

Research Article

Hybrid Fuzzy Sliding Mode Control for Uncertain PAM Robot Arm Plant Enhanced with Evolutionary Technique

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ABSTRACT

This paper introduces an enhanced fuzzy sliding mode control (EFSMC) algorithm used for controlling the uncertain pneumatic artificial muscle (PAM) robot arm containing external disturbances. The nonlinear features of investigated PAM robot arm system are approximated using fuzzy logic. Moreover, the coefficients of fuzzy model are optimum selected by evolutionary differential evolution (DE) technique. The new EFSMC algorithm is designed based on the traditional sliding mode controller in which the adaptive fuzzy rule is developed based on the Lyapunov stability theory and is fuzzified with Mandani fuzzy scheme. As a consequent, the closed-loop stability of nonlinear uncertain PAM robot arm system is guaranteed to follow the global asymptotic stability. Experimental results are shown. It is evident that the proposed adaptive fuzzy rule suitable with the EFSMC controller which ensures an outperforming method in comparison with other advanced control approaches.

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1. INTRODUCTION

Fuzzy concept is initiatively proposed by Zadeh in 1965 [1]. Since that date there were numerous researches focused on this section. Then it also existed different fuzzy-based applications in various technological domains [2]. Fuzzy concept has been efficiently used in control, identification domain, and so on. Among various fuzzy structures, Takagi–Sugeno (T-S) fuzzy logic is widely using in control and identification purposes. Especially, it can be efficiently combined with soft-computing algorithms [3].

In another way, sliding mode control (SMC) is now successfully used in numerous applications. The distinguished benefit of SMC control is the robustness against uncertain nonlinear disturbances. A SMC, in term of its on-off rules, confirms an asymptotic stability to the tested uncertain scheme. Hence SMC approach has been efficiently used in versatile technological applications [4,5]. Nevertheless the principal drawback of SMC induced from its on-off control issue, namely chattering effect. In order to remove such phenomenon, a saturated equation is often used [3] linked to the sliding surface. The disadvantage of this is that such linkage can spoil Lyapunov asymptotical stability of the investigated nonlinear system. Thus standard SMC method encounters drawback in

control of uncertain disturbances. A combined Fuzzy-SMC controller can be used to solve this difficulty. Then several adaptive fuzzy SMC approaches [6–9] proposed in which fuzzy rules were implemented based on Lyapunov principle. As a consequent numerous researches have introduced the hybrid fuzzy SMC algorithms of which the closed-loop system stability is partly proved [9–13]. The merit of this hybrid system is focused on the fact that the adaptive fuzzy laws conduct fuzzy systems to arbitrarily approximating functions. Moreover, in order to successfully approximate a complex nonlinear system, it needs a great amount of fuzzy rules from the constructed fuzzy set. As a result, a tremendous number of fuzzy rules will take a great burden of computational cost. Then it raises the demand of a novel adaptive fuzzy rule innovatively and effectively used to a fuzzy SMC algorithm as to successfully adjust the characteristics of the adaptive fuzzy laws with an adequate computation load.

One of promising fuzzy models recently developed relates to the multilayer fuzzy structure which is improved from hierarchical fuzzy one [14,15] in which the output of the previous fuzzy layer is the input of the following one with the last output is through a fuzzy model. Nowadays the hierarchical fuzzy model is increasingly improved and successfully applied in the field of intelligent identification and control [16–18] such as Kien *et al.* [19,20] optimized

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the multilayer fuzzy logic identify the nonlinear uncertain double-coupled water tanks system by using cascade training method.

Nowadays evolutionary and meta-heuristic optimization algorithms have been increasingly applied to optimally identify the parameters of intelligent controllers used in numerous optimization problems. Precup *et al.* [21] introduced a new adaptive GSA-based algorithm as for optimally modifying of PI controlled uncertain servo systems. Wang and Guo [22] proposed a new hybrid bat algorithm with harmony search for global optimization of uncertain nonlinear systems. Fe *et al.* [23] applied specific soft-computing methods for automatic selection of optimum parameters of micro-milling processes, and so on.

Nowadays modified versions of particle swarm optimization (PSO) and differential evolution (DE) algorithms have shown convincingly as the most promising candidates among meta-heuristic algorithms in efficiently solving optimization problems. Tharwat and Hassanien [24] introduced a new quantum-behaved particle swarm optimization (QPSO) for parameter optimization of SVM processes. Beruvides *et al.* [25] proposes an improved cross-entropy PSO method for parameter optimization of a micro-scaled manufacturing process. Anh and Kien [26] suggested a new way for optimal energy management of hybrid micro-grid system using advanced multi-objective PSO. Author in [27] introduced an approach for identifying parameters using modified PSO of a Fuzzy NARX IMC structure for MISO dynamic system control. Authors in [28] applied DE technique for optimizing parameters of an adaptive evolutionary neural controller used in an uncertain nonlinear serial PAM robot system. Son *et al.* [29] applied a hybrid fuzzy LQR-SMC technique optimized with modified DE to control uncertain nonlinear systems. Recently, several advanced intelligent digital twin-based controllers, including fault-tolerant tracking T-S fuzzy-based control against sensor faults introduced by Kukurowski *et al.* [30] and digital twin-based optimal fuzzy control proposed by Guerra *et al.* [31], Lermer and Reich [32], have obtained promising results in adaptively and precisely optimal control of highly uncertain nonlinear systems. Several of those control approaches have been also supported on MatLab/RTW.

Improving from results abovementioned this paper innovatively introduce a new adaptive law applied in the enhanced fuzzy EFSMC that is efficiently applied with outstanding quality and superb accuracy for tracking guide of uncertain dynamic plants, including the 1-DOF pneumatic artificial muscle (PAM) manipulator investigated in this paper.

