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Research Article

Adaptive multilayer T-S fuzzy controller for nonlinear SISO system optimized by differential evolution algorithm

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ABSTRACT

In this paper, the authors propose a novel adaptive multilayer T-S fuzzy controller (AMTFC) with a optimize soft computing algorithm for a class of robust control uncertain nonlinear SISO systems. First, a new multilayer T-S fuzzy was created by combined multiple simple T-S fuzzy model with a sum function in the output. The multi-layer fuzzy model used in nonlinear identification has many advantages over conventional fuzzy models, but it cannot be created by the writer's experience or the trial and error method. It can only be created using an optimization algorithm. Then the parameters of multilayer fuzzy model is optimized by the differential evolution DE algorithm is used to offline identify the inverse nonlinear system with uncertain parameters. The trained model was validated by a different dataset from the training dataset for guarantee the convergence of the training algorithm. Second, for robustly and adaptive purposes, the authors have proposed an additional adaptive fuzzy model based on Lyapunov stability theory combined with the optimized multilayer fuzzy. The adaptive fuzzy based on sliding mode surface is designed to guarantee that the closed-loop system is asymptotically stable has been proved base on a lyapunov stability theory. Furthermore, simulation tests are perfomed in Matlab/Simulink environment that controling a water level of coupled tank with uncertain parameters are given to illustrate the effectiveness of the proposed control scheme. The proposed control algorithm is implemented in simulation with many different control parameters and it is also compared with the conventional adaptive control algorithm and inverse controller. The simulation results also shows the superior of proposed controller than an adaptive fuzzy control or inverse controller when using the least mean square error standard.

Key words: Multilayer T-S Fuzzy, Inverse Controller, Adaptive Control, Differential Evolution, Lyapunov Theory

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INTRODUCTION

Fuzzy logic was first proposed in 1965 by Zadeh[1]. There are many studies developed based on this fuzzy-based domain, such as Fuzzy type-2, Fuzzy type-*n*, neural fuzzy, hierarchical fuzzy to model and control nonlinear system,[2,3]. Recently, Takagi–Sugeno (T–S) fuzzy model can provide a modeling frame for nonlinear systems. The advantage of T–S fuzzy systems is that they allow us to use a set of local linear systems with corresponding membership functions to represent nonlinear systems. The T-S fuzzy model is widely accepted as a powerful modeling tool and it's applications to various kinds of non-linear systems can be found in[4–9]. Based on the T-S fuzzy model of a plant, papers[10–13] introduced a fuzzy control design method for nonlinear systems with a guaranteed $H_{2/\infty}$ model reference tracking performance. However, if the membership functions of the T–S fuzzy system encounter parametric-uncertainty problem, the T–S fuzzy system cannot operate efficiently. Moreover, with a complex system, the more time it requires for training, the more complex membership functions that eventual fuzzy rule-table will become. To achieve a higher precision from the Fuzzy model, its parameters are required to be optimized and the fuzzy structure is needed to be changed. Recently, Type-2 fuzzy sets[14–16] have been shown that they prove better than type-1 ones both on representing the nonlinear systems and handling the uncertainties. Paper[17] presented the problem of fuzzy control for nonlinear networked control systems with packet dropouts and parameter uncertainties based on the interval type-2 fuzzy-model-based approach. Paper[18] introduced an inverse controller based on a type-2 fuzzy model control. Moreover, many researchers used the optimization algorithms such as a cuckoo search algorithm (CSA)[19], Particle Swarm Optimization (PSO)[20], genetic algorithm (GA)[21], differential evolution (DE)[22,23] to optimize the parameters of the fuzzy Type-1 logic controller as to handle the nonlinear characteristics. Unlike a traditional Fuzzy set, multilayer Fuzzy model can't be built

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based on the experience of the designer. It is only available to be trained with soft computing optimization algorithm. Then it can be applied to identify and control of complex MIMO systems and be easy to scale for both of large or simple system [24]. Paper [25] successfully proposed the concept of Multilayer Fuzzy model for identifying uncertain nonlinear MISO system.

Furthermore, in order to compensate the uncertainties and guarantee the asymptotic stability, there are many different adaptive fuzzy control methods based on the classic advanced control algorithm such as sliding mode control (SMC) [26–32], $H_{2/\infty}$ technique [10–13], linearization feedback control [33–36], back-stepping technique [37–40]. However, these above-mentioned techniques require knowing in advance the characteristics of nonlinear uncertain SISO or MIMO system. Moreover, the adaptive fuzzy controller starts with the random coefficients which make the initial process difficult to control. It issues the system response will be overshoot with long settling time.

To overcome these drawbacks above-mentioned, this paper proposes the adaptive multilayer T-S fuzzy control approach for a class of uncertain nonlinear SISO systems. First, a new multilayer T-S fuzzy model optimized by the DE algorithm is used to offline identify the inverse nonlinear dynamic system with uncertain parameters. However, the fact is that the inverse controller is difficult to ensure system asymptotically stable. It needs an additional demonstration based on Lyapunov stability principle. Second, based on Lyapunov stability theory, an adaptive fuzzy control using a sliding mode surface is designed to guarantee that the closed-loop system operation is asymptotically stable. Furthermore, some simulation benchmark tests are investigated to illustrate the effectiveness of the proposed control scheme.

The rest of this paper is organized as follows. Section II describes the formulation problem. Section III presents the proposed adaptive multilayer T-S Fuzzy controller design. Section IV presents the simulation results to show the effectiveness and robustness of the proposed controller and section V concludes the paper.

