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Paper:

SIRMs (Single Input Rule Modules) Connected Fuzzy Inference Model

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A new fuzzy inference model, SIRMs (Single Input Rule Modules) Connected Fuzzy Inference Model, is proposed for plural input fuzzy control. For each input item, an importance degree is defined and single input fuzzy rule module is constructed. The importance degrees control the roles of the input items in systems. The model output is obtained by the summation of the products of the importance degree and the fuzzy inference result of each SIRM. The proposed model needs both very few rules and parameters, and the rules can be designed much easier. The new model is first applied to typical second-order lag systems. The simulation results show that the proposed model can largely improve the control performance compared with that of the conventional fuzzy inference model. The tuning algorithm is then given based on the gradient descent method and used to adjust the parameters of the proposed model for identifying 4-input l-output nonlinear functions. The identification results indicate that the proposed model also has the ability to identify nonlinear systems.

Keyword: Fuzzy inference model, Identification, Importance degree, Plural input fuzzy control, Single input rule module

1. Introduction

In Mamdani's conventional IF-THEN fuzzy inference model,[4] all the input items of a given system are usually placed in the antecedent part of each fuzzy rule. If the system has only one or two input items, such a structure is effective because fuzzy rules can visually be designed on a rule table. According to this structure, however, both the number of fuzzy rules and the number of parameters increase exponentially with the number of input items. In large-scale systems, the number of fuzzy rules and the number of parameters both get very large, and defining the fuzzy rules becomes a difficult task. To reduce the number of fuzzy rules and the number of parameters, a hierarchical fuzzy mode[1] has been proposed which defines sub-level fuzzy models with two or three input items in each layer. For setting of fuzzy rules automatically, on the other hand, several learning algorithms[1,8,9] have been reported.

In this paper, a new model, SIRMs (Single Input Rule Modules) Connected Fuzzy Inference Model, is proposed for plural input fuzzy control. For each input item, degree of importance is defined according to the contribution of the input item to the system performance, and a SIRM is constructed which has only a single input item in the antecedent part of its fuzzy rules. The summation of the products of the importance degree and the fuzzy inference result of each module is then taken as the output of the proposed model. Although the architecture is very simple, the proposed model can solve the above-stated problems of the conventional model.

Ohnishi's ordinal structure model[7] is composed of 1-input 1-output fuzzy rules, and each rule is assigned with a weight indicating the ordinal relation among the rules. In the fuzzy singleton-type reasoning method,[6] the weight of a singleton-type membership function of one output item in the consequent part of a fuzzy rule can be regarded as the weight of the whole fuzzy rule; this is essentially as Ohnishi's model. However, the weights in these two cases are designed, not for each input item, but for the whole fuzzy rule. From the stand point of control, it is more desirable to directly strengthen or restrain, not the fuzzy rules, but the input items, based on intuitive experience. In this model, independent degree of importance is defined directly for each input item, and the summation of the products of the importance degree and the fuzzy inference result of each SIRM is the output. Therefore, the influence of input items on the system output can be intuitively realized, in addition to a major reduction in both the number of fuzzy rules and the number of parameters. Kuwahara et al.[2] used two weight coefficients to combine the fuzzy results of two fuzzy rule groups. Since the two weights were naturally complementary to each other, this method can be considered to be a special case in the model proposed here.

In the next section, the SIRMs connected fuzzy inference model is explained and its attractive properties are shown. In the third section, the new model is applied to typical second-order lag systems, and control simulation results are indicated in detail. A tuning algorithm is then given, and identification tests of the nonlinear functions are done. The last section concludes that the proposed model can improve control performance, requires fewer fuzzy rules and makes definition of the fuzzy rules easier.

2. SIRMs Connected Fuzzy Inference Model

A system with n inputs and 1 output is considered here, for simplicity. And the simplified reasoning method[6] is used. However, the results below are also true for other inference methods, like the min-max gravity method,[4] etc., and the model can easily be extended to systems with plural inputs and plural outputs.