The contributed aspects of this paper are tri-fold as follows:

1. Propose adaptive fuzzy rules of novel fuzzy EFSMC approach innovatively implemented for the PAM-based manipulator modeling and control.
2. Propose candidate Lyapunov function and exactly prove the asymptotically convergent property for the nonlinear PAM manipulator based on Lyapunov stability principle.
3. Propose DE algorithm to optimally identify the parameters of fuzzy EFSMC control.

The rest of this paper is structured as follows: Section 2 presents problem statement. Section 3 introduces the novel adaptive fuzzy

SMC algorithm for PAM manipulator robust control. Section 4 proposes new adaptive fuzzy rules used in proposed fuzzy EFSMC controller. Section 5 relates to the experiment set-up in which the fuzzy structures optimized by DE method and the experiment tests on the PAM-based robot arm system are fully presented. Eventually, Section 6 is conclusions.

2. PROBLEM PRESENTATION

The mathematical description of a SISO n -th nonlinear system is described as follows:

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

with $f(x, t)$ and $g(x, t)$ denote unknown relations in which $g(x, t)$ represents nonzero value; $x = [x, \dot{x}, \dots, x^{(n-1)}]^T$ represents state space matrix of plant; u denotes control signal; y represents the plant output matrix.

The control motivation is to implement an efficient control rule as to x exactly tracking a required referential value x_d .

The error is calculated by (2)

$$e = x_d - x = [e, \dot{e}, \dots, e^{(n-1)}] \in R^n \quad (2)$$

Then the sliding plane is chosen as

$$s = c_1 e + c_2 \dot{e} + \dots + c_{n-1} e^{(n-2)} + e^{(n-1)} \quad (3)$$

with $c = [c_1, c_2, \dots, c_{n-1}, 1]$ represent factors followed from the Routh–Hurwitz criterion. The \dot{s} denotes the derivation of s with respect to time which is determined as

$$\dot{s} = c_1 \dot{e} + c_2 \ddot{e} + \dots + c_{n-1} e^{(n-1)} + e^{(n)} \quad (4)$$

$$\dot{s} = \sum_{i=1}^{n-1} c_i e^{(i)} + \dot{x}_d^{(n)} - x^{(n)} \quad (5)$$

Based on Lyapunov principle, \dot{s} follows as

$$\dot{s} = -K \text{sign}(s) \quad (6)$$

Replacing (6) in (5), the fuzzy SMC control rule is written as in (7)

$$u = \frac{1}{g(x, t)} \left[- \sum_{i=1}^{n-1} c_i e^{(i)} - f(x, t) + \dot{x}_d^{(n)} - K \text{sign}(s) \right] \quad (7)$$

The $\text{sign}()$ equation in (7) is to be changed by *saturation* equation as one of an efficient way to ameliorate the chattering issue. Then control rule is now described as

$$u = \frac{1}{g(x, t)} \left[- \sum_{i=1}^{n-1} c_i e^{(i)} - f(x, t) + \dot{x}_d^{(n)} - K \text{sat}(s) \right] \quad (8)$$

The sliding mode approach needs mathematical form of $f(x, t)$ & $g(x, t)$, which make difficult in implementing an effective SMC control for an uncertain dynamic plant. As to overcome such difficulties, an enhanced fuzzy sliding mode controller (EFSMC) approach is proposed which is totally described from Section 3 up to Section 5.

3. PROPOSED ENHANCED FUZZY EFSMC APPROACH

3.1. Design the Fuzzy SMC Control

For designing the SMC control used to uncertain plant control with undetermined $f(x, t)$ and $g(x, t)$, there exists various SMC-based methods. Park *et al.* [11] using adaptive neural model for online approximating $f(x, t)$ and $g(x, t)$. Authors in [12,13] using adaptive fuzzy models to identify $f(x, t)$ & $g(x, t)$.

In this paper, the unknown functions $f(x, t)$ & $g(x, t)$ will be optimally identified using DE-based fuzzy T-S model. Then the state space equations are rewritten as

$$\begin{aligned}\hat{x}_*^{(n)} &= \hat{f}(x, t) + \hat{g}(x, t)u \\ \hat{y} &= \hat{x}\end{aligned}\quad (9)$$

with $\hat{f}(x, t)$ and $\hat{g}(x, t)$ are output of proposed adaptive fuzzy T-S model. The new fuzzy T-S structure for identifying $f(x, t)$ and $g(x, t)$ have inputs is the state vector x .

Then the error of real model and identified one is computed with (10)

$$e_m^* = x^{(n)} - \hat{x}^{(n)} \quad (10)$$

Continually by using (8), the fuzzy SMC controller is described with (11)

$$u = \frac{1}{\hat{g}(x, t)} \left[- \sum_{i=1}^{n-1} c_i e^{(i)} - \hat{f}(x, t) + x_d^{(n)} - Ksat(s) \right] \quad (11)$$

In practice, since $\hat{f}(x, t)$ & $\hat{g}(x, t)$ seem not perfect, it always issues an error between $x^{(n)}$ and $\hat{x}_*^{(n)}$ partly caused by outside noises and partly relied on the precision of identified system.

We assume that if $\|e_m^*\| < \varepsilon$ then closed-loop plant becomes stable meanwhile steady-state error cannot decrease to zero.

3.2. Proposed Enhanced Fuzzy EFSMC Method

We proposed a novel fuzzy adaptive (FA) law to guarantees the error of system which surely converges to 0 with constraints. Then the proposed FA law is added into state space model as follows:

$$\begin{aligned}\hat{x}_*^{(n)} &= \hat{f}(x, t) + \hat{g}(x, t)u + FA \\ \hat{y} &= \hat{x}\end{aligned}\quad (12)$$

Based on Eqs. (11) and (12), the proposed fuzzy SMC rule can be determined as

$$u = \frac{1}{\hat{g}(x, t)} \left[- \sum_{i=1}^{n-1} c_i e^{(i)} - \hat{f}(x, t) - FA + x_d^{(n)} - Ksign(s) \right] \quad (13)$$

with FA is the fuzzy adaptive function proposed.