METHODOLOGY

Problem formulation

General mathematical of SISO n-th order nonlinear systems is as follows:

$$\begin{aligned} x^{(n)} &= f(x,t) + g(x,t)u \\ y &= x \end{aligned} \qquad (1)$$

with $f(x,t)$ and $g(x,t)$ representing unknown nonlinear functions, $0 \quad g(x,t) < +$, $x = x, x^2, \ldots, x^{(n-1)}$, as state vector of the system, u as the control input and y as the output of system.

The control problem is to design a stable control law for the state x tracking a desired reference signal x_d. Inverse nonlinear controller represents open-loop control whose controller denotes an inverse model of the system. The inverse system is modelled through the use of a neural network NN or fuzzy logic FL with delay at its input and output and a feedback loop (see Figure 1).

The inverse control takes advantage of optimized algorithm. Inverse controller can efficiently control nonlinear system without knowing exactly the mathematical model of system. It only requires an inverse model identified in advance. In practice, designing the perfect inverse controller is very difficult. Practically, inverse control can ensure the nonlinear system is stable, but it is podifficult to make the system asymptotically stable.

Multilayer Fuzzy logic

In this paper, Multilayer Fuzzy logic is proposed for identifying inverse model. We propose Multilayer Fuzzy model to identify inverse model includes multiple fuzzy models.

It depends on the concrete complex system and if the structure of multilayer fuzzy model is scalable with more or less single T-S Fuzzy model in the system with a fixed number of inputs.

The proposed Multilayer Fuzzy structure used for identifying inverse model is shown in Figure 2. This is an example of the structure of multilayer fuzzy model. It composes of 2 Fuzzy models for the first layer. The output is sum of the two fuzzy model outputs.

Each T-S Fuzzy system consists of two-input with 3 triangular membership functions. That means each fuzzy system includes 9 rules and 6 variables for membership structure. Consequently, the inverse model has 30 variables total.

From Figure 2, it is easy to see that there are 2 T-S Fuzzy models in the inverse model. The first T-S Fuzzy describes the effect of previous water level (y_{n-1}, y_{n-2},...) to output (u_n), the other describes effect of previous voltage control (u_{n-1}, u_{n-2},...) to output (u_n) and the output is sum of two T-S Fuzzy model outputs.

Differential evolution algorithm

Nowadays, Differential evolution (DE) algorithm [10] is a popular optimization algorithm.

