IEEE Access
Multidisciplinary | Rapid Review | Open Access Journal

Received October 7, 2019, accepted October 27, 2019, date of publication November 1, 2019, date of current version November 15, 2019.

Digital Object Identifier 10.1109/ACCESS.2019.2950895

Adaptive Fuzzy Control Method for a Single Tilt Tricopter

HUU KHOA TRAN[1,2], JUING-SHIAN CHIOU[3], NGUYEN THANH NAM[4], AND VO TUYEN[5]
[1]Industry 4.0 Center, National Taiwan University of Science and Technology, Taipei 10607, Taiwan
[2]Center for Cyber-Physical System Innovation, National Taiwan University of Science and Technology, Taipei 10607, Taiwan
[3]Department of Electrical Engineering, Southern Taiwan University of Science and Technology, Tainan 71005, Taiwan
[4]National Key Laboratory for Digital Control and System Engineering (DCSELAB), Ho Chi Minh University of Technology, Vietnam National University-HCM, Ho Chi Minh City 700000, Vietnam.
[5]Faculty of Mechanical Engineering, Ho Chi Minh City University of Food Industry, Ho Chi Minh City 700000, Vietnam

Corresponding author: Juing-Shian Chiou (jschiou@stust.edu.tw)

This work was supported in part by the Center for Cyber-Physical System Innovation through the Featured Areas Research Center Program within the framework of the Higher Education Sprout Project by the Ministry of Education (MOE), Taiwan, in part by the National Key Laboratory of Digital Control and System Engineering (DCSELAB), HCMUT, VNU-HCM, and in part by the Ministry of Science and Technology, Taiwan, under Grant MOST 106-2221-E-218-001-MY2 and Grant MOST 108-2221-E-218-028.

ABSTRACT This article proposes an adaptive fuzzy gain scheduling (FSG) design of the traditional proportional integral derivative (PID) control method by using fuzzy logic rules to schedule controlled gains at different phases. Owing to minimization of the tracking error of the controller design using three parameters and the integral of time weighted-squared error (ITSE) minima criterion of the controller design process, the fuzzy rules of the triangular membership functions are exploited online to verify the PID controller gains in different operated scheduling modes. For that reason, the controller designs can be used to tune the system models during the whole operation time period to enable efficient error tracking. The continuous genetic algorithm (GA) is considered an innovation because in it, the decode chromosome step is totally neglected. Owing to this improvement, it is superior to the standard GA because it requires less storage and enables naturally faster convergence. In this research, the controlled parameters were optimized using the continuous GA to enhance the efficiency of the proposed method. Thereafter, it was implemented to a single tilt Tricopter model to test whether the control performance is better when compared with the conventional PID control method.

INDEX TERMS Fuzzy gain scheduling (FGS), proportional integral derivative (PID) control, continuous genetic algorithm (GA), integral of time weighted-squared error (ITSE), single tilt tricopter UAV.

I. INTRODUCTION

In controller design, processing requires quick setting, reliability, and stability. Furthermore, the performance of control system is expected to be high, with high precision and better reliability. To achieve better performance, the developers of new control methods often need to find a balance between decreasing the response time and large overshoots while spending a fair amount of time to tune the control gains [1]. To account for both conditions, a controller is designed such that it has a faster response in the beginning when there is no oscillation in the target destination region. Hence, the system performance may vary depending on different time response values at different phases, consequently, a gain scheduled controller can be established.

Belonging to the "divide and conquer" control procedures type, the gain scheduling [1]–[3] is a widely used control design approach, in which a nonlinear design task is decomposed into a set of linear sub-problems [2]. As different gains may be employed within individual regions, the key purpose of implementing a suitable controller is to regulate the scheduled variables according to the process dynamics [4]. Moreover, the regions might be verified by the scheduling variables magnitude. In this article, we proposed an effective control scheme for fast positioning based on the proportional integral derivative (PID) control characteristics. To enable the fast convergence of the controlled system, the parameters are frequently set to be large when the scheduling variables are large, and vice versa, to make the system

The associate editor coordinating the review of this manuscript and approving it for publication was Zhiguang Feng.

stabilizes without significant fluctuation, the parameters are chosen small when the scheduling variables are small [3]–[5]. Beaven *et al.* [6]first developed the gain scheduling appropriate to the high-speed independent two-phase driving.