The error in Eq. (10) is rewritten as

$$e_m = x^{(n)} - \hat{x}^{(n)} = x^{(n)} - (\hat{f}(x, t) + \hat{g}(x, t)u + FA) \quad (14)$$

$$e_m = x^{(n)} - \hat{x}^{(n)} = x^{(x)} - (\hat{x}_*^{(n)} + FA) = e_m^* - FA \quad (15)$$

where \dot{e}_m , represents the derivation of e_m , is defined as

$$\dot{e}_m = \dot{e}_m^* - \dot{FA} \quad (16)$$

Give,

$$\dot{e}_m = -K_A sign(e_m) \quad (17)$$

$$\dot{e}_m^* - \dot{FA} = -K_A sign(e_m) \quad (18)$$

Let's assume,

$$|\dot{FA}| > |\dot{e}_m^*| \quad (19)$$

$$sign(\dot{FA}) = sign(e_m) \quad (20)$$

Supposing that \dot{FA} is chosen based on Eqs. (19) and (20). From (18), we have

$$-sign(\dot{FA}) |\dot{e}_m^* - \dot{FA}| = -K_A sign(e_m) \quad (21)$$

$$|\dot{e}_m^* - \dot{FA}| = K_A \quad (22)$$

Using the state equations in (12) and the derivative of the SMC surface in (5), it induces

$$\begin{aligned}\dot{s} &= \sum_{i=1}^{n-1} c_i e^{(i)} + x^{(n)} - x_d^{(n)} \\ &= \sum_{i=1}^{n-1} c_i e^{(i)} + x_d^{(n)} + f(x, t) + g(x, t)u \\ &= \sum_{i=1}^{n-1} c_i e^{(i)} + (f(x, t) - \hat{f}(x, t)) + (g(x, t) - \hat{g}(x, t))u \\ &\quad - \sum_{i=1}^{n-1} c_i e^{(i)} - FA - Ksign(s) \\ &= (f(x, t) - \hat{f}(x, t)) + (g(x, t) - \hat{g}(x, t))u \\ &\quad - FA - Ksign(s) \\ &= e_m^* - FA - Ksign(s) \\ &= e_m - Ksign(s)\end{aligned}\quad (23)$$

Now we propose the candidate Lyapunov function as (24)

$$V_1 = \frac{1}{2}s^2 + \frac{1}{2}e_m^2 \quad (24)$$

The derivative of V with respect to time,

$$\begin{aligned}\dot{V}_1 &= \dot{s}s + e_m \dot{e}_m \\ &= s(e_m - Ksign(s)) - e_m K_A sign(e_m) \\ &= se_m - K|s| - K_A |e_m|\end{aligned}$$

Using (17), it gives $e_m \rightarrow 0$ if $t \rightarrow \infty$. Thus $\dot{V}_1 \leq 0$ as $t \rightarrow \infty$. Hence the closed-loop variables are bounded with the error which can decrease to zero.

Suppose we use the Fuzzy model for approximating the FA function described in (18). The fuzzy model was chosen with absolute output value larger than $|\dot{e}_m^*|$ at all time and the estimated fuzzy output has the same sign with e_m .

The main subject in this paper is to initiatively introduce a fuzzy logic optimally approximate the operation of Eq. (18). Original functions are convoluted with high-order derivation, containing different terms. Thus the new fuzzy model is completely compact and well respond to Lyapunov criterion. The principle of newly proposed adaptive fuzzy law is implemented based on following Table 1.

In which PO is positive and NE is negative, both are selected in order to respond the requirement $|\dot{FA}| > |\dot{e}_m^*|$.

4. EXPERIMENTAL RESULTS

4.1. Experimental Setup

The EFSMC control algorithm is applied to control the uncertain 1-DOF PAM-based manipulator. It is known that the PAM actuator is activated based on air in compression. In case a certain pressure is used, PAM shrinks and provides a force. In case pressure is not held, PAM returns to its initial form.

Up to now, there has not existed an efficient strict model to exactly describe the highly nonlinear features of PAM. Then intelligent approaches are often used to identify the PAM-based robot-arm model. Such intelligent model is considered as an effective approach as to be able to effectively control the PAM.

The PAM-based 1-DOF manipulator configuration is a SISO uncertain nonlinear plant that combines “one PAM - one bias spring” linkage and then functions as a SCARA robot. The 1-DOF PAM manipulator configuration is illustrated in Figure 1. The abovementioned configuration includes a single input variable which denotes the voltage-based electro-pneumatic regulator, and a single output

which denotes the angular rotation measured via an incremental encoder.

Figure 1 presents the arrangement of the experimental 1-DOF PAM manipulator. In this arrangement, one PAM actuator with one bias-spring form is used. An encoder is used for measuring the coupling angle. The PCI-6221 card provides a control voltage to regulate the PAM pressure and gathers data under sampled time of 10 [ms]. Link-length is 20 cm. The load weight is 500 g. The working range of manipulator is bounded in range of 1 rad. Then the steps of EFSMC controller design are as follows:

1. Estimate the $\hat{f}(x, t)$ and $\hat{g}(x, t)$.
2. Determine the maximum value of \dot{e}_m^* .
3. Building Adaptive Fuzzy model.

Let's define the nonlinear system of the 1-DOF PAM manipulator as (25)

$$\begin{aligned}\dot{x} &= f(x, t) + g(x, t)u \\ y &= x\end{aligned}\quad (25)$$

with $f(x, t)$, $g(x, t)$ represent an unknown nonlinear function; x and \dot{x} represent the angle and the angle velocity of joint 1, respectively.

