

Data-driven Based 3-D Fuzzy Logic Controller Design Using Nearest Neighborhood Clustering and Linear Support Vector Regression

Xianxia Zhang, Ye Jiang
Shanghai Key Laboratory of
Power Station Automation
Technology
School of Mechatronics and
Automation
Shanghai University
Shanghai 200072, China
e-mail:ye924@shu.edu.cn

Tao Zou
College of Information
Engineering
Zhejiang University of
Technology
Hangzhou 310014, China

Chenkun Qi
School of Mechanical
Engineering
State Key Laboratory of
Mechanical System and
Vibration
Shanghai Jiao Tong
University
Shanghai 200240, China

Guitao Cao
Software Engineering
Institute
East China Normal
University
Shanghai 200062, China

Abstract—Three-dimensional fuzzy logic controller (3-D FLC) is a novel FLC developed for spatially distributed parameter systems. In this study, we are concerned with data-based 3-D FLC design. A nearest neighborhood clustering algorithm is employed to extract fuzzy rules from input-output data pairs, and then an optimization algorithm based on geometric similarity measure is used to reduce the obtained rule base. The consequent parameters are estimated using linear support vector regression. Finally, a catalytic packed-bed reactor is taken as an application to demonstrate the effectiveness of the 3-D FLC.

Keywords—3-D fuzzy set; three-dimensional fuzzy logic controller; nearest neighborhood clustering; linear support vector regression

I. INTRODUCTION

In the real world, many physical processes and systems have the characteristics of spatial distribution, and are usually called spatially distributed systems. Recently, A novel three-dimensional fuzzy logic controller (3-D FLC) [1] has been developed for the control of such systems. 3-D FLC employs 3-D fuzzy sets [1], which is composed of the traditional fuzzy set plus a third dimension for the spatial information, and carries out 3-D rule inference engine. It has an inherent capability to express and process spatial information. The design of 3-D FLC is usually divided into two different approaches: expert experience based approach and data-driven based approach. When much domain knowledge from human experts or operators is obtained, a satisfied 3-D FLC can be designed by expert experience such as in [1]. On the other hands, if the domain knowledge is not available, or the domain knowledge is very hard to be extracted or described by human's words, but effective input-output data is available, the 3-D FLC can also be designed using the data information such as in [2].

In [2], a table look-up scheme that took into account the tempo-spatial nature sufficiently was applied to the 3-D FLC

design. Each input-output data pair generates one rule; as a result, the number of rules is very large. To reduce the number of rules, a degree is assigned to a rule, and then only the rule with maximum degree from a conflict group is accepted. However, it is equal to the number of boxes of the base when the fuzzy rule base is complete, and then, it increases exponentially as the dimension of the input space increases. Instead of the most direct way to partition the input space, fuzzy clustering algorithms provide a more flexible partition, such as the nearest neighborhood clustering in [3]. In this study, we adopt the Frobenius norm as a distance measurement, instead of the Euclidean norm in the traditional counterpart. Via comparing the inverse of sum of unit and distance with a given threshold, a new fuzzy rule is determined whether to be generated. To simplify the redundancy fuzzy sets in the input space partition, similarity measures techniques are usually used, such as in [4]- [6], which can be divided into two categories [6]: geometric similarity measures and set-theoretic similarity measures. For the 3-D fuzzy set, a distance-based similarity measure [4], as a special geometric similarity measures method, is employed to combine similar fuzzy sets. After constructing the antecedent parts, the linear support vector regression (SVR, i.e. ε -linear support vector regression) will be used to determine the parameters in consequent parts.

The paper is divided into five sections. In Section II, preliminaries on 3-D FLC and SVR are described. In Section III, the proposed data-based 3-D FLC design is presented in detail. Application to the catalytic packed-bed reactor and experimental results are given in Section IV. Finally, conclusions and future works are given in Section V.

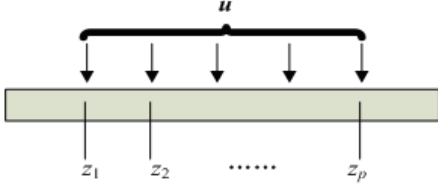


Figure 1. Sketch of a DPS with a distributed actuator u and p point measurement sensors.

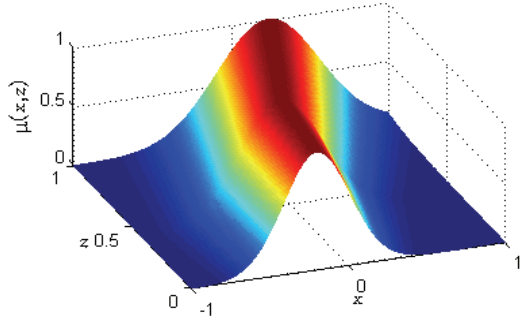


Figure 2. 3-D fuzzy set.

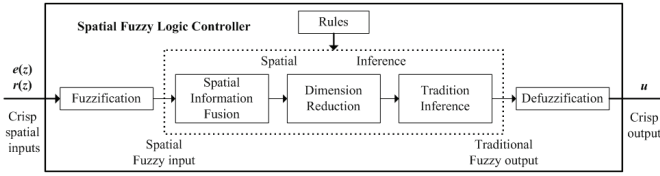


Figure 3. Basic structure of 3-D FLC.