Fuzzy logic systems (FLS) based on expert knowledge can be modified through simply adding or deleting rules. A fuzzy rule-based model is appropriate in the case where the physical model information is imprecise. Fuzzy logic control (FLC), as a one-branch application, has been applied successfully for the first time in the field of controller design [7], [8]. Thereafter, the combination of fuzzy logic rules and gain scheduling concepts, namely, fuzzy gain scheduling, has been developed [9]–[12]. Later, Dounis *et al.* [13] and Chandrakala *et al.* [14] also used the same idea in the photovoltaic and hydrothermal energy systems. Recently, Kanagasabai, and Jaya revised this idea to control the MIMO process [15]. Considering these research works that have achieved impressive results, the adaptive fuzzy method for the gain scheduled PID parameters in the controller design has been adopted in the present study.

In the initiation of the motion control, we propose a controller of the PI-D (PI and D) type built in a system with fixed high proportional gain and high integral gain, but with the small derivative gain. Thereafter, the fuzzy gain scheduling method is used to gradually decrease the proportional gain and integral gain, while increasing the derivative gain until another phase is set. Aiming to reach the target position and settle it down as fast as possible, after determining the suitable regions through the use of the gain scheduling ideal, the next step is to identify the applicable control design parameters to achieve the scope. Consequently, the optimization technique is utilized. It is expected that better performance can be achieved with the optimization comparing against the method employing the arbitration.

Furthermore, in the artificial intelligence (AI) discipline, fuzzy logic is often associated with the genetic algorithm (GA) [16] to solve many optimization tasks, from the steel structure analysis [17] to face recognition [18] and control of moving cars to avoid rear-end collisions [19]. Hence, in this research, a heuristic search continuous GA, which was inspired by the natural evolution, is modified to provide the higher optimal efficiency for faster searching and convergence. Genetic algorithms firstly introduced by Holland in 1975 [20] continue being discussed in recent years [21]–[27]. Each GA operates on a population of artificial chromosomes. Each chromosome has a real number fitness and symbolizes a problem solution. In addition, the chromosomes are not compulsory to decode prior to the evaluation of the cost function. Therefore, we proposed the continuous GA as an innovation, in which the decode chromosome step is completely neglected [24]. This improvement allows achieving such advantages as requiring less storage and having the faster convergence pace.

The fitness function is utilized to estimate the appropriateness of a solution with respect to a specific issue. The fitness function minimization / maximization value is optimized to

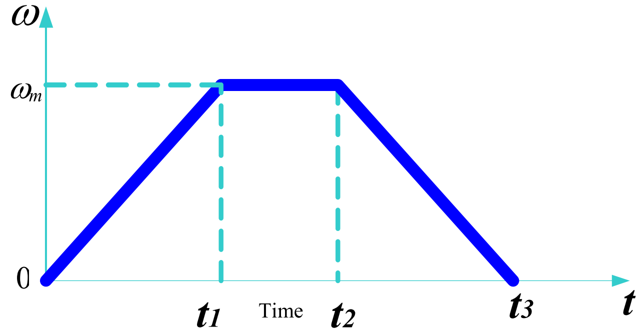


FIGURE 1. Trapezoidal motion curve.

illustrate the best-achieved performance [28]–[31]. In this paper, the integral of time weighted-squared error (ITSE) is introduced as the performance metric of the controller design criterion.

