15 A New Approach for Plant Monitoring Using Type-2 Fuzzy Logic and Fractal Theory

We describe in this chapter a new approach for plant monitoring and diagnostics using type-2 fuzzy logic and fractal theory. The concept of the fractal dimension is used to measure the complexity of the time series of relevant variables for the process. A set of type-2 fuzzy rules is used to represent the knowledge for monitoring the process. In the type-2 fuzzy rules, the fractal dimension is used as a linguistic variable to help in recognizing specific patterns in the measured data. The fuzzy-fractal approach has been applied before in problems of financial time series prediction and for other types of problems, but now it is proposed to the monitoring of plants using type-2 fuzzy logic. We also compare the results of the type-2 fuzzy logic approach with the results of using only a traditional type-1 fuzzy logic approach. Experimental results show a significant improvement in the monitoring ability with the type-2 fuzzy logic approach.

15.1 Introduction

Diagnostic systems are used to monitor the behavior of a process and identify certain pre-defined patterns that are associated with well-known problems (Du, 1998). These problems, once identified, imply suggestions for specific solutions. Most diagnostic systems are in the form of a rule-based expert system: a set of rules is used to describe certain patterns (Chiang et. al, 2000). Observed data are collected and used to evaluate these rules. If the rules are logically satisfied, the pattern is identified, and the problem associated with that pattern is suggested (Jain, et. al, 2000). In general, the diagnostic systems are used for consultation rather than replacement of human expert (Russell et. al, 2000).

Most current plant monitoring systems only check a few variables against individual upper and lower limits, and start an audible alarm should each variable move out of its predefined range (Chen and Pham, 2001). Other more complicated systems normally involve more sensors that provide more data but still follow the same pattern of independently checking individual sets of data against some upper and lower limits

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(Saez and Cipriano, 2001). The warning alarm from these systems only carries a meaning that there is something wrong with the process in the plant (Yang et. al, 1999). Monitoring means checking or regulating the performance of a machine, a process, or a system (Scharf, 1991). Diagnosis, on the other hand, means deciding the nature and the cause of a diseased condition of a machine, a process, or a system by examining the symptoms. In other words, monitoring is detecting suspect symptoms, whereas diagnosis is determining the cause of the symptoms (Castillo and Melin, 2002).

In this chapter a new fuzzy-fractal approach for plant monitoring is proposed. The concept of the fractal dimension is used to measure the complexity of the time series of relevant variables for the process (Castillo and Melin, 1994). A set of type-2 fuzzy rules is used to represent the knowledge for monitoring the process (Castillo and Melin, 2001). In the type-2 fuzzy rules, the fractal dimension is used as a linguistic variable to help in recognizing specific patterns in the measured data. The fuzzy-fractal approach has been applied before in problems of financial time series prediction (Castillo and Melin, 1996) and for other types of problems (Castillo and Melin, 1998), but now it is proposed to the monitoring of plants using type-2 fuzzy logic. Fuzzy systems are comprised of rules (Yen and Langari, 1999). Quite often, the knowledge that is used to build these rules is uncertain. Such uncertainty leads to rules whose antecedents or consequents are uncertain, which translates into uncertain antecedent or consequent membership functions (Mendel, 2001). Type-1 fuzzy systems (Jang et. al, 1997), whose membership functions are type-1 fuzzy sets, are unable to directly handle such uncertainties (Wang, 1997). We describe briefly in this paper, type-2 fuzzy systems, in which the antecedent or consequent membership functions are type-2 fuzzy sets.

15.2 Monitoring and Diagnosis

Monitoring means checking or regulating the performance of a machine, a process, or a system (Du et. al, 1993). Diagnosis, on the other hand, means deciding the nature and the cause of a diseased condition of a machine, a process, or a system by examining the symptoms (Patton et. al, 2000). In other words, monitoring is detecting suspect symptoms, whereas diagnosis is determining the cause of the symptoms.

The importance of monitoring and diagnosis of plant processes now is widely recognized because it results in increased productivity, improved product quality and decreased production cost (Melin and Castillo, 2001). As a result, in the past decade, a large number of research and development projects have been carried and many monitoring and diagnosis methods have been developed (Du, 1998). The commonly used monitoring and diagnosis methods include modeling-based methods, pattern recognition methods (Yager and Filev, 1994), fuzzy systems methods (Margaliot and Langholz, 2000), knowledge-based systems methods (Melin and Castillo, 2002), artificial neural networks (Omidvar and Elliot, 1997), and genetic algorithms (Mitchell, 1998). It is interesting to note that even though these methods are rather different, they share a very similar structure as shown in Figure 15.1.

