Preface

Real-life problems in industries or service sectors are usually filled with a lot of uncertainties, sometimes because of the unpredictability of what lies ahead, sometimes it is in part due to the subjectivity of the decision-maker, and sometimes it are technical limitations. For example, in building models for decision making, many coefficients are based on forecasts, and therefore cannot be certain. Some constraints can also be relaxed to a certain degree. These considerations may involve subjective judgments that are beyond the scope of parametric analyses or probabilistic methods. The concept of fuzzy sets proposed by Zadeh in 1985 provides us with an effective tool to solve these problems. Fuzzy logic is a form of many-valued logic. Contrary to the traditional binary logic theory, fuzzy logic variables have a truth value that ranges between 0 and 1. Reasoning in fuzzy logic is similar to human reasoning. It allows for approximate values and inferences as well as incomplete or ambiguous data. In addition, compared to nonlinear or stochastic methods, problems are generally easier to solve using fuzzy methods, since they are more flexible, and better reflect and incorporate human judgment. These features allow fuzzy techniques to be widely applied, including decision making, problem solving, system learning, clustering, system control, simulation, optimization, and others.

From a theoretical point of view, fuzzy control systems have advanced rapidly since the late 1980s. The rapid advances in computer technology have resulted in the proposal of many advanced computing techniques such as machine intelligence, artificial neural networks, data mining, soft computing, computing with words/expressions, semantic web, ubiquitous computing, and others. The combination of fuzzy sets with these new computing techniques has received a lot of attention. For example, Figure 1 shows the numbers of relevant articles on fuzzy neural networks in the past ten years. On average, more than one thousand papers are published and indexed each year.

In 2011, with the full support of IGI Global, we started a new journal on fuzzy systems – International journal of Fuzzy System Applications, which focuses on:

- Fuzzy clustering
- Fuzzy data analysis
- Fuzzy decision support systems
- Fuzzy evolutionary computing
- Fuzzy expert systems
- Fuzzy mathematical programming
- Fuzzy modeling and fuzzy control of biotechnological processes
- Fuzzy neural systems or neuro-fuzzy systems
- Fuzzy pattern recognition
- Fuzzy process control
- Fuzzy reasoning system
This book collected fourteen representative articles from this journal. Most articles included in this book are reprinted in their original form. New typesetting was employed only for those articles whose original form was not of sufficiently high quality. In certain articles, we made some minor adjustments to avoid confusion possibly caused if the articles are not entirely read.

With the popularity of the Internet and inexpensive data storage devices, massive amounts of data are stored everywhere. These huge amounts of data lead to difficulties when they need to be analyzed. Data clustering is an important task in fields such as data mining, statistical data analysis, machine learning, pattern recognition, image analysis, information retrieval, and bioinformatics, and thus encounters the same difficulties of these fields. Clustering is the task of assigning a set of objects to certain groups (called clusters) such that the objects in the same cluster are more similar to each other than to those in the other clusters. In the first chapter, Winkler et al. discusses the clustering of high dimensional data, which is especially meaningful for solving the difficulties in high dimensional data analyses. Fuzzy c-means (FCM) is an effective clustering approach, and works quite well in low dimensions. FCM and a number of its variants have been proven to be useful for data summarization. In addition, the clustering results using these FCM approaches are flexible in interpretation, since an object can be simultaneously assigned to different categories and to different degrees. However, one of the problems of FCM is that the prototypes tend to run into the center of gravity of the complete data set. Winkler et al. showed this property with some interesting examples. They also provided some clues to answer the following questions: What is the minimum number of dimensions necessary to cause unacceptable behavior by FCM? How does the number of prototypes influence unacceptable behavior? Why does the objective function have a local minima in the center of gravity, and how must FCM be initialized to avoid the local minima?
in the center of gravity? The answers to these questions allow FCM to be effectively applied to the clustering of high dimensional data, such as sales data, shop floor data, and others.

