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## Fuzzy modeling by Active Learning Method

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### 1. Introduction

The constructions of different modeling methods are similar. The models are consisted of the following major stages:

- 1- Recognizing the true or most effective inputs.
- 2- Finding the numerical relationship between inputs and output.
- 3- Explaining the numerical relationship mathematically.
- 4- Utilizing the mathematical expressions to calculate the output using different inputs.
- 5- Comparing the calculated and actual outputs and calculating the error.
- 6- Modifying the mathematical expressions based on the calculated error.

These stages seem to be complicated. This complexity seems to be due to the quantitative and exact definitions of the mentioned stages (Bagheri Shouraki and Honda, 1998). There are some demonstrations that the mentioned stages are performed qualitative with non-exact concepts in the human brain (Schmidt, 1985), therefore any effort toward of expressing them using exact expressions (such as mathematics) are expected to have some differences with human thinking or modeling method. In the other words, the utilizing of exact mathematics in modeling has contradiction with human abilities (Bagheri Shouraki and Honda, 1999).

Fuzzy concepts (e.g. Zadeh 1965) and related inferences (e.g. Mamdani 1974) proposed a new approach to human modeling and calculation methods. Although, different powerful fuzzy modeling methods have been developed up to now, but some of these methods are different with real human modeling method, because of utilized mathematics and exact calculations in their constructions (Bagheri Shouraki and Honda, 1999). The construction of human modeling is similar to the above stages, but avoids of mathematical complexities. Active Learning Method (ALM) is one of the fuzzy modeling methods Which uses basic level of mathematics. ALM was innovated by Bagheri Shouraki and Honda (1997). ALM has very simple algorithm that avoids of mathematical complexity and its accuracy and exactness increase unlimitedly by increasing the number of iterations of its algorithm.

It is very difficult for human to memorize the numerical data points but tries to memorize the general behavior function of data points. In addition, for modeling, the human converts a MIMO (Multi Inputs - Multi Outputs) system to some SISO (Single Input - Single Output) systems and then human tries to find the general behavior function in each SISO system and the effects of other inputs are considered as the deviation of data points around of the general behavior function. In addition, human can save the data points on a continuous path

which means the general behavior function, but usually can not save the randomly distributed data points in the space of variable. ALM algorithm uses all of these mentioned constructions of human modeling method.

Taheri Shahraiyi (2007) developed new heuristic search, fuzzification and defuzzification methods for ALM algorithm. In the next sections of this chapter, ALM algorithm with these modifications is explained and the ALM abilities and applications are illustrated.

2. ALM algorithm

The ALM algorithm has been presented in figure 1.

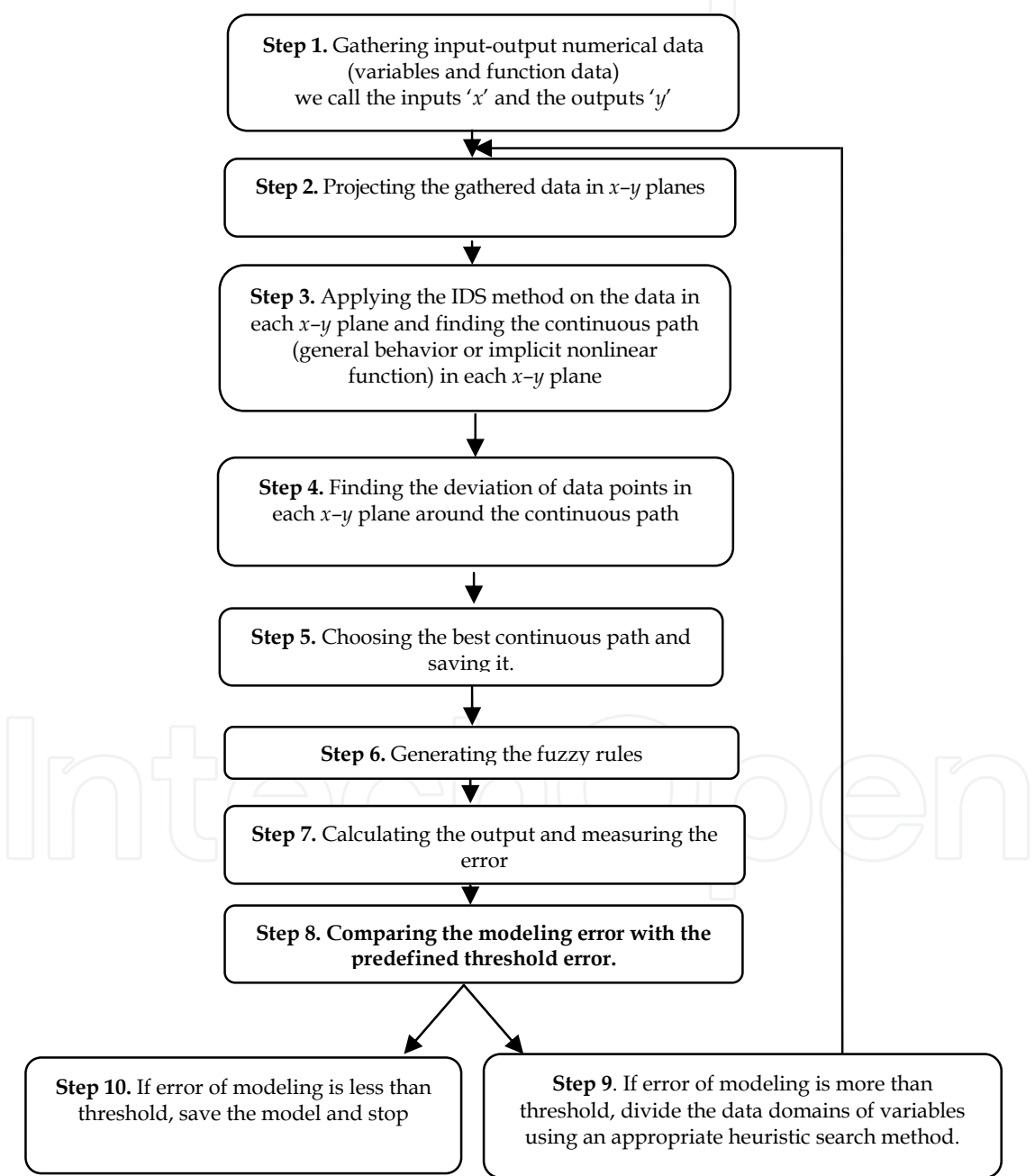


Fig. 1. Proposed algorithm for Active Learning Method.

For the purpose of explaining the ALM algorithm, the Sugeno and Yasukawa (1993) dummy non-linear static problem (equation (1)) with two input variables ( $x_1$  and  $x_2$ ) and one output ( $y$ ) is solved by this method.

$$y = (1 + x_1^{-2} + x_2^{-1.5})^2, \quad 1 \leq x_1, x_2 \leq 5 \quad (1)$$

First, some data are extracted from equation 1 and some random noises are added to data (step 1). Then the data are projected on  $x$ - $y$  plane (figures 2a and 2b) (step 2).