Unmanned aerial vehicles (UAV) are flying aerial vehicles, which is able to operate autonomously. Owing to their flight capabilities, such as high agility and autonomy, its application is widely used in the fields from civilian information to rescue operations and even military surveillance [32]–[34]. The control methods for aerial robots have difficulties in empirical application in terms of achieving appropriate performance and robustness. Therefore, a single tilt tricopter UAV, hereinafter, referred to as the tricopter, is chosen as a model to perform the efficiency testing of the proposed controller design.

In general, the proposed controller design utilizes the benefit of the continuous GA that is associated with the system performance metric, ITSE, to optimize the fuzzy gain scheduling for the PID control parameters. The rest of the paper is organized as follows. In Section 2, we propose the development of a fuzzy gain scheduling (FGS) scheme for the dynamic reset of the PID controllers. Continuous GA is implemented onto the FGS controller to identify the optimal PID gains in Section 3. Next, the single tilt tricopter UAV models are introduced, and the performance results of the proposed controller are discussed in Section 4. Finally, the conclusions are provided in Section 5.

II. CONTROLLER DESIGN

A. PID CONTROLLER

The formulation of the PID controller is described in equation (1) as follow

$$u(t) = K_P e(t) + K_I \int e(t)dt + K_D \frac{d}{dt} e(t) \quad (1)$$

Here, u(t) is the input control, e(t) is the error. The variables KP, KI, and KD denote the proportional, integral, and derivative gains, respectively. It can be manipulated to produce various responses from a given process.

The PID controller continuously calculates error values and applies a correction using three terms, namely, proportional, integral, and derivate of the controller design.

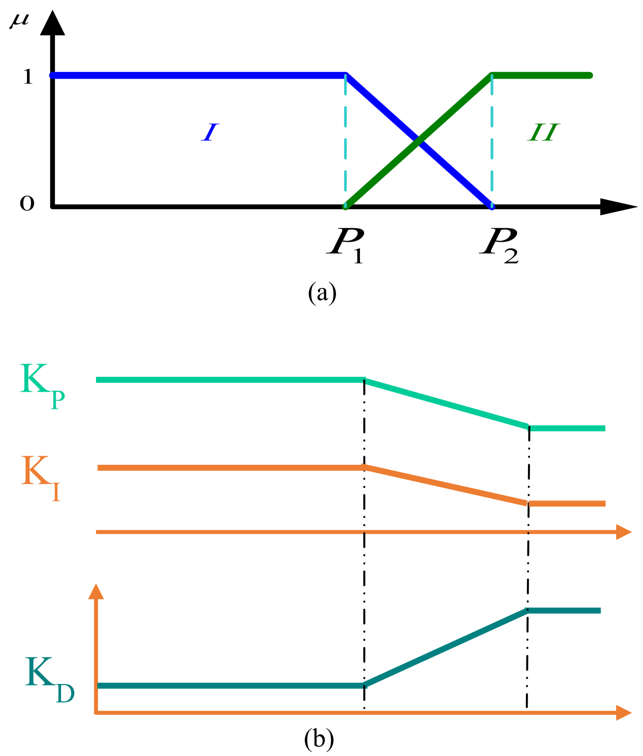


FIGURE 2. a) Membership functions at phases I and II, b) Tuning of control parameters.

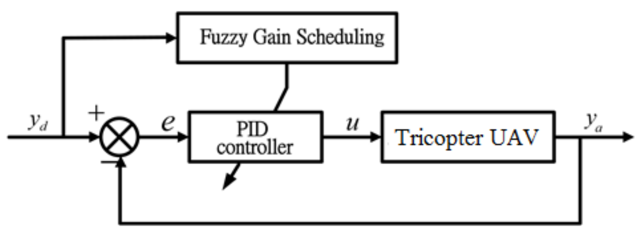


FIGURE 3. Adaptive fuzzy gain scheduling diagram.

