Applications of Soft Computing Techniques in Response Surface Based Approximate Optimization

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The paper describes the construction of global function approximation models for use in design optimization via global search techniques such as genetic algorithms. Two different approximation methods referred to as evolutionary fuzzy modeling (EFM) and neuro-fuzzy modeling (NFM) are implemented in the context of global approximate optimization. EFM and NFM are based on soft computing paradigms utilizing fuzzy systems, neural networks and evolutionary computing techniques. Such approximation methods may have their promising characteristics in a case where the training data is not sufficiently provided or uncertain information may be included in design process. Fuzzy inference system is the central system for of identifying the input/output relationship in both methods. The paper introduces the general procedures including fuzzy rule generation, membership function selection and inference process for EFM and NFM, and presents their generalization capabilities in terms of a number of fuzzy rules and training data with application to a three-bar truss optimization.

Key Words : Fuzzy Logic, Soft Computing, Genetic Algorithms, Function Approximations

1. Introduction

There have been significant recent applications of formal optimization methods in industry level engineering design problems (Sobieski et al., 2000). In simulation-based design, an optimum solution is obtained through iterative search process of an optimizer in conjunction with finite element analysis and/or CAE tools. Modern optimization techniques employ the state of the art response surface methods (RSM) for savings in computational resource requirements (Carpenter and Barthelemy, 1993; Roux et al., 1996; Lee and Hajela, 2000). RSM is especially efficient when the optimization is performed based on experimental design data. Highly reliable RSM could be established by an optimal number of design data obtained from the design of experiments via analyses of variance (Giunta et al., 1997; Kim and Kang, 2000). Neural network based global function approximations may be used as alternatives when global search strategies such as genetic algorithms (GA's) and/or simulated annealing are adopted (Hajela and Berke, 1992; Hajela and Lee, 1995; Lee and Hajela, 1996). In practical situations where, for example, dynamic responses pertinent to noise and vibration are calculated via an unsteady finite element analysis or a single execution of experiment is expensive, one must develop approximation models using an insufficient number of design data within a limited time frame of product development. In such cases, both polynomial based RSM and neural networks may generate poor generalization capabilities due to their requirements of a considerable number of input-output training data.

The paper proposes the application of fuzzy inference systems (FIS) in constructing global function approximations for subsequent use in design optimization when the number of design

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data for training response surface models is not enough. Two different methods using FIS are discussed: one is evolutionary fuzzy modeling (EFM) and the other is neuro-fuzzy modeling (NFM). Building an optimal and robust fuzzy model has a critical effect on the performance of the fuzzy logic. EFM (Satyadas and KrishnaKumar, 1994) is an optimization process to determine the types of membership functions and their parameters of interest by adapting fuzzy rules, where the optimization process is performed by evolutionary computing methods such as genetic algorithms. When the training data is of the type of fuzzy rules, a function approximation model should be obtained by determining the optimal parameters for input and output membership functions that describe the conditions and actions in fuzzy rules, respectively. Therefore, GA's will treat a set of membership function parameters as design variables and evolve them until the error between defuzzified outputs and actual target values is minimized. NFM is another adaptive system identification model (Jang, 1993) wherein a neural network-like architecture is constructed from a number of fuzzy rules that are to be expressed by fuzzy membership functions and polynomials to represent nonlinear behaviors between neurons of each layer; it should be noted that membership parameters could be optimally adjusted as well.

EFM and NFM belong to a category of soft computing (SC) utilizing fuzzy systems, neural networks and evolutionary computing. Soft computing is an emerging approach to computing which parallels the remarkable ability of the human mind to reason and learn in an environment of uncertainty and imprecision (Zadeh, 1992); SC enables to incorporate human knowledge effectively, deal with imprecision and uncertainty, and learn to adapt to unknown or changing environment for better performance (Jang et al., 1997). Such approach received promising attention in analysis and design of nonlinear systems in the context of adaptive control (Takagi and Sugeno, 1985; Yamakawa, 1992), learning process (Berenji and Khedkar, 1992), and artificial life (Sipper, 1995). One may consider the construction of global approximate response surface (in design optimization) as the modeling and identification of nonlinear systems (in controls). The present study proposes EFM and NFM for global function approximation for use in the optimization of nonlinear structural systems when the number of training data and their quality are of concern. The present paper examines their generalization capabilities in terms of fuzzy rules and training data for a three-bar truss design problem, and extracts the prospective characteristics from such approximation methods for further extensive applications.