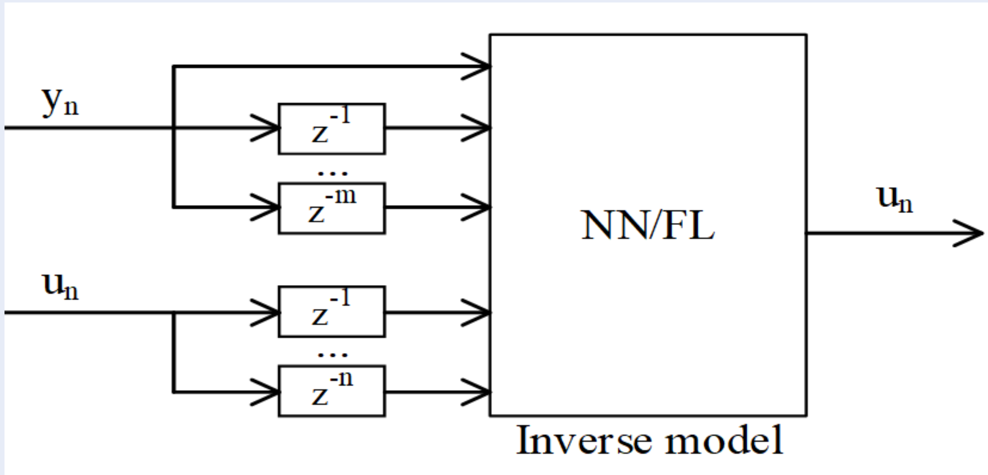

Figure 1: Generalized Inverse model

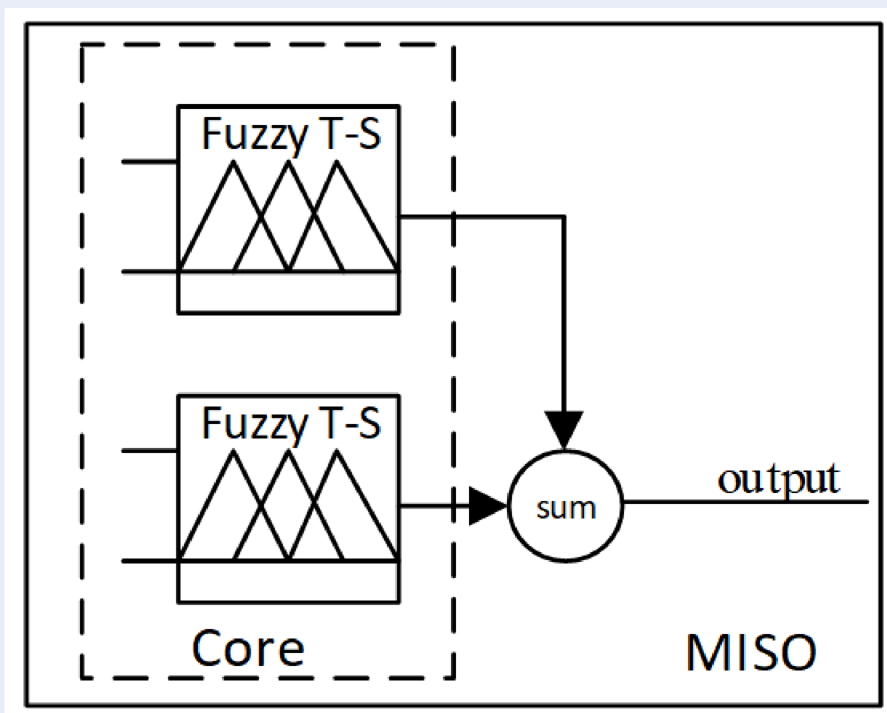

Figure 2: Proposed Multilayer Fuzzy system

In this paper, it is used for learning Multilayer Fuzzy membership structures and rules by minimizing the cost function that denotes the error between actual output and multilayer Fuzzy predicted output.

The cost function follows the mean squared error (MSE) standard and is defined as:

$J = \frac{1}{N}\sum e^2$ (2)

In which : $e = y - \hat{y}$

N represents number of samples, $\hat{y}$ denotes output of Fuzzy models and y represents output of real data collected from experiment.

The principal steps of DE algorithm are described as follows:

Initialization

The initial vector is randomly chosen with NP D-dimension and should cover the entire parameter

$X_{i,G} = \left[x_{1,i,G}, x_{1,i,G}, \ldots, x_{D,i,G}\right]$ (3)

In which, G represents the number of generations: $G = 0, 1, \ldots, G_{max}$, and $i = 1, 2, \ldots, NP$

Mutation

DE generates new parameter vectors by adding the weight difference between two population vectors to a third vector. This operation is called mutation. For each target vector , a mutant vector is generated as follows,

$v_{i,G+1} = x_{r_1,G} + F(x_{r_2,G} - x_{r_3,G})$ (4)

with $r_1, r_2, r_3 \in$ 1, 2, ..., NP represent random indexes.

The randomly chosen values r_1, r_2, r_3 are selected from the running index i. F represents the real and constant coefficient $F \in [0, 2]$

Crossover

After generating the resulting vector through mutation, the crossover step is carried out to enhance the diversity of the population pool. The donor vector exchanges its components with the target vector $\overrightarrow{X}_{i,G}$ to form the trial vector $\overrightarrow{U}_{i,G} = [u_{1,i,g},\ u_{2,i,g},\ \ldots,\ u_{D,i,g}]$. The DE algorithm often uses the binomial crossover method. The binomial crossover scheme may be outlined as

$u_{j,i,G} = \begin{cases} v_{j,i,G}\ If\ (rand_{j,i}[0,1] < C) \\ x_{j,i,G}\ otherwise \end{cases}$ (5)

Selection

This phase is used to decide whether it should become a member of generation (*G+1*). The target vector $\overrightarrow{X}_{i,G}$ is compared to the trial vector $\overrightarrow{U}_{i,G}$, and the one with a lower function value survives to the next generation. The selection operation is described as:

$x_{i,G+1} = \begin{cases} u_{i,G}\ If\ f(u_{i,G}) < f(x_{i,G}) \\ x_{i,G}\ otherwise \end{cases}$ (6)

Termination

This is a condition to stop the loop process of DE algorithm. The algorithm stops when one of the followed conditions is satisfied:

- When maximum generation is reached
- When the best fitness is lower than desired fitness
- When the best fitness cannot increase for a long time

The flow chart of DE algorithm is shown in Figure 3. This is the process of DE algorithm. By the end of the process, the termination is satisfied with the predicted output will be nearly the same with actual output.

Adaptive Inverse Multilayer Fuzzy controller

Adaptive Inverse Multilayer Fuzzy controller with structure presented in Figure 4 is combined between the Inverse Multilayer Fuzzy and the Adaptive Fuzzy model.

The parameters of Inverse Multilayer Fuzzy model will be optimally trained by DE algorithm. Since Inverse controller is difficult in practice to ensure system asymptotically stable, it needs an additional proof based on Lyapunov stability principle.

The system control law consists of 2 components, including Inverse control law and Adaptive control law.

$$\hat{u} = u^*_{ifm} + q_u^T x(x) \quad (7)$$

with u^*_{ifm} represents the output of optimized inverse fuzzy model of which parameters are optimized with DE algorithm. In detail u^*_{ifm} is described as

$$u^*_{ifm} = arg_{u_{ifm}\hat{I}W_u} min(sup\left|u_{ref} - u_{ifm}\right||) \quad (8)$$

where W_u represents constraint sets for u_{ifm}

$q_u^T x(x)$ is the output of Adaptive Fuzzy model.

The inverse control had to guarantee the stability of close-loop system. There may be some steady-state error with inverted controller. The Adaptive law is designed to guarantee that the closed-loop system is asymptotically stable.