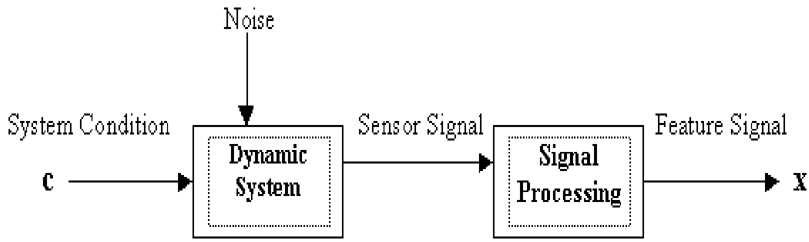

Fig. 15.1. Plant Monitoring and Diagnosis

The "health" of a machine, a process, or an engineering system (which will be referred to as system condition and denoted by $c \in \{c_1, c_2,..., c_m\}$) can be considered as the "input", the system working conditions and noises (including system noise and sampling noise) can be considered as the "noise", and the sensor signals are the "outputs" from the system. Typically, the sensor signals are processed by a computer, after which the signals are transformed into a set of features called feature signals, denoted as $\mathbf{x} = \{x_1, x_2,..., x_n\}$. In general, the systems conditions are predefined, such as normal, critical, etc. On the other hand, the features may be the mean of a temperature signal, the variance of a displacement signal, etc (Melin and Castillo, 1998). Sensing and signal processing are very important to the success of plant monitoring and diagnosis (Hsu, 2000).

More formally, the goal of monitoring is to use the feature signals, x, to determine whether the plant is in an acceptable condition(s) (a subset of $\{c_1, c_2,..., c_m\}$). On the other hand, the objective of diagnosis is to use the feature signals, x, to determine the system condition, $c \in \{c_1, c_{2,...,} c_m\}$. No matter how monitoring and diagnosis methods may differ, monitoring and diagnosis always consist of two phases: training and decision making. Training is to establish a relationship between the feature signals and the systems conditions. Without losing generality, this relationship can be represented as

$$\mathbf{x} = F(c). \tag{15.1}$$

It should be pointed out that F(c) represents a fuzzy system, a neural network or another method that could be used to obtain this relationship. In fact, it is the form of the relationship that determines the methods of monitoring and diagnosis, as well as the performance of the methods. The relationship F(c) is established based on training samples, denoted by $\mathbf{x}_1, \mathbf{x}_2,..., \mathbf{x}_k,..., \mathbf{x}_N$, where the system condition for each training sample is known [and denoted as $c(\mathbf{x}_k)$]. The conditions on F(c), so that monitoring or decision making is successful, are that F(c) is one-to-one and bounded. In this way, we can always obtain the inverse relationship, which is needed below for achieving decision making.

After the relationship is established, when a new sample is given (from an unknown system condition), its corresponding condition is estimated based on the inverse relationship

$$c = F^{-1}(\mathbf{x}). \tag{15.2}$$

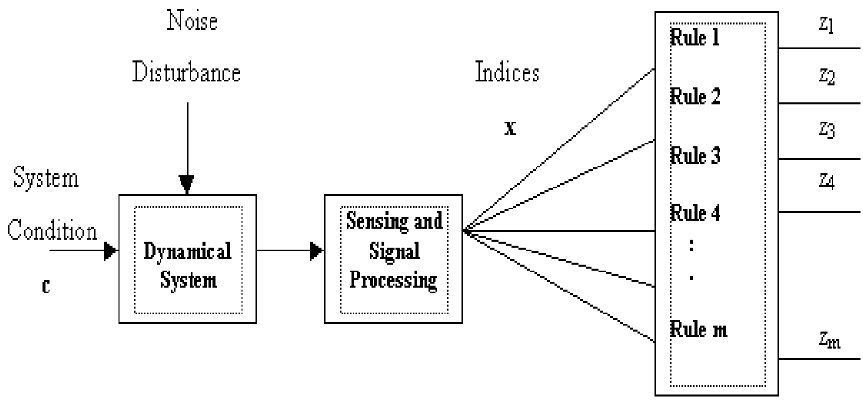

Fig. 15.2. Fuzzy system for plant monitoring and diagnosis

This is called decision-making, or classifying. Whereas it is not likely that the training samples will cover all possible cases, decision making often involves reason ing or inferencing. In particular, when a fuzzy system is used, the relationship is given by a set of fuzzy rules as shown in Figure 15.2. The input to the fuzzy system is the feature signal and the output of the fuzzy system is the estimated plant condition(s) [i.e., $\mathbf{z} = (z_1, z_2,..., z_m)$ is an estimate of $\mathbf{c} = (c_1, c_2,..., c_m)$]. In other words, the fuzzy system models the inverse relationship between the system conditions and the feature signals.

15.3 Fractal Dimension of a Geometrical Object

Recently, considerable progress has been made in understanding the complexity of an object through the application of fractal concepts (Mandelbrot, 1987) and dynamic scaling theory (Mandelbrot, 1997). For example, financial time series show scaled properties suggesting a fractal structure (Castillo and Melin, 1999). The fractal dimension of a geometrical object can be defined as follows (Peitgen et. al, 1992):

$$d = \lim_{r \to 0} [\ln N(r)] / [\ln(1/r)] \tag{15.3}$$

where N(r) is the number of structuring elements (boxes, balls, line segments, etc.) covering the object and r is the size of the box (Pesin, 1999). An approximation to the fractal dimension can be obtained by counting the number of boxes covering the boundary of the object for different r sizes and then performing a logarithmic regression to obtain d (box counting algorithm). In Figure 15.3, we illustrate the box counting algorithm for a hypothetical curve C.