In order to objectively identify clusters in a data set, it is usually necessary to define a measure of similarity or proximity to establish a rule for assigning patterns to the domain of a particular cluster center. As expected, the measure of similarity is problem dependent, and thus most FCM algorithms adopt the iterative optimization scheme. However, FCM only considers the distances from the data to the cluster centers and their memberships. If two distinct clusters have a common mean, then the performance of FCM is poor. In addition, FCM variants are well designed for finding local optimal solutions, but may derive several different local solutions in the multi-starting strategy. Since the optimal cluster number is not known a priori, a validation measure for selecting the optimal cluster partition from multiple solutions is needed. In the next chapter, Honda et al. discusses the issue of clustering validation for FCM. Cluster validation is an important issue in fuzzy clustering research. Many validity measures have been developed, most of which are motivated by intuitive justification based on geometrical features, Honda et al. proposes a new validation approach, which evaluates the validity degree of cluster partitions from the point of view of the optimality of objective functions in FCM-type clustering. Their approach makes it possible to evaluate the validity of robust cluster-partitions, in which geometric features are not available because of their possibilistic nature.

In the third chapter, Zarandi and Razaee propose a fuzzy cluster model based on a new distance measure for classifying the fuzzy data. Their model can be used in noisy environments. The authors also added some weighting factors to reduce the effects of outliers. In short, their approach presents the results of successfully solving the problems of transforming the fuzzy data into the crisp data. Furthermore, for determining the optimal number of clusters, there is no need to define a cluster validity index for fuzzy data. The ones existing in literature for crisp data can be applied.

A fuzzy system can be divided into three parts: input, processing, and output. Typical fuzzy systems include the general fuzzy system, the Takagi-Sugeno-Kang (TSK) fuzzy system, the Mamdani fuzzy system, and the adapted network-based fuzzy inference system (ANFIS). Inputs to a fuzzy system usually have to undergo the fuzzification step. In this step, each input dimension is fuzzily partitioned. That is to say, it is segmented into several intervals with equal or unequal widths. These intervals overlap each other according to pre-defined membership functions. The partition method has a great influence on the performance of the fuzzy system. In Chapter 4, with the focus on this issue, Liao proposes a grid partitioning method. Here the domain space is partitioned by the fuzzy equalization method, one dimension at a time, followed by the computation of rule weights based on the max-min composition. Liao also proposed an enumeration method to determine the best combination of fuzzy terms for each variable. After applying it to five datasets (weld recognition, welding flaw identification, Haberman’s survival, Pima diabetes, and Wisconsin breast cancer datasets), and comparing it with some existing approaches (FCM variants, ant colony optimization (ACO)-based fuzzy partitioning, Wang and Mendel (WM) method, fuzzy subtractive (FS), ANFIS, FS-ANFIS, and fuzzy equalization), the proposed methodology produced the lowest average test errors and required less time to build the fuzzy models.

Information used in decision making generally comes from multiple sources. The fusion of multi-source information is an important issue, but not an easy one, especially not when the information provided has some uncertainty. There are however many different viewpoints and methods for dealing with uncertainty, including probabilistic, possibilistic, fuzzy, grey, chaotic, and other ways. Each method has its own merits and disadvantages, and is suitable for dealing with certain topics. The results obtained by these methods tend to differ by their basic nature. If we split a problem into different parts and then treat each part using a different approach, then the question of how to integrate the results from these
approaches becomes important. For example, as a fuzzy clustering approach, FCM can be generalized many ways, including generalizing the memberships to include possibilities. In addition, if there is a discrepancy in these results, then the question remains of how to solve the problem. In Chapter 5, Yager investigated the fusion of possibilistic and probabilistic information. He discussed the basic features of information provided in terms of possibilistic uncertainty, and pointed out the entailment principle, “a tool that allows one to infer less specific from a given piece of information”. He then provided a procedure for addressing the problems that arise when the information to be fused has some conflicts.