Let define u* which represents optimized control law.

$$u^* = u^*_{ifm} + q_u^{*T} x(x) \quad (9)$$

From (7) to (9),

$$\hat{u} - u^* = \overset{0/0}{q}{}^T_u x(x) \quad (10)$$

where

$\overset{0/0}{q_u} = q_u - q_u^*$

Furthermore, the control signal is determined as:

$u = \hat{u} + u_{sw}$ (11)

$e^{\&} + he = -g(x).\overset{0/0}{q}{}^T_u x(x) - g(x).u_{sw}$ (12)

Lyapunov function is selected as,

$V = \frac{1}{2g(x)}e^2 + \frac{1}{2}\overset{0/0}{q}{}^T_u\, a\, \overset{0/0}{q_u}$ (13)

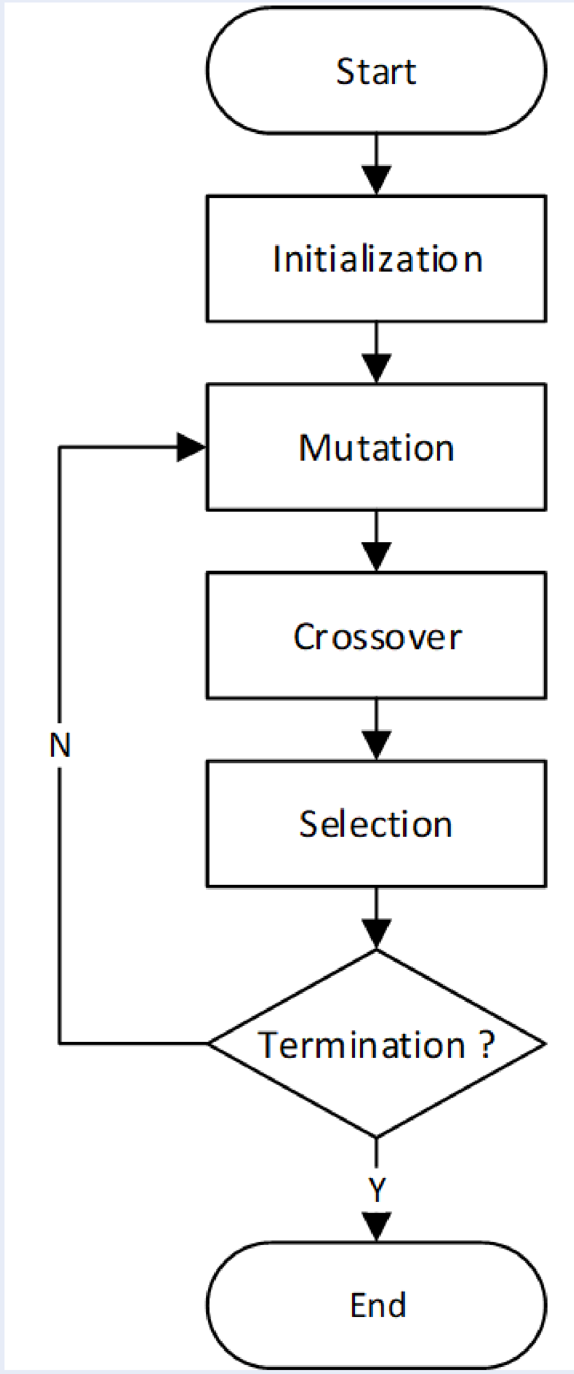

Figure 3: Flow chart of DE algorithm

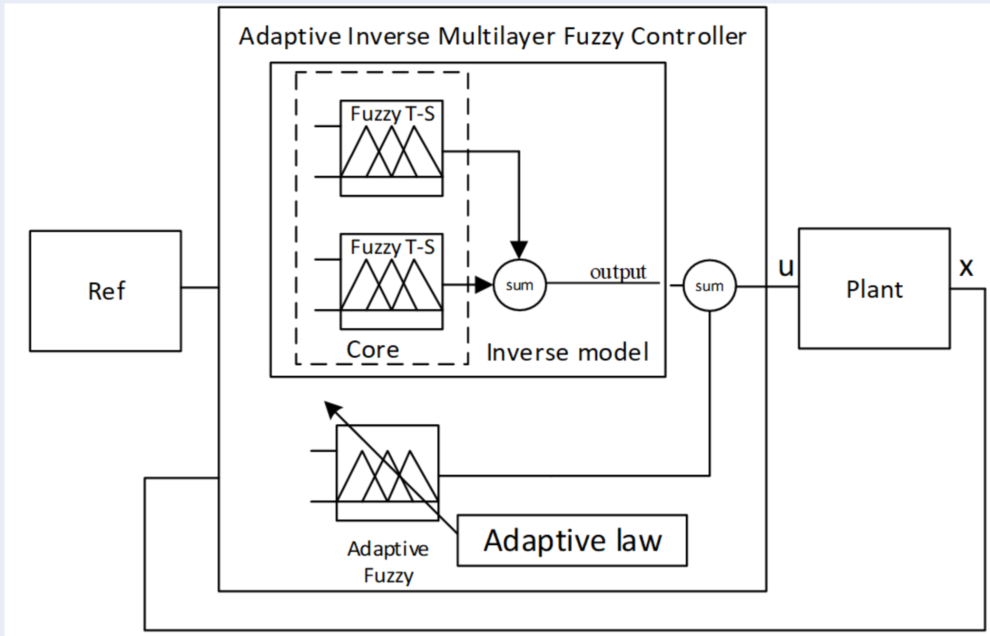

Figure 4: Block diagram of proposed fuzzy controller scheme

$V^{\&} = \frac{ee^{\&}}{}\ don't\ understand$

The equation (*) proves that system satisfy asymptotically stable condition. Based on (*), adaptive law is then selected as,

$$q_u^{\&} = a^{-1}ex(x) \qquad (14)$$

$$u_{sw} = Ksign(e) \qquad (15)$$

with K represents positive constant.