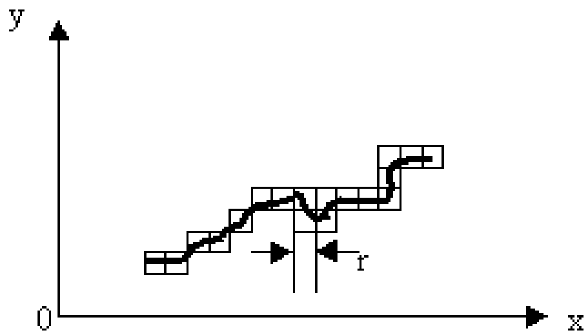

Fig. 15.3. Box Counting Algorithm for a Curve C

Counting the number of boxes for different sizes of r and performing a logarithmic linear regression, we can estimate the box dimension of a geometrical object with the following equation (Melin and Castillo, 2002):

$$\ln N(r) = \ln\beta - d \ln r \quad (15.4)$$

this algorithm is illustrated in Figure 15.4.

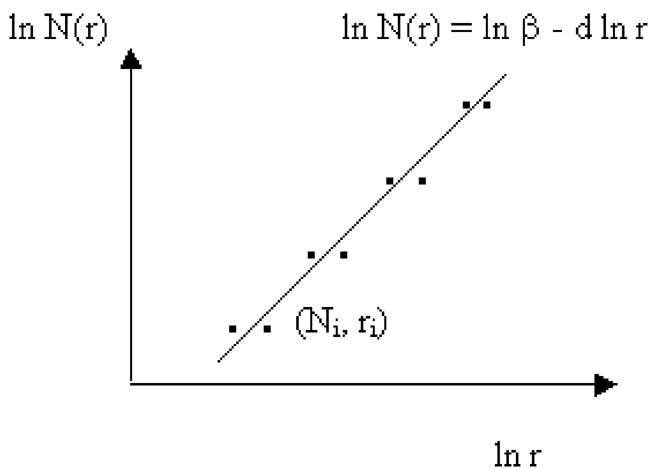

Fig. 15.4. Logarithmic Regression to find the Fractal Dimension

The fractal dimension can be used to characterize an arbitrary object (Tricot, 1995). The reason for this is that the fractal dimension measures the geometrical complexity of objects (Moon, 1992). In this case, a time series can be classified by using the numeric value of the fractal dimension (d is between 1 and 2 because we are on the plane xy).

15.4 Fuzzy Estimation of the Fractal Dimension

The traditional fractal dimension of a geometrical object assigns a crisp numerical value, which measures the geometrical complexity of the object (Semmes, 2000). However, in practice it is difficult to assign a unique numerical value to an object due to uncertainty (Peters, 1994). It is more appropriate to assign a range of numerical values in which there exists a membership degree for this object. For this reason, we will assign to an object O a fuzzy set μ_o, which measures the membership degree for that object. Lets consider, for simplicity, that the object O is in the plane xy, then a suitable membership function could be a generalized bell function (Zadeh 1971):

$$\mu_o = 1 / [\, 1 + |\, (d-c) / a\, |^{2b}\,] \qquad (15.5)$$

where a, b and c are the parameters of the membership function and d is the traditional crisp value of the fractal dimension. Of course other types of membership functions could be used depending on the characteristics of the application. By using the concept of a fuzzy set (Zadeh, 1965) we are in fact generalizing the mathematical concept of the fractal dimension because now we can take into account the uncertainties that may arise due to sampling and experimental errors. In fact, our definition of the fuzzy fractal dimension for this case is as follows.

Definition 15.1. Let O be an arbitrary geometrical object in the plane xy. Then the fuzzy fractal dimension is the pair: (d_o, μ_o)

where d_o is the numerical value of the fractal dimension calculated by the box counting algorithm, and μ_o is the membership function for the object.

With this new definition we can account for the uncertainty in the estimation of the fractal dimension of an object. We are, in fact, using this concept of the fuzzy fractal dimension in this paper to consider the uncertainty in the time series analysis required by the monitoring applications. Also, this new definition enables easier pattern recognition for objects, because it is not necessary to match an exact numerical value to recognize a particular object (Yager and Filev, 1994).

15.5 Type-2 Fuzzy Logic

The concept of a type-2 fuzzy set was introduced by Zadeh in 1973 as an extension of the concept of an ordinary fuzzy set (henceforth called a "type-1 fuzzy set"). A type-2 fuzzy set is characterized by a fuzzy membership function, i.e., the membership grade for each element of this set is a fuzzy set in [0,1], unlike a type-1 set where the membership grade is a crisp number in [0,1]. Such sets can be used in situations where there is uncertainty about the membership grades themselves, e.g., an uncertainty in the shape of the membership function or in some of its parameters (Mendel, 2001). Consider the transition from ordinary sets to fuzzy sets. When we cannot determine the membership of an element in a set as 0 or 1, we use fuzzy sets of type-1. Similarly, when the situation is so fuzzy that we have trouble determining the membership grade even as a crisp number in [0,1], we use fuzzy sets of type-2.

Example: Consider the case of a fuzzy set characterized by a Gaussian membership function with mean m and a standard deviation that can take values in $[\sigma_1,\sigma_2]$, i.e.,

$$\mu(x)=\exp\{-½[(x-m)/\sigma]^2\};\quad \sigma\in[\sigma_1,\sigma_2] \tag{15.6}$$

Corresponding to each value of σ, we will get a different membership curve (see Figure 15.5). So, the membership grade of any particular x (except x=m) can take any of a number of possible values depending upon the value of σ, i.e., the membership grade is not a crisp number, it is a fuzzy set. Figure 15.5 shows the domain of the fuzzy set associated with x=0.7.