2. Fuzzy Inference Systems

The fuzzy inference system (FIS) is a computing framework based on the traditional concepts of fuzzy set theory, fuzzy if-then rules and fuzzy reasoning (Jang et al., 1997). The fuzzy logic and fuzzy inference system have been widely applied in the area of control systems design, and have also received recent attention in multiobjective optimization of structural and mechanical systems. The basic structure of FIS consists of three components: fuzzy rules are expressed by linguistic rule base information, fuzzy membership functions are introduced to represent a set of fuzzy rules, and a reasoning mechanism performs the inference procedure upon the rules and given facts to derive a reasonable output or conclusion.

Using fuzzy sets, the linguistically expressed rules can be defined for a given set of input and output variables. The fuzzy rules use the conditional statements of if-then rules. For example, a standard fuzzy if-then rule assumes the following form:

$$\text{If } x \text{ is A, then } y \text{ is B.} \qquad (1)$$

In the above, A and B are the linguistic values of the input variable x and the output variable y, respectively. The if-part of the rule "x is A" is called the antecedent or condition, and the then-part of the rule "y is B" is called the consequent or action. In the case of boolean logic, if the antecedent part of the if-then rule is true, then the consequent part of the if-then rule is also true. However, the fuzzy if-then rules do not operate in the same manner since they use the fuzzy statement. Instead, in fuzzy if-then rules, if the antecedent is partially true to some degree, then the consequent is also partially true to that same degree. If-then rules can also have more than one part in both the antecedent and consequent. In this case, all antecedent parts are calculated simultaneously that generate a single value by using the logical operators. This results from the antecedent part and affects all the consequents equally by an implication function.

The definition of a fuzzy set is a simple extension of the definition of a classical set in which the characteristic function is permitted to have any values between 0 and 1. From the definition of a fuzzy set, for example, the linguistic values of the input variable in the antecedent in Eq. (1) could be expressed as a set of ordered pairs:

$$A=\{(x,\ \mu_A(x))\mid x\in X\} \tag{2}$$

where $\mu_A(x)$ is called the membership function for the fuzzy set A. The membership function can be selected as any arbitrary curve according to one's subjective perception based on the behavior of a function. One can introduce such membership function to the consequent as well. It should be noted that the basic FIS can take either fuzzy inputs or crisp inputs, but the outputs it produces are almost always fuzzy sets. It is necessary to have a crisp output, especially in a case where FIS is used as a decision-making device. Therefore, a method of generating an aggregated decision value, referred to as defuzzification, is needed to extract a crisp value that best represents a fuzzy set. The procedure for fuzzy rule aggregation and subsequent defuzzification is summarized for completeness.

Consider a case where a number of fuzzy rules are made of more than one part in the antecedent and a single part in the consequent. For each of fuzzy rules, all antecedent parts are calculated simultaneously to generate a single value by using the logical operators; this process results from the antecedent parts, and then affects the consequent equally by an implication function. The defuzzification is then performed based on the multiply aggregated values of output fuzzy sets from each of fuzzy rules. When the maximum method as an implementation of aggregation process is considered for example, the order in which the rules are aggregated does not matter for more than two output fuzzy sets due to its commutative characteristics in aggregation. The aggregation of two output fuzzy sets returned by the implication process generates another fuzzy set. In order to extract useful information from newly aggregated fuzzy set, it must be defuzzified to obtain a single value as well. Although the conversion of a fuzzy set into a single crisp value is possible in several different ways, the present study adopted the centroid method to calculate the center of a region generated by all aggregated output fuzzy sets. FIS with a crisp output is shown in Fig. 1, where a basic FIS transforms an aggregated output fuzzy set into a single crisp value.