The functions $f(x, t)$ and $g(x, t)$ will be approximated with proposed fuzzy model in which the FA term represents an adaptive factor, then proposed enhanced fuzzy EFSMC control rule is defined as

$$u = \frac{1}{\hat{g}(x, t)} [-f(x, t) - FA + \dot{x}_d + Ksat(s)] \quad (26)$$

Figure 2 illustrates the block diagram described the proposed EFSMC control algorithm, where x_d is reference signals, x represents the real joint angle value. In Figure 2, we can see the output of proposed fuzzy adaptive function \dot{FA} is performed as a change of adaptive function FA , it requires an integral term to be fully converted into an adaptive law.

4.2. Training Unknown Functions of Uncertain System

In control law Equation (26), we have unknown $f(x, t)$ & $g(x, t)$ functions, then two fuzzy T-S structures with Gaussian shape will

Table 1 | Proposed adaptive fuzzy rules.

	e_m		
	NE	ZE	PO
\dot{FA}	NE	ZE	PO

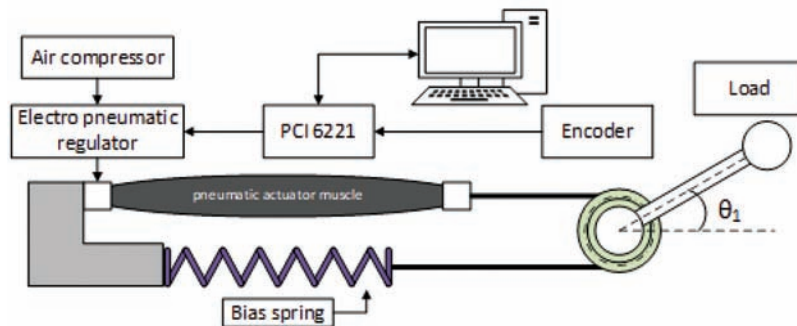


Figure 1 | The 1-DOF pneumatic artificial muscle (PAM) manipulator configuration.

be used for identifying those unknown functions. The new contribution here is to improve the performance of proposed control method in which the Fuzzy T-S structure and output parameters are online optimized using optimization DE algorithm [33].

The data set was collected with random input voltage from 0 to 6V in no-load operation.

Thus the fitness function is defined and calculated in (27)

$$J = \frac{1}{N} \sum_{n=1}^N (\dot{x}_n - \hat{\dot{x}}_n) \quad (27)$$

in which \dot{x} represents the derivation of rotating angle x , which was collected from experiment; $\hat{\dot{x}}$ represents result of the predictive block located in fuzzy model in which value $\hat{\dot{x}}$ determined as

$$\hat{\dot{x}} = \hat{f}(x, t) + \hat{g}(x, t) u + FA \quad (28)$$

In the identification process, the adaptive fuzzy function was not used and equal zero. The DE algorithm was used for optimizing parameters of Fuzzy T-S models used in approximating of $f(x, t)$ & $g(x, t)$. DE algorithm was firstly proposed by Storn and Price [33]. The DE flow chart is described in Figure 3 which is applied in this research.

The essential stages of DE technique will be concisely presented as follows:

4.2.1. Initializing phase

This initial vector is selected at random composing of NP D -sized and covers the whole coefficient area.

$$X_{i,G} = [x_{1,i,G}, x_{2,i,G}, \dots, x_{D,i,G}] \quad (29)$$

with G represents iteration counts in which

$$G = 0, 1, \dots, G_{\max}, \text{ and } i = 1, 2, \dots, NP$$

4.2.2. Mutating phase

DE provides novel parametric vectors by adding the weighting off-set of 2 population sets into a 3rd one, namely mutation stage. With every aim-vector $x_{i,G}$, a mutant vector is provided based on (30)

$$v_{i,G+1} = x_{r_1,G} + F(x_{r_2,G} - x_{r_3,G}) \quad (30)$$

in which random indexes $r_1, r_2, r_3 \in 1, 2, \dots, NP$

The randomly selected r_1, r_2, r_3 values will be chosen as to differ from the floating index i . F denotes the unchanged parameter, $F \in [0, 2]$

4.2.3. Crossover phase

After providing the off-spring vector via mutating phase, the crossover phase is activated to improve the versatility of the particle space. The donation vector bargains its elements with the target one $\vec{X}_{i,G}$ as to structure the tested vector $\vec{U}_{i,G} = [u_{1,i,G}, u_{2,i,G}, \dots, u_{D,i,G}]$. In general the DE approach often applies the binomial crossover technique. This technique is described as

$$u_{j,i,G} = \begin{cases} v_{j,i,G} & \text{If } (rand_{j,i}[0, 1] < C) \\ x_{j,i,G} & \text{otherwise} \end{cases} \quad (31)$$

In this paper the originally initiated DE coefficients F and C are equal $[F \ C] = [0.7 \ 0.4]$.

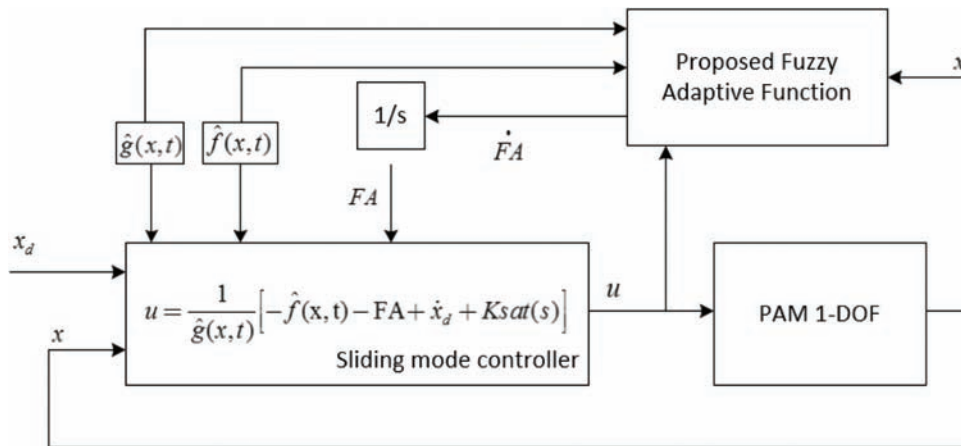


Figure 2 Block diagram for proposed adaptive fuzzy enhanced fuzzy sliding mode control (EFSMC) control system.

