FUZZY LOGIC FOR SEMICONDUCTOR MANUFACTURING

The past decade has witnessed rapid growth of the semiconductor industry. Semiconductor manufacturing technology is one of the most crucial enabling technologies that contribute to this astonishing advancement and growth. Semiconductor manufacturing technology is a very diversified engineering discipline. Its formal definition may be derived directly from the coverage of the IEEE annual conference on electronics manufacturing technology, organized by the IEEE Component, Packaging, and Manufacturing Society. The scope of the technology includes understanding, characterization, design, development, and delivery of enabling techniques for process or equipment control to improve and enhance the manufacturing practice and manufacturing process planning. It is a challenging task to address fuzzy logic applications in this diversified field. However, it is possible to examine the fundamental and common needs in semiconductor manufacturing to address the requirements of managing uncertainty, coping with unexpected random disturbances, and achieving better, faster, more reliable, and cost-effective performance.

The development of semiconductor manufacturing technology has been one of the most dynamic fields. The constant growth of the semiconductor industry is characterized by Moore's law, which states that the performance of semiconductor devices and computer systems doubles every 18 months, and reflects the progress in manufacturing. However, many processes and equipment control are yet to be fully understood because most of these systems are highly nonlinear and often time-variant and also because of the uncertainty involved in the operations. It is difficult to characterize the mathematical nature of the equipment or processes and to design a controller to achieve desired performance objectives. The challenges are magnified when random disturbances exist and uncertainties are involved in measuring and determining system parameters.

Starting in the early 1990s, we have seen increasing effort in developing an alternative approach to address these challenges in semiconductor manufacturing. Intelligent control based on artificial neural networks and fuzzy logic, in addition to the traditional PID (proportional–integral–derivative) and SPC (statistical process control) techniques, have opened new avenues for coping with these difficult, ill-defined problems. Successful applications of using fuzzy logic in semiconductor manufacturing have demonstrated the applicability and versatility of this technique. The purpose of this article is to discuss the basic mathematical principles of fuzzy logic and its applications in the semiconductor industry.

The article is organized as follows: in the first section, we briefly state the objective of the article. Then we discuss the theoretical foundation of fuzzy logic and the mathematical treatment of membership functions. The discussion includes operations on fuzzy sets, the fuzzy inference engine, fuzzy reasoning, the design process, and a design example for solving the Astrom problem, a nonlinear real-time control problem involving uncertainty management. In the next section, we survey some of the latest developments in fuzzy logic applications in the semiconductor manufacturing industry. We discuss the technique of combining fuzzy logic and artificial neural networks for machining process selection (MPS) and describe briefly the technique of fuzzy statistical process control (SPC) design and one of its applications in device control. To address the needs of highly nonlinear process control, we include one example in the area of on-line pH neutralization with some common applications in etching, acid treating, and wastewater neutralization. We conclude this article with a discussion of future directions in this field.

THE THEORETICAL FOUNDATION

Fuzzy logic was introduced by Zadeh in 1965 (1). This technique is a tool for dealing with uncertainty, for exploiting the tolerance for imprecision, and for dealing with mathematically ill-defined problems. In the real world, there are many problems which can not be uniquely defined.

Membership Functions

A fuzzy set A of an universe of discourse U can be denoted as follows:

$$A = \int_U U_{\mathrm{A}}(x)/x$$

It consists of two critical components:

1. A membership function U_{A}: $U \rightarrow [0,1]$, which associates a membership in the interval [0,1], with each element x of U.
2. The support of the fuzzy set which is the set of elements x.

The value of the membership function represents the grade of x in A. Fuzzy membership function can be constructed on the basis of the heuristics of human expert knowledge. This allows fuzzy logic to capture human expertise acquired through engineering practice and to deal with real-world problems too complex to be described in a close-form mathematical equation or to lacking precise knowledge of the parameters to construct a mathematical description. In particular,

1. Fuzzy membership function $u(\mathrm{x})$ describes the belongingness of a fuzzy variable x.
2. Many functions can be derived on the basis of heuristics, and they take the form of simple triangular functions or piecewise linear functions.

Operations of Fuzzy Sets

Now we describe some commonly used fuzzy set operations. Among them the most commonly used are "AND" and "OR" operations. Given that both A and B are fuzzy sets, then

1. For "AND" operation,

$$A \cap B = \int_u \min\{u_{\mathrm{A}}(x), u_{\mathrm{B}}(x)\}/x$$

2. For "OR" operation,

$$A \cup B = \int_u \max\{u_{\mathrm{A}}(x), u_{\mathrm{B}}(x)\}/x$$

Note that the previous integral sign is adopted in fuzzy set theory, but the actual calculation is just simple *min* or *max* operation of the given collection of membership functions $u_{\mathrm{A}}(x)$ and $u_{\mathrm{B}}(x)$.