2.1. Conventional Fuzzy Inference Model

For systems of n inputs and 1 output, the j-th rule of the conventional fuzzy inference model can be expressed as follows:

$$\text{if } \mathop{\text{AND}}_{i=1}^{n} x_i = A_j^i \text{ then } y = c_j \quad \cdots\cdots\cdots (1)$$

Here, x_i is the i-th variable in the antecedent part and corresponds to the i-th input item of the system, while y is the variable in the consequent part and corresponds to the output item of the system. A_j^i is the membership function of the i-th variable x_i in the j-th rule, and c_j is the real number output value of the variable y in the j-th rule. $j = 1, 2, \cdots, m$ is the index number of rules, and $i = 1, 2, \cdots, n$ is the index number of both the input items and the variables of the antecedent part.

When a set of observation values $\{x_i^0\}_{i=1}^{n}$ is given, the fuzzy grade of the i-th variable in the antecedent part of the j-th rule is calculated by $A_j^i(x_i^0)$, and the agreement h_j of the whole antecedent part of the j-th rule is defined by algebraic products as Eq.(2). The inference result y^0 can then be obtained using Eq.(3) from the simplified reasoning method.

$$h_j = A_j^1(x_1^0) \cdots A_j^i(x_i^0) \cdots A_j^n(x_n^0) \quad \cdots\cdots\cdots (2)$$

$$y^0 = \frac{\sum_{k=1}^{m} h_k \cdot c_k}{\sum_{k=1}^{m} h_k} \quad \cdots\cdots\cdots (3)$$

As shown in Eq.(1), in the conventional fuzzy inference model all the input items are usually put into the antecedent part of each fuzzy rule. Therefore, the maximum number of fuzzy rules is determined by the number of all the combinations of the membership functions among the different input items. Even though setting fuzzy rules empirically is possible for systems with fewer input items, it becomes extremely difficult to establish fuzzy rules when the number of the input items increases because all of the input items, have to be taken into consideration in defining each fuzzy rule.

2.2. The Proposed Model

To solve the problems of the conventional fuzzy inference model, such as the necessity of large number of fuzzy rules and the difficulty in defining fuzzy rules, "SIRMs Connected Fuzzy Inference Model" is proposed here. Two new concepts are introduced in this new model: one is the so-called SIRM and the other is the importance degree. SIRM means a module of single input fuzzy rules. Each SIRM corresponds to only one separate input item and has that input item in the antecedent part of its fuzzy rules. For systems with n inputs and 1 output, the proposed model has just n SIRMs as shown in Eq.(4).

$$\begin{array}{ll} \text{SIRM-1:} & \{R_j^1: \text{ if } x_i = A_j^1 \text{ then } y_1 = c_j^1\}_{j=1}^{m_1} \\ \cdots\cdots & \cdots\cdots \\ \text{SIRM-}i\text{:} & \{R_j^i: \text{ if } x_i = A_j^i \text{ then } y_i = c_j^i\}_{j=1}^{m_i} \\ \cdots\cdots & \cdots\cdots \\ \text{SIRM-}n\text{:} & \{R_j^n: \text{ if } x_n = A_j^n \text{ then } y_n = c_j^n\}_{j=1}^{m_n} \end{array} \quad \cdots\cdots\cdots (4)$$

Here, SIRM-i means the i-th single input rule module, and R_j^i is the j-th rule in the SIRM-i. x_i, corresponding to the i-th input item of the given system, is the sole variable in the antecedent part of the SIRM-i. y_i is the variable in the consequent part of the SIRM-i, and $y_1, \cdots, y_i, \cdots, yMIVn$ all correspond to the same output item of the given system. A_j^i is the membership function of the variable x_i in the antecedent part of the j-th rule of the SIRM-i, while c_j^i is the real number output value of the variable y_i in the consequent part of the j-th rule of the SIRM-i. Furthermore, $i = 1, 2, \cdots, n$ is the index number of the SIRMs or the input items, and $j = 1, 2, \cdots, m_i$ is the index number of the rules in the SIRM-i.

If the observation value x_i^0 of the variable in the antecedent part of the SIRM-i is known, then the agreement h_j^i of the antecedent part of the j-th rule in the SIRM-i simply becomes Eq.(5), and the inference result y_i^0 of the SIRM-i is expressed as Eq.(6).

$$h_j^i = A_j^i(x_i^0) \quad \cdots\cdots\cdots (5)$$

$$y_i = \frac{\sum_{k=1}^{m_i} h_k^i \cdot c_k^i}{\sum_{k=1}^{m_i} h_k^i} \quad \cdots\cdots\cdots (6)$$

Usually, each input item can be considered to play an unequal role in the system performance. Among the input items, some may contribute significantly to the system performance while the contribution of others relatively small. Some input items may improve the performance of the system more if their roles are strengthened, while others may not have a positive influence on the performance if emphasized. Therefore, assigning larger weights to those input items that contribute positively or significantly improve the system performance, and at the same time assigning smaller weights to other input items in order to restrain their roles, would be in accordance with the experts' experience and would be expected to improve the total performance of the system.