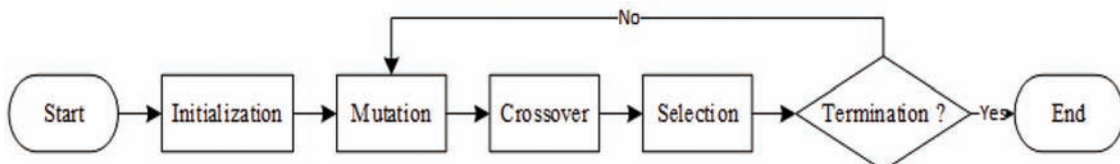


Figure 3 Block diagram of differential evolution (DE) technique.

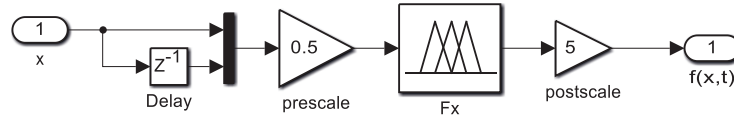


Figure 4 | Proposed Takagi-Sugeno (T-S) fuzzy model for identifying $f(x, t)$.

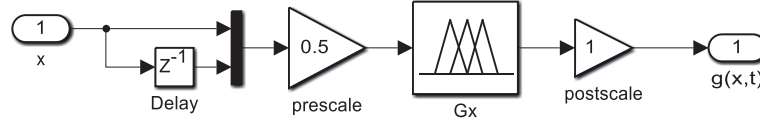


Figure 5 | Proposed Takagi-Sugeno (T-S) fuzzy model for identifying $g(x, t)$.

4.2.4. Selecting phase

To specify if it can participate as a generation element ($G + 1$) or not, the $\vec{X}_{i,G}$ vector will be compared with the trial one $\vec{U}_{i,G}$ and the vector possessing better fitness value will be passed to the next iteration. Then such selecting function is presented as

$$\vec{X}_{i,G+1} = \begin{cases} \vec{U}_{i,G} & \text{If } f(\vec{U}_{i,G}) < f(\vec{X}_{i,G}) \\ \vec{X}_{i,G} & \text{otherwise} \end{cases} \quad (32)$$

4.2.5. Terminating phase

This phase aims to terminate the DE loop. The DE loop is ended in case one of followed requirements is met:

- The maximal iterations reached.
- The best obtained fitness value is better than a chosen minimum one.
- The best obtained fitness value cannot be improved for an enough long generations.

Data for training and evaluation is gathered from different data set. Input and output data were collected in real experiment without load.

Fuzzy T-S logic used for the approximation $f(x, t)$ and $g(x, t)$ have two inputs are $[x \ x_{n-1}]$, in which one output is $f(x, t)$ and another is $g(x, t)$, respectively. Fuzzy T-S models for approximate $f(x, t)$ and $g(x, t)$ are trained at the same time.

Figures 4 and 5 show proposed T-S fuzzy scheme presented in Simulink for approximating $f(x, t)$ & $g(x, t)$. It's having the identical prescale coefficient of 0.5 for x in the range of $[-2, 2]$ rad. The postscale coefficient for both of $f(x, t)$ and $g(x, t)$ signals is 5 and 1, respectively.

The verifying resulted graphs are presented in Figure 6. It is important to note that this verifying process using different data sets selected from the training data set.

Figures 7 and 8 show the final results related to the novel fuzzy structure applied to estimate $f(x, t)$ and $g(x, t)$ equations.

4.3. Implementation of Proposed Fuzzy EFSMC Control Law

The adaptive Fuzzy law makes sure error of actual and fuzzy output converges to zero. Base on training and evaluation results, we can define the boundary of $f(x, t)$ and $g(x, t)$. Using that boundary it helps to find out the minimum bounded values of adaptive Fuzzy rules.

The Mamdani fuzzy model is applied in the new fuzzy model design which contains 1 input/1 output. Input value is the difference of actual with predicted output values. It is also clear to note that the output value of proposed fuzzy structure is derivation of adaptive value (\vec{F}_A). Both input/output are arranged under 3 fuzzy MFs {Negative (N), Zero (Z), and Positive (P)} as illustrated in Figure 9.

The fuzzy rules are selected and adequately presented in Table 1.

In Figure 10, proposed fuzzy rule contains a saturating component located in the input as to ensure all values go to the input belong to the range of $[-1, 1]$. Meanwhile the output contains a variable-valued gain G , called the punishing rate for modifying convergent time with respect to fuzzy model output.

4.4. Experimental Results

Experiments applied in the 1-DOF PAM-based manipulator system are performed in both cases, no-load and pay-load with value of 500 g. For each experiment, we performed 3 times with different controllers in comparison between proposed EFSMC with standard fuzzy and optimal PID control methods. It is necessary to note that all three comparative controllers used the identical referential data.

The comparison is realized with classic fuzzy and optimal PID control approaches. The PID parameters are optimally designed as $[P \ I \ D] = [-10 \ -30 \ 0]$. Then fuzzy PID controller is implemented with e and \dot{e} which are used as inputs and \dot{u} as the output which denotes the voltage variation. Integral term is required to make it become a control signal. Then the parameters of fuzzy PID controller are optimally identified using DE optimization algorithm. It ensures steady-state error stays at zero with the quickest transient time at no-load operation.