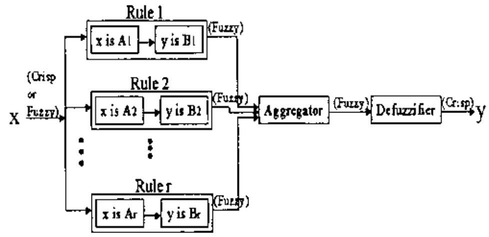

Fig. 1 Fuzzy inference system

3. Evolutionary Fuzzy Modeling

EFM employs evolutionary algorithms to evolve the fuzzy model of a nonlinear and/or multimodal system. The general approach to using any parameter optimization technique for fuzzy modeling has been to tune the parameters of predefined rules. Both antecedent and consequent are expressed by fuzzy membership functions in EFM. In the present study, genetic algorithms are used to evolve near-optimum fuzzy membership parameters and fuzzy rule structure through an iterative procedure using appropriate performance index and available system information. Building an optimal and robust fuzzy model has

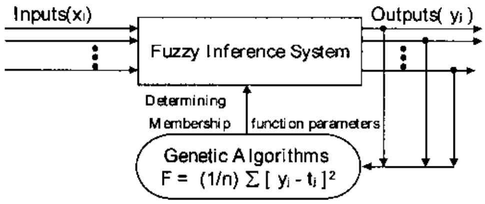

Fig. 2 Schematic of evolutionary fuzzy modeling

a critical effect on the performance of the fuzzy logic. In order to tune a fuzzy model, EFM approach is introduced in the present study. Even though the type of membership functions and the number of rules can be varied during the GA evolution, the only tuning parameters in this work are membership parameters used to define the shape of each membership function. It should be noted that the additional consideration of selecting the type of membership functions produces more intelligent EFM framework, however, resulting in the increase in the computational costs during the GA based optimization process. GA's will treat a set of membership function parameters as design variables and evolve them until the error between defuzzified outputs and actual target values is minimized.

The GA based optimization statement for optimal tuning of a model with m number of inputs (the number of input and output membership parameters) and n number of outputs (the number of training data) can be written as follows (Kim and Lee, 1999):

$$\text{minimize } E_{EFM}=\frac{1}{n}\sum_{j=1}^{n}(y_j-t_j)^2 \quad (3)$$
$$\text{subject to } \nu_i^L \leq \nu_i \leq \nu_i^U,\ i=1,\cdots,m$$

The objective function in EFM was considered as the mean square error between the predicted output, y_j, and the actual output, t_j. As mentioned earlier, the approximated value y_j is evaluated through the input and output membership functions for the antecedent and consequent, respectively. The design variables in this approach are membership function parameters, limited by proper lower and upper bounds. It should be noted that each design variable represents a parameter that defines the membership function. The optimal solution for this design problem is

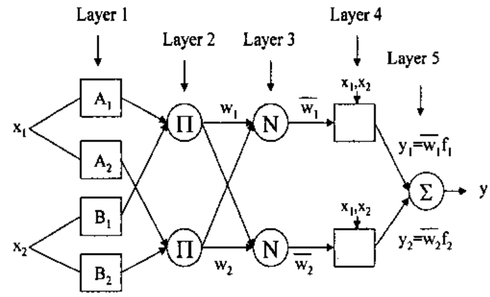

Fig. 3 Architecture of neuro-fuzzy modeling

the set of membership parameters generating the most accurate approximation. The general procedure for EFM based optimal membership parameter extraction is shown in Fig. 2.

4. Neuro-Fuzzy Modeling

Neuro-fuzzy model adopted in this work is based on the original version of the adaptive network-based fuzzy inference system, referred to as ANFIS. NFM is a class of adaptive networks that are equivalent to fuzzy inference systems whose basic architecture is mostly similar to backpropagation neural networks. This system utilizes a hybrid learning rule to optimally tune the fuzzy system parameters of a first order Sugeno model (Sugeno and Kang, 1988); the consequent part in fuzzy rule is represented by a first order polynomial that is a linear function of input design variable(s), while the antecedent parts are described by a parameterized membership function. Assume that a couple of fuzzy rules for two inputs x1 and x2, and one output y are expressed as follows (Hines, 1997):

If x_1 is A_1 and x_2 is B_1, then $y=p_1x_1+q_1x_2+r_1$
If x_1 is A_2 and x_2 is B_2, then $y=p_2x_1+q_2x_2+r_2$ (4)

where A's and B's are linguistic expressions for input variables, and p's, q's and r's are constant coefficients in the consequent part. The basic NFM architecture consisting of the aforementioned fuzzy rules is shown in Fig. 3. It should be noted that the architecture has 5 layers between input variables and output response, and each layer has a number of nodes depending on the number of rules and their antecedent parts. A brief summary of how NFM is established is explained for completeness.