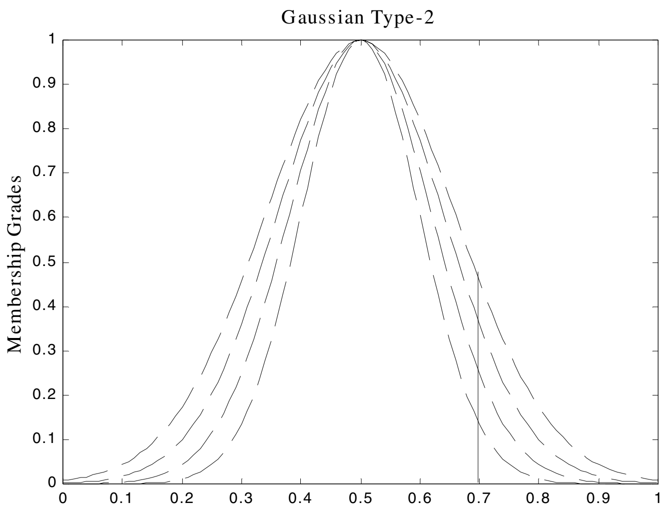

Fig. 15.5. Type-2 fuzzy set representing a type-1 set with uncertain deviation

We can formally define two kinds of type-2 sets as follows.

Definition 2. Gaussian type-2
A Gaussian type-2 fuzzy set is one in which the membership grade of every domain point is a Gaussian type-1 set contained in [0,1].

Definition 3. Interval type-2
An interval type-2 fuzzy set is one in which the membership grade of every domain point is a crisp set whose domain is some interval contained in [0,1].

The basics of fuzzy logic do not change from type-1 to type-2 fuzzy sets, and in general, will not change for any type-n (Mendel, 2001). A higher-type number just indicates a higher "degree of fuzziness". Since a higher type changes the nature of the membership functions, the operations that depend on the membership functions change; however, the basic principles of fuzzy logic are independent of the nature of

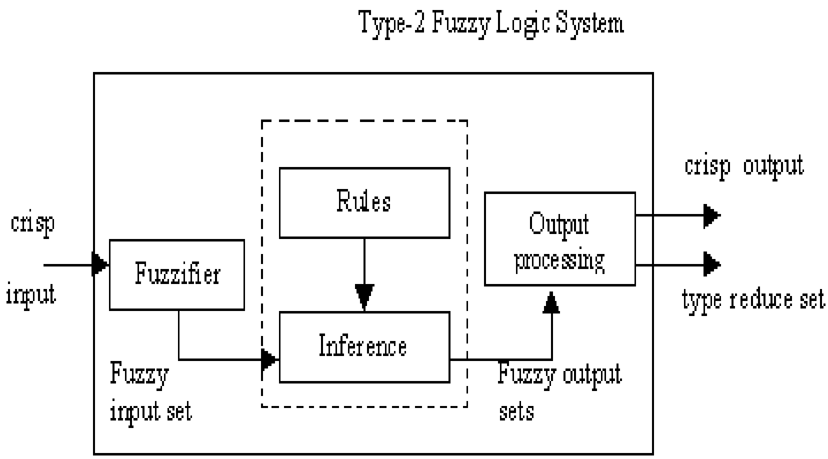

Fig. 15.6. Structure of a type-2 fuzzy system

membership functions and hence, do not change. In Figure 15.6 we show the general structure of a type-2 fuzzy system. We assume that both antecedent and consequent sets are type-2; however, this need not necessarily be the case in practice.

The structure of the type-2 fuzzy rules is the same as for the type-1 case because the distinction between type-2 and type-1 is associated with the nature of the membership functions. Hence, the only difference is that now some or all the sets involved in the rules are of type-2. In a type-1 fuzzy system, where the output sets are type-1 fuzzy sets, we perform defuzzification in order to get a number, which is in some sense a crisp (type-0) representative of the combined output sets. In the type-2 case, the output sets are type-2; so we have to use extended versions of type-1 defuzzification methods. Since type-1 defuzzification gives a crisp number at the output of the fuzzy system, the extended defuzzification operation in the type-2 case gives a type-1 fuzzy set at the output. Since this operation takes us from the type-2 output sets of the fuzzy system to a type-1 set, we can call this operation "type reduction" and call the type-1 fuzzy set so obtained a "type-reduced set". The type-reduced fuzzy set may then be defuzzified to obtain a single crisp number; however, in many applications, the type-reduced set may be more important than a single crisp number.

Type-2 sets can be used to convey the uncertainties in membership functions of type-1 fuzzy sets, due to the dependence of the membership functions on available linguistic and numerical information. Linguistic information (e.g. rules from experts), in general, does not give any information about the shapes of the membership functions. When membership functions are determined or tuned based on numerical data, the uncertainty in the numerical data, e.g., noise, translates into uncertainty in the membership functions. In all such cases, any available information about the linguistic/numerical uncertainty can be incorporated in the type-2 framework. However, even with all of the advantages that fuzzy type-2 systems have, the literature on the applications of type-2 sets is scarce (Mendel, 2001). Some examples are for decision-making (Yager, 1980), and for solving fuzzy relational equations (Wagenknecht and Hartmann, 1988). For the specific case of plant monitoring, the use of type-2 fuzzy rules is justified when the degree of uncertainty is high (for example, due to noise or complexity of the process) in the measured time series. Of course, a type-1 fuzzy system could be enough for plant monitoring in the case of relatively simple processes in the plant (Zadeh, 1975). However, in other cases there are highly non-linear processes present in the plant, like in biochemical reactors or electrochemical processes. For this reason, we are proposing that to model the uncertainty in this type of highly non-linear processes, we need to use type-2 fuzzy logic. We illustrate the application of the type-2 fuzzy logic approach with the case of monitoring the electrochemical process in battery production in a real plant.