However, in the conventional fuzzy inference model all the input items are treated equally. Although there has been attempts at tuning the weight of the output value of the consequent part of fuzzy rule[6] and assigning weights to fuzzy rules,[7] the result is essentially that each input item in the antecedent part is given an equal weight. To distinguish the differences of the roles of the input items, an importance degree is introduced for each input item. The value of the importance degree of an input item should be determined according to its contribution to the system performance. A larger importance degree means that the role of its corresponding input item is strengthened, and a smaller one means that the role of its corresponding input item is weakened.

Suppose that the importance degree of each input item is given as $w_i(i = 1, 2, \cdots, n)$, the output y^0 of the proposed model is then defined as the summation of the products of the importance degree and the fuzzy inference result of all the SIRMs. As shown in Eq.(7), the model output is linear to the reasoning result of each rule module. If the reasoning result of each rule module is identical, then the ratio of the contribution of one input item to the model output is controlled by the importance degrees. Therefore, the input items with larger importance degrees contribute more to the model output, while the input items with smaller importance degrees contribute less to the model output. Moreover, since the relationship among the input items, defined by the importance degrees, is linearly mapped to the model output, it is expected that the desired results can be obtained by intuitively changing the importance degrees.

$$y^0 = \sum_{i=1}^{n} w_i \cdot y_i^0 \quad \cdots\cdots\cdots\cdots \quad (7)$$

If the nominal scaling factor of the output item is taken into consideration in Eq.(7), then one will notice that the nominal scaling factor of the output item and the importance degree of one input item together composite the scaling factor of the variable in the consequent part of the rules of the corresponding SIRM. And the importance degree is actually a part of the scaling factor of the variable in the consequent part of the rules of the corresponding SIRM. Therefore, tuning the importance degree causes the change of the scaling factor of the variable in the consequent part of the rules of the corresponding SIRM. On the other hand, although the variable of the consequent part from SIRM-1 to SIRM-n is given different names, all the variables correspond to the same output item of the given system. If the importance degrees are set up to different values from each other, then the output item actually has different scaling factors in different SIRMs at the same time. Moreover, if the nominal scaling factor of the output item is fixed, then each of these scaling factors of the SIRMs is determined independently by the corresponding importance degree which reflects only one input item.

The importance degrees not only connect all the SIRMs into a united whole but also adjust the roles of the input items. Since the values of the importance degrees are defined independently, it is not necessary to normalize the summation of all the importance degrees to 1.0. After the nominal scaling factor of the model output is determined, the values of the importance degrees can be set by trial and error, or by learning algorithm to be given later if training data are possible.

2.3. Properties of the Proposed Model

In spite of the structure simplicity, the new model has following attractive properties compared with the conventional fuzzy inference model.

a) Sharp reduction in the numbers of fuzzy rules

Under the conventional fuzzy inference model, the maximum number of fuzzy rules is decided by the combination of the membership functions of all the input items. On the contrary, the new model consists of SIRMs with the same number of the input items, and each SIRM has only one variable in the antecedent parts of its fuzzy rules. Therefore, the total number of available fuzzy rules under the new model equals the summation of the numbers of the membership functions of the input items. This fact leads to a dramatic cut in the number of fuzzy rules when the number of the input items increases. For example, if each input item is given 5 membership functions, then the maximum number of fuzzy rules is indicated in **Table 1** for the two models with 2 to 5 input items. Since the number of the parameters necessary for establishing a fuzzy system depends mainly on the number of the fuzzy rules, the number of the parameters can also be reduced sharply.

Table 1. Maximum number of fuzzy rules.