SIMULATION & RESULTS

Research methodology

This paper uses simulation method to verify theoretical results on matlab/simulink environment.

Simulation Experimental setup

We perform the experiment controlling the fluid level of single tank system in simulation (see Figure 5).

The coupled tank system possesses the state equation as,

$$\begin{aligned} x_1^{\&} &= \frac{Ku}{A_1} - \frac{b_1C}{A_1}\sqrt{2gx_1} \\ x_2^{\&} &= \frac{b_1C}{A_2}\sqrt{2gx_1} - \frac{b_2C}{A_2}\sqrt{2gx_2} \\ y &= x_2 \end{aligned} \qquad (16)$$

with parameters of coupled tank system described in Table 1.

Training Inverse Fuzzy model

Inverse model used in inverse Multilayer Fuzzy controller needs to be trained at first. In the simulation platform, training data was collected by step time of 1 second. Data for training and validating are shown in Figure 6. Input data are random values from 3V to 13V, and experiment collected data is updated every 100 seconds. The data for training is from 0 to 10000 samples, the other is data for validating.

For training inverse fuzzy model, proposed Multilayer Fuzzy model is used with 2 inputs (y[n], y[n-1) and one output (u[n]). All parameters of the proposed Multilayer Fuzzy model were trained by DE algorithm. Results was validating of prediction method. In this paper, one step prediction is applied. Figure 7 shows the validating results based on another data set with the same resulting fuzzy structure from previous training phase. The results show that predicted output seems nearly equal to the actual system output.

Control results

In simulation platform, three tests are realized. The first test is for the proposed Adaptive Inverse Multilayer Fuzzy controller (AIMFC or IFC+AF), the second is for the inverse Multilayer Fuzzy controller without adaptive fuzzy (IFC), and the last test is for only Adaptive Fuzzy controller (AFC). All tests run with the same reference signal.

The unique input of Adaptive Fuzzy control composes of 5 Gaussian membership functions with and its *mean* values of [0, 7.5, 15, 22.5, 30].

Adaptive Fuzzy parameter starts with random value. The random number in simulation gives [8.573,

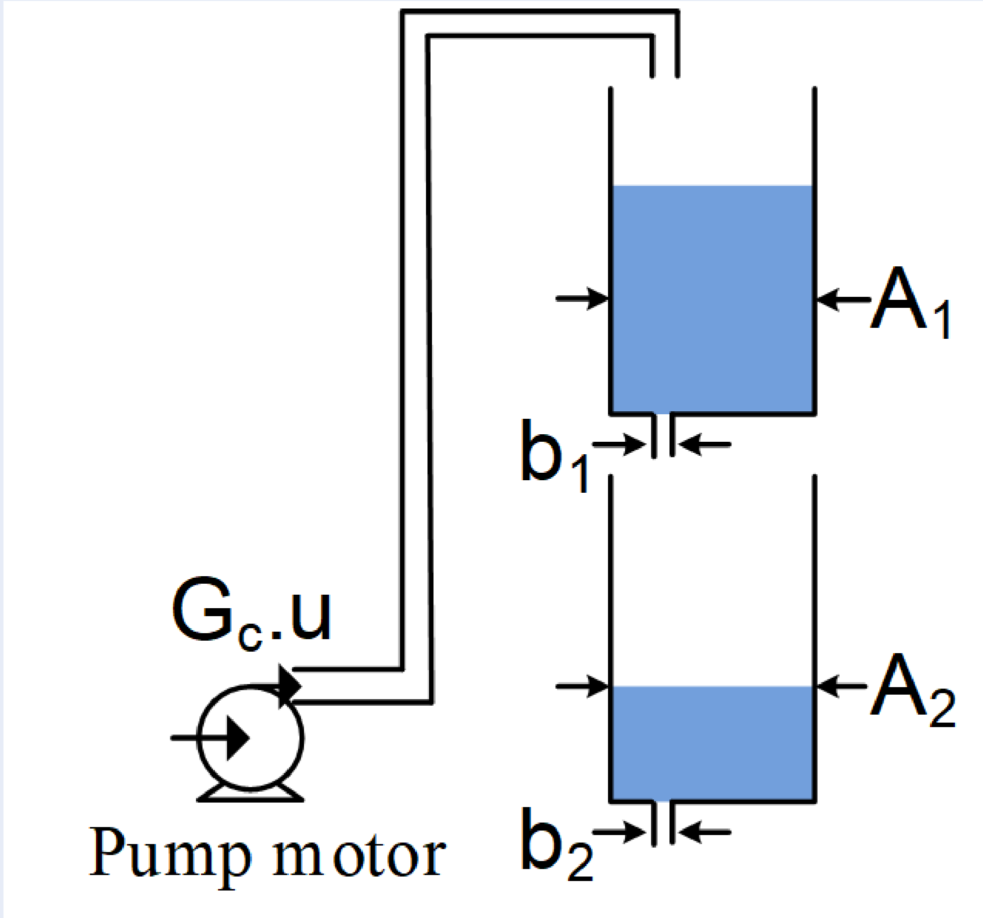

Figure 5: Coupled tank model

Table 1: PHYSICAL MEANING AND NUMERICAL VALUE USED IN THE SIMULATION

Notation	Physical Meaning	Value (unit)
A1	Cross sectional area of Tank 1	16.619 (cm2)
A2	Cross sectional area of Tank 2	16.619 (cm2)
b1	Cross sectional area of outlet of Tank 1	0.4 (cm2)
b2	Cross sectional area of outlet of Tank 2	0.5 (cm2)
C	The discharge coefficient of the outlet	0.8
g	Gravity	981 (cm/s2)
Gc	Gain of the pump	6.94 (cm3/(s.V))