15.6 Plant Monitoring Using a Type-1 Fuzzy-Fractal Approach

In this section, we show how to implement a fuzzy rule-based expert monitoring system with two basic sensors: temperature, and pressure. These two physical variables are very important in understanding any chemical process. Our particular case, is the monitoring of an electrochemical process, like the one used in battery formation. We also use as input the fuzzy fractal dimension of the time series of the measured variables. Of course, this fuzzy fractal dimension is not a real physical variable, but we can use it to measure the complexity of the dynamic behavior of the process. We have assigned linguistic values to the fuzzy fractal dimension, with the help of experts in the process in such a way as to help in the diagnostic of the different conditions. Individual sensors can identify three linguistic values (normal, high, and low) for the two real physical variables. The three inputs can be combined to give 9 different real scenarios. Of course, there could be in theory at most 27 scenarios in this case, but there are only 9 real ones for the particular application of the electrochemical process. This is perfectly clear if we notice that there are only two real physical variables with three linguistic values for each one. With the perfectly normal case (where all three input variables have normal values), there are additionally 8 more cases where combinations of abnormal readings can be observed.

Let x_1 be the temperature, x_2 the pressure, x_3 the fuzzy fractal dimension, and y the diagnostic statement. Let L_i, N_i, and H_i, represent the three sets of low range, normal range, and high range for input data x_i, where i = 1, 2, or 3. Furthermore, let C_1, C_2,..., C_9 be the individual scenarios that could happen for each combination of the different data sets. The fuzzy rules have the general form:

$R^{(0)}$: IF x_1 is N_1 AND x_2 is N_2 AND x_3 is N_3 THEN y is C_1

... ...

$R^{(i)}$: IF x_1 is V_1 AND x_2 is V_2 AND x_3 is V_3 THEN y is C_i (15.7)

... ...

$R^{(26)}$: IF x_1 is H_1 AND x_2 is H_2 AND x_3 is H_3 THEN y is C_9

In this case, V_i represents L_i, H_i, or N_i, depending on the condition for the plant. Experts have to provide their knowledge in plant monitoring to label the individual cases Ci for i = 1, 2,..., 9. Also, the membership functions for the linguistic values of variables have to be defined according to historical data of the problem and expert knowledge. Of course, expert knowledge for temperature and pressure is based on the