Figures 11 and 12 illustrate the comparative results of proposed EFSMC with optimal PID and fuzzy PID controllers applied in the

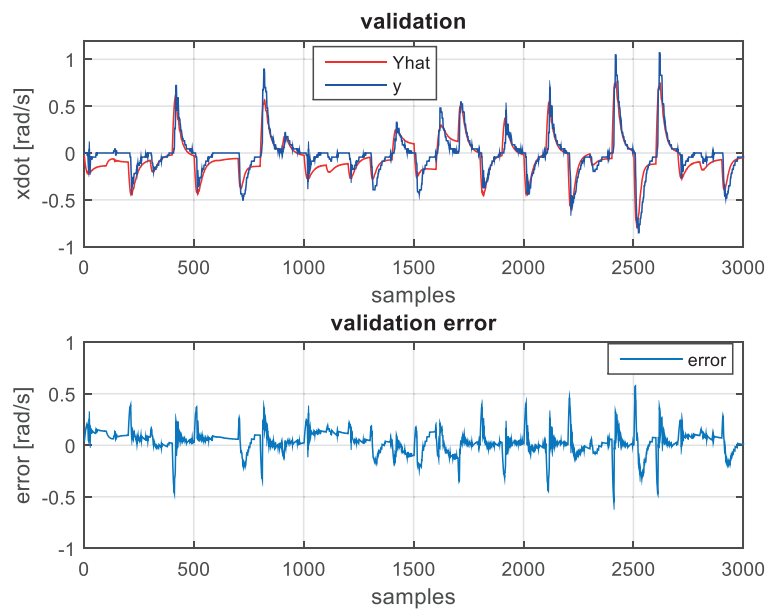
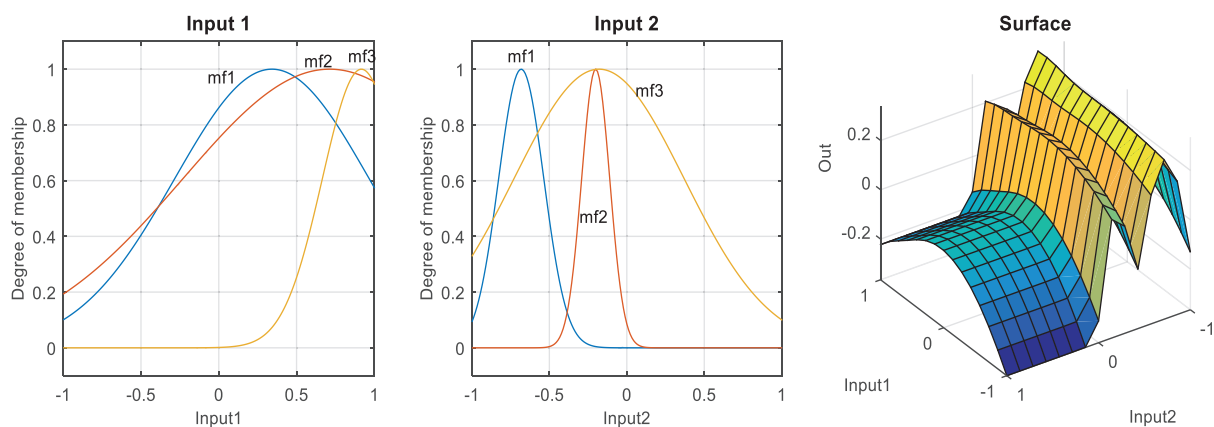
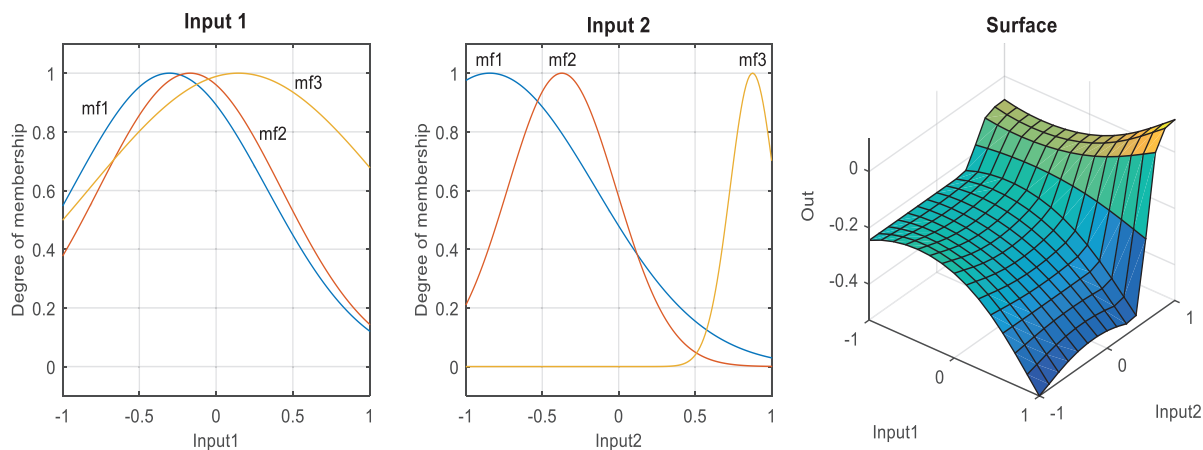


Figure 6 | Validation result.

Figure 7 | Input/output of resulted Takagi–Sugeno (T-S) fuzzy model and surface of uncertain $f(x, t)$.Figure 8 | Input/output of resulted Takagi–Sugeno (T-S) fuzzy model and surface of uncertain $g(x, t)$.