Step 3: The heart of calculation in ALM is a fuzzy interpolation and curve fitting method which is entitled IDS (Ink Drop Spread). The IDS searches fuzzily for continuous possible paths on data planes. Assume that each data point on each  $x$ - $y$  plane is a light source with a cone or pyramid shape illumination pattern. Therefore, with increase of distance of each data point, the intensity of light source decreases and goes toward zero. Also the illuminated patterns of different data points on each  $x$ - $y$  plane are combined and new bright areas are formed. The IDS is exerted to each data point (pixel) on the normalized and discretized  $x$ - $y$  planes. The radius of the base of cone or pyramid shape illumination pattern in each  $x$ - $y$  plane is related to the positions of data in it. The radius increases until the all of the domain of variable in  $x$ - $y$  plane be illuminated. Figures 2c and 2d show the created illumination pattern (IL values) after the combination of the illumination patterns of different points in  $x_1$ - $y$  and  $x_2$ - $y$  planes, respectively. Here, pyramid shape illumination pattern has been used.

Now, the paths, general behaviour, or implicit nonlinear functions are determined by applying the center of gravity on  $y$  direction. The center of gravity is calculated using this

$$\text{equation: } y(x_i) = \frac{\sum_{j=1}^M [y_j \times IL(x_i, y_j)]}{\sum_{j=1}^M IL(x_i, y_j)}, \text{ Where } j:1 \dots M, M \text{ is the resolution of } y \text{ domain,}$$

$y_j$  is the output value in  $j$ th position,  $IL(x_i, y_j)$  is the illumination value on  $x$ - $y$  plane at the  $(x_i, y_j)$  point or pixel, and  $y(x_i)$  is the corresponding function (path) value to  $x_i$ .

Hence, by applying the centre of gravity method on figures 2c and 2d, continuous paths are extracted (figures 2e and 2f).

Subsequently, the deviation of data points around each continuous path can be calculated by various methods such as coefficient of determination ( $R^2$ ), Root Mean Square Error (RMSE) or Percent of Absolute Error (PAE). The PAE values of continuous paths on  $x_1$ - $y$  and  $x_2$ - $y$  planes (figures 2e and 2f) are 20.4 and 13.5%, respectively (Step 4).

The results show that the path of figure 2f is better than the path of figure 2e. The selected paths should be saved because these are implicit non-linear functions. The paths can be saved as a look-up table, heteroassociative neural network memory (Fausset, 1994) or fuzzy curve expressions such as Takagi and Sugeno method (TSM) (Takagi and Sugeno, 1985). Look up tables are most convenient method and it is used for path saving in this example (Step 5).

We have no rules in the first iteration of ALM algorithm, hence we go to step 7.

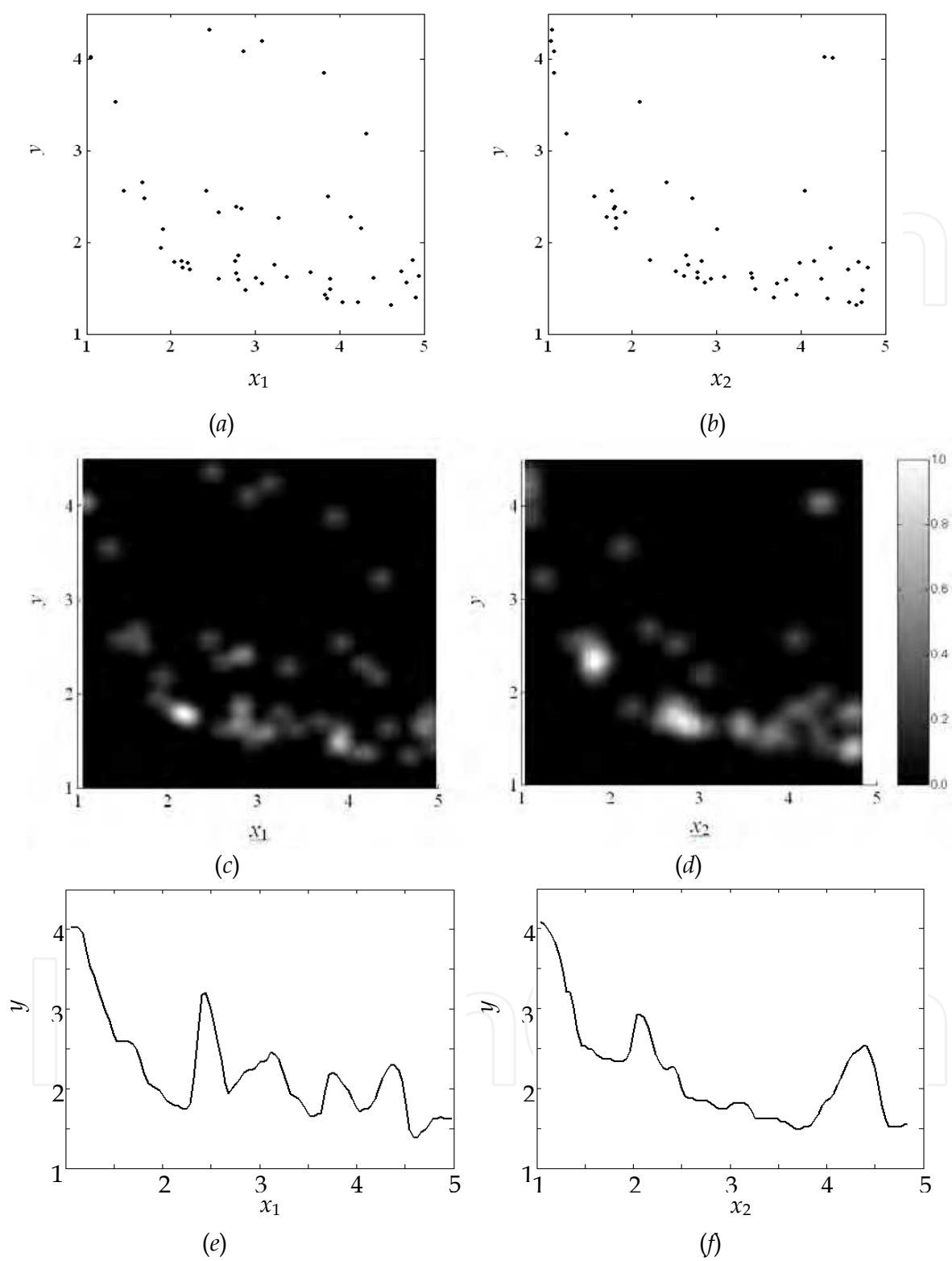


Fig. 2. (a) Projected data on  $x_1$ - $y$  plane, (b) projected data on  $x_2$ - $y$  plane; (c) Results of applying IDS method on the data points in  $x_1$ - $y$  plane, (d) results of applying IDS on the data points in  $x_2$ - $y$  plane; (e) Extracted continuous path by applying center of gravity method on figure 2c, (f) extracted continuous path by applying center of gravity method on figure 2d.