Layer-1: Generate the membership function for each of the antecedent parts. It should be noted that the membership function parameters are design variables during the backward pass of NFM.

Layer-2: Create the rule strength between antecedent parts; each node output represents the firing strength of a rule. At this point, any T-norm operators that perform fuzzy AND' can be used as the node function in the layer.

Layer-3: Normalize the firing strength of a rule. The i-th node calculates the ratio of the i-th rule's firing strength to the sum of all rule's firing strengths.

Layer-4: Compute the rule in consequent part. The Sugeno representation in the i-th rule is multiplied by the i-th rule's normalized strength ratio. The polynomial coefficients are design variables in the forward pass of NFM.

Layer-5: Sum all the rules obtained up to Layer-4. The single node in the layer is a fixed node that computes the overall output as the summation of all incoming signals.

NFM is a tuning process to optimize both membership function parameters in antecedent parts and Sugeno coefficients in consequent parts using separate optimization strategies. That is, two-pass procedure in hybrid learning of NFM is considered; the forward pass determines polynomial coefficients with the antecedent membership parameters fixed, while the backward pass may use any optimization methods to obtain the best combination of membership parameters holding Sugeno coefficients fixed. Since NFM adopts two different optimization procedures to reduce the error between the actual response value and the approximate value, the training rule is called hybrid. In the present study, the consequent coefficients are obtained via singular value decomposition (Golub and Van Loan, 1989), and the antecedent parameters are updated by backpropagating the existing errors as usually done in gradient based backpropagation neural networks. The optimization process during the

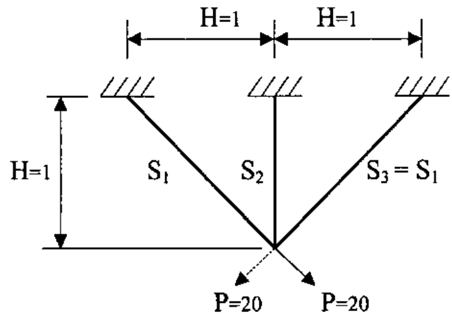

Fig. 4 Three-bar planar truss

forward pass is stated as follows:

$$\text{minimize } E_{NFM}=\sum_{i=1}^{N}\frac{1}{2}(y_i-t_i)^2 \tag{5}$$
$$\text{subject to } \nu_j^L\leq\nu_j\leq\nu_j^U,\ j=1,\cdots,m$$

The squared error is taken as an objective function, where N denotes the number of training data and m is the number of input parameters in antecedent parts, while yi and ti represent the approximate output obtained through Layer-5 and actual output, respectively. This optimization process is conducted via the gradient based search method, constrained by lower and upper bounds on input membership parameters.

5. Design Problem

A three-bar planar truss problem is explored as a test bed to support the proposed strategies of EFM and NFM. Consider the three-bar truss problem with two cross sectional areas S_1 and S_2 as design variables as in Fig. 4. The objective is to minimize both the weight of the structure and the vertical displacement subjected to constraints on static stresses. The mathematical statement of this optimization problem can be written as follows:

$$\text{minimize } f(S)=\left(\frac{W}{W^*}-1\right)^2+\left(\frac{\delta}{\delta^*}-1\right)^2 \tag{6}$$
$$\text{subject to } \sigma_1(S_1,\ S_2)\leq 20.0$$
$$\sigma_2(S_1,\ S_2)\leq 20.0$$
$$\sigma_3(S_1,\ S_2)\leq -15.0$$
$$0.1\leq S_i\leq 5.0,\ i=1,\ 2$$

where the multiobjective function in Eq. (4) includes two components of the weight of the structure W and the tip deflection δ, where W^* and δ^* denote the corresponding optimal objec-

Table 1 Fuzzy rules generated by 9 design data

S_2 \ S_1	δ S	δ M	δ H	σ_1 S	σ_1 M	σ_1 H
S	VLA	LA	LO	VLA	LA	LA
M	LA	LA	LO	LO	LO	LO
H	LA	LO	LO	VLO	LO	VLO
S_2 \ S_1	σ_2 S	σ_2 M	σ_2 H	σ_3 S	σ_3 M	σ_3 H
S	VLA	LA	LO	LO	LO	VLO
M	LA	LA	LO	VLA	VLA	VLA
H	LA	LO	LO	VLA	VLA	VLA

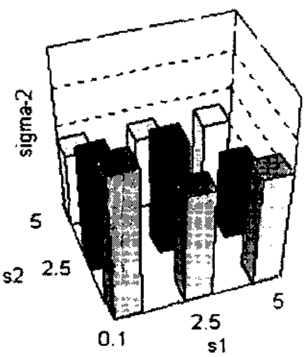

Fig. 5 Levels of σ_2 from 9 design data

tive function values obtained from single objective design problem.