II. PRELIMINARIES

A. Three-dimensional fuzzy logic controller

The 3-D FLC is designed to have the inherent capability to deal with spatial information and its basic structure is shown in Fig. 3. It has a similar functional structure similar to the traditional FLC, which consists of three basic blocks: fuzzification, rule inference, and defuzzification. However, it will differ in the detailed operations because of the spatial processing requirement [1]. Generally, the 3-D FLC will be involved with the following basic designs: 3-D membership function (MF), 3-D fuzzification, 3-D rule base, 3-D rule inference, and defuzzification. One can refer to [1] for detailed description. In this study, we consider the multi-input single-output (MISO) cases where the finite sensors are employed; extensions to general multi-input multi-output (MIMO) cases are straightforward. Given N fuzzy rules with the following form

$\bar{R}^l$: IF $x_i(z)$ is $\bar{C}_i^l$ and...and $x_s(z)$ is $\bar{C}_s^l$, THEN u is B^l (1)

where $x_i(z)$ ($i=1, \dots, s$) denotes the i th spatial input variable; $z \in Z$ is a point in one-dimensional space Z ; In discrete space, Z can be represented by $Z = \{z_1, z_2, \dots, z_p\}$, $z_1, z_2, \dots, z_p$ denote the discrete space positions; $\bar{C}_i^l$ denotes a 3-D fuzzy

set; u denotes output variable (the control action). B^l denotes a traditional fuzzy set; $l=1, \dots, N$.

To design a 3-D fuzzy set, for instance $\bar{C}_i^l$ ($i=1, \dots, s$, $l=1, \dots, N$) in (1), one simple method is to decompose the 3-D fuzzy set into the multiple 2-D fuzzy sets. As a result, the design method from the traditional 2-D fuzzy sets can be used. Similarly, the 3-D fuzzification can be regarded as the assembly of the traditional 2-D fuzzification at each sensing location. When the Gaussian type fuzzy set is chosen for 3-D fuzzy set, it means that MF of the i th spatial input variable $x_i(z)$ at the sensing location $z = z_j$ is Gaussian MF, which can be written as

$$\mu_{Gij}(x_i(z_j)) = \exp\left(-(x_i(z_j) - v_{ij}^l)^2 / (\sigma_{ij}^l)^2\right) \quad (2)$$

$(i=1, \dots, s, j=1, \dots, p, l=1, \dots, N)$

where v_{ij}^l and σ_{ij}^l are center and width of the Gaussian MF, respectively.

If we choose singleton fuzzification, product for the spatial information fusion operation, the centroid approach for the dimension reduction, product inference, center-of-sets defuzzification, and Gaussian MF in (2), then the input-output mapping of the 3-D FLC, $u: R^{p \times s} \rightarrow R$, is given by

$$u(x_z) = \frac{\sum_{l=1}^N u^l \sum_{j=1}^p a_j^l \prod_{i=1}^s \mu_{Gij}(x_i(z_j))}{\sum_{l=1}^N \sum_{j=1}^p a_j^l \prod_{i=1}^s \mu_{Gij}(x_i(z_j))} \quad (3)$$

where u^l is the centroid of the consequent set, i.e. the center of Gaussian MF, such that $\mu(u^l) = 1$; a_j^l denotes the time-variant weight with the following form

$$\begin{cases} a_1^l = \Delta \theta_1^l / (2 \sum_{k=1}^{p-1} \Delta \theta_k^l) \\ a_j^l = (\Delta \theta_{j-1}^l + \Delta \theta_j^l) / (2 \sum_{k=1}^{p-1} \Delta \theta_k^l) \quad j=2, \dots, p-1 \\ a_p^l = \Delta \theta_{p-1}^l / (2 \sum_{k=1}^{p-1} \Delta \theta_k^l) \\ \Delta \theta_k^l = \sqrt{(\mu_{w^l}(z_{k+1}) - \mu_{w^l}(z_k))^2 + (z_{k+1} - z_k)^2} \\ \mu_{w^l}(z_k) = \prod_{i=1}^s \mu_{Gik}(x_i(z_k)) \end{cases} \quad (4)$$

Let

$$\phi^l(x_z) = \frac{\sum_{j=1}^p a_j^l \prod_{i=1}^s \mu_{Gij}(x_i(z_j))}{\sum_{l=1}^N \sum_{j=1}^p a_j^l \prod_{i=1}^s \mu_{Gij}(x_i(z_j))} \quad l=1, \dots, N \quad (5)$$

be the fuzzy basis functions (FBF) of 3-D FLC and u^l be constants, then (3) can be viewed as a linear combination of fuzzy basis functions.

$$u(x_z) = \sum_{l=1}^N \phi^l(x_z) \theta^l \quad (6)$$

where $\theta^l \in R$ are constants, i.e. $\theta^l = u^l$.

From (1) and (5), we can see that each FBF corresponds to a fuzzy IF-THEN rule.

B. Linear support vector regression

In this subsection, we will briefly introduce the basic theory of linear SVR (i.e. ε -linear support vector regression) [7].