The PAE of chosen path is more than a predefined threshold PAE value (5%). Hence, the error is more than predefined error (Steps 7 & 8) and we divide each space in two by using only one variable (Step 9) and go to the step 2 of figure 1. Dividing can be performed crisply or fuzzily, but for simplicity, a crisp dividing method is used here and the fuzzy dividing will be illustrated later. The results of ALM modeling after crisp division of space to four subspaces using a heuristic search method has been presented in figure 3. According to figure 3, the following rules are generated (Step6):

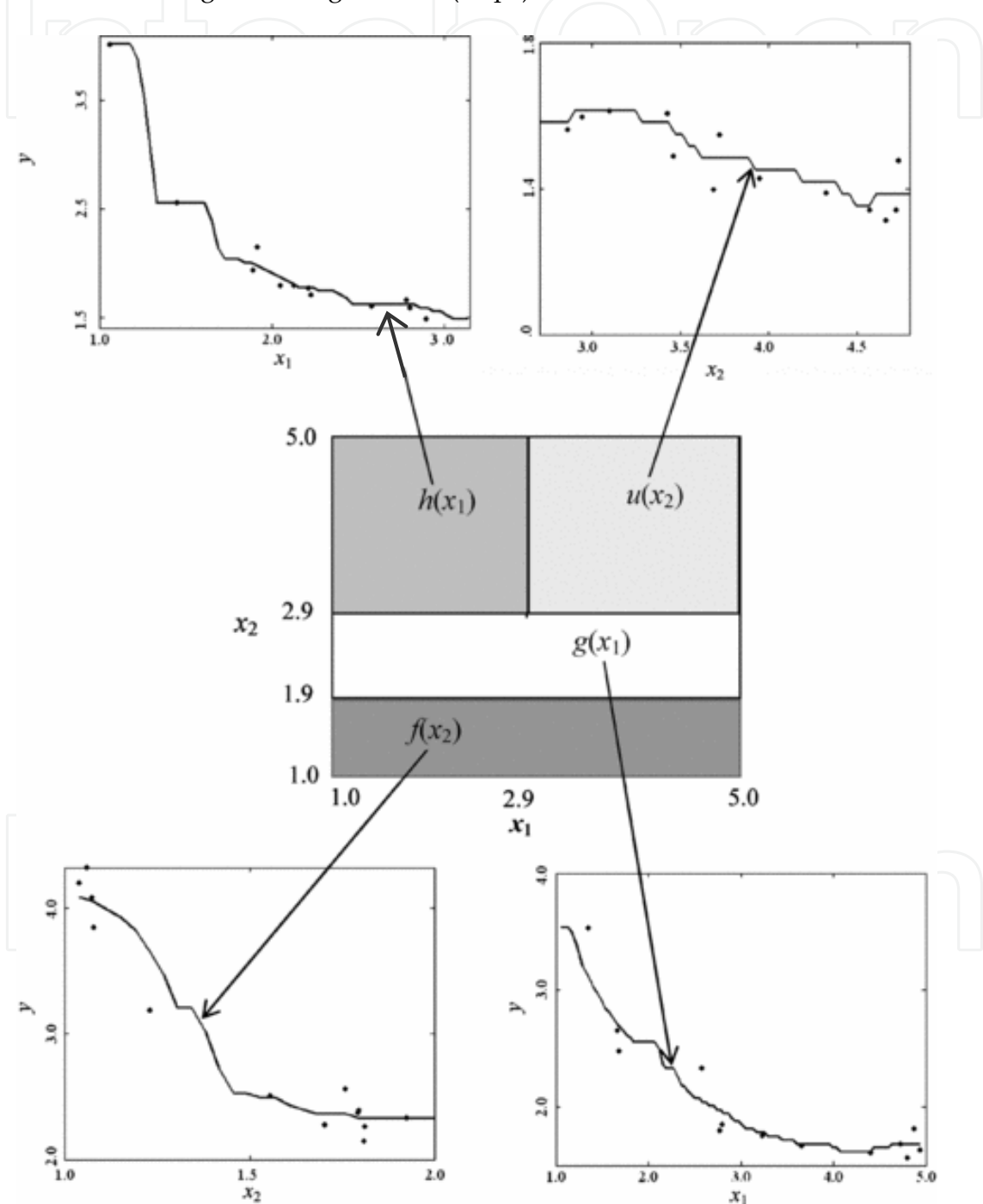


Fig. 3. Divided entire space to four subspaces using the heuristic search method and the best continuous path (implicit non-linear function), extracted for each subspace (the data points in each subspace have been shown by black circles).

If ( $x_2 \geq 1.0$  &  $x_2 < 1.9$ ) then  $y=f(x_2)$   
 If ( $x_2 \geq 1.9$  &  $x_2 < 2.9$ ) then  $y=g(x_1)$   
 If ( $x_2 \geq 2.9$  &  $x_1 < 2.9$ ) then  $y=h(x_1)$   
 If ( $x_2 \geq 2.9$  &  $x_1 > 2.9$ ) then  $y=u(x_2)$

Whenever the PAE value of the above rules is less than the threshold of 5%, the procedure of ALM modeling is stopped. Here, using four rules, a PAE of 3.8% is achieved.

## 2.1 The new heuristic search method

In this section, a new heuristic search method is introduced for dividing space in the ALM algorithm.

Partitioning of multi-dimensional space is a combinatorial problem. There is no theoretical approach for it; therefore, heuristic search methods are used (Takagi and Sugeno 1985).

The heuristic search is a guided search and it does not guarantee an optimal solution. However, it can often find satisfactory solutions (Abbass et al. 2002).

Consider  $k$  inputs ( $x_1, x_2, \dots, x_k$ ), and a single output ( $y$ ) system. The algorithm of the new heuristic search method for this system is depicted in figure 4.

Step 1. The domain of  $x_1$  is divided into two parts (small and big). Using the ALM algorithm, the best continuous path is determined for each part of the  $x_1$  domain. Assume these paths are  $f_{11}(x_j)$  and  $f_{12}(x_m)$ , which are the best paths for the first dividing step and for the small and big parts of the divided variable that are the functions of the  $j$ th and  $m$ th variables, respectively. Here, the rules for modeling are:

If ( $x_1$  is small) then  $y=f_{11}(x_j)$   
 If ( $x_1$  is big) then  $y=f_{12}(x_m)$

Then, the modeling error ( $e_{11}$ ) is calculated for the above rules. Similarly, the domain of other variables are divided and their modeling errors are calculated and a set of  $k$  errors ( $e_{11}, e_{12}, \dots, e_{1k}$ ) are generated. For example,  $e_{1k}$  shows the minimum modeling error after dividing the domain of  $k$ th variable in the first step of dividing. The variable corresponding to the minimum error is the best one for dividing of space. Suppose  $e_{1s}$  is the minimum error and it is correspond to  $x_s$ , then, the  $x_s$  domain is divided into small and big values. If  $e_{1s}$  is more than the threshold error, the dividing algorithm should continue.