6. Results and Discussion

6.1 Approximation by EFM

Suppose that four different response functions such as the vertical displacement (δ) and three stress levels (σ_1, σ_2, and σ_3) need to be approximated, while the weight of the structure is easily obtained by a simple equation. In EFM, an initial number of design data is necessary to establish the fuzzy rules. One can first establish the fuzzy rules using 9 design data that are evenly selected from an entire design space, referred to as CASE-1; design points are chosen at 0.1 (small), 2.5 (medium) and 5.0 (high) for each design variable, resulting in a combination of 9 design data; each of design data corresponds to a fuzzy rule. Figure 5 shows a graphical representation of the second stress level σ_2 with respect to design variable. From this figure, one of fuzzy rules describing σ_2 in CASE-1 can be expressed as follows:

If S_1 is small and S_2 is small, then σ_2 is very large. (7)

After the visual observation of all the response function values, a total of 36 rules are generated as shown in Table 1. Fuzzy membership functions for input variables and/or output responses are selected based on their changes in magnitude. In the present study, a Gaussian membership function is used to describe the behavior of individual input design variable. Two different types of membership functions are applied to model the output responses; a triangular membership function is used when the individual output value is obviously different from adjacent values, while trapezoidal membership functions are employed in a case where more than two response values are considered to be located within a moderate range of magnitude. Consider the second case (CASE-2) such that fuzzy rules are generated from 16 design data. Design points are selected at 0.1 (small), 1.7 (less small), 3.3 (less large) and 5.0 (large) for each design variable, resulting in a total of 16 design data that establish the same number of fuzzy rules available. The idea of how input/output fuzzy membership functions are determined in this case is the same as that in the previous case.

Genetic search based optimization of the three-bar truss problem is conducted using the EFM based global approximation model. Two cases, CASE-1 and CASE-2 employ a number of sets of training data to enhance the generalization capability. Table 2 shows the optimized objective function values according to the number of training data, which are evenly selected over the entire design space as well. An increase in the number of training data produces more accurate solution in both cases, as expected. CASE-2 of 16 rules is better than CASE-1 of 9 rules, which implies that the number of fuzzy rules is more critical than the number of training data in generalization; EFM

Table 2 EFM based optimization results

	9 rules		16 rules	
# of data	W*	δ^*	W*	δ^*
9	10.52	7.23	-	-
16	7.62	6.91	7.03	4.92
25	6.68	5.25	5.21	3.79
36	6.23	4.74	5.19	3.74
49	5.47	4.11	5.17	3.69
64	-	-	5.14	3.65
Exact Solution	$W^*=5.12,\ \delta^*=3.63$			

by 16 rules with 25 training data locates approximate values that are close to exact solutions, while a case of 9 rules with 49 data is still very off.

6.2 Approximation by NFM

Neuro-fuzzy modeling requires a greater number of initial training data compared to evolutionary fuzzy modeling since each of rules in NFM has 3 coefficients in the consequent part as shown in Eq. (4). For example, CASE-1 with 9 rules has a total of 27 coefficients, which implies that at least 27 training data is necessary to perform the SVD procedure. CASE-1 and CASE-2 that were used in EFM are also applied to NFM without imposing the output membership functions on the consequent parts; Gaussian membership functions are considered to express the antecedent parts of fuzzy rules in NFM. Solutions by NFM based global approximate optimization are shown in Table 3 in terms of the number of rules and the number of training data. As in the case of EFM, the accommodation of larger number of rules and larger number of training data improves the generalization capability. From results in Tables 2 and 3, EFM and NFM are similar to each other when CASE-2 of 16 rules with 49 or 64 training data is compared. However, EFM using CASE-1 of 9 rules with 36 or 49 training data is better than NFM under the same conditions. That is, both EFM and NFM generate reliable approximate solutions when a large number of design data is available. EFM is more efficient than NFM in a case where the design data is not sufficiently provided. Another advantage of EFM is that when the fuzzy model should be optimally tuned, it requires a smaller number of design variables (membership parameters) than NFM as shown in Table 4; the number of parameters for modeling the second stress level σ_2 is presented, where G, TR, and TZ denote Gaussian, triangular, and trapezoidal membership functions, respectively, and S represents the linear Sugeno model. However, EFM employs the membership functions to express the consequent parts, thereby increasing the degree of complexity such that what kind of membership function should be considered; the quality of system modeling and identification is subject to the choice of the membership function as well.