Fuzzy Inference Engine

The fuzzy inference engine plays an important role in approximate reasoning. The engine can be briefly described as follows,

1. The inference engine consists of a set of IF-THEN rules which perform so-called "fuzzy reasoning."
2. The design and creation of the fuzzy inference rules are based on knowledge from either a human expert or from other empirical sources, such as the neural network approach.

A simple example of such rules is given as follows:

Rule 1: If x_1 is A_{11} and x_2 is A_{12}, then y is B_1.
Rule 2: If x_1 is A_{21} and x_2 is A_{22}, then y is B_2.

Based on this example, we can construct more complex inference rules by connecting multiples of "AND" or "OR."

Evaluating Fuzzy Reasoning Results

Now let us consider the evaluation of fuzzy reasoning. Without loss of generality, for simplicity we will continue using the previous simple example involving only two elements, x_1 and x_2 of a given fuzzy set.

Suppose that the true values of the premises are

$$w_1 = \min\{u_{\mathrm{A}_{11}}(x_1), u_{\mathrm{A}_{12}}(x_2)\}$$

and

$$w_2 = \min\{u_{\mathrm{A}_{21}}(x_1), u_{\mathrm{A}_{22}}(x_2)\}$$

Then the actual result of this fuzzy reasoning is given by the following defuzzification formula. Note that there are many different defuzzification techniques. A good discussion of this subject can be found in Mizumoto's paper in Li and Gupta's edited book (2). A graphical representation of this process is given in Fig. 1.

$$y = \frac{\sum_{k=1}^{2} w_k y_k}{\sum_{k=1}^{2} w_k}$$

A Five-Step Design Process

Having gone through some basic concepts in fuzzy set theory, now, based on my experience, I would like to summarize the major steps in fuzzy logic design.

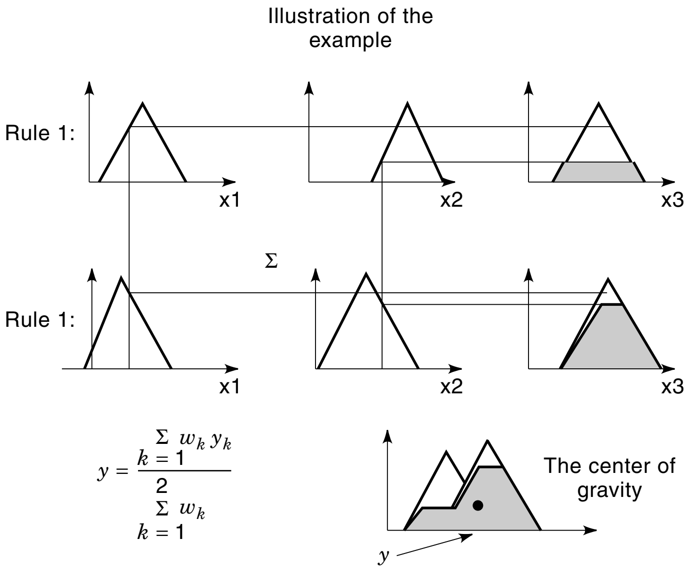

Figure 1. Graphical illustration of the fuzzy inference and defuzzification example.

1. Formulate the problem and select input variables and the output function or functions which are affected by input variables. Then perform quantization to divide the range of each variable into pieces to match heuristics, such as positive large (PL), positive median (PM), negative small (NS).
2. Design fuzzy membership functions to describe each quantization interval of the given variables.
3. Derive fuzzy inference rules in the IF–THEN form based on the defined variables and the quantization levels.
4. Select an aggregation method as a part of the fuzzy reasoning process. Among others, the min–max model is the most commonly employed.
5. Compute the inference result based on the defuzzification method, such as the center-of-gravity technique.

Design Examples: Solving the Astrom Problem

Many good applications can be found these days in the *IEEE Transactions on Fuzzy Systems,* the *IEEE International Conference on Fuzzy Systems,* the *IEEE International Conference on Neural Networks,* or the *Journal of Fuzzy Systems.* Mentioned in this section is an example of using fuzzy logic to solve the Astrom problem in real time. This work was given an Industrial Neural Networks Award at the 1994 World Congress Neural Network Conference in San Diego, California. The detailed design is given in Li and Gupta's book (2).

A so-called Astrom problem is a problem of real-time nonlinear system control by a modern control technique. In his book Astrom conceptualized the control problem of balancing a beam-and-ball system in real time (3). The control objective is to move the ball to the center of the beam and let it stay there with as little overshot as possible and as quickly as possible. This work is more challenging when no explicit parameters, such as mass, torque, and friction distribution are given. In our fuzzy logic controller design, we built two control systems:

1. The first is based on human control through joystick interface to drive the dc motor so as to tilt the beam and move the ball to the center of the beam. This human control system is used as a reference to allow future comparison with the fuzzy logic controller.
2. The second system is a fuzzy logic controller without human intervention. We went through the five-step design procedure, designed, and implemented the controller. The algorithm was written in C and assembly language, and the hardware was realized by using FPGA. The prototype system was tested and shipped to the *1994 World Congress Neural Network Conference* for a three-and-a-half-day demo. The result demonstrated that the fuzzy logic controller outperforms most human operators.