Number of Input Items	Conventional Model	Proposed Model
2	25	10
3	125	15
4	625	20
5	3125	25

b) Easy design of fuzzy rules

Even for large-scale systems, each SIRM in the new model has only one variable in the antecedent part of its rules. Therefore, there is no need to take all the input items into consideration for each rule. In designing a fuzzy rule, exploring the relationship between the current input item and the system performance is sufficient. Consequently, establishing fuzzy rules is expected to become much easier than before.

c) Desired results are possible by adjusting the importance degrees

Although the method[6] of adjusting the weight of fuzzy rules in order to control the role of the rules has been reported, the relationship between the control result and the rules is not very intuitive. From the viewpoint of control, directly adjusting the role of the input items instead of the fuzzy rules corresponds better with intuitive experience. The proposed model assigns the importance degrees directly to the input items. By adjusting the importance degrees, the role of the input items can be strengthened or weakened, thereby either enhancing or weakening the system performance. For instance, let's consider the control of a first-order lag system where the output error and its change are taken as two input items. If the rise time is to be shortened, then the importance degree of the output error should be strenghtend. If vibration is to be suppressed, then the importance degree with regard to the change in the output error should be stressed.

d) Easy realization of fuzzy chip

As stated before, the proposed model needs very few fuzzy rules and parameters. This relaxes the demand on, memory which used to be a big bottleneck. In addition, since each antecedent part of a SIRM includes only one variable, the fuzzy grade of the variable becomes the agreement of the antecedent part. Hence, the inference time can be significantly shortened. All these factors make a fuzzy chip of this model an easy possibility.

3. Control Simulations

To verify the effectiveness of the proposed model, the proposed model is applied to typical second-order lag systems.

The transfer function of the second-order lag systems discussed here is expressed as Eq.(8) where *A, B, C* are coefficients and *L* is the dead time. In the following simulations, three plants[3] listed below, are selected as the control objects.

$$G(s) = \frac{A}{s^2 + B \cdot s + C} \cdot e^{-L \cdot s} \quad \ldots\ldots\ldots\ldots (8)$$

Plant (1) A = 1.228, B = 0.6380, C = 0.0340, L = 0.0
Plant (2) A = 19.54, B = 0.4000, C = 0.5400, L = 0.0
Plant (3) A = 0.231, B = 0.0994, C = 0.0064, L = 1.0

To realize fuzzy control of the second-order lag systems, three input items, i.e., the output error x_1, the change x_2 in the output error, the second-order change x_3 in the output error are usually used as the variables of the antecedent part, and the change Δy in the manipulated variable is as the variable of the consequent part. Thus, the fuzzy rules of the conventional model can be constructed as in **Table 2**. On the other hand, the proposed model is composed of three SIRMs as shown in **Table 3**. Each SIRM has one of the three input items as the sole variable in its antecedent. The sum of the products of the importance degrees and the inference results of the three SIRMs gives the change Δy in the manipulated variable. Evidently the conventional model needs 27 rules while the proposed model needs only 9 rules. Here, the membership functions NB, ZO, and PB are defined in **Fig.1**. The sampling period is fixed to 0.1s.

For desired value of 60.0, the simulation results are displayed separately in **Fig.2-4**. In the figures, S(65.000, 0.2200, 0.0500, 1.5000) stands for a set of the scaling factors of the three input items, and the nominal scaling factor of the change in the manipulated variable. W(5.5110, 2.8856, 1.9000) is a set of the importance degrees for the three input items. Furthermore, the dotted line represents the desired value, and the upper and lower curves indicate the controlled variable and the manipulated variable respectively.

As shown in Fig.2(a), although the conventional model can approach the desired value without any steady-state error, it spends about 10s reaching the desired value from the control start. On the other hand, from Fig.2(b), the proposed model shortens the time required to reach the desired value by about 50% of that needed by the conventional model, with almost no any overshoot.

It can be seen from Fig.3 that even though the conventional model reaches the desired value in less than 6s, the proposed model further reduces the time required to reach the desired value by more than 30%, and at the same time,causes no steady-state error with just a little overshoot.

Since Plant (3) has dead time, controlling such an object is a little more difficult. In Fig.4(a), under the conventional fuzzy inference model the control object vibrates after reaching the desired value. The vibration phenomena can be understood clearly from the curve of the manipulated variable. Nevertheless, the proposed model entirely eliminates the vibration although the time required to reach the desired value is about 10% longer.