Table 3 NFM based optimization results

	9 rules		16 rules	
# of data	W*	δ^*	W*	δ^*
36	6.54	5.01	-	-
49	5.59	4.23	5.19	3.71
64	-	-	5.14	3.64
Exact Solution	$W^*=5.12,\ \delta^*=3.63$			

Table 4 Number of tuning parameters for σ_2

	9 rules		16 rules	
	EFM	NFM	EFM	NFM
antecedent	12-G	12-G	16-G	16-G
consequent	3-TR / 8-TZ	27-S	3-TR / 12-TZ	48-S
total	23	39	31	64

6.3 Comparison between EFM and NFM

It is necessary to compare the approximated response functions obtained from EFM and NFM; for detailed implication, the paper examines the predicted behaviors of σ_2 as a representative. Figs. 6 through 8 demonstrate the global approximation by EFM and NFM with 9 rules. Figure 7 shows more improved results compared to Fig. 6; the use of a large number of training data facilitates to tune the membership parameters more effectively, resulting in more accurate generation of approximated response. Figure 8 is a result done by NFM using 49 training data; this result is comparable with that from EFM in Fig. 7, but one can realize that NFM result follows the linear fashion due to the use of the linear Sugeno model. Such approximation results can be interpreted in terms of

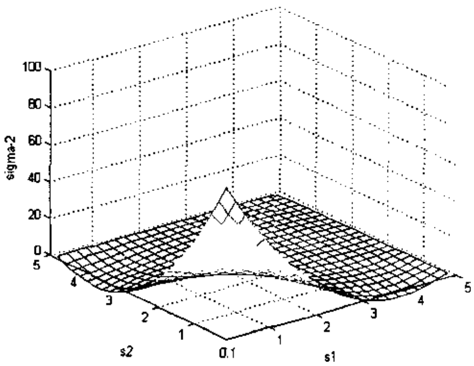

Fig. 6 EFM result using 9 rules and 9 data

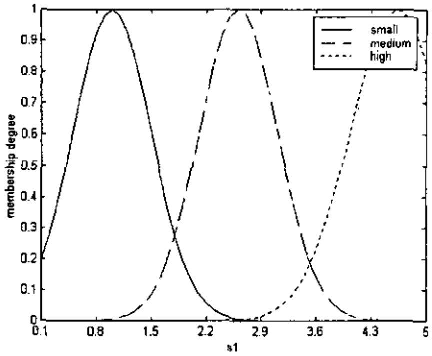

Fig. 9 Input MF using 9 rules and 9 data in EFM

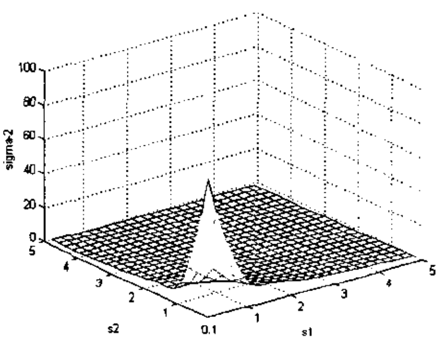

Fig. 7 EFM result using 9 rules and 49 data

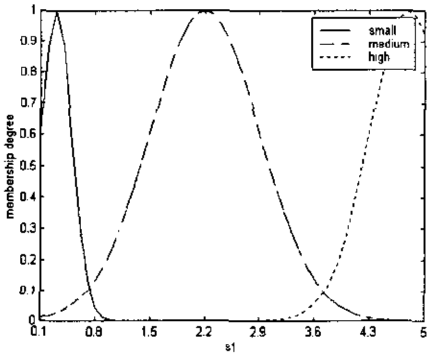

Fig. 10 Input MF using 9 rules and 49 data in EFM

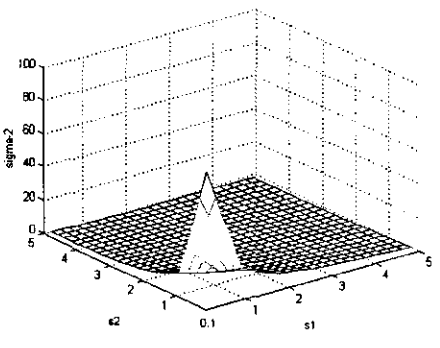

Fig. 8 NFM result using 9 rules and 49 data

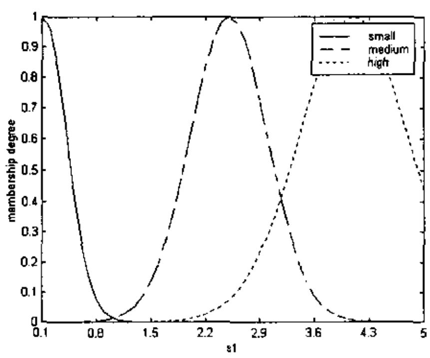

Fig. 11 Input MF using 9 rules and 49 data in NFM