In recent years, many advanced evolutionary algorithms have been proposed, such as the ant colony optimization, swarm intelligence, genetic algorithms, genetic programming, artificial neural networks, immunological computing, morphic computing, and others. As a result of the pioneering studies of Pedrycz, fuzzy collaborative intelligence approaches have been shown to have the potential for improving the accuracy of forecasting. In addition, seeing a problem from different perspectives ensures that no parts are ignored when solving the problem. Collaborative forecasting is not derived from academic discussion, but arises from practical applications. However, in fuzzy collaborative systems, fuzzy collaborative clustering is one of the more often discussed issues. It relies on information granules rather than on data type to optimize the process. Fuzzy information granulation and granular computing are important concepts in fuzzy set and rough set theories. Fuzzy set, rough set and their combinations seem to be efficient tools for granular computing – the approaches to generating fuzzy information granules from data. Why use a system that seems complex, time consuming, and requires the collaboration of a number of domain experts? Although the existing methods can provide the same forecast in a more realistic manner and in a shorter time, the accuracy of that method of forecasting is often far from perfect, mainly due to unpredictable changes in observation. In Chapter 6, Chen proposed a fuzzy and neural approach for forecasting the foreign exchange rate. The foreign exchange rate between two currencies specifies how much one currency is worth in terms of the other. Accurately forecasting the foreign exchange rate is very important for export-oriented enterprises. Unfavorable foreign exchange rates result in the increase of raw material costs and the decrease of gross margin for these enterprises. In the fuzzy and neural approach, a group of domain experts are asked to configure their fuzzy linear regression equations to forecast the foreign exchange rate based on their views. A collaboration mechanism is therefore established to develop the views. To facilitate this collaboration process and to derive a single representative value from these forecasts, Chen used the fuzzy intersection and back propagation network approach. He used the historical data of the foreign exchange rate from NTD to USD to evaluate the effectiveness of the fuzzy and neural approach.

Forecasting the stock market is another concern. There are so many stock market gurus and experts out there suggesting ways to forecast the stock market. Basically, making the right buying/selling action at the right time is the only way to get rich in stock market. There are two viewpoints when it comes to forecasting the stock market of a future period. One is the input-output relationship viewpoint. It determines the factors that are influential in the stock market, and then applies different approaches such as multiple linear regression (MLR) or artificial neural network (ANN), to model the relationship between the stock market and these factors in order to forecast the stock market. The other viewpoint, the time-series viewpoint, is to treat fluctuations in the stock market as a type of time series. Theoretically there are many approaches, e.g. moving average (MA), weighted moving average (WMA), exponential smoothing (ES), MLR, ANN, auto-regressive integrated moving average (ARIMA), and others that can be applied to forecast the stock market. Generally speaking, ANN is suitable for modeling a short-term nonlinear pattern of the stock market, while traditional approaches such as MA, WMA, ES, and MLR have good performances when the trend in the stock market is stable. In Chapter 7, Quek et al. proposed
a novel stock trading framework based on a neuro-fuzzy associative memory (FAM) architecture. They incorporated the approximate analogical reasoning schema (AARS) to resolve the problem of discontinuous (staircase) response and inefficient memory utilization with uniform quantization in the associative memory structure. Their experimental results showed that a more advanced prediction allows the stock to be switched earlier to the correct position, which in turn leads to a substantial increase in wealth.