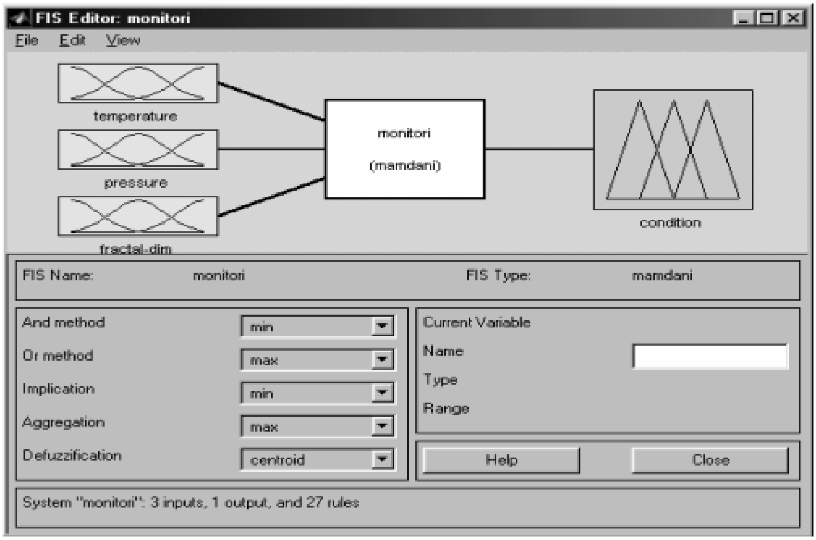

Fig. 15.7. Architecture of the fuzzy system for plant monitoring

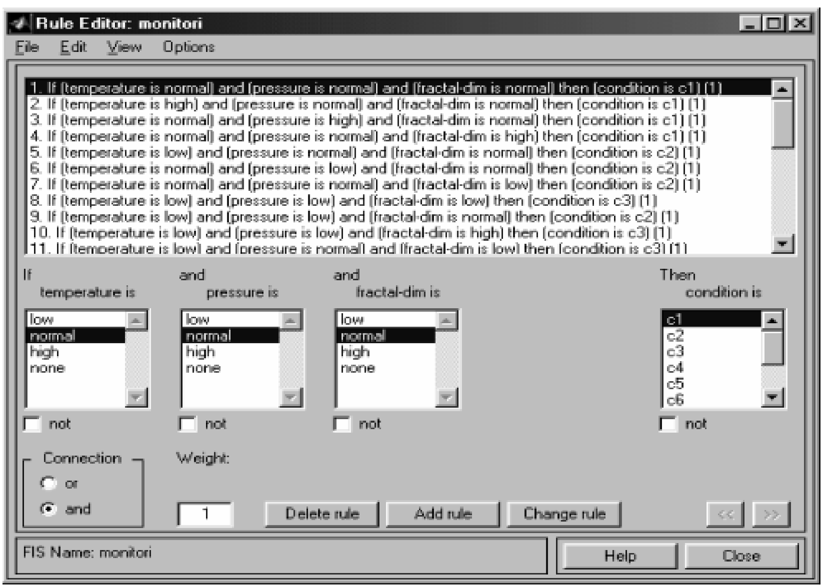

Fig. 15.8. Fuzzy rule base for plant monitoring

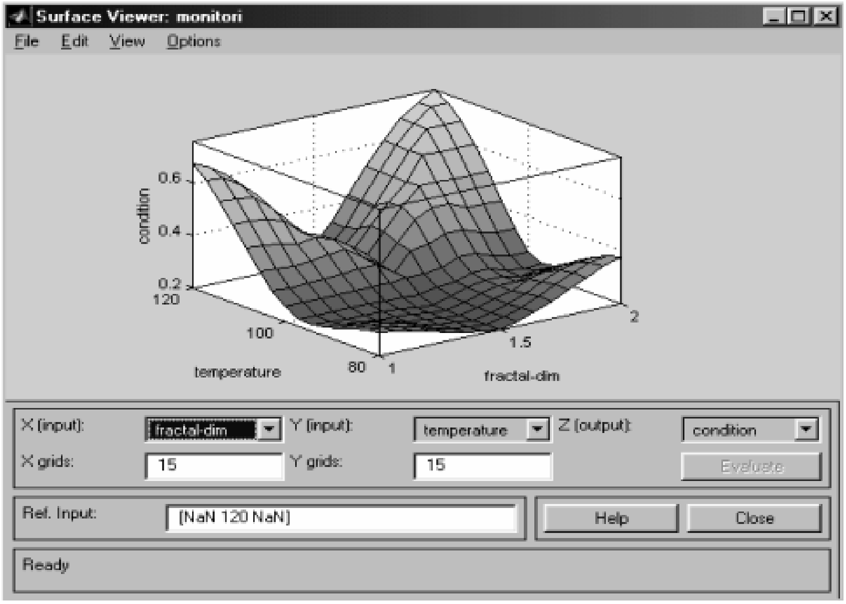

Fig. 15.9. Non-linear surface for plant monitoring with respect to temperature and fractal dimension

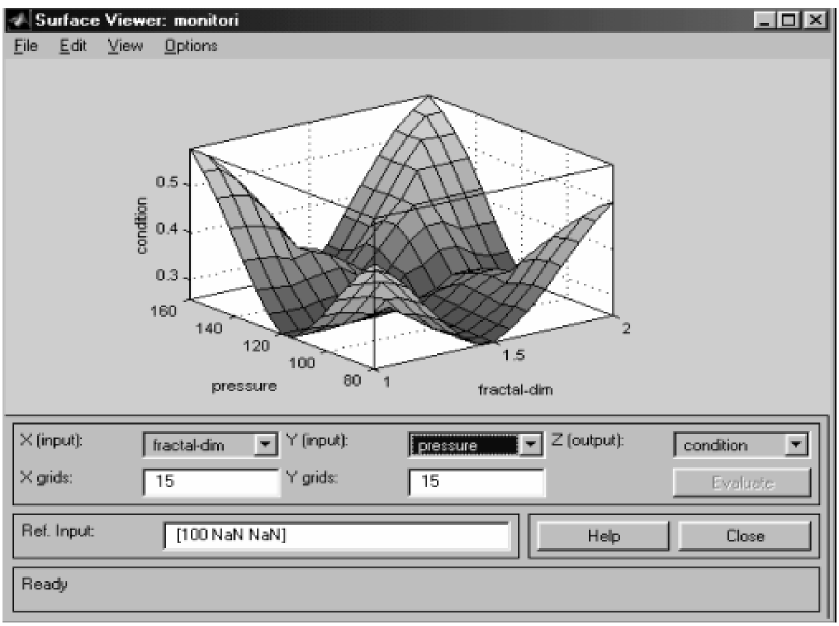

Fig. 15.10. Non-linear surface for plant monitoring with respect to pressure and fractal dimension

dynamics of the process, which experts have gained with their experience. On the other hand, expert knowledge for the fuzzy fractal dimension is more of a combination of expertise on the problem and expertise on the mathematics of fractal theory. Perhaps, this can be explained as follows: we need expert knowledge to know if the dynamics of the process are abnormal or normal, on the other hand we need knowledge on fractal theory to relate the dynamics to a higher or lower value of the fractal dimension.

We can use the Fuzzy Logic Toolbox of the MATLAB language to implement the fuzzy monitoring system described above. In this case, we need to specify the particular fuzzy rules and the corresponding membership functions for the problem. First, we show in Figure 15.7 the general architecture of the fuzzy monitoring system. In this figure, we can see the input linguistic variables (temperature, pressure, and fractal dimension) and the output variable (condition of the plant) of the fuzzy monitoring system. Of course, in this case the fractal dimension is estimated using the box counting algorithm, which was implemented also in MATLAB. In Figure 15.8 the implementation of the fuzzy rule base is shown. The actual 27 rules were defined according to expert knowledge on the process. In Figures 15.9 and 15.10 the non-linear surface for the problem of monitoring is shown.

