتالف:

١. البدء بنظام التحكم النسبف التكاملف التفاضلف (PID).
٢. إدراج نظام التحكم (FLC) الخطف المكافئ.
٣. تحويل تدرجف لنظام (FLC) الخطف إلى نظام غير خطف للوصول إلى تصميم نظام بسطف للمنطق الغامض (FLC) والذف فحتوف على معظم أجهزة القياس والحاسبات الممكنة فف هندسة التصنيع الغذائي.