Step 2. Consider all possible combinations of  $x_s-x_j$  ( $j=1,2,\dots,k$ ) for each part of  $x_s$  and then divide the domain of  $x_j$  again into two parts. Thus,  $2k$  combinations are generated ( $k$  combinations of  $x_{s(\text{small})}-x_j$  and  $k$  combinations of  $x_{s(\text{big})}-x_j$ ) where each combination has two parts. For example,  $x_{s(\text{big})}-x_j$  means that when  $x_s$  has a big value, the domain of  $x_j$  is divided into small and big parts. Similarly, the ALM algorithm is applied to each part and the minimum modeling error is calculated for each  $k$ -combinations. Suppose these are  $e_{2m}$  and  $e'_{2n}$ . They imply that the minimum modeling errors in the second step of dividing the space of variables is related to dividing of  $m$ th and  $n$ th variables for the small and big parts of  $x_s$ , respectively. Based on minimum errors,  $x_m$  and  $x_n$  are divided and the rules for modeling after dividing are:



If ( $x_s$  is small &  $x_m$  is small) then ...  
If ( $x_s$  is small &  $x_m$  is big) then ...  
If ( $x_s$  is big &  $x_n$  is small) then ...  
If ( $x_s$  is big &  $x_n$  is big) then ...

$e_{2m}$  and  $e'_{2n}$  are the local minimum errors. The appropriate global error ( $e_2$ ) can be calculated using minimum local errors ( $e_{2m}$  and  $e'_{2n}$ ). Dividing continues until the global error is less than the threshold error. In this heuristic search method, the global error decreases simultaneously by decreasing the local errors. Figure 4 depicts the next step of dividing algorithm which is step 3. This heuristic search method uses an appropriate criterion to select a variable for dividing and the median of data is used as the boundary for crisp dividing. Hence, the number of data points in the subspaces are equal.

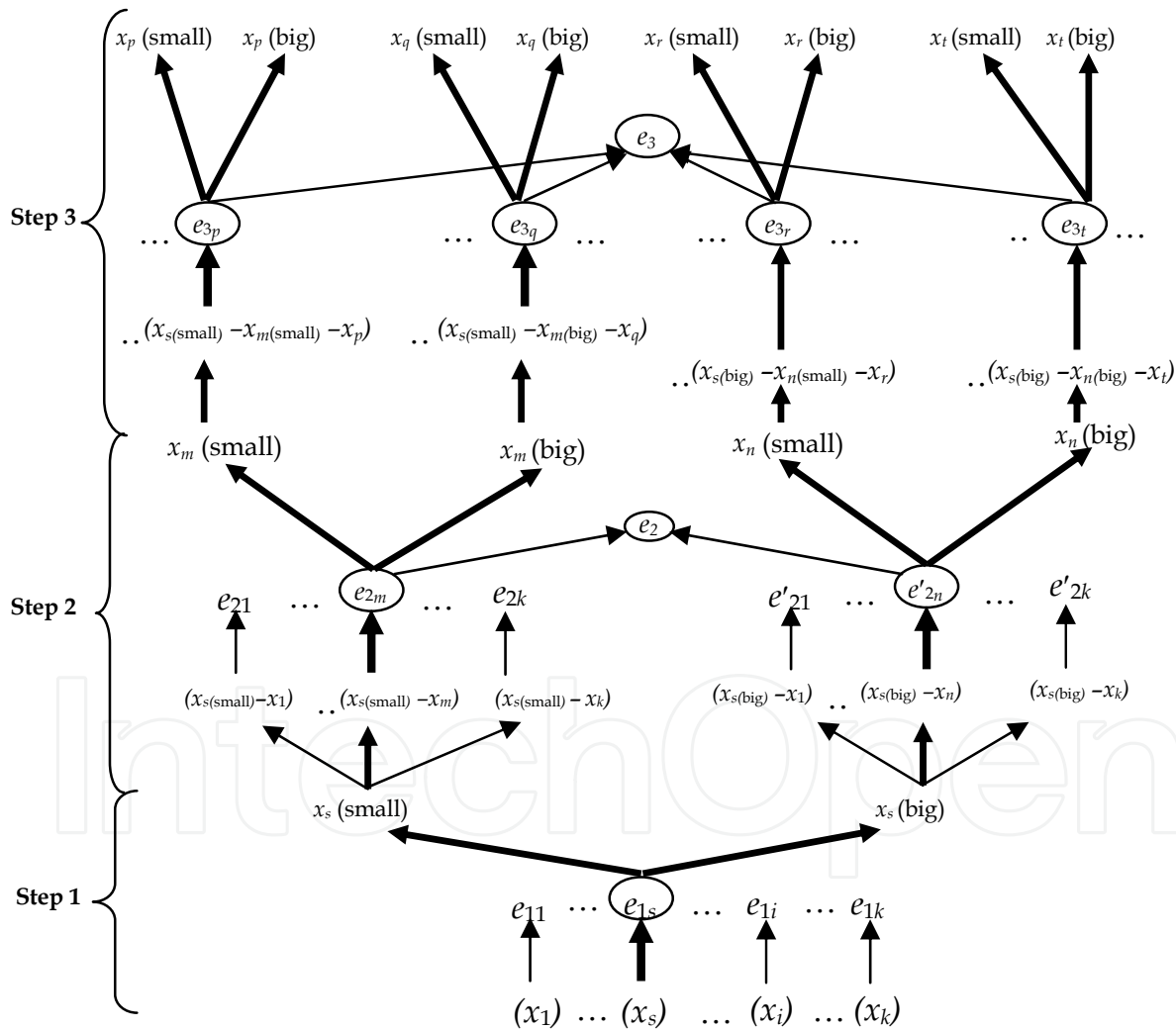


Fig. 4. Algorithm of the new heuristic search method for dividing the space.



## 2.2 Fuzzy dividing

Although, ALM implements crisp or fuzzy dividing methods, but fuzzy dividing and modeling methods can improve the ALM performance by:

- 1- Satisfaction of continuity condition,
- 2- Better knowledge extraction of multi-variable non-linear systems,
- 3- Decrease of ALM sensitivity to noise.

Fuzzy dividing is similar to crisp dividing. In crisp dividing, the dividing point of a variable is the median as shown in figure 5a. But in fuzzy dividing, the boundary of small values of a variable is bigger than the median (figure 5b) and vice versa (figure 5c). Hence, the regions of small and big values of a variable can overlap.

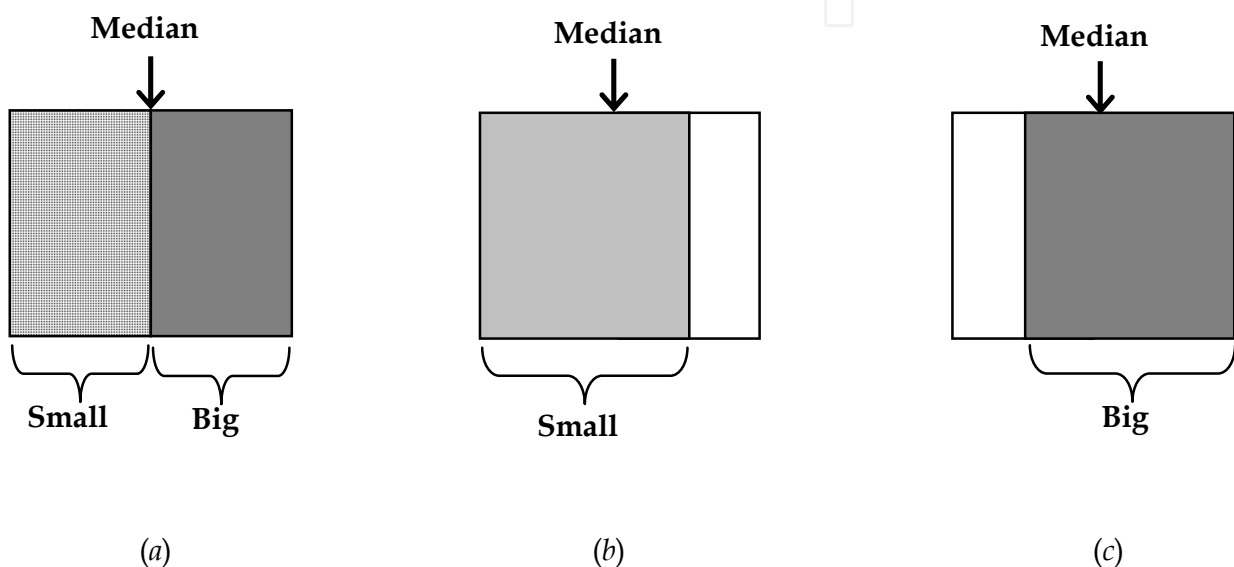


Fig. 5. Schematic view of different dividing methods, (a) crisp dividing, (b) small part of variable domain in fuzzy dividing, (c) big part of variable domain in fuzzy dividing.

The fuzzy systems are not too sensitive to the dividing points. Therefore, the appropriate points for fuzzy dividing can be calculated by investigating various alternatives to select the most appropriate one.

## 2.3 Fuzzy modeling in ALM

Since the presented new heuristic method (section 2.1) utilizes a complicated dividing method, the typical fuzzification methods are not compatible with it. Here, a new simple fuzzy modeling method is presented which is attuned to the heuristic search method. This fuzzy modeling method has been developed by Taheri Shahraiyani (2007).

We denote the membership function of a fuzzy set as  $A_{ij}^{ks}(x_k^m)$  in which  $i$  is the dividing step,  $j$  is the number of dividing in each  $i$  which has a value between 1 and  $2^{i-1}$ .  $s$  is the membership function that is related to small ( $s=1$ ) and big parts ( $s=2$ ) of a variable domain.  $k$  denotes the divided variable number and  $x_k^m$  is the  $m$ th member of the  $k$ th variable ( $X_k$ ) ( $x_k^m \in X_k$ ) and  $X_k \in X$ .  $X = \{X_1, \dots, X_n\}$  is a set of  $n$  variables. ALM can be implemented by fuzzy modeling with miscellaneous shapes of membership functions and the performance of ALM

as a fuzzy modeling method is not sensitive to the shape of membership function. Trapezoidal membership functions are one of the most used membership functions. In addition, implementation of a fuzzy modeling method using trapezoidal membership functions is very straightforward. Hence, trapezoidal membership functions are applied here.

The truth value of a proposition is calculated by a combination of membership degrees. For example, the truth value of ' $x_1^1$  is  $A_{11}^{11}$  and  $x_2^1$  is  $A_{21}^{22}$ ' is expressed as:

$$(x_1^1 \text{ is } A_{11}^{11} \text{ and } x_2^1 \text{ is } A_{21}^{22}) = (A_{11}^{11}(x_1^1) \wedge A_{21}^{22}(x_2^1)) = (A_{11}^{11}(x_1^1) \times A_{21}^{22}(x_2^1)).$$

In this fuzzy method, the general fuzzy rules are defined as below:

$$R_p: \quad \text{If} \quad (x_{k_1}^m \text{ is } A_{1j_1}^{k_1s_1} \ \& \ x_{k_2}^m \text{ is } A_{2j_2}^{k_2s_2} \ \& \dots) \quad \text{then} \quad y_p^m = f_p(x_{k_3}^m)$$

Where  $p$  is the rule number and has a value between 1 and  $h$  ( $h$  is total number of fuzzy rules),  $R_p$  is the  $p$ th rule and  $f_p$  is the  $p$ th one-variable non-linear function for the  $p$ th subspace ( $p$ th rule).

$1/P(f_p)$  is considered as the weight of the  $p$ th rule ( $W_{rp}$ ) where  $P(f_p)$  is PAE of  $f_p$  (continuous path in the  $p$ th rule). Fire strength or membership degree of the  $p$ th rule,  $W_{fp}^m$  is equal to the truth value of the proposition which is:

$$W_{fp}^m = A_{1j_1}^{k_1s_1}(x_{k_1}^m) \times A_{2j_2}^{k_2s_2}(x_{k_2}^m) \times \dots \quad (2)$$

Obviously, the summation of truth values of all of the propositions should be equal to 1

$$\left(\sum_{p=1}^h W_{fp}^m = 1\right).$$

Finally, the corresponding output ( $y^m$ ) to  $m$ th set of input dataset ( $x_1^m, \dots, x_k^m, \dots, x_n^m$ ) is calculated as:

$$y^m = \frac{\sum_{p=1}^h (y_p^m \times W_{fp}^m \times W_{rp})}{\sum_{p=1}^h (W_{fp}^m \times W_{rp})} \quad (3)$$

## 2.4 An example for fuzzy modeling in ALM

Now, we present a small example to show the simplicity of the described fuzzy modeling method.

Consider a system with two variables ( $X = \{X_1, X_2\}$ ) and  $x_1^m \in X_1, x_2^m \in X_2$  that its fuzzy rules are:

- R<sup>1</sup>: If ( $x_1^m$  is small &  $x_1^m$  is very small) then  $y_1^m = f_1(x_1^m)$   
 R<sup>2</sup>: If ( $x_1^m$  is small &  $x_1^m$  is moderate small) then  $y_2^m = f_2(x_2^m)$   
 R<sup>3</sup>: If ( $x_1^m$  is big &  $x_2^m$  is small) then  $y_3^m = f_3(x_2^m)$   
 R<sup>4</sup>: If ( $x_1^m$  is big &  $x_2^m$  is big) then  $y_4^m = f_4(x_1^m)$

The above linguistic propositions are expressed by the following rules:

- R<sup>1</sup>: If ( $x_1^m$  is  $A_{11}^{11}$  &  $x_1^m$  is  $A_{21}^{11}$ ) then  $y_1^m = f_1(x_1^m)$   
 R<sup>2</sup>: If ( $x_1^m$  is  $A_{11}^{11}$  &  $x_1^m$  is  $A_{22}^{12}$ ) then  $y_2^m = f_2(x_2^m)$   
 R<sup>3</sup>: If ( $x_1^m$  is  $A_{11}^{12}$  &  $x_2^m$  is  $A_{23}^{21}$ ) then  $y_3^m = f_3(x_2^m)$   
 R<sup>4</sup>: If ( $x_1^m$  is  $A_{11}^{12}$  &  $x_2^m$  is  $A_{24}^{22}$ ) then  $y_4^m = f_4(x_1^m)$

Suppose the PAE of  $f_1, f_2, f_3$  and  $f_4$  are 5, 10, 5 and 20. Then,  $W_{r1}, W_{r2}, W_{r3}$  and  $W_{r4}$  are equal to 0.2, 0.1, 0.2 and 0.05, respectively.

Figure 6 shows the fuzzy dividing and the membership functions for this example

As seen in figure 6, the membership degrees for  $x^1 (x_1^1, x_2^1)$  are:

$$A_{11}^{11}(x_1^1) = 0.34, A_{12}^{11}(x_1^1) = 0.66, A_{21}^{11}(x_1^1) = 0, A_{22}^{12}(x_1^1) = 1, A_{23}^{21}(x_2^1) = 0.1, \\ A_{24}^{22}(x_2^1) = 0.9,$$

In accordance with the membership degrees of different membership functions, the truth values of different rules ( $W_{fp}^m$ ) can be determined using the following calculations.

$$W_{f1}^1 = A_{11}^{11}(x_1^1) \times A_{21}^{11}(x_1^1) = 0.34 \times 0 = 0 \\ W_{f2}^1 = A_{11}^{11}(x_1^1) \times A_{22}^{12}(x_1^1) = 0.34 \times 1 = 0.34 \\ W_{f3}^1 = A_{11}^{12}(x_1^1) \times A_{23}^{21}(x_2^1) = 0.66 \times 0.1 = 0.066 \\ W_{f4}^1 = A_{11}^{12}(x_1^1) \times A_{24}^{22}(x_2^1) = 0.66 \times 0.9 = 0.594$$

Assume the rule functions ( $y_p^m$ ) values for point  $x^1$  are:

$$y_1^1 = f_1(x_1^1) = 2.0, y_2^1 = f_2(x_2^1) = 1.8, y_3^1 = f_3(x_2^1) = 2.2 \text{ and } y_4^1 = f_4(x_1^1) = 1.7.$$

According to the equation 3, the output ( $y^1$ ) can be calculated as below:

$$y^1 = \frac{\sum_{p=1}^4 (y_p^1 \times W_{fp}^1 \times W_{rp})}{\sum_{p=1}^4 (W_{fp}^1 \times W_{rp})} = \frac{(y_1^1 \times W_{f1}^1 \times W_{r1}) + (y_2^1 \times W_{f2}^1 \times W_{r2}) + (y_3^1 \times W_{f3}^1 \times W_{r3}) + (y_4^1 \times W_{f4}^1 \times W_{r4})}{(W_{f1}^1 \times W_{r1}) + (W_{f2}^1 \times W_{r2}) + (W_{f3}^1 \times W_{r3}) + (W_{f4}^1 \times W_{r4})}$$
$$= \frac{(2.0 \times 0 \times 0.2) + (1.8 \times 0.34 \times 0.1) + (2.2 \times 0.066 \times 0.2) + (1.7 \times 0.594 \times 0.05)}{(0 \times 0.2) + (0.34 \times 0.1) + (0.066 \times 0.2) + (0.594 \times 0.05)} = 1.83$$

It could be observed that the calculations in this fuzzy modeling method are simple and straightforward.

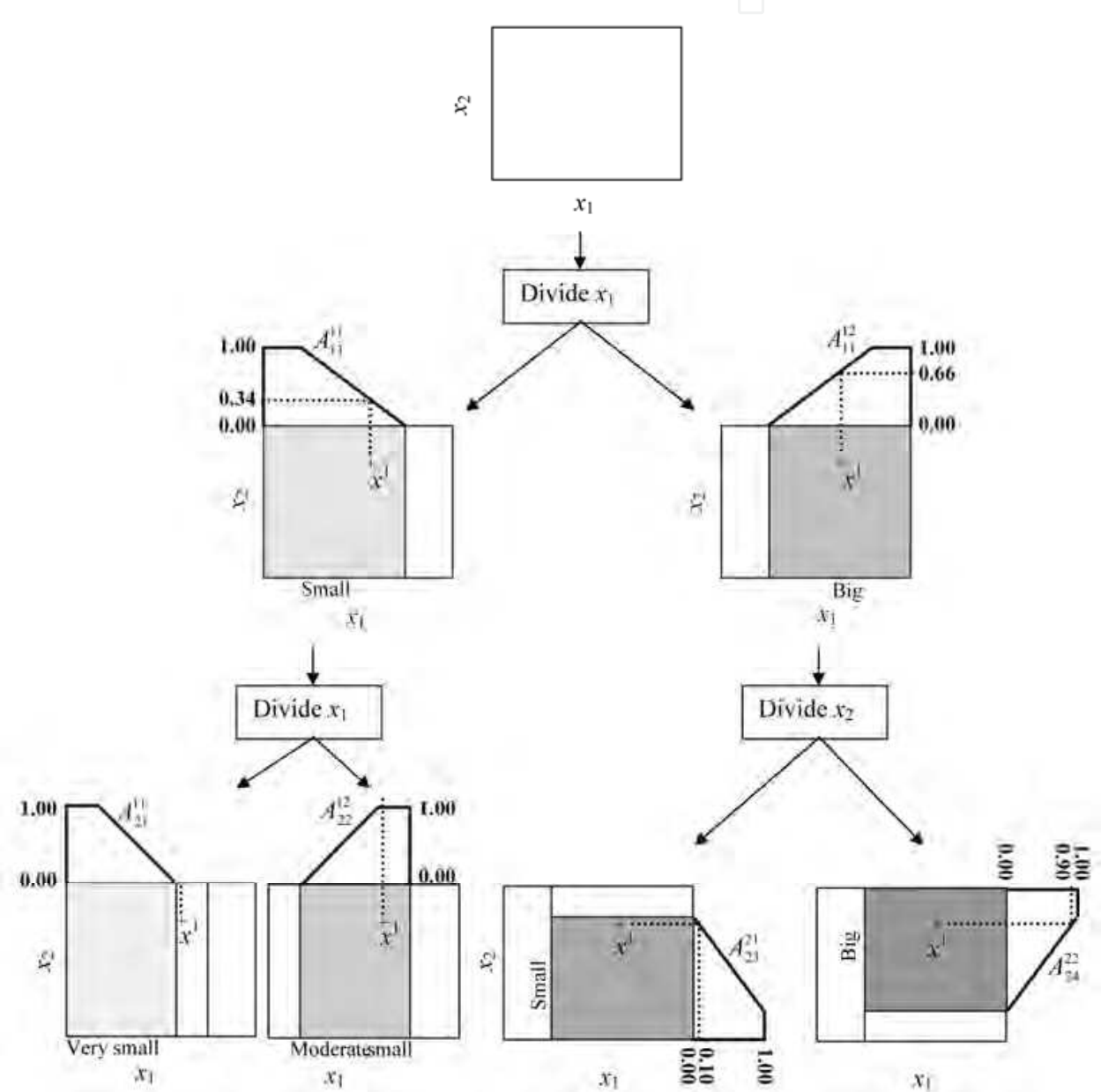


Fig. 6. Fuzzy dividing, trapezoidal membership functions and membership degrees for point  $x^1(x_1^1, x_2^1)$ .

### 3. The specific abilities of ALM

#### 3.1 Initial parameters for training

In spite of many other well-known modeling methods (e.g. Neural Networks), ALM does not need initial parameters to start the training and thus it does not repeat the training, hence ALM training is very easy and straightforward and it is not time consuming.

#### 3.2 Finding and ranking the effective variables

Although, the appropriate inputs to models are often determined before the beginning of modeling by physical or empirical based methods, but ALM can determine and rank the important input variables. Because it is very easy for ALM to find the important or divided variables and one-variable function in each step of modeling. Then, the variables can be ranked according to their roles in modeling easily. Suppose that the ranking criterion for used variables in one-variable functions is the number of subspaces which have been estimated using each variable. Similarly, suppose that the ranking criterion for the used variables for dividing is dividing times of each variable. Hence, ALM similar to human can find and rank the effective variables in a system.

#### 3.3 Sensitivity to noise

In general, ALM has low sensitivity to noise. The main factor of robustness of ALM is IDS operator and it is similar to adding a cone shaped distribution noise to the inputs and output data using cone shaped illumination (distribution) pattern (solid line in figure 7). As shown in figure 7, the cone shaped noise which is added automatically by IDS is very similar to a normal distribution (solid line) noise.

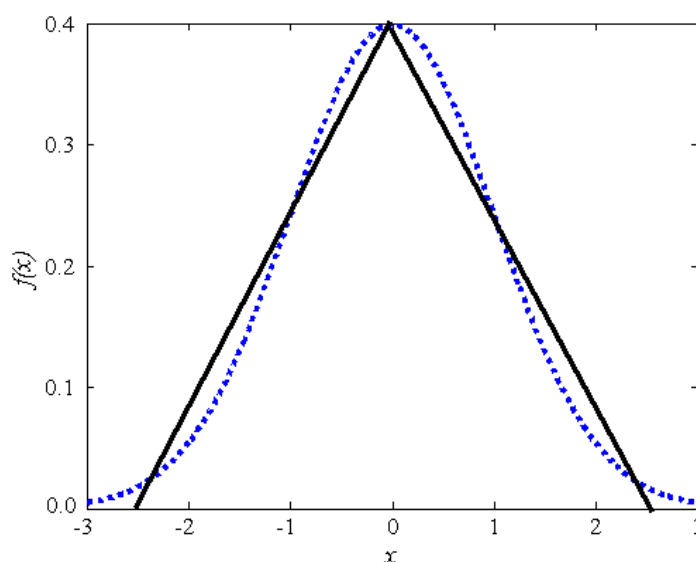


Fig. 7. Schematic view of normal distribution function  $(f(x) = \frac{1}{\sqrt{2\pi}} e^{-\frac{x^2}{2}})$  (dotted line) and cone shape illumination (distribution) pattern of IDS (solid line).

For the low sensitivity to noise (robust) modeling, it is necessary to add some noises to data and then train the model with noisy data. In the crisp modeling methods (e.g. neural networks), adding noise to data should be performed by repeating the dataset (for example 100 times) and adding noise (often normal distribution noise) to the repeated dataset. It is time consuming to repeat the dataset, add random noise to data and train the model using the large repeated dataset. Therefore robust modeling is time consuming. But ALM does not need to repeat the dataset nor add noise to it. Because the cone shaped noise which is added automatically by IDS operator is very similar to a normal distribution (dotted line) noise (see figure 7). Thus, ALM is more rapid than any other crisp modeling method in training stage.

In the crisp modeling methods, because of lack of necessary knowledge about the noise level in the system (e.g. noise level for different variables and functions), a constant level of noise is added to the functions and variables. But ALM determines the appropriate noise level for different variables by calculation of the optimum slopes of cone shaped illumination (distribution) patterns in the IDS operator for variables. Also ALM is able to add different levels of noise to the function and variables data by changing the resolution in x and y axes.

For more details about the ALM abilities and demonstration of the mentioned abilities, refer to Taheri Shahraiyani (2007) and Taheri Shahraiyani et al. (2009).

#### 4. An application of ALM modeling

Here, ALM is used for modeling of a very important problem (Algal bloom in marine environment) and its abilities and performances are investigated.

Algal bloom is the result of interaction between physiological and ecological characteristics of the species as well as physiochemical processes in the water column. Algal bloom detection in the water bodies and the monitoring of its spatiotemporal changes is necessary for water quality or marine ecosystem modeling and management. Chlorophyll-a is an indicator for the phytoplanktonic biomass, hence the retrieved spatial distribution of chlorophyll concentration in a water body can be used for the monitoring of spatiotemporal changes of algal bloom.

Remote sensing can provide a complementary tool for the chlorophyll retrieval in varying water bodies. Due to the very high level inherent noises in satellite images, the low sensitivity to noise method is needed for the extraction of chlorophyll concentration from satellite images. ALM is promising to be low sensitive to noise, hence used for solving of this problem. The reflected radiations of sea surface, measured in different wavelengths by satellite, are the input variables to ALM and the output is the corresponding chlorophyll concentration.

We need to a dataset for training of ALM. The training dataset was generated by numerical solution of radiative transfer equation. Radiative transfer equation simulates the radiative transfer in atmosphere-ocean system.

ALM was trained by this dataset and tested by satellite images and concurrent in-situ measurements of chlorophyll in Caspian Sea.

The Caspian Sea is a land-locked sea between Asia and Europe. It is the largest inland water body in the world. It covers a surface area more than 370,000 km<sup>2</sup>, reaches a maximum depth of about 1000 m. An algal bloom happened in the Caspian Sea on August 2005 in the southern part of Caspian Sea and it disappeared in October 2005. The sampling and analysis of species in the algal bloom showed that the bloom is related to toxic specie of the Cyanobacteria (Blue-green algae) which is named *Nodularia*.



The utilized satellite images in the study were MERIS images. MERIS has been located on board of the ENVISAT satellite (European Space Agency). MERIS takes 15 images in different wavelengths between 412 and 900 nm. For details about MERIS refer to Rast et al. (1999).

The results of test of trained ALM showed that it can derive the chlorophyll concentration with appropriate accuracy (percent of absolute error = 44%). This shows that ALM is very robust to noise. The developed ALM model had only 8 rules. The processing time of fuzzy models is highly related to the number of rules and this number of rules (8 rules) is small enough to allow for an appropriate processing time in operational applications. In addition, it could find that {490, 510, 560, 685, and 885 nm} are important and necessary wavelengths for chlorophyll modeling and remove the other ones. For details about this Chlorophyll estimation by ALM modeling refer to Taheri Shahraini et al. (2007).

Finally, the satellite images were used as input to developed ALM model and the output chlorophyll concentration maps in Caspian Sea were extracted. Figure 8 shows these results from August to October.

As you see in figure 8 and explanations on the figure 8, ALM has been successful for the appropriate monitoring of change of chlorophyll concentration in the Caspian Sea.

The results demonstrated that ALM model is an appropriate and useful method for modeling of chlorophyll concentration and consequently, detection and monitoring of algal bloom in marine environment.

## 5. Other applications

Although we focused on the ALM abilities for modeling, but according to the structure of ALM, its application is not limited to modeling and it is applicable in different fields of engineering. Here we hint to some of ALM applications.

### 5.1 Large scale optimization problems

The large scale optimization problems are important in different fields of science, engineering and operation research. Unfortunately most of them are NP (Non-Polynomial) problems and finding their optimum solution in reasonable time is almost impossible (Garey and Johnson, 1976). ALM can be used for solution of these problems and it presents satisfactory results.

An example: Bin-Packing problem is a NP problem (Garey and Johnson, 1976) and it has many different applications such as loading trucks subject to weight limitations. Lotfi and Bagheri Shouraki (2004) used ALM for solution of Bin-packing problem. They showed, in spite of very simple construction of ALM, it can obtain very good results for solving Bin Packing problem.

### 5.2 Control problems

Human modeling method has low sensitivity to noise. ALM is similar to human modeling methods and it is very robust to noise. Therefore it is very useful method for control problems. Up to now, several researches has been performed on the application of ALM in control problems. Some of these control researches are as below:

Bagheri Shouraki and Honda (1998) showed the ability of ALM for stable controlling of dynamic systems such as invert pendulum.

Shahdi and Bagheri Shouraki (2002) used of ALM for design of controller for Beam and Ball problem and showed the ability of ALM for control of this system.



Shahdi and Bagheri Shouraki (2003) used of ALM for design of an intelligent control system in an automated vehicle. The problem was the control of a truck which is moving at the back of another truck in one line. The automated truck doesn't contact to another truck. The ALM has been used to extract driver's behavior and control rules for control system. Also, the effective parameters of controller were derived using ALM.

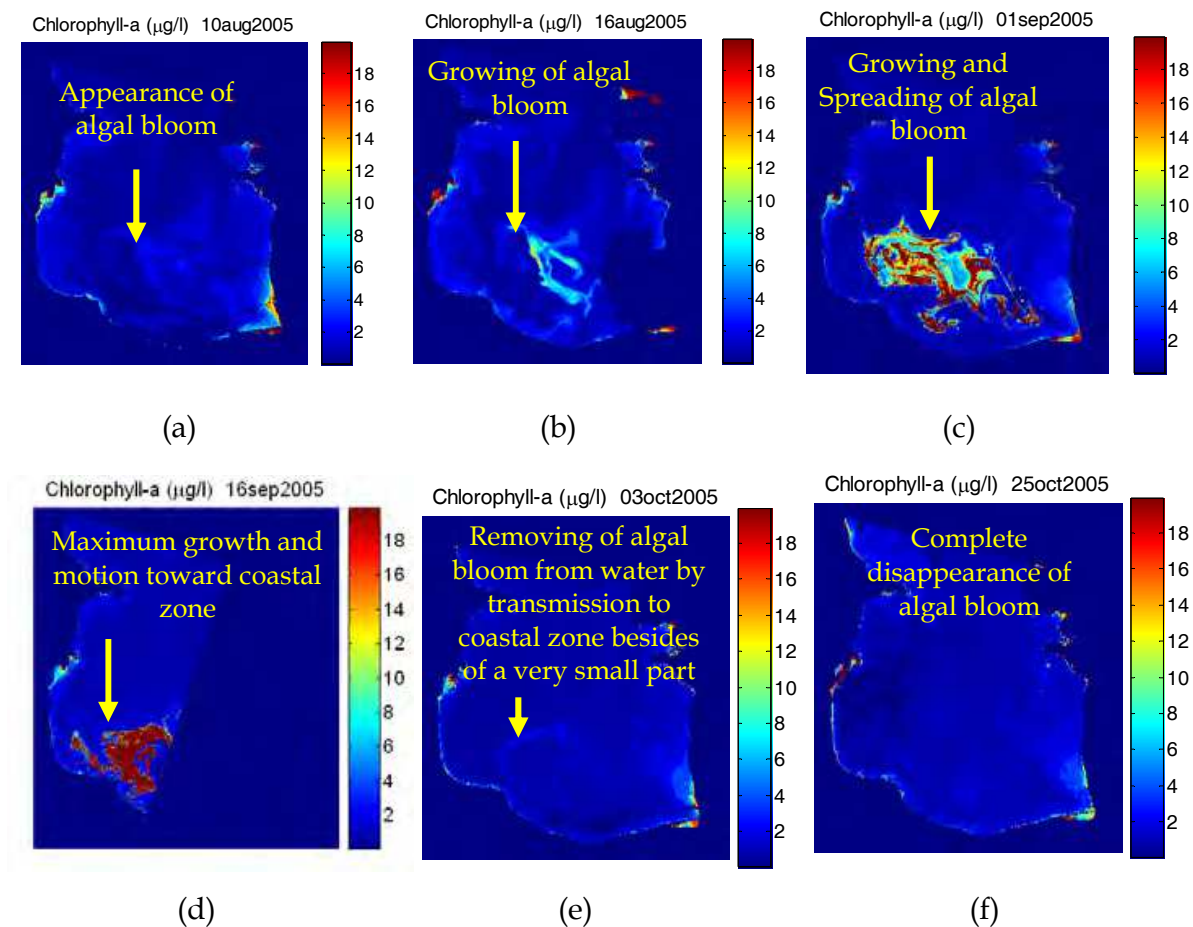


Fig. 8. Chlorophyll concentration ( $\mu\text{g/lit}$ ) maps in Caspian Sea, derived by developed ALM model which shows the algal bloom appearance on August and its disappearance until October, 2005

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