Fuzzy systems are increasingly common in daily life, and there have been many innovative applications based on the needs of people, such as a fuzzy washing machine, fuzzy air conditioner, the antilock braking system, and so on. These applications allow us to interact with the objects around us in more intelligent ways. For example, we may want to communicate with computers using gestures instead of, screens, and keyboards. Several new concepts have emerged lately, one of them being ambient intelligence (AmI). Ambient Intelligence is the vision of a future in which environments support the people inhabiting them. In this vision the traditional computer input and output media disappear, and instead processors and sensors are integrated in everyday objects. We can communicate with our clothes, household devices, and furniture, which in turn may communicate with each other and with the devices and furniture of other people. In this vision the environment is sensitive to the needs of its inhabitants, and capable of anticipating their needs and behavior. As an interesting investigation in this field, in Chapter 8, Jeon et al. recognizes hand gestures using a multivariate fuzzy decision tree and user adaptation. Recognizing the human hand gestures, that are usually culture-specified and can convey very different meanings in different social or cultural settings, is very important for understanding human intention. To reliably recognize hand gestures, it is necessary to resolve several major difficulties such as inter-person variation, intra-person variation, and false positive error caused by meaningless hand gestures. In their viewpoint, the efficient control of fuzzified decision boundary leads to the reduction of intra-person variation, while the proper selection of a user dependent recognition model contributes to the minimization of inter-person variation.

In Chapter 9, Yang et al. provides another way to achieve the same objective. With the rapid advances in human-computer interaction technologies, it is becoming easier for the elderly and/or people with disabilities to operate a variety of electrical systems, such as using gestures to operate home appliances. The gesture-based machine control system, allows you to wave your arm or hand in such a way that it is picked up by sensors, which is then translated into the movement of a device. This device can be a robotic surgical device, equipment control, an energy delivery system, or any other device. Gesture recognition is a prerequisite for gesture-based machine control. Gesture recognition is a field in the area of computer science and language technology that focuses on interpreting human gestures via computer hardware and software. Gestures can originate from any motion or state of your body but the face or hand are most commonly used. The current focus is on emotion recognition from the face and on hand gesture recognition. However, hand gesture recognition may fail when a predefined command gesture is similar to a common but meaningless behavior of the user. Thus, a gesture spotting procedure was developed to distinguish designated gestures from other similar gestures. In particular, a fuzzy garbage model was established to provide a variable reference value to determine whether the user’s gesture is a command gesture or not.

Fuzzy systems have been applied to a wide variety of fields ranging from control, signal processing, communication, to circuit design optimization and manufacturing. In system control, for example, Canon developed an autofocusing camera that uses a fuzzy control system with 12 inputs, 13 rules, and an output to determine the position of the lens. An industrial air conditioner designed by Mitsubishi uses a fuzzy control system with 25 heating rules and 25 cooling rules. Maytag invented an intelligent dishwasher that uses a fuzzy controller. The operation procedure of a fuzzy controller can be divided into three
stages. First, the input stage maps the sensor or other inputs, such as switches, thumbwheels, and so on, to the appropriate membership functions and truth values. Subsequently, the processing stage invokes each appropriate rule and generates a result for each rule, then combines the results of the rules. Finally, the output stage converts the combined result back into a specific control output value. In Chapter 10, Laboid et al. proposes two indirect adaptive fuzzy control schemes for a class of uncertain continuous single-input single-output (SISO) nonlinear dynamic systems with a known and an unknown control direction, respectively. In these schemes, fuzzy systems are used to approximate unknown nonlinear functions, and the Nussbaum gain technique is applied to deal with the unknown control direction. The effectiveness of the proposed methodology was verified through simulation experiments. The actual trajectories were found to be quite close to the desired ones.

Sometimes, to be able to control a system more precisely, we need to build a considerable number of fuzzy rules. This of course reduces the efficiency of the system, and results in a dilemma. In order to solve this problem, some researchers tried to achieve the effects of many rules while using fewer rules. For example, Singh et al. explored how relatively fewer rules can achieve similar control performance. In Chapter 11, a 49-rule fuzzy logic controller (FLC) used to control the shunt active power filter is approximated by a 4-rule one using compensating factors. Traditionally conventional PI controllers are used to regulate the dc link voltage of the shunt APF. They provide efficient harmonic compensation but suffer from poor dynamic response. This drawback is overcome by the 49-rule FLC. As the number of rules increases the control action becomes more efficient due to the smooth transition from one membership function to another. However, this is achieved at the cost of increased complexity. On the other hand, the 4-rule FLC is less complex and computationally more efficient due to the significant reduction in rule base size. In addition, computational time and memory requirement are also significantly reduced. The simulation results showed that the dynamic performance of the approximated simplest FLC is comparable with that of the 49-rule FLC, under transient and steady state conditions. Therefore, the 4-rule FLC is a suitable alternative for a large-rule FLC. In addition, the proposed scheme has several important features – it is system independent, is less complex in design, takes less memory, reduces computational time and provides efficient control action that satisfies the demand of effective compensation and provides a better dynamic response.