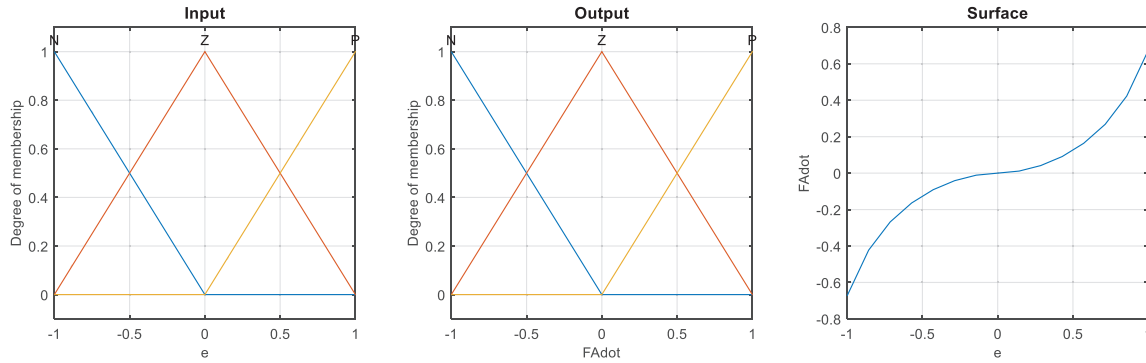


Figure 9 | MF and surface of proposed fuzzy law.

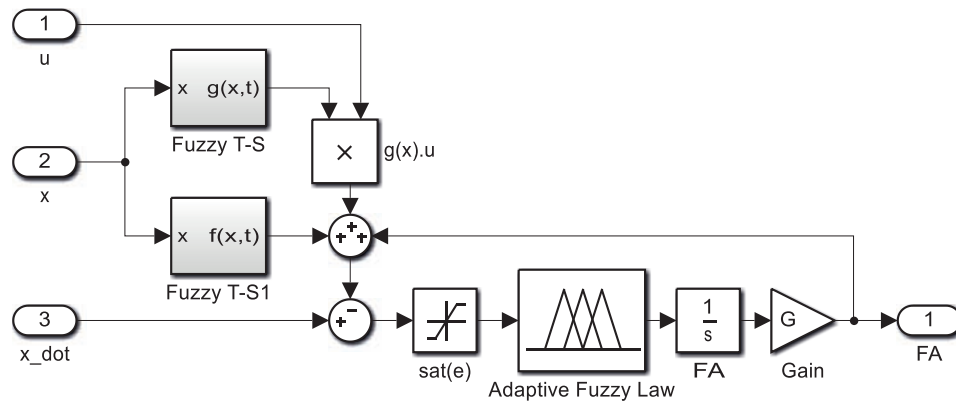


Figure 10 | Design of fuzzy rule diagram.

PAM-based robot arm in two cases, no-load and pay-load of 0.5 kg respectively.

The results presented in Figure 11 comparatively show the performance of tested control methods in no-load operation of the 1-DOF PAM robot arm. The comparative results convincingly demonstrate that the proposed EFSMC method give the best performance among the 3 tested control approaches. The tracking angular error of proposed EFSMC method seems perfectly quite small, especially in transient-state durations, in comparison with poorly transient response of optimal PID and fuzzy PID controllers. Hence it is clear to see that the referential values and real output values of proposed fuzzy model are strongly similar. On the contrary optimal PID and fuzzy PID controllers show a large marginal error at the moments the reference signal abruptly changes.

The superiority of proposed EFSMC in comparison with optimal PID and fuzzy PID controllers in case of pay-load 0.5 kg is clearly shown in Figure 12. The results presented in this figure demonstrate the perfect performance of proposed EFSMC controllers applied to the uncertain 1-DOF manipulator system in pay-load operation. Due to the increase of load weight, the uncertainty of the PAM robot arm system becomes dramatic which is totally subjugated by proposed EFSMC method. The superiority of EFSMC control over optimal PID and fuzzy PID control approaches in pay-load PAM robot arm operation strongly verifies the robustness of the proposed EFSMC technique.

Table 2 | Comparative performance of investigated controllers applied on the PAM-1DOF system.

Method	Mean Square Error (No-load)	Mean Square Error Rated Load (500 g)
Proposed EFSMC	0.0952	0.5878
Optimal PID	2.5276	2.6905
Adaptive Fuzzy PID	1.4009	1.8930

Furthermore, the experiment results are clearly tabulated in Table 2 based on the mean square error (MSE) standard in which the proposed controller proves the best performance in comparison with other optimal PID and fuzzy PID controllers.

The results from Table 2 convincingly demonstrate the superiority of proposed AFSMC controller over other comparative advanced control methods, not only in no-load condition (MSE error value 0.0592 of proposed EFSMC over 2.5276 and 1.4009 of optimal PID and adaptive fuzzy PID, respectively) but also in rated load condition (MSE error value 0.5878 of proposed EFSMC control over 2.6905 and 1.8930 of optimal PID and adaptive fuzzy PID controller, respectively).

In summary the experiment results confirm that the proposed EFSMC yields the outperforming performance and proves its