optimized membership functions as well. Figures 9 through 11 are optimal input membership functions for a cross sectional area, S_1. It should be reminded that a Gaussian membership function is used to represent the antecedent parts. In Fig. 9, three rules have been tuned using only 3 training data that are selected at the S_1 axis, thereby resulting in the even distribution of each membership function over the bound on design variable, $0.1 < S_1 < 5.0$; each training data should take care of each rule. On the other hand, the use of more training data (in Fig. 10) produces uneven distributions in membership function locations; one or two out of 7 training data tune the membership functions representing small' and high', while most of the training data are used to optimize the medium' membership function. NFM result in Fig. 11 is almost similar to EFM result in Fig. 10.

Results by the use of 16 rules are also presented in Figs. 12 to 14. They show the compatible trends in result as in the case of 9 rules; especially NFM with 16 rules in Fig. 14 becomes almost nonlinear around the peak value of σ_2 due to the increase in the number of rules. Optimized output membership functions ac-

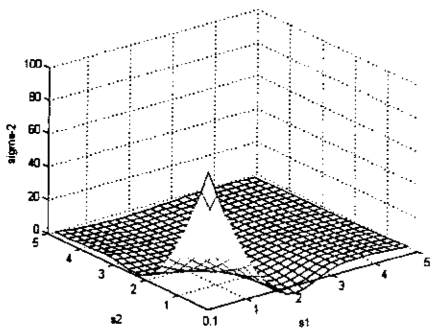

Fig. 12 EFM result using 16 rules and 16 data

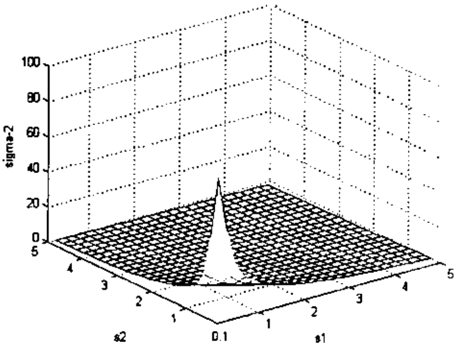

Fig. 13 EFM result using 16 rules and 64 data

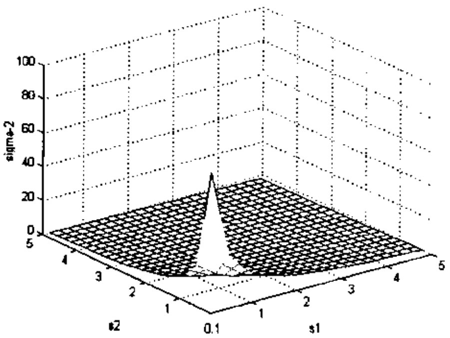

Fig. 14 NFM result using 16 rules and 64 data

cording to the number of rules and the number of training data are shown in Figs. 15 through 18. As mentioned earlier, triangular and trapezoidal functions are employed to describe the consequent parts when the approximation is conducted via EFM. In comparison between Figs. 15 and 16, one can detect the major difference in coverage of membership function; low' membership function in Fig. 15 fills in most of output region since 9 training data is not enough to represent the realistic response, while in the case of 49 training data as shown in Fig. 16, most of response function values are approximated to locate at the highest and smallest. Such output membership