Suppose there is a set T composed of n input-output training data pairs

$$T = \{(x_i, y_i) | x_i \in R^s, y_i \in R, i = 1, \dots, n\} \quad (7)$$

In ε -linear SVR, the aim is to find a decision function $f(x)$ that has at most ε deviation from the actually obtained targets y_i for all the training data pairs, and at the same time is as flat as possible. $f(x)$ has the following form

$$f(x) = \langle w, x \rangle + b \quad \text{with } w \in R^s, b \in R \quad (8)$$

where $\langle \cdot, \cdot \rangle$ denotes the dot product in R^s ; w is a high-dimensional weight vector, and b is a bias term. Flatness in the case of (8) means that one seeks a small w . One way to ensure this is to minimize $\|w\|^2 = \langle w, w \rangle$.

If the considered problem is infeasible or some errors are allowed, then the task is to minimize the following convex optimization problem by introducing slack variables ξ_i, ξ_i^* .

$$\begin{aligned} \min_{w, b, \xi_i^*} \quad & \frac{1}{2} \|w\|^2 + C \sum_{i=1}^n (\xi_i + \xi_i^*) \\ \text{s.t.} \quad & \begin{cases} y_i - (w \cdot x_i + b) \leq \varepsilon + \xi_i \\ (w \cdot x_i + b) - y_i \leq \varepsilon + \xi_i^* \\ \xi_i, \xi_i^* \geq 0, i = 1, \dots, n \end{cases} \end{aligned} \quad (9)$$

where constant C determines the trade-off between the flatness of f and the amount up to which deviations larger than ε are tolerated. This corresponds to dealing with a so called ε -insensitive loss function $|\xi|_\varepsilon$ described by

$$|\xi|_\varepsilon := \begin{cases} 0 & \text{if } |\xi| \leq \varepsilon \\ |\xi| - \varepsilon & \text{otherwise.} \end{cases}$$

The corresponding dual optimization problem of convex optimization problem in (9) is given by

$$\begin{aligned} \max_{\alpha^{(*)} \in R^{2l}} \quad & \begin{cases} -\frac{1}{2} \sum_{i,j=1}^n (\alpha_i - \alpha_i^*)(\alpha_j - \alpha_j^*) \langle x_i, x_j \rangle \\ -\varepsilon \sum_{i=1}^n (\alpha_i + \alpha_i^*) + \sum_{i=1}^n y_i (\alpha_i - \alpha_i^*) \end{cases} \\ \text{s.t.} \quad & \sum_{i=1}^n (\alpha_i - \alpha_i^*) = 0 \text{ and } \alpha_i, \alpha_i^* \in [0, C] \end{aligned} \quad (10)$$

The vector w has the form: $w = \sum_{i=1}^n (\alpha_i - \alpha_i^*) x_i$ and therefore

$$f(x) = \sum_{i=1}^n (\alpha_i - \alpha_i^*) \langle x_i, x \rangle + b \quad (11)$$

The points with $(\alpha_i - \alpha_i^*) \neq 0$ are defined as support vectors.

III. DATA-BASED 3-D FLC DESIGN

The design of 3-D FLC includes two steps: structure learning and parameter learning. In structure learning, the nearest neighborhood clustering is employed to mine the underlying knowledge of the data set S such that fuzzy rules and Gaussian 3-D MFs in the antecedent part are constructed, and then an optimization algorithm based on similarity measure is utilized to combine similar MFs and then simplify the rule base. In parameter learning, the linear SVR algorithm is used to estimate the parameters of the traditional Gaussian-type fuzzy sets in the consequent part.

Firstly, the concerned 3-D FLC can be defined as follows.

Definition 1: The set of 3-D FLC with fuzzy rule base in (1), singleton fuzzification, product inference, center-of-sets defuzzification, and Gaussian MF can be described mathematically in (12)

$$u(x_z) = \frac{\sum_{l=1}^N u^l \sum_{j=1}^p a_j^l \prod_{i=1}^s \mu_{Gij}(x_i(z_j))}{\sum_{l=1}^N \sum_{j=1}^p a_j^l \prod_{i=1}^s \mu_{Gij}(x_i(z_j))} + b \quad (12)$$

From (12), we can see that each 3-D FLC in the set combines a 3-D FLC in (3) and a constant b . b is included for the bias term in the linear SVR. The motivation of this study is to determine a mapping u in (12) using the fuzzy rules generated from a set S represented by (13), which consists of input-output data pairs from a spatially distributed system.

$$S = \{(x_z^k, u^k) | x_z^k \in R^{p \times s}, u^k \in R, k = 1, \dots, n\} \quad (13)$$

where $x_z^k = (x_1^k(z), \dots, x_s^k(z))$ denotes the value of all s spatial input variables at the k th sampling time, $x_i^k(z) = (x_i^k(z_1), \dots, x_i^k(z_p))^T$ ($i = 1, \dots, s$), u^k denotes the output value at the k th sampling time, n denotes the number of sampling time, and p denotes sensor number.