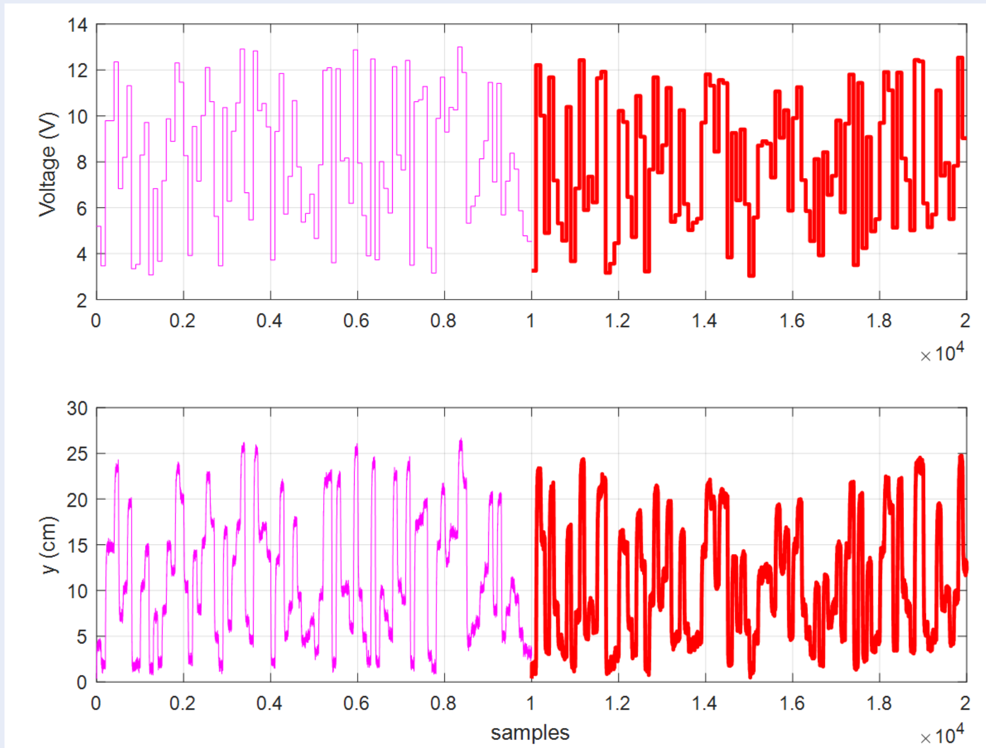

Figure 6: Training and evaluating dataset

0.1714, 4.537, 0.0326, 6.109].

Figures 8, 9 and 10 and Table 2 show that the proposed Adaptive Inverse Multilayer Fuzzy controller (IFC+AF) obtains the best performance compared to the Inverse Fuzzy controller (IFC) and Adaptive Fuzzy controller (AFC).

Table 2 tabulates the comparative performance of three controllers through standard LMSE errors computed as follows,

$$LMSE = \frac{1}{T}\sum_{T} e^2 \qquad (17)$$

DISCUSSION

The proposed method starts with identifying the inverse control model. The identification results in Figures 6 and 7 show that the identified inverse model can be easily controlled the system. Figures 8, 9 and 10 show the control results after applying the additional adaptive algorithm. At the end of process, AFC and IFC+AF show the same performance because both of them utilize the same adaptive law. The difference between AF and IFC+AF is related to the start-up feature. Meanwhile the IFC+AF starts up based on identified multilayer Fuzzy inverse model, and the AFC starts up with random parameter. The IFC controller has poor performance but it shows that proposed controller can handle it. With poor performance IFC, the proposed controller has better performance than AF controller. With better IFC controller, the proposed controller can be even better.

Table 2 also shows the control quality through the least mean squares error standard. The results also show that the proposed algorithm for control quality is superior to inverse fuzzy control methods and adaptive fuzzy control.

CONCLUSIONS

In this paper, we propose an adaptive inverse multilayer fuzzy control coupled tanks system fluid level regulation. The adaptive inverse multilayer fuzzy logic controller is created from the multiple T-S Fuzzy models and adaptive fuzzy model. The simulation results show that proposed adaptive multilayer fuzzy logic controller can be efficiently applied for control nonlinear system. The proposed controller possesses better control quality and proves strongly robust due to satisfy Lyapunov stability principle. It is available for applying a scalable multilayer fuzzy model to a more complex nonlinear uncertain system. Thus, these results also ensure that proposed multi-