15.7 Plant Monitoring Using the Type-2 Fuzzy-Fractal Approach

For the case of the type-2 fuzzy-fractal approach, we have to change our way of calculating the output of the fuzzy system. Now, we use interval computations to find the minimum and maximum values for obtaining the outputs of the type-2 fuzzy system. We basically, compute the outputs of two type-1 fuzzy systems, one for computing the minimum value and the other for the maximum value. Then, if we need to further reduce the type of the output, we can apply the traditional deffuzzification methods. Fortunately, in this way we can take advantage of the machinery that we already have for type-1 fuzzy logic, as well as the computer programs in the MATLAB language.

We show below in Table 15.1 the results of a type-2 fuzzy system for monitoring different conditions of the plant. We also show the corresponding values of the type-1 fuzzy logic approach. A comparison, of both approaches can be made in this way. Of course, it is easy to appreciate that in the case of type-2 fuzzy logic the output result is an interval, instead of a single numeric value. In some applications, this is closer to reality, since we are expecting something similar to a confidence interval. However, in other areas of application, like in control, a unique result is needed, so in this case we need to defuzzify again (or type-reduce the result). This is also shown in Table 15.1.

From Table 15.1 we can appreciate that in some cases the output of the type-2 fuzzy system is almost the same as in the type-1 case, but in other situations the results are somewhat different. For our application, we find out that the results of the type-2 fuzzy logic approach were better for monitoring the plant. The main reason for saying that the type-2 approach is better, in this case, is that we are really predicting

Table 15.1. Comparison between the type-2 and type-1 fuzzy logic approaches

Temperature	Pressure	Fractal Dim.	Type-1 F. L.	Type-2 Min	Type-2 Max
105	130	1.6	0.4498	0.4391	0.5030
100	120	1.5	0.2688	0.2774	0.2775
95	115	1.4	0.2263	0.2216	0.2539
90	110	1.3	0.2460	0.2282	0.2783
102	122	1.7	0.3604	0.3321	0.4210
85	90	1.2	0.2690	0.2540	0.2750
75	100	1.8	0.2652	0.2251	0.3039
55	105	1.3	0.2700	0.2700	0.2701
130	90	1.1	0.5710	0.5586	0.5855
112	115	1.6	0.4136	0.4092	0.4138

possible problems in the plant, and the type-2 intervals are closer to what the experts were expecting to see in the monitoring of the process.

We show in Figures 15.11 and 15.12 the non-linear surfaces for the type-1 and type-2 fuzzy systems, respectively. From these figures, we can appreciate the difference between both fuzzy logic approaches. It is obvious that the type-2 fuzzy logic surface is smoother, which is better for modeling the monitoring problem. Finally, we show in Figure 15.13 a comparison between the predicted outputs for the type-2 and type-1 fuzzy systems. In this figure we can appreciate that the type-2 fuzzy logic approach is really modeling our uncertainty about the membership functions of the fuzzy system. For this reason, the type-1 result is almost always in between the minimum and maximum values of the type-2 approach. Of course, the type-2 approach is more realistic because we do not know the exact parameter values of the type-1 membership functions.

Based on the examples presented in this section and the previous one, we see that using fuzzy logic in monitoring and diagnostics always results in improved performance. Also, the use of the fractal dimension improves the accuracy of the method. We have compared the success rate of the type-2 fuzzy-fractal approach, the type-1 fuzzy-fractal approach, and the use of only fuzzy logic, using the data from electrochemical processes in a real plant. The results are shown in Table 15.2. We are using in all of the cases a specific electrochemical process for battery formation. The process is considered to be in a different condition in each of the three cases. The comparison is between the results of the intelligent system using the type-2 fuzzy-fractal approach, the type-1 approach, and a computer program using only fuzzy logic with the Mamdani approach.