A. Structure Learning

Define abbreviations and acronyms the first time they are used in the text, even after they have been defined in the abstract. Abbreviations such as IEEE, SI, MKS, CGS, sc, dc, and rms do not have to be defined. Do not use abbreviations in the title or heads unless they are unavoidable.

1) *Nearest neighborhood clustering:* Different from the traditional vector input-output data pairs, the input-output data pairs S in (13) are of matrix form. Therefore, the Frobenius norm will be used for defining the distance in a nearest neighborhood clustering algorithm [3]. By comparing the inverse of sum of unit and distance with a given threshold, we can determine whether to add a new fuzzy rule. The nearest neighborhood clustering algorithm is summarized as follows:

Step 1: Begin from the first input-output data pair x_z^1 . Let the first cluster center c_z^1 be x_z^1 , the number of data pairs m_1 be 1 in this cluster, and the threshold be ρ_0 for generating new fuzzy rules.

Step 2: Suppose that the k th input-output data pair x_z^k ($k = 2, \dots, n$) is considered, when N clusters have been generated and their centers are $c_z^1, \dots, c_z^N$, respectively. Firstly, the distance between x_z^k and each center of N clusters is computed using $\|x_z^k - c_z^l\|_F$ ($l = 1, \dots, N$), where $\|\cdot\|_F$ denotes the Frobenius norm, $\|X\|_F = \sqrt{\text{tr}(X^T X)}$ ($X \in R^{p \times s}$). Then, threshold ρ is given by (14)

$$\rho = \max_{l=1, \dots, N} \left(\frac{1}{1 + \|x_z^k - c_z^l\|_F} \right) \quad (14)$$

Hence, the corresponding cluster center c_z^k is taken as the nearest neighborhood cluster of x_z^k .

Step 3: If $\rho < \rho_0$, then x_z^k is taken as the new cluster center. Let $N = N + 1$, $m_N = 1$, and $c_z^N = x_z^k$. Otherwise, x_z^k belongs to the cluster $c_z^{l_k}$, by introducing a learning rate $\eta = \eta_0 / (m_k + 1)$ ($\eta_0 \in [0, 1]$) [1] described by (15) for tuning the center of l_k th cluster;

$$c_z^{l_k} = c_z^{l_k} + \eta(x_z^k - c_z^{l_k}); m_{l_k} = m_{l_k} + 1 \quad (15)$$

Step 4: Let $k = k + 1$. If $k \geq n + 1$, then quit; otherwise, back to Step 2.

2) *Rule extraction and 3-D MF construction:* After clustering learning, we can obtain an input space partition with N cluster centers $c_z^1, c_z^2, \dots, c_z^N$. Then, we will produce antecedent part of rule base and construct 3-D MF in terms of the partition. Each cluster corresponds to a fuzzy rule, and the cluster center corresponds to the center of Gaussian 3-D MFs in the antecedent part. Thus, the number of fuzzy rules is equal to the number of clusters N . Finally, let the width of 3-D Gaussian MFs have the same value as in (16) [1] at each sensing location.

$$\sigma(z_j) \approx \max_{1 \leq i \leq S} ((x_i^{\max}(z_j) - x_i^{\min}(z_j)) / 10) \quad (16)$$

where $x_i^{\max}(z_j)$ and $x_i^{\min}(z_j)$ are the maximum and the minimum bound value of the i th spatial input in S , respectively. Similarly, the width of traditional Gaussian MF in the consequent part is given as

$$\sigma_B \approx (\max(u) - \min(u)) / 10 \quad (17)$$

where $\max(u)$ and $\min(u)$ are the maximum and the minimum bound value of the output in S , respectively.

3) *Optimization algorithm:* The obtained input space partition may have redundancy in terms of highly overlapping membership functions. It is necessary to optimize the above obtained fuzzy partition. The optimization task includes: removing 3-D fuzzy sets similar to the universal set or the singleton set, and merging some similar 3-D fuzzy sets and some rules with similar antecedent part.

Firstly, the definition of the similarity of two 3-D fuzzy sets is given as follows.

Definition 2: Define the similarity of two 3-D fuzzy sets $\bar{A}$ and $\bar{B}$ as

$$\bar{S}(\bar{A}, \bar{B}) = \frac{1}{1 + d(\bar{A}, \bar{B})} \quad \bar{S}(\cdot) \in (0, 1] \quad (18)$$

where $d(\bar{A}, \bar{B})$ is the distance between $\bar{A}$ and $\bar{B}$. Since Gaussian type membership functions are chosen, the following simple expression can be used to approximate the distance.

$$d(\bar{A}, \bar{B}) = \left\| \begin{bmatrix} c_{\bar{A}(z_1)} & \sigma_{\bar{A}(z_1)} \\ \vdots & \vdots \\ c_{\bar{A}(z_p)} & \sigma_{\bar{A}(z_p)} \end{bmatrix} - \begin{bmatrix} c_{\bar{B}(z_1)} & \sigma_{\bar{B}(z_1)} \\ \vdots & \vdots \\ c_{\bar{B}(z_p)} & \sigma_{\bar{B}(z_p)} \end{bmatrix} \right\|_F \quad (19)$$

where $c_{\bar{A}(z_j)}$ ($c_{\bar{B}(z_j)}$) and $\sigma_{\bar{A}(z_j)}$ ($\sigma_{\bar{B}(z_j)}$) are center and width of Gaussian MF at sensing location $z = z_j$ ($j = 1, \dots, p$) respectively.