Table 2. Fuzzy rules of the conventional model.

if x_1 = NB

Consequent Part Δy		x_3 NB	x_3 ZO	x_3 PB
x_2	NB	-1.000	-1.000	-0.667
	ZO	-1.000	-0.667	-0.333
	PB	-0.667	-0.333	0.000

if x_1 = ZO

Consequent Part Δy		x_3 NB	x_3 ZO	x_3 PB
x_2	NB	-0.667	-0.333	0.000
	ZO	-0.333	0.000	0.333
	PB	0.000	0.333	0.667

if x_1 = PB

Consequent Part Δy		x_3 NB	x_3 ZO	x_3 PB
x_2	NB	0.000	0.333	0.667
	ZO	0.333	0.667	1.000
	PB	0.667	1.000	1.000

Table 3. SIRMs of the proposed model.

Antecedent Part x_i (i = 1, 2, 3)	Consequent Part Δy_i (i = 1, 2, 3)
NB	-1.0
ZO	0.0
PB	1.0

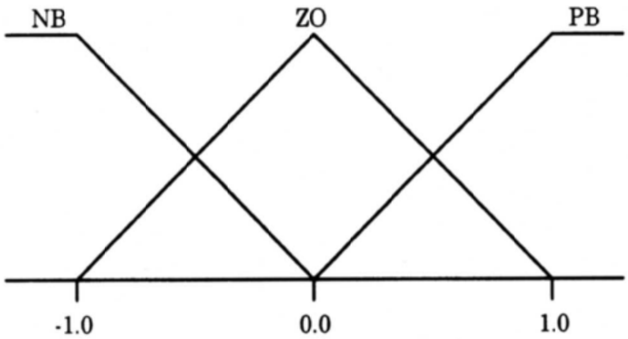
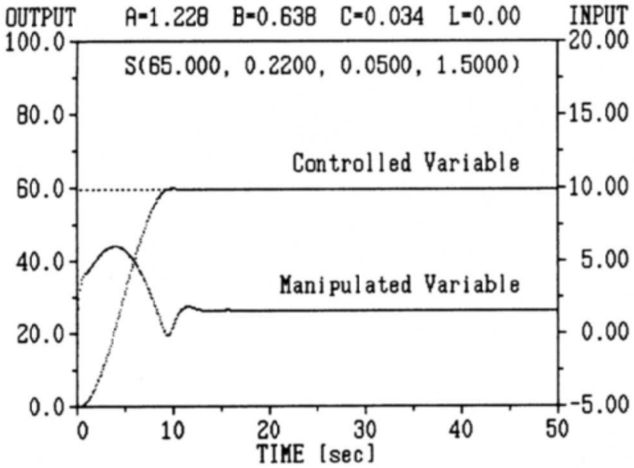
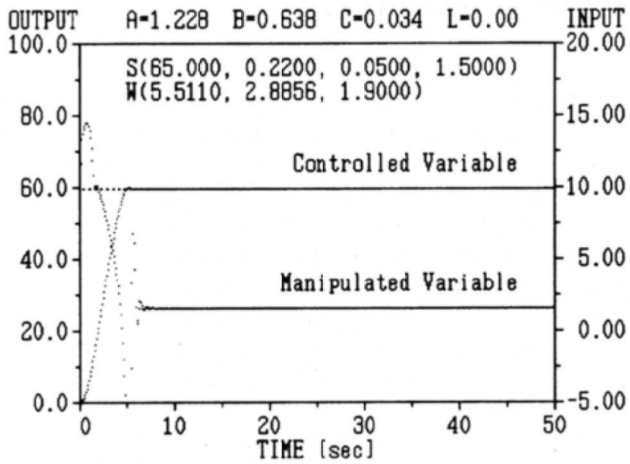


Fig.1. Definition of the membership functions.

Therefore, the above results show that the proposed model can also significantly improve control performance. In addition, it can be observed that the scaling factor of the output error in Fig.2 and Fig.4 was set up very specially. Since the desired value was 60.0, the same value, 60.0, is usually taken as the scaling factor of the output error. In the above simulations, however, such a setting would lead to bad result using the conventional model. To obtain more satisfactory results, the above listed scaling factors were selected by trial and error. And the same sets of scaling factors, used in the conventional model, were also adopted