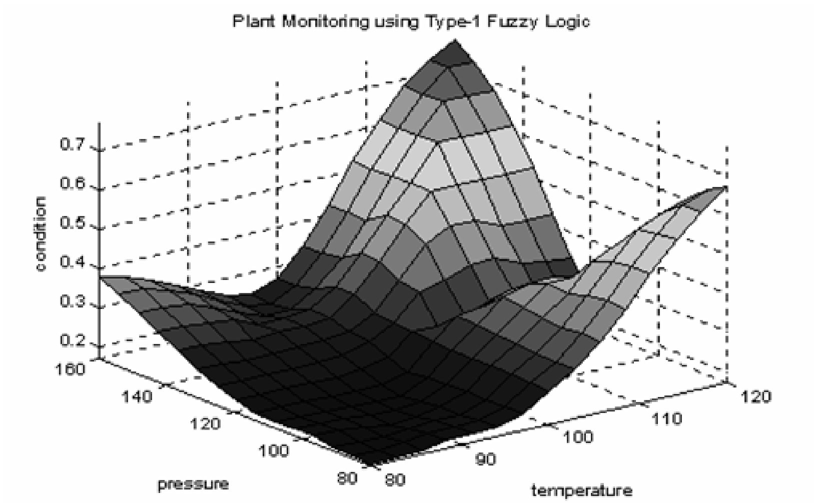

Fig. 15.11. Non-linear surface for the type-1 fuzzy system

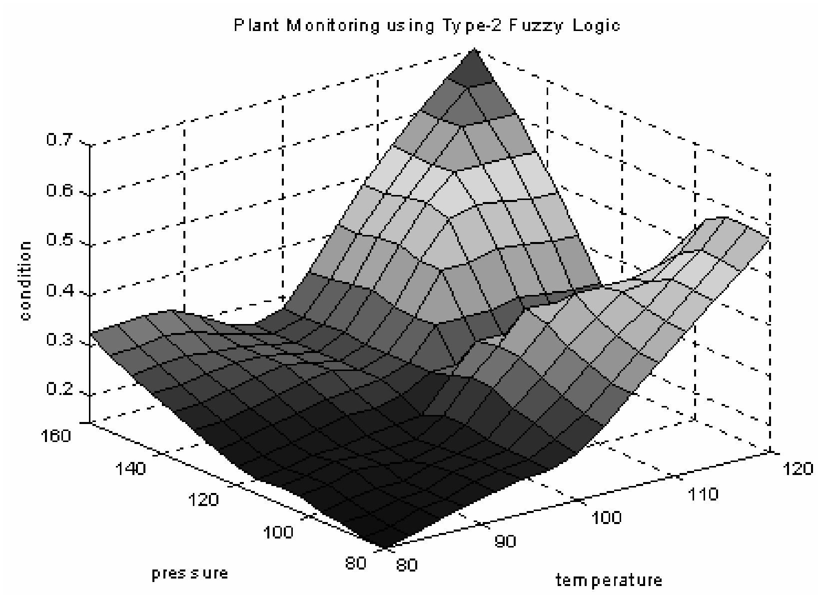

Fig. 15.12. Non-linear surface for the type-2 fuzzy system

It should be pointed out that no matter what techniques are used, there is no guarantee of success because monitoring and diagnosis is a process of abduction. First, the training samples may not represent all the patterns of different system conditions. An

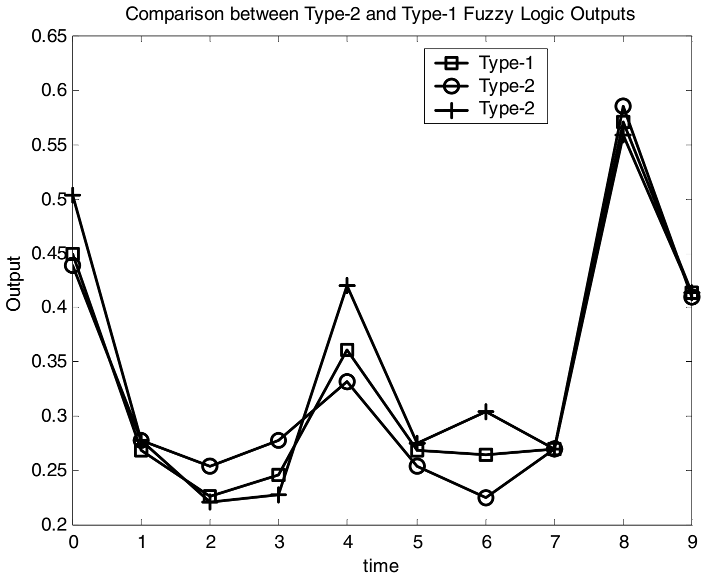

Fig. 15.13. Comparison of outputs of the type-2 and type-1 fuzzy systems

Table 15.2. Success rates of the type-2 and type-1 fuzzy-fractal approaches for monitoring

Applications	Type-2 Fuzzy-Fractal	Type-1 Fuzzy-Fractal	Fuzzy Logic
condition monitoring in an electro-chemical process (case 1)	99%	98%	82%
condition monitoring in an electro-chemical process (case 2)	88%	86%	73%
condition monitoring in an electro-chemical process (case 3)	93%	90%	79%

effective solution to this problem is to add more training samples. Second the patterns of different system conditions overlap and/or are inseparable owing to the definition of system conditions and the use of monitoring indices.

Finally, it is interesting to compare the performance of the fuzzy-fractal approaches with that of using only fuzzy logic (see Table 15.2). We see that the type-1 fuzzy-fractal approach outperforms the fuzzy logic approach by at least 10% in all the cases. We also can appreciate that the type-2 fuzzy-fractal approach outperforms by 2%

(average) the type-1 approach. This demonstrates that the type-2 fuzzy-fractal approach is indeed the more effective method and, in general outperforms the use of type-1 fuzzy logic.

15.8 Summary

In this chapter a hybrid fuzzy-fractal approach for plant monitoring has been proposed. Type-2 fuzzy logic is used to model the uncertainty of plant monitoring and diagnostics. An implementation in MATLAB has been shown, to describe in more detail the advantages of the new approach. The hybrid fuzzy-fractal approach combines the advantages of fuzzy logic (expert knowledge representation) with the advantages of the fractal dimension concept (ability to measure object complexity), to achieve efficient monitoring and diagnostics. A problem yet to be considered, is how to automatically learn (or adapt) the membership functions and rules of the fuzzy system using real data for the problem.