A videotape of the fuzzy controller can be obtained from the author of this article. Figure 2 is a photograph of the prototype system which was given the industrial award. Note

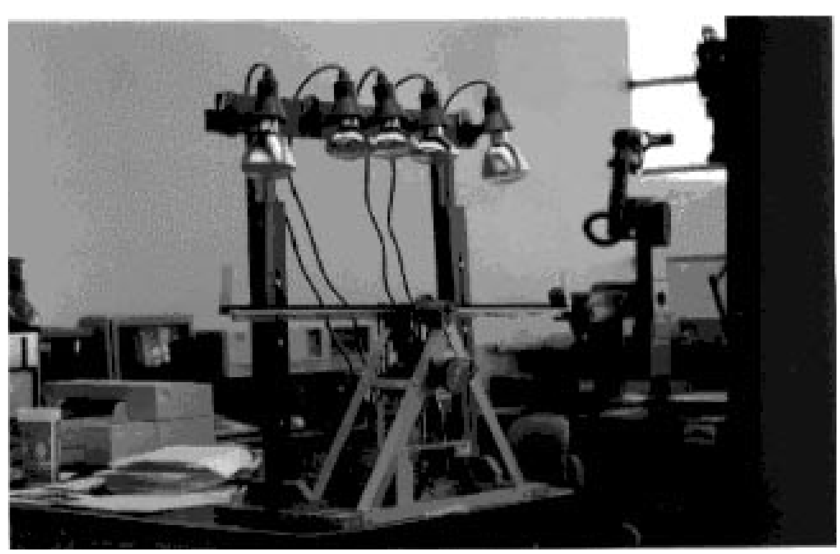

Figure 2. The prototype system of a real-time fuzzy logic controller for solving the Astrom problem (4).

that this system employs only modest computational power, an 80286 computer. In our design implementation, we also had to add delay functions in the control loop to accommodate the speed of the ball's motion and actual computer computation of the control action. This modest computational power requirement contrasts with the modern control approach.

APPLICATION EXAMPLES IN THE SEMICONDUCTOR INDUSTRY

Having discussed the basic fundamental principles of fuzzy logic for uncertainty management, let us now look into some of its applications in semiconductor manufacturing.

The Current State

Since the first special section on fuzzy logic, neural networks, and their applications in semiconductor manufacturing by *IEEE Transactions on Component, Packaging, and Manufacturing Technology* in 1994, there has been an increasing number of applications.

One of these applications is in matching process selection (MPS) in the manufacturing environment, which is usually a crucial step in semiconductor manufacturing and constitutes a critical link between computer-aided design (CAD) and computer-aided manufacturing (5). Integrating neural networks and fuzzy logic provides a unique tool for improving the solution of ill-defined, nonlinear problems. It has been reported that by incorporating the artificial neural network's learning and adaptive capability with fuzzy logic's structured knowledge manipulation and reasoning, the training time of neural networks can be reduced and the predictive accuracy can be improved.

Recently there has been work reported combining statistical process control (SPC) and fuzzy PID control in semiconductor manufacturing and control applications (6). The work focused on solving the problem of excessive control actions becasue random noise causes undesirable system responses "under-and/or-over" the set point. The SPC technique was used as a supervisor to monitor the random disturbances and to identify the need for control actions against the random noise. The performance of either a neural fuzzy controller or fuzzy PID controller can be disrupted by random disturbances. The random signal superimposed either on the input signal or on the internal state of the system causes unnecessary control action. In other words, the controller responds to both random variations and system deviations. An SPC-based fuzzy logic controller filters out the random noise, hence eliminates or reduces noise-caused control action. Then a well-designed SPC fuzzy controller can determine the need for control action based on the process faults or shifts. To detect small process deviations, a weighted moving average is first defined with an adjustable weighting factor between the current sample versus the previous sample. Assuming that independent measurement is performed and the samples follow a normal distribution, then a pair of warning lines is defined at two sigma levels of the mean value of the sample signal, and a pair of action lines is defined at three sigma levels. The action rules and warning rules are developed accordingly. The control action is derived from the inferential result based on the rules.