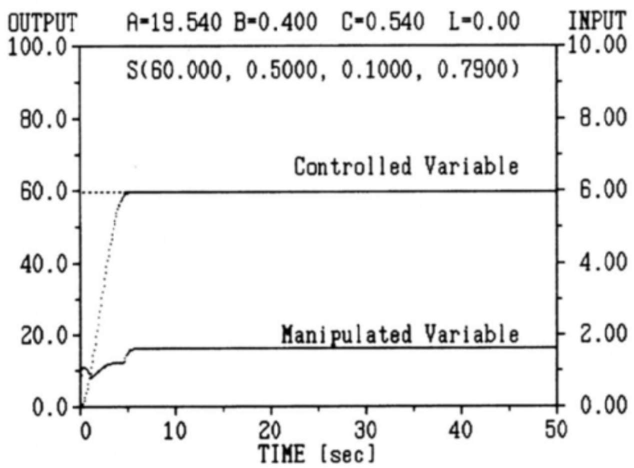


(a) Result by the conventional model

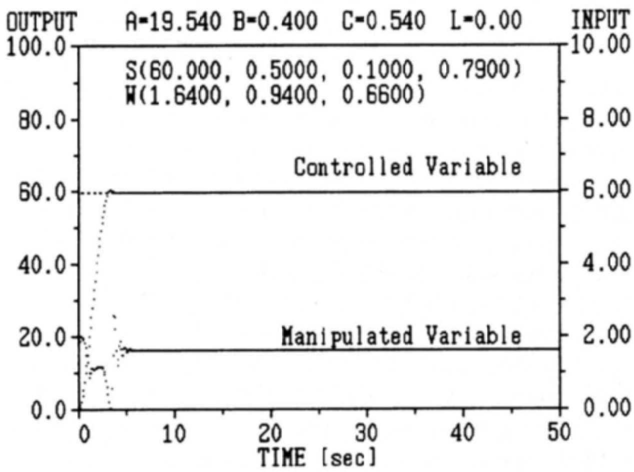


(b) Result by the proposed model

Fig.2. Control simulation of Plant (1).

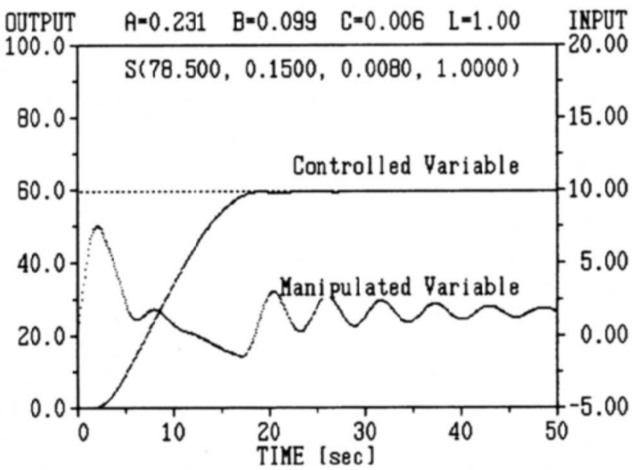


(a) Result by the conventional model

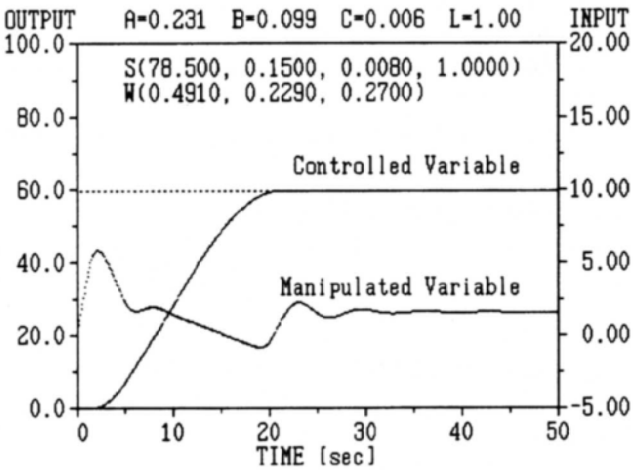


(b) Result by the proposed model

Fig. 3. Control simulation of Plant (2).



(a) Result by the conventional model



(b) Result by the proposed model

Fig. 4. Control simulation of Plant (3).

in the corresponding simulations in the proposed model, for fair comparison under completely the same conditions. If ordinary settings of the scaling factors are possible even better results can be achieved.[10)]

4. System Identification

4.1. Tuning Algorithm

As shown above, the fuzzy rules of the SIRMs are rather easily established. However, when the given system gets complicated, defining the fuzzy rules and the importance degrees is difficult. So it would be helpful to be able to automatically tune all the parameters based on the input-output data of the system. The parameters to be tuned here are those determining the membership functions of the variable in the antecedent part, the real number output values of the variable in the consequent part, and the importance degree of all the SIRMs.