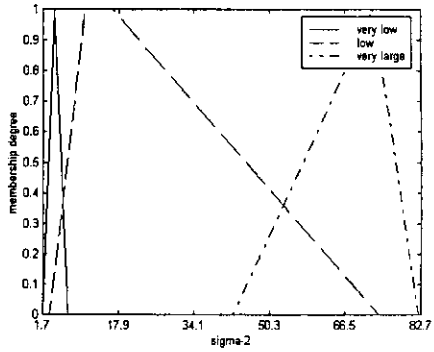

Fig. 15 Output MF using 9 rules and 9 data in EFM

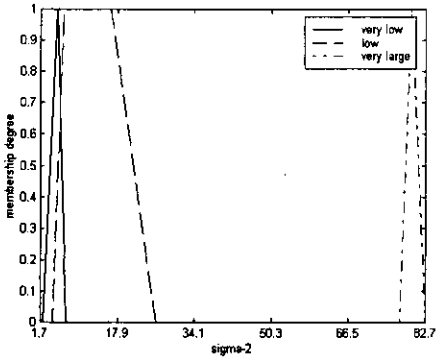

Fig. 16 Output MF using 9 rules and 49 data in EFM

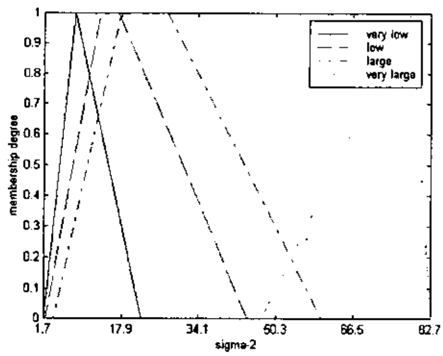

Fig. 17 Output MF using 16 rules and 16 data in EFM

function results may produce corresponding approximations of σ_2 in Figs. 6 and 7. When 16 rules are used, similar results are obtained for optimized output membership functions as shown in Figs. 17 and 18.

Throughout the numerical experiments in both EFM and NFM, the present paper may be summarized as follows: the success in fuzzy logic based global response modeling depends on the number of fuzzy rules to describe the system behavior, the type of

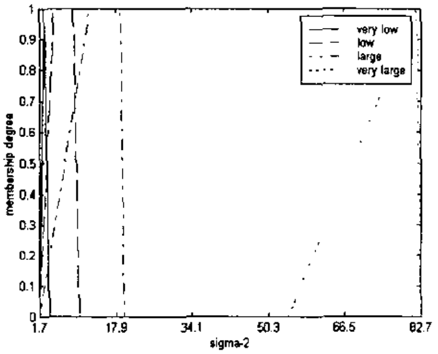

Fig. 18 Output MF using 16 rules and 64 data in EFM

membership functions to realize the fuzzy expressions, the number of training data to tune the membership parameters, and the optimization strategies to minimize errors between actual and predicted responses.

7. Closing Remarks

The paper explores the applications of fuzzy inference systems in modeling global function approximations for use in design optimization. A minimal number of design data is selected from an entire design space to generate the fuzzy rules describing the input-output relationships in the global nature. An increase in the number of training data enhances the generalization capability in both EFM and NFM. EFM is more efficient when the design data is not sufficiently provided. NFM in the present study employs the first order Sugeno model; such method is easy to implement, and works well with a smaller number of membership functions during system modeling. Main drawbacks of NFM reside in the fact that it necessitates a greater number of training data to determine the coefficients of polynomial in the consequent parts. Through the numerical experiments in both EFM and NFM, the present paper points out that the success of response modeling depends on the number of fuzzy rules to describe the system behavior, the type of membership functions to realize the fuzzy expressions, the number of training data to tune the membership parameters, and the optimization strategies to minimize errors between actual and predicted responses. For further study, data clustering technique for automatic fuzzy rule generation scheme is underway to improve the modeling quality.

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