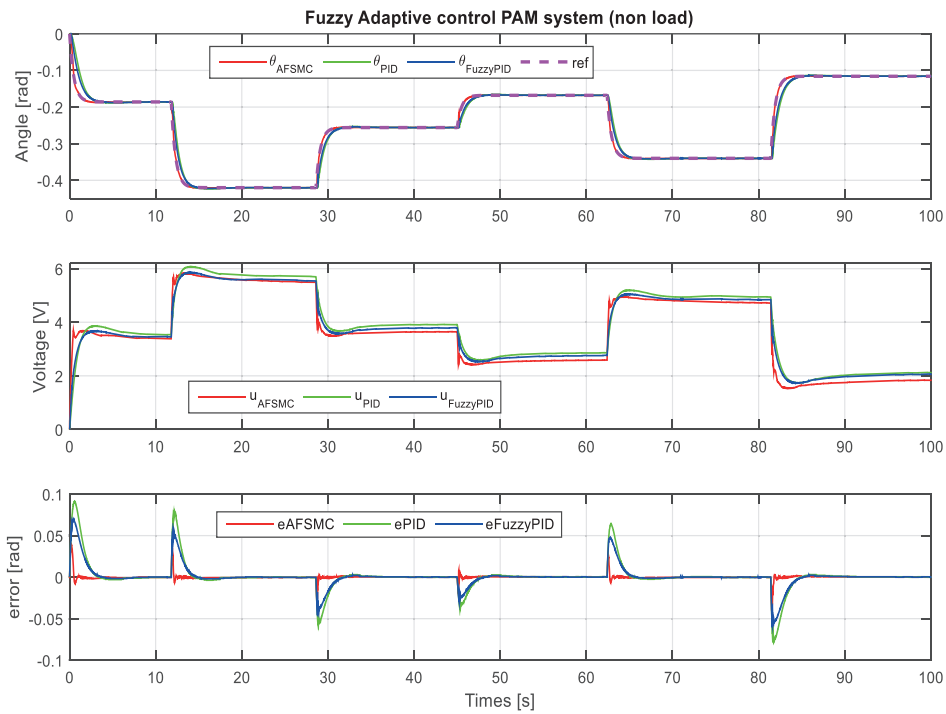


Figure 11 | Comparative results of proposed enhanced fuzzy sliding mode control (EFSMC) with optimal PID and fuzzy PID controllers in no-load operation.

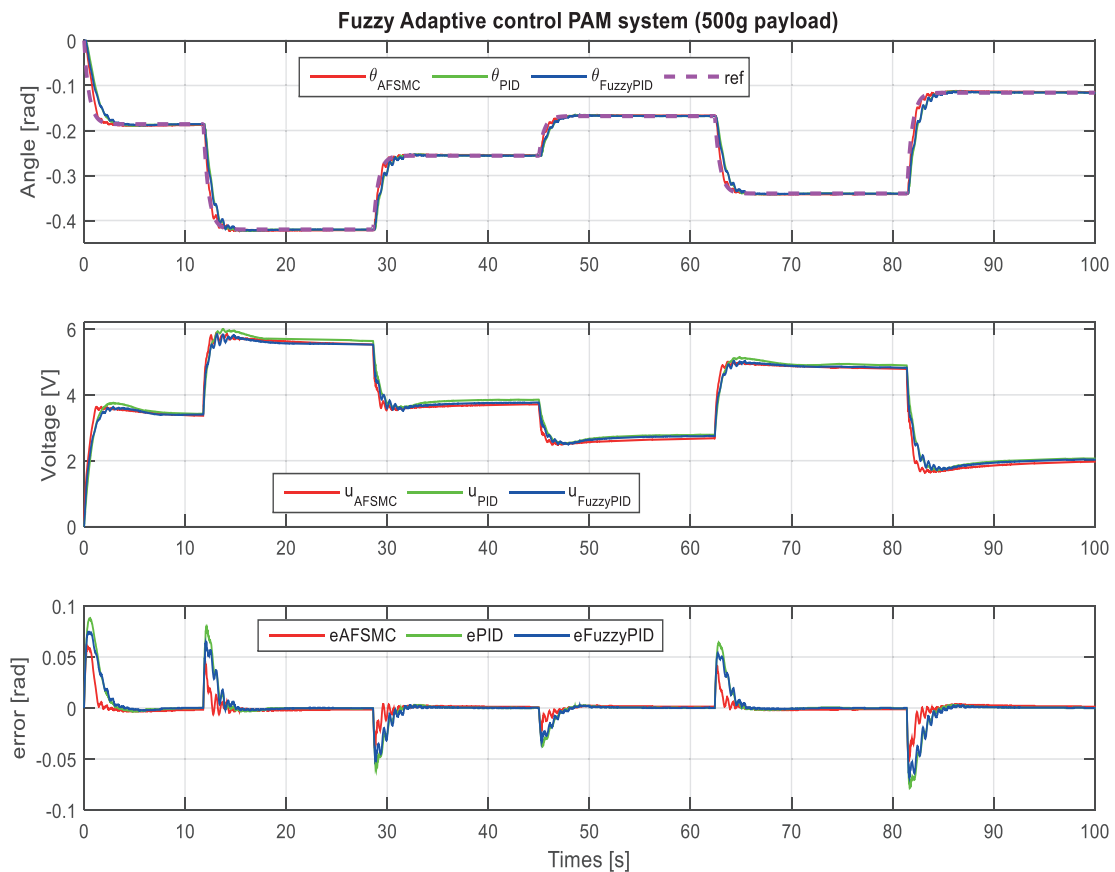


Figure 12 | Comparative results of proposed enhanced fuzzy sliding mode control (EFSMC) with optimal PID and fuzzy PID controllers in case pay-load of 0.5 kg.

robustness at all transient durations in comparison with other advanced control methods.

5. CONCLUSIONS

This paper proposes a novel enhanced fuzzy rule for conventional fuzzy SMC method, which applied for robust controlling an uncertain PAM-based manipulator. The new hybrid fuzzy SMC algorithm, whose adaptive fuzzy structure coefficients are optimally identified by DE algorithm. The newly proposed fuzzy law is successful in term of controlling uncertain nonlinear system to precise tracking a referential value. The result of tracking reference trajectory of new algorithm is verified not only on computer simulation but also on an actual 1-DOF PAM-based robot arm system. Compared to fuzzy PID technique, proposed adaptive EFSMC method gives a better result in both performance and robustness. Moreover, the stability of PAM manipulator in operation will be ensured since the perfect satisfaction of EFSMC method with Lyapunov stability criterion. As a consequent, proposed EFSMC algorithm ensures an efficient tool for controlling a wide range of uncertain dynamic structures.

CONFLICTS OF INTEREST

Authors confirm that there is no any conflict of interest related to the content of this paper.

AUTHORS' CONTRIBUTIONS

Contributions of author Ho Pham Huy Anh focus on editing and revising. Contributions of author Cao Van Kien focus on original idea, simulating and experimenting resulted preparation and revising

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