If 3-D fuzzy sets $\bar{A}$ and $\bar{B}$ are similar, then they will be merged into a new spatial fuzzy set $\bar{C}$, the center and width of which are viewed as the average value of the two original 3-D fuzzy sets, i.e. $c_{\bar{C}(z_j)} = (c_{\bar{A}(z_j)} + c_{\bar{B}(z_j)}) / 2$, $\sigma_{\bar{C}(z_j)} = (\sigma_{\bar{A}(z_j)} + \sigma_{\bar{B}(z_j)}) / 2$.

The similarity of fuzzy rules only measures their similarity in antecedent part. Therefore, the similarity between two fuzzy rules $\bar{R}^{l_1}$ and $\bar{R}^{l_2}$ can be computed by (20).

$$\bar{S}_{rule}(\bar{R}^{l_1}, \bar{R}^{l_2}) = \min_{1 \leq i \leq S} \{\bar{S}(\bar{C}_i^{l_1}, \bar{C}_i^{l_2})\} \quad (20)$$

The rule base simplification algorithm in [1] can be extended to this study only for antecedent part, where the similarity measure is replaced by (18) and two thresholds γ (for removing fuzzy sets similar to the universal set) and λ (for merging two similar fuzzy sets) are required. In this study, we choose $\gamma \in (\lambda, 1]$ and $\lambda \in [0.6, 0.9]$.

B. Parameter Learning

For a complete rule base, the rest task is to determine the consequent part parameters. In this subsection, a linear SVR algorithm is applied to estimate the consequent part parameter b^l ($l = 1, \dots, N$) in the 3-D FLC. Each input x_z^k ($k = 1, \dots, n$) in S is transformed into a corresponding FBF $\phi(x_z^k) = (\phi^1(x_z^k), \phi^2(x_z^k), \dots, \phi^N(x_z^k))$. Hence, the original data set S in (13) can be represented by (21)

$$S = \{(\phi(x_z^k), u^k) | \phi(x_z^k) \in R^N, u^k \in R, k = 1, \dots, n\} \quad (21)$$

From (13), the final decision function $f(\phi(x_z^k))$ can be described in the following form

$$f(\phi(x_z^k)) = \sum_{k=1}^n (\alpha_k - \alpha_k^*) \langle \phi(x_z^k), \phi(x_z) \rangle + b \quad (22)$$

where α_k^* and α_k are obtained by solving the dual optimization problem in (10). Then (22) can further be expressed as follows

$$\begin{aligned} u(x_z) &= \sum_{k=1}^n (\alpha_k - \alpha_k^*) \sum_{l=1}^N \phi^l(x_z^k) \phi^l(x_z) + b \\ &= \sum_{l=1}^N \left(\sum_{k=1}^n (\alpha_k - \alpha_k^*) \phi^l(x_z^k) \right) \phi^l(x_z) + b \\ &= \sum_{l=1}^N u^l \phi^l(x_z) + b \end{aligned} \quad (23)$$

We can see that (23) is equal to (12), namely, $u^l = \sum_{k=1}^n (\alpha_k - \alpha_k^*) \phi^l(x_z^k)$. Thus, the parameters u^l ($l = 1, \dots, N$) in consequent parts are obtained, which can be modified as follows.

$$u^l = \sum_{k \in SV} (\alpha_k - \alpha_k^*) \phi^l(x_z^k) \quad (24)$$

where SV denotes the support vectors of linear SVR. It is noted that C in (9) is an adjustable parameter. In this study, we choose a better one through several turns of simulation."

IV. APPLICATION TO CATALYTIC PACKED-BED REACTOR

We take a catalytic packed-bed reactor [1] [10] as an example. A reaction of the form $C \rightarrow D$ takes place on the catalyst. The reaction is endothermic and a jacket is used to

heat the reactor. A dimensionless model that describes this nonlinear tubular chemical reactor is provided as follows:

$$\begin{aligned} \varepsilon_p \frac{\partial T_g}{\partial t} &= -\frac{\partial T_g}{\partial z} + \alpha_c (T_s - T_g) - \alpha_g (T_g - u) \\ \frac{\partial T_s}{\partial t} &= \frac{\partial^2 T_s}{\partial z^2} + B_0 \exp\left(\frac{\gamma T_s}{1 + T_s}\right) - \beta_c (T_s - T_g) - \beta_p (T_s - b(z)u) \end{aligned} \quad (25)$$

Subject to the boundary conditions

$$z = 0, T_g = 0, \frac{\partial T_s}{\partial z} = 0; z = 1, \frac{\partial T_s}{\partial z} = 0 \quad (26)$$

where T_g , T_s , and u denote the dimensionless temperature of the gas, the catalyst, and jacket, respectively. The values of the process parameters are given as follows:

$$\varepsilon_p = 0.01, \gamma = 21.14, \beta_c = 1.0, \beta_p = 15.62, B_0 = -0.003, \alpha_c = 0.5, \alpha_g = 0.5$$

A sin distribution heat source is used with $b(z) = 1 - \cos(\pi z)$, $0 \leq z \leq 1$. The spatial reference profile is given as $T_{sd}(z) = 0.42 - 0.2 \cos(\pi z)$.