Li and Yu discussed another approximation problem. In Chapter 12, they proposed a semi-definite programming-based method for implementing linear fitting to interval-valued data. The central concern of fuzzy regression is linear regression analysis involving fuzzy data. Tanaka was the first to propose a fuzzy linear regression model by minimizing the index of fuzziness of the system. Diamond then introduced a metric on the set of fuzzy numbers and used this metric to define a least-sum-of-squares criterion function in the usual sense. In the field of symbolic data analysis, at the interval level, a similar topic has also been discussed extensively. Especially, building a linear fitting model for a given interval-valued data set is challenging since the minimization of the residue function leads to a huge combinatorial problem. Diamond first cast the fitting model to a problem of quadratically constrained quadratic programming (QCQP), and then derived two formulae to develop the lower bound on the optimal value of the non-convex QCQP by semi-definite relaxation and Lagrangian relaxation. In many cases, their method solves the fitting problem by giving the exact optimal solution. Even though the lower bound is not the optimal value, their solution is still a good approximation of the global optimal solution. According to the numerical results, their method performs very well in solving relatively large-scale interval-fitting problems.
In Chapter 13, Lin, Chang and Lee proposes a novel fuzzy modeling approach for identification of dynamic systems. They construct a recurrent interval type-2 fuzzy neural network (RIT2FNN) by using a recurrent neural network which recurrent weights, mean, and standard deviation of the membership functions are updated. The complete back propagation (BP) algorithm tuning equations used to tune the antecedent and consequent parameters for the interval type-2 fuzzy neural networks (IT2FNNs) are developed to handle the training data corrupted by noise or rule uncertainties for nonlinear system identification involving external disturbances. By using the current inputs and most recent outputs of the input layers, the dynamic system can be completely identified based on RIT2FNNs. According to the simulation results, the proposed methodology yielded more improved performance than those using recurrent type-1 fuzzy neural networks (RT1FNNs).

Nowadays, the electromagnetic compatibility (EMC) analysis of integrated circuit (IC) design has become an important issue due to the rapid increasing of electromagnetic interference (EMI) and the tendency of adopting tremendous technologies such as higher operating frequency, higher dissipation and lower supply voltage. The next paper written by Lin et al. demonstrates the extraction capability of a single model to predict the electromagnetic emission of a digital circuit by using a fuzzy logic system. This paper also evaluates the overall variation of the output response in the circuit and automatically extracts suitable values for the critical parameters of the ICEM.

The incorporation of fuzzy sets into the traditional mathematical programming models leads to the fuzzy versions, such as fuzzy linear programming (FLP), fuzzy integer programming (FIP), fuzzy goal programming (FGP), and fuzzy nonlinear programming (FNP). The previous studies on fuzzy mathematical programming are largely limited in the range of LP or multiple-objective LP, but FNP is rarely involved. In many practical problems, however, these are many kinds of nonlinearity and uncertainty, and they cannot be described or solved by traditional crisp or linear mathematical programming models. Therefore, the modeling and optimization methods for nonlinear programming under a fuzzy environment are not only important in theory, but also have a great application value for a wide range of practical problems. Chapter 15 is by Al-Refaie and Li. They propose a goal programming model to optimize the performance of the injection molding process by considering three important quality responses: number of defects, cycle time, and weight of the products. The injection molding process has become increasingly important because it provides high-quality products, short product cycles, and is light weight. The process consists of first constructing a weighted additive goal programming model. The three quality responses and process factors are described by appropriate membership functions. Then, Taguchi’s orthogonal array is utilized to provide the experimental layout. A linear optimization based on the weighted additive goal programming model is built to minimize the deviations of the product/process targets from their corresponding imprecise fuzzy values specified by the process engineer’s preferences. The result shows that a good setting can be obtained for the controllable factors of the plastic injection modeling process by integrating the Taguchi method with their proposed fuzzy model.