Suppose that teacher patterns (pairs of input patterns and desired output values) are given, and the p-th input pattern and the corresponding desired output value are $(x_1^P, \cdots, x_i^P, \cdots, x_n^P)$ and y^{T_p}, respectively. If the actual output value of the proposed model is y^{0_p} for the p-th input pattern, then the evaluation function E^p can be defined by Eq.(9). It is well known by the gradient descent method[1,8,9] that the evaluation function will converge to its minimum if searching is done along the reverse direction of the gradient vector of the function to all the parameters. Based on this knowledge, the tuning algorithm can be deduced as follows.

If the simplified reasoning method is used and the membership function $A_j^i(x_j)$ of the variable in the antecedent part is defined as Gaussian-type in Eq.(10), the increments of the importance degree w_i, the real number output value c_j^i of the variable in the consequent part, and the parameters a_j^i, b_j^i of the Gaussian-type membership function of the variable in the antecedent part are obtained by Eq.(11)-(14), respectively. Here, $i = 1, 2, \cdots, n$ is the index number of the SIRMs, $j = 1, 2, \cdots, m_i$, is the index number of the rules in the SIRM-i. Furthermore, t is the current tuning iteration number, α, β, γ, η are the learning coefficients for the different kinds of the parameters, separately.

$$E^p = \frac{1}{2}(y^{T_p} - y^{0_p})^2 \quad \cdots\cdots (9)$$

$$A_j^i(x_i) = \exp\left(-\frac{(x_i - a_j^i)^2}{b_j^i}\right) \quad \cdots\cdots (10)$$

$$\Delta w_i(t+1) = \alpha \cdot (y^{T_p} - y^{0_p}(t)) \cdot y_i^0(t) \quad \cdots\cdots (11)$$

$$\Delta c_j^i(t+1) = \beta \cdot w_i(t) \cdot (y^{T_p} - y^{0_p}(t)) \cdot \frac{h_j^i(t)}{\sum_{k=1}^{m_i} h_k^i(t)} \quad \cdots\cdots (12)$$

$$\Delta a_j^i(t+1) = \gamma \cdot w_i(t) \cdot (y^{T_p} - y^{0_p}(t)) \cdot (c_j^i(t) - y_i^0(t)) \cdot \frac{h_j^i(t)}{\sum_{k=1}^{m_i} h_k^i(t)} \cdot \frac{2 \cdot (x_i^p - a_j^i(t))}{b_j^i(t)} \quad \cdots\cdots (13)$$

$$\Delta b_j^i(t+1) = \eta \cdot w_i(t) \cdot (y^{T_p} - y^{0_p}(t)) \cdot (c_j^i(t) - y_i^0(t)) \cdot \frac{h_j^i(t)}{\sum_{k=1}^{m_i} h_k^i(t)} \cdot \left(\frac{x_i^p - a_j^i(t)}{b_j^i(t)}\right)^2 \quad \cdots\cdots (14)$$

4.2. Identification Simulations

Identification ability is also an important index for measuring a new model. To show the identification ability, the proposed model is utilized to identify two 4-input 1-output nonlinear functions[8] listed below. All of the 4 inputs are limited to [–1.0, +1.0], and the output is restricted into [0.0, 1.0].

$$\text{(F1)} \quad y = (2 \cdot x_1 + 4 \cdot x_2^2 + 0.1)^2 / 74.42 + (3 \cdot e^{3 \cdot x_3} + 2 \cdot e^{-4 \cdot x_4})^{-0.5} - 0.077) / 4.68$$

$$\text{(F2)} \quad y = (2 \cdot x_1 + 4 \cdot x_2^2 + 0.1)^2 / 37.21 \; (2 \cdot \sin(\pi \cdot x_3) + \cos(\pi \cdot x_4) + 3) / 6$$

Since there are 4 inputs in the identification functions, the proposed model has to arrange 4 SIRMs, each corresponding separately to one of the 4 inputs. On the universe of discourse of each input item, 5 Gaussian-type membership functions are initially defined such that the adjacent membership functions cross over at the fuzzy grade 0.5. All of the real number output values of the variable in the consequent part of each SIRM are initialized to 0.0. Furthermore, the initial values of the importance degrees for the input items are all set to 0.25.