Five point sensors are uniformly located along the length of the reactor with $z = (0, 0.25, 0.5, 0.75, 1)^T$ for collecting the spatial distribution of the temperature T_s . Two spatial inputs are error $e^*(z) = [e_1^*, \dots, e_5^*]^T$ and error in change $r^*(z) = [r_1^*, \dots, r_5^*]^T$, where $e_i^* = T_s(z_i, q) - T_{sd}(z_i)$, $r_i^* = e_i^*(q) - e_i^*(q-1)$; q and $q-1$ denotes the q th and $q-1$ th sampling time, respectively. Δu^* denotes the incremental output at the q th sampling time.

It should be noted that the model represented by (25)-(26) is just used to unveil the system dynamics and is employed as the simulated model by the method of lines [11] to evaluate the control scheme. The only information we can utilize is the measured input-output data pairs.

Two groups data set are obtained from [1] by adding Pseudo-Random Quinary Sequence (PRQS) signal [12] with different amplitude (i.e. 0.447 and 0.1) to the control input. The scaling factors of 3-D FLC in [1] are set as 2.0, 0.001 and 0.8716 respectively. Each group has 150 data pairs composed of $e^*(z)$, $r^*(z)$ and Δu^* with the sampling time 0.2s. The group generated from the control input with amplitude 0.447 is taken as the training data set, while the other group is taken as the test data set. The design process of data-based 3-D FLC is given as follows:

- Apply the nearest neighborhood clustering algorithm to partition the input space. Let $\rho_0 = 0.7$ and $\eta_0 = 0$. Then 16 fuzzy rules were generated, where the width of 3-D MF was $\sigma_z \approx [0.0620, 0.0902, 0.1518, 0.2008, 0.2175]^T$ as in (16).
- Optimization algorithm with $\gamma = 0.95$ and $\lambda = 0.9$ was used to simplify the obtained fuzzy rules and 3-D fuzzy sets.
- The linear SVR algorithm was used to obtain optimal consequent part parameters, where the width of Gaussian MF is set as $\sigma_B \approx 0.1247$ by (17). Let ε be 0.01, and C be a real number in $[10, 10^7]$. Root Mean-

Squared Error (RMSE) defined in (27) was chosen as the quantitative performance to select the best approximated 3-D FLC, and then the *RMSEs* of the training data set and the test data set under different parameter C were listed in the Table I. From Table I, we can find that when $C = 10^7$, *RMSE* has a minimal value. Therefore, we choose $C = 10^7$ in this study. The extracted 3-D rule base and the related MFs were depicted in Fig. 4.

The proposed data-based 3-D FLC is applied to the control of catalytic packed-bed reactor, where simulation time is 10s. We select the same quantitative performance criteria as in [1]: steady-state error (SSE), integral of the absolute error (IAE), and integral of time multiplied by absolute error (ITAE). The control performance is given in Table II, and the control profile is given in Fig. 5. We can find that the data-based 3-D FLC has comparable control performance with the expert experience based 3-D FLC in [1] both in ideal condition and in disturbed condition.

TABLE I. RMSEs OF THE TRAINING AND TEST DATA SETS FOR DIFFERENT C

C	RMSE(training)	RMSE(test)
10	0.0452	0.0324
10^2	0.0452	0.0325
10^3	0.0452	0.0324
10^4	0.0451	0.0322
10^5	0.0441	0.0317
10^6	0.0401	0.0253
10^7	0.0401	0.0249

TABLE II. PERFORMANCE COMPARISONS

Performance index	Data-based 3-D FLC	Expert-based 3-D FLC [1]
Number of rules	16	49
No disturbance		
ISS ($\times 10^{-2}$)	1.74	1.69
IAE ($\times 10^{-1}$)	2.603	2.557
ITAE ($\times 10^{-1}$)	8.896	8.646
With 50% increase disturbance in velocity of gas		
ISS ($\times 10^{-2}$)	1.82	1.78
IAE ($\times 10^{-1}$)	2.721	2.680
ITAE ($\times 10^{-1}$)	9.297	9.062

V. CONCLUSION

In this paper, a new data-based 3-D FLC is designed by using a nearest neighborhood clustering algorithm, fuzzy similarity measurement techniques, and a linear SVR algorithm. Firstly, the nearest neighborhood clustering algorithm is used to partition the input space and construct 3-D rule base and 3-D MFs. Then, geometric similarity measure is employed to reduce the rule base. Finally, a linear SVR algorithm is used to estimate the optimal consequent part parameters. The proposed 3-D FLC was applied to the control of catalytic packed-bed reactor. The simulation results show that the designed 3-D FLC had a satisfied control performance compared with the expert experience based 3-D FLC.

ACKNOWLEDGMENT

This work was supported in part by the National Nature Science Foundation of China under Grant 60804033, Grant 61074059, and Grant 61004047, in part by the Shanghai Municipal Natural Science Foundation (Grant: 09ZR1409600), in part by Specialized Research Fund for the Doctoral Program of Higher Education of China (20100073120045), and in part by National Hi-Tech Research and Development Program of China (863 Program, Grant No. SQ2011AA0403839001).