Competitiveness is the ability and performance of a firm, sub-sector or country to sell and supply goods and/or services in a given market. Competitiveness engineering is a systematic procedure, and includes a series of activities to assess and enhance competitiveness, with competitiveness assessment being one of the major tasks. There have been many relevant references in this field, but most of them focused on exploring the factors affecting competitiveness (such as cost, quality, customer satisfaction, technical competence, etc.) and ways to improve competitiveness (such as balanced scorecard, blue ocean strategy, lean production, green supply chain, learning organization, etc.). However, how to assess competitiveness in a quantitative way is rarely discussed. Chapter 16 discusses the fuzzy approach for
assessing the long-term competitiveness of a semiconductor product proposed by Chen. Initially, the fuzzy linear regression approach is applied to estimate the unit cost of a semiconductor product. Then the cost region for the semiconductor product to be competitive is specified. The mid-term cost competitiveness of the semiconductor product is assessed by comparing the estimated unit cost and the competitive region. To obtain the long-term cost competitiveness, the mid-term competitiveness trend is taken into consideration. A practical example with data collected from a real semiconductor-manufacturing factory is used to demonstrate the applicability of the proposed methodology.

Chapter 17 by Li and Nan extends the technique for order preference by similarity to ideal solution (TOPSIS) for solving multi-attribute group decision making (MAGDM) problems under Atanassov intuitionistic fuzzy set (IFS) environments. The basic principle of TOPSIS is that the chosen alternative should have the shortest distance from the ideal solution and the farthest distance from the negative-ideal solution. This principle can also be used to demonstrate that any alternative which has the shortest distance from the ideal solution is also guaranteed to have the longest distance from the negative-ideal solution, while there will be a compromise solution at the point where the level of satisfaction of both criteria are the same. However, the highest ranked alternative by TOPSIS is the best in terms of the ranking index, which does not mean that it is always the closest to the ideal solution. Many studies have combined fuzzy logic and TOPSIS for applications under an uncertain environment. In Li and Nan’s method, the weights of the attributes and the ratings of the alternatives for the attributes are extracted from the fuzziness inherent in the decision data and the decision making process, and are described using Atanassov IFSs. An Euclidean distance measure is then developed to calculate the differences between the alternatives for each decision maker and the Atanassov IFS positive ideal solution (IFSPIS) as well as the Atanassov IFS negative ideal solution (IFSNIS). The degree of relative closeness to the Atanassov IFSPIS are then calculated for all alternatives with respect to each decision maker in the group. Then all decision makers in the group may be regarded as “attributes” and a corresponding classical MAGDM problem is generated and then solved by the TOPSIS.

In the field of supply chain management, Wang, Chang, and Wang develop a comprehensive framework to determine supplier behavior in the last chapter. They employ a 2-tuple linguistic variable to perform the initial evaluation and final assessment while keeping track of both fuzzy linguistic information and data from suppliers. Their study also draws the complete framework for the issue of supplier performance assessment without limitations on categories of variables and scales.

The purpose of this book is twofold. First, it is intended to provide audiences with an extensive exploration of fuzzy technologies, computing, and systems, while providing pragmatic examples of application, making this book valuable to practitioners and professionals in various industries. Second, it is expected to play a useful role in higher education, as a rich source of supplementary readings in relevant courses and seminars. We hope that this book will serve its purpose well.

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