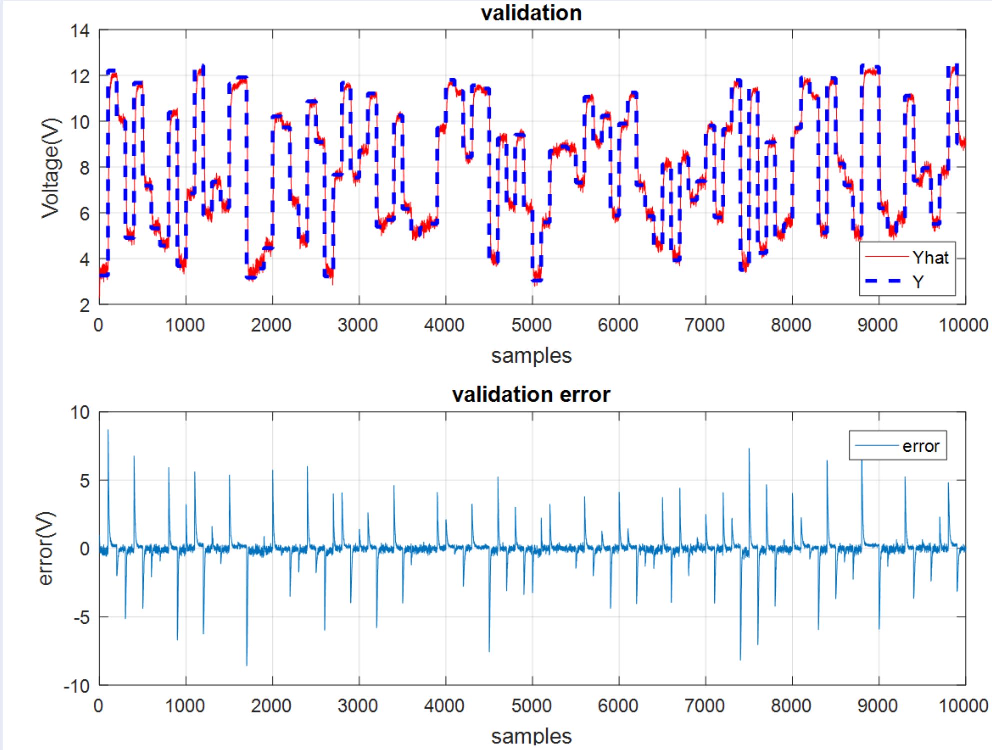

Figure 7: Validation result

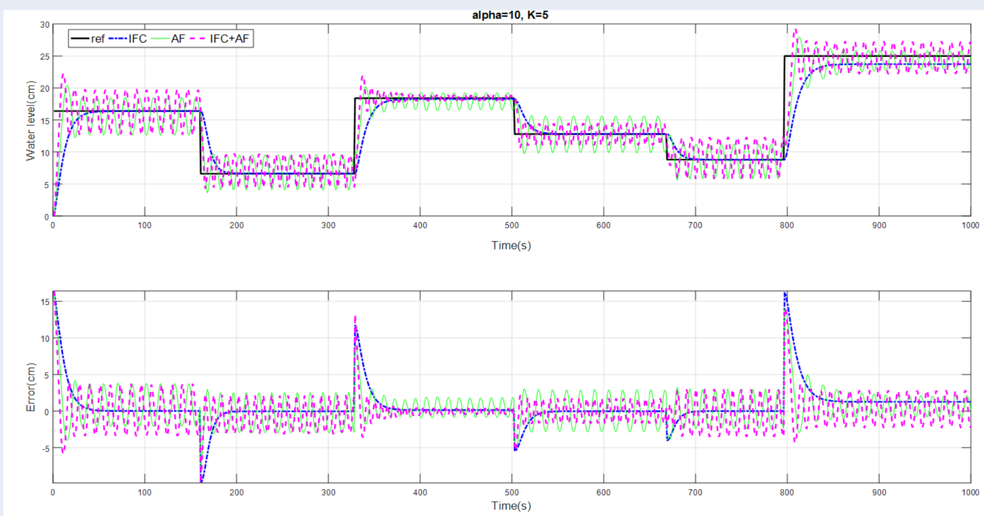

Figure 8: Comparison results of algorithms with alpha=10, K=5

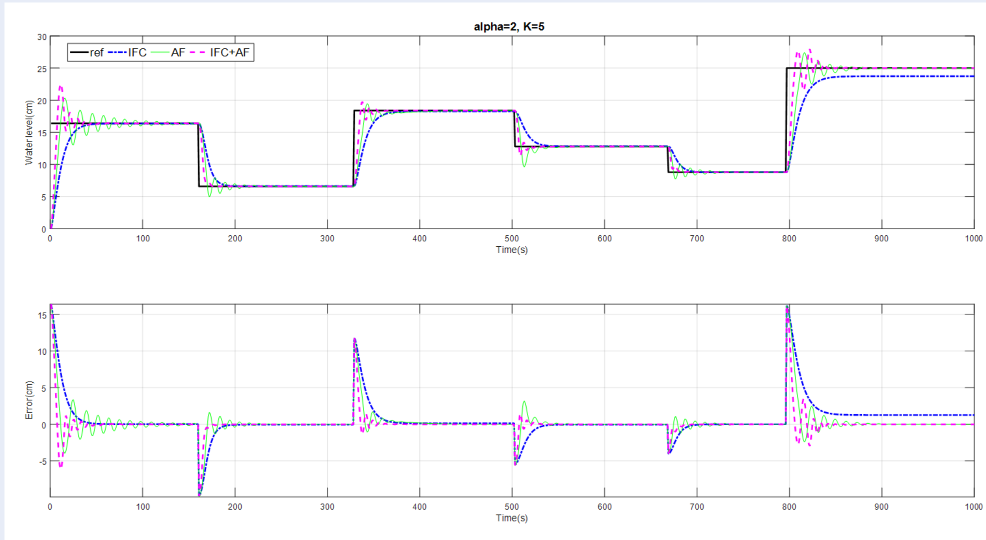

Figure 9: Comparison results of algorithms with alpha=2, K=5

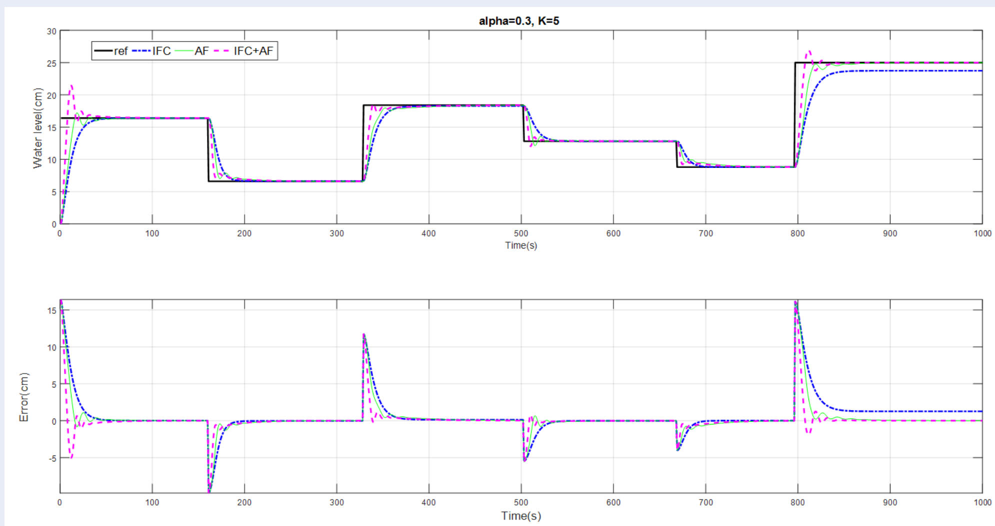

Figure 10: Comparative results of algorithms with alpha=0.3, K=5

Table 2: COMPARATIVE PERFORMANCE OF THREE CONTROLLERS

Method	LMSE	
Inverse Fuzzy Control (IFC)	6.322	6.322
Adaptive Fuzzy Control (AFC)	4.229	4.675
Proposed Inverse Fuzzy Control with Adaptive Fuzzy (IFC+AFC)	2.648	2.8

layer fuzzy controller can be used to successfully control of uncertain nonlinear complex system in near future study.

ABBREVIATION

SISO: Single Input – Single Output
MISO: Multi Input – Single Output
MIMO: Multi Input – Multi Output
DE: Differential Evolution
GA: Genetic Algorithm
PSO: Particle Swarm Optimization
T-S Fuzzy: Takagi-Sugeno Fuzzy

CONFLICT OF INTEREST

The authors declare that there is no conflict of interest.

AUTHOR CONTRIBUTIONS

Cao Van Kien: Designed and performed experiments, analysed data and co-wrote the paper.
Ho Pham Huy Anh: Supervised the research and co-wrote the paper.

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Bài Nghiên cứu

Điều khiển mờ nhiều lớp thích nghi áp dụng cho mô hình phi tuyến SISO tối ưu với giải thuật tiến hóa vi sai

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TÓM TẮT