REFERENCES

- [1] H. X. Li, X. X. Zhang, S. Y. Li, "A three-dimensional fuzzy control methodology for a class of distributed parameter systems", IEEE Trans. Syst., Vol. 15, No. 3, pp. 470-481, Jun. 2007.
- [2] Y. Jiang, X. X. Zhang, T. Zou, G. T. Cao, A novel 3-D fuzzy logic controller design using table look-up scheme, 2010 International Conference on Computer Application and System Modeling (ICCSM), pp.V4388-V4393, Oct. 2010.
- [3] L. X. Wang, Y. J. Wang, A course in fuzzy systems and control, Beijing: Tsinghua University Press, 2003. (in Chinese)
- [4] Yaochu Jin, Fuzzy modeling of high-dimensional systems: Complexity reduction and interpretability improvement, IEEE Trans. On Fuzzy System 8 (2) pp.212-221, 1994.
- [5] Min-You Chen, D.A. Linkens, Rule-base self-generation and simplification for data-driven fuzzy models, Fuzzy Sets and Systems 142 pp.243-265, 2004.
- [6] M. Setnes, R. Babuška, U. Kaymak, and H. R. van Nauta Lemke, Similarity measures in fuzzy rule base simplification, IEEE Trans. Systems, Man, and Cybernetics – Part B: Cybernetics, 28(3) pp.379-386, Jun. 1998.
- [7] A. J. Smola, B. Schölkopf, A tutorial on support vector regression, Statistics and Computing, 14(3) pp.199-222, Sep. 2003.
- [8] Jia Li, J. P. Shi, M. S. Qiu, Fuzzy neural model with global convergence for batch process, Information and Control, 38(6) pp.685-691, Dec. 2009.(in Chinese)
- [9] Yinghua Lin, A fuzzy approach to input variable identification, Proceedings of the Third IEEE Conference on Fuzzy Systems, Orlando, 3: pp.2031-2036, 1994.
- [10] W. H. Ray, Advanced process control, New York: McGraw-Hill, 1981.
- [11] W.E. Schiesser, The Numerical Methods Of Lines Integration Of Partial Differential Equations, Academic Press, San Diego, 1991.
- [12] X. F. Wang, G. Z. Lu, System modelling and identification, Beijing: Publishing House of Electronics Industry, 2004. (in Chinese)