The above tuning algorithm is then used to adjust the parameters for the identifier. Given a certain number of teacher patterns, the tuning algorithm continues searching until the following mean squared error D is less than a specified threshold. Here, the learning coefficients α, β, γ, η are separately selected as 0.10, 0.10, 0.01, 0.01. After the tuning is finished, test patterns are inputted into the identifier. The mean squared error of the same Eq.(15) for all the test patterns is then calculated as the evaluation error. In addition, the maximum of the absolute values of the differences between the desired output values and the actual output values is indicated as the maximum error.

$$D = \frac{1}{P}\sum_{p=1}^{P}(y^{T_p} - y^{0_p})^2 \quad \cdots\cdots (15)$$

For the two identification functions, the identification simulation is performed using 10 trials each. In every trial, 20 teacher patterns and 20 test patterns are generated at random. For the threshold 0.001, the identification results of the two functions are shown separately in **Table 4** and **5**. In Table 4, the average iteration number, the average evaluation error, and the average maximum error are about 68, 0.0061, and 0.1585, respectively. In Table 5, the average values become 80, 0.0056, and 0.1827, respectively. From either of the two tables, it can be seen that the tuning converges fast; the evaluation error and the maximum error are small and stable.

Further, the proposed model is also tested using exactly the same data as Shi et al.[8] For the identification function (F1), the proposed model produces an evaluation error 0.0031 and a maximum error 0.1107, while the evaluation error and the maximum error shown by them were 0.0063 and 0.1618. For the other function (F2), the proposed model obtains the evaluation error 0.0031 and the maximum error 0.1734, while theirs, the evaluation error 0.0069 and the maximum error 0.1939. Compared with their results, the identification results of the proposed model apparently can be said to have, at least, the same precision. More important, the proposed model used only 20 fuzzy rules, while their

Table 4. Identification result of (F1).

Trial No.	Iteration Number	Evaluation Error	Maximum Error
1	78	0.0070	0.1718
2	85	0.0048	0.1742
3	98	0.0075	0.1875
4	94	0.0050	0.1254
5	29	0.0084	0.1917
6	65	0.0048	0.1157
7	58	0.0043	0.1575
8	43	0.0058	0.1367
9	80	0.0044	0.1481
10	47	0.0091	0.1766

Table 5. Identification result of (F2).

Trial No.	Iteration Number	Evaluation Error	Maximum Error
1	107	0.0062	0.2069
2	72	0.0072	0.1638
3	44	0.0043	0.1661
4	115	0.0050	0.1616
5	85	0.0063	0.1508
6	35	0.0048	0.1798
7	46	0.0054	0.1738
8	45	0.0049	0.2382
9	93	0.0050	0.1897
10	158	0.0068	0.1963

method required 625 fuzzy rules.

The proposed fuzzy inference model seems weak for nonlinear systems. But through tuning, each rule module comes to have a complicated nonlinear relationship between its input and output. And furthermore, the importance degrees also help to form complex relationship among the input items and the output item. These two operations elicit the nonlinearity of the proposed model and create a different input-output characteristic from that of the conventional model. As a result, the proposed model has the ability to rather accurately identify systems with strong nonlinearity.

5. Conclusions

The SIRMs Connected Fuzzy Inference Model was proposed for plural input control systems. The model consists of SIRMs of the same number as the input items. Each SIRM has only one variable in the antecedent part of its rules. An importance degree is also defined for each input item. The importance degrees adjust the roles of the input items according to their contribution to the system performance. The model output is obtained by summing the products of the importance degree and the fuzzy inference result of each SIRM.

The model was first applied to typical second-order lag systems. Compared with the conventional fuzzy inference model, the simulation results show that the proposed model can significantly improve control performance, besides simplifying the design of the fuzzy rules, and can dramatically reduce both the number of fuzzy rules and the number of parameters. The tuning algorithm was then given based on the simplified reasoning method and the gradient descent method. Finally, the tuning algorithm was used to adjust the parameters of the proposed model in order to identify 4-input 1-output nonlinear functions. The identification results indicate that the proposed model also has the ability to identify nonlinear systems.

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