Another example is in the area of on-line pH neutralization (7). pH control is important in semiconductor manufacturing. Some common applications including etching, acid treating, and wastewater neutralization. pH neutralization is notorious for its severe process nonlinearity, which is reflected in the titration curve and shows process gain changes of up to 10,000 to 1 over a very small region. A fuzzy logic controller has been designed for this application. The design process starts from the titration curve which is the steady-state relationship of a process response to manipulated action. A first principles model, often described by a set of differential equations, is almost impossible to achieve, especially when the system is highly nonlinear and time-varying. Hence, the titration curve becomes one of the effective tools for characterizing system behavior. However, the following problems associated with this model have to be solved:

1. The lack of proper treatment of the system's time constants, which arise from delays of fluid transport, sensors, and actuators.
2. The high nonlinearity of the process and its time-varying nature are yet to be fully described and readily dealt with.
3. Ramp type random disturbances from the unknown characteristics of an acid are yet to be taken care of.

To address these challenges, mathematical formulation is conducted and variables for fuzzy control are selected. Based on the formulation and the experimental data, fuzzy reasoning rules are constructed, and then the inference engine is generated. After many fine-tunings and experiments, the finalized controller works very well and it outperforms a conventional controller. Among many test results, one convincing case is control of the counterintuitive process. It demonstrates that the fuzzy controller is superior to a ratio or a simple feedforward controller.

Another example is a response surface map method for process optimization. This technique is based on fuzzy logic, and it was developed for application in the field of vertical chemical vapor deposition (CVD) (8). The algorithm starts with a fuzzy logic model based on the experimental data. The gradient search method is employed with a specified step size, and a confirming experiment is conducted at each step. The search continues until no further improvement in the objective function is observed in that gradient direction. The fuzzy logic model is trained with experimental data, and a new gradient is evaluated. This process is repeated until the working point is close to the optimum. Then the algorithm switches to the optimal search mode. It calculates the optimum, and a confirming experiment is conducted at the suggested optimum settings. This process is repeated until it reaches the exit criterion. Fuzzy logic is utilized to replace the combination of linear and nonlinear regression models. As a result, the fuzzy logic method is more user-friendly and efficient.

The Future

It has been a long journey since the early days when fuzzy logic was conceived and mathematically formulated for practical applications in semiconductor manufacturing. Many theoretical results have been reported which add to the knowledge of dealing with uncertainty, and many successful engineering applications have been achieved through engineering design. Less satisfactory engineering designs and failures have inspired further effort and development, which have led to better understanding of fuzzy logic and better tools of theoretical analysis and of engineering development and implementation. The future directions of the fuzzy logic technique for manufacturing applications are briefly summarized in the following.

Adding Learning and Adaptive Capability. The fuzzy logic technique is developed primarily to deal with uncertainty through approximate reasoning. The development of the inference engine and the design and selection of the fuzzy membership function are very often heavily influenced by the designer. On the positive side, this influence, is the dictating factor for capturing human experience and mimicking expert decision making. When dealing with complex systems or complex processes, the human may or may not be able to understand the interaction of multiple parameters, uncertainty factors, and random disturbances. In this case, a better technique is needed to assist the design or the normal function of the fuzzy based technique.

One such possible solution is to introduce learning or adaptive capability into the fuzzy logic technique. Artificial neural networks provide one of the best solutions to this challenge. As we have often noted, one of the problems in fuzzy logic is the subjective nature of designing membership functions, which now can be addressed by using neural networks to generate, modify, and possibly update the membership functions on-line. This bridges the gap between empirical data and expert knowledge.

Accessing Stability. The other area where we have seen progress is in stability analysis. Understanding and characterizing the existing fuzzy logic controller, in particular, how well the controller performs with clearly defined performance indexes and stable margins is crucial for evaluating and improving the design. In conventional and modern control theory, the stability analysis and performance indexes are well defined. We have seen a lot of good work in this area for fuzzy logic applications. Clearly there is a need to see more work in this fast moving field.

Integrating with Existing Techniques. The other commonly encountered challenge in fuzzy logic control is designing and fine-tuning the inference engine. It is well known that not all physical phenomena are intuitive. In fact, some of the best control actions may seem counterintuitive in a situation involving many unknowns and uncertainty. In this case, designing fuzzy logic control rules based on intuition is formidable. However in the past few years, progress in the design of fuzzy PID controllers by the integrating neural networks with fuzzy logic has significantly improved the design process. Now it is possible and practical to pursue a fuzzy logic controller design based on the error, the derivatives of error, and the history of the error. This is where fuzzy PID (proportional, integral, and derivative) controller comes in. Using this technique, without bothering "if engine temperature is high, then reduce speed," the design engineer can focus on the abstract level of the design based on the behavior of error, the derivatives of the error, and/or the history of the error.

In general, the fuzzy logic controller design process is just a superset of the conventional control design process. As we learn more about the process or the system, then there is less uncertainty. Therefore fuzzy logic plays less of a role, and the conventional approach becomes a more dominating part of the design. But this world will continue to be full of uncertainty, and we have to deal with uncertainty to achieve better process or equipment control.

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