Bài báo đề xuất giải thuật điều khiển mờ nhiều lớp thích nghi (AMTFC) kết hợp giải thuật tính toán mềm tối ưu áp dụng cho điều khiển hệ phi tuyến SISO có các tham số không chắc chắn. Đầu tiên, mô hình mờ nhiều lớp được tạo ra bằng cách ghép nhiều mô hình mờ đơn giản với ngõ ra là một hàm tổng. Mô hình fuzzy nhiều lớp dùng trong nhận dạng hệ phi tuyến có nhiều đặc điểm vượt trội hơn so với mô hình mờ thông thường, tuy nhiên nó không thể tạo ra bằng kinh nghiệm của người viết hay phương pháp thử sai nên chỉ có thể kết hợp với một giải thuật tối ưu. Các tham số của mô hình mờ nhiều lớp ngược sau đó được nhận dạng với giải thuật tiến hóa vi sai (DE) nâng cao để nhận dạng mô hình ngược của hệ phi tuyến với các tham số không chắc chắn. Kết quả mô hình ngược được đánh giá trên một tập dữ liệu khác so với tập dữ liệu huấn luyện để đảm bảo tính hội tụ của mô hình nhận dạng. Tiếp theo, để tăng tính ổn định và sự thích nghi của giải thuật điều khiển, tác giả đã có những đề xuất thêm vào một mô hình mờ thích nghi được xây dựng dựa vào lý thuyết ổn định Lyapunov kết hợp với mô hình điều khiển ngược trước đó. Mô hình mờ thích nghi dựa vào mặt trượt được thiết kế để đảm bảo hệ kín ổn định tiệm cận đã được các tác giả chứng minh thành công theo lý thuyết ổn định Lyapunov. Thêm nữa, kết quả mô phỏng điều khiển mực nước mô hình bồn nước đôi với nhiều tham số điều khiển khác nhau và chất lượng điều khiển theo tiêu chuẩn tổng bình phương sai số đã chứng minh sự hiệu quả của giải thuật đề xuất so với các giải thuật điều khiển thích nghi truyền thống hoặc giải thuật điều khiển ngược.
Từ khoá: Mô hình mờ nhiều lớp, điều khiển ngược, điều khiển thích nghi, giải thuật tiến hóa vi sai, ổn định Lyapunov

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