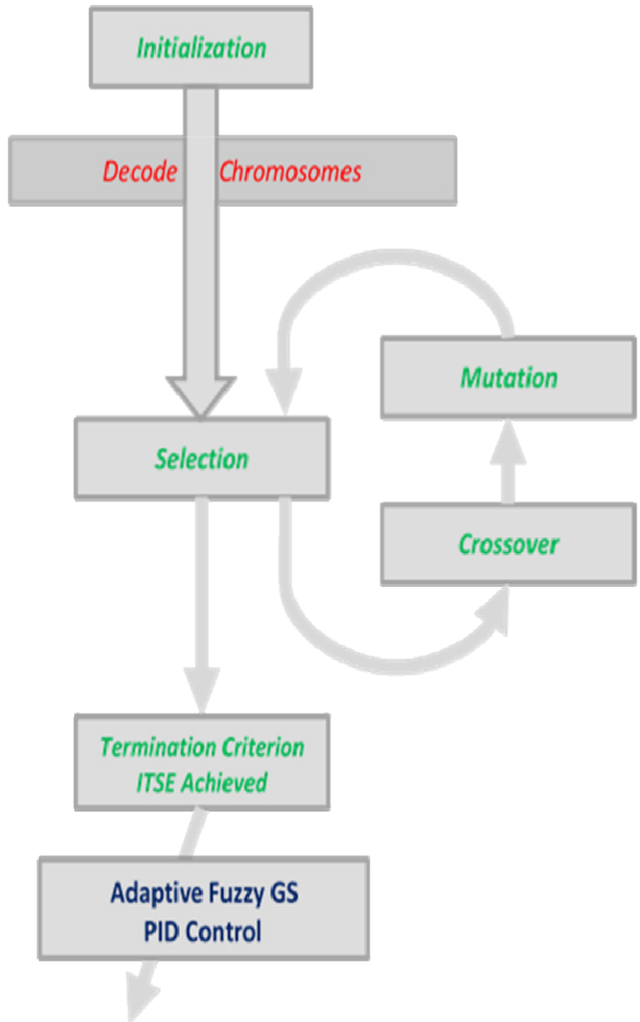


FIGURE 4. Continuous genetic algorithm optimized using adaptive fuzzy gain scheduling for PID control parameters.

The P-term increase will reduce the rise time, the I-term increase will eliminate the steady-state error, and the D-term increase will reduce the overshoot and upgrade the system stability.

B. ADAPTIVE FUZZY GAIN SCHEDULING

The proposed idea is to develop a PID-type controller with fixed high proportional (P) and integral (I) gains, and a small derivative (D) gain in the beginning. Thereafter, the fuzzy gain scheduling method is implemented to reduce the P and I gains, while increasing the D gain at the next phase. Hence, the control system will function smoothly, and the desired response performance at each stage will be retained [12].

For the majority of schemes describing the gain scheduling design process, it is essential to define the suitable regions for the scheduling variables. The T-curve (trapezoidal curve), whereas the ω_m is the angular velocity, of each motion system has three parts: acceleration t ϵ $[0, t_1]$, constant speed t ϵ $[t_1, t_2]$, and deceleration t ϵ $[t_2, t_3]$, which are defined to identify the best regions for the tuning process as shown in Figure 1.

Aiming to design the controller using the most effective technique, fuzzy logic inference is implemented to the deceleration phase $[t_2, t_3]$ to make the variation of the parameters continuous and linear. The two membership functions μ_1 and μ_2 are shown in Figure 2a. The inference rules are stated as follows:

If $p < p_1$, then $\mu_1 = 1$ and $\mu_2 = 0$.
If $p_1 \leq p \leq p_2$, then $\mu_1 = \frac{p_2 - p}{p_2 - p_1}$ and $\mu_2 = \frac{p - p_1}{p_2 - p_1}$.
If $p > p_2$, then $\mu_1 = 0$ and $\mu_2 = 1$.

The weighting μ_i for the *i-th* membership function is then determined by the current command position $p = yd_{(t)}$. At phase I of fixed PI-D gains, $\mu_1 = 1