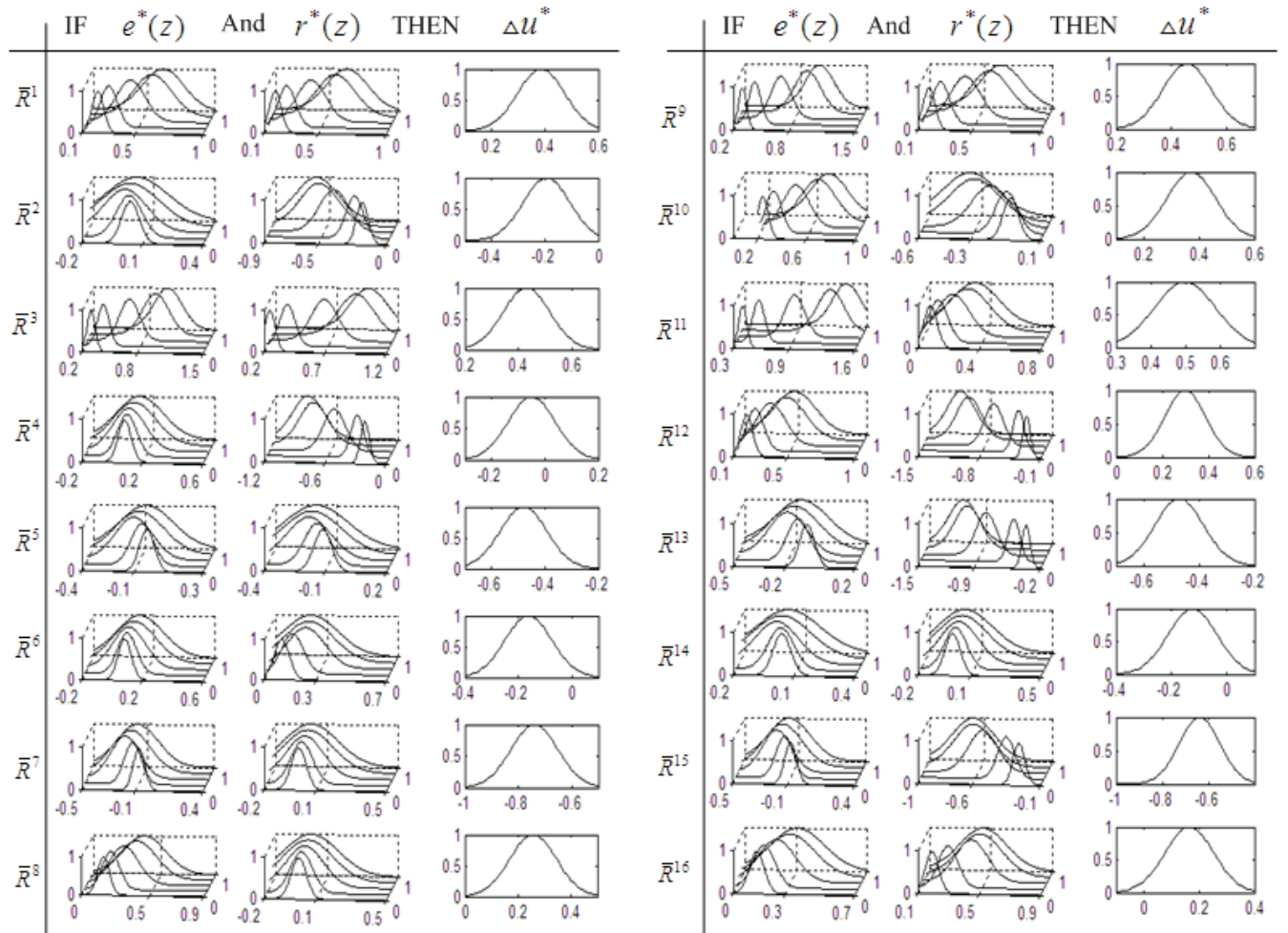


Figure 4. 3-D rule base extracted from input-output data pairs.

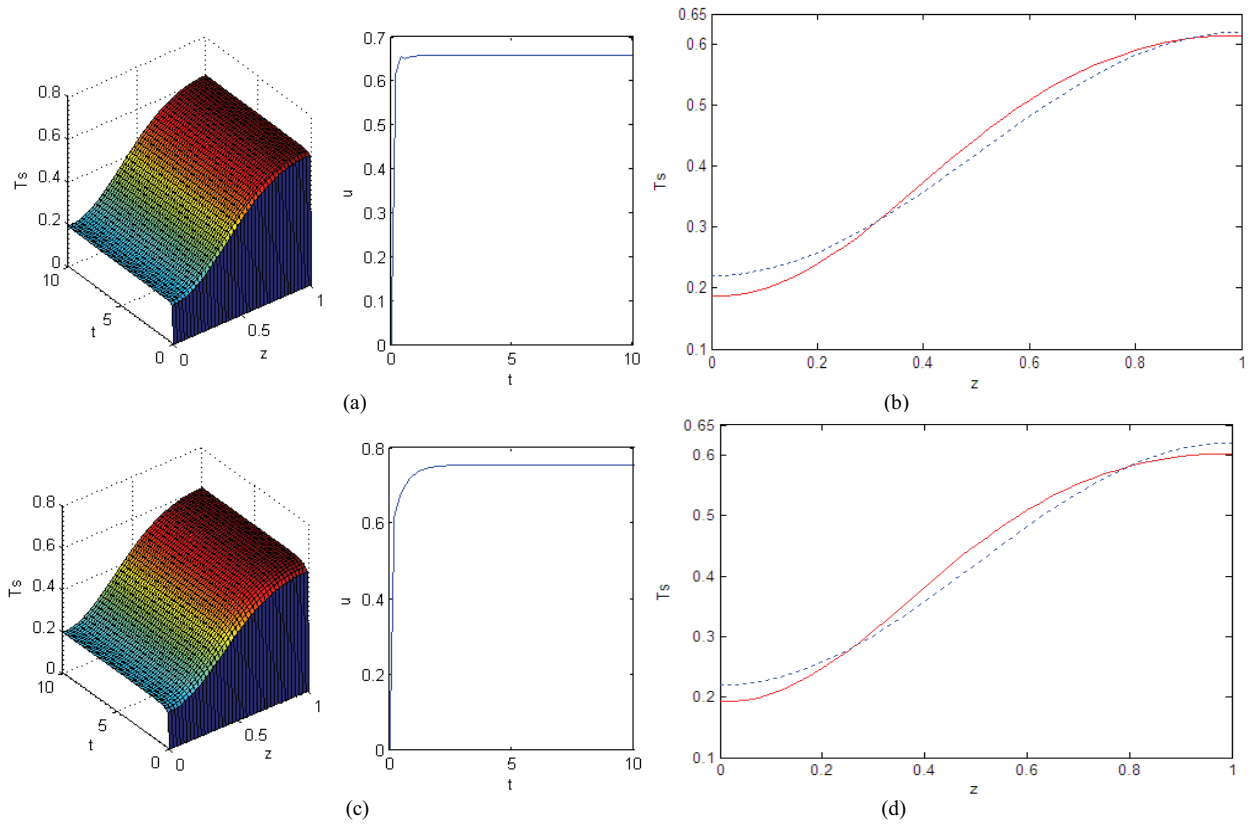


Figure 5. Data-based 3-D FLC controlled catalyst temperature evolution profile and manipulated input under ideal situations, respectively. (b) Catalyst temperature profiles in steady state under ideal condition. (c) Data-based 3-D FLC controlled catalyst temperature evolution profile and manipulated input under disturbance situations, (d) Catalyst temperature profiles in steady state under disturbed condition. (Dotted line: Reference profile. Solid line: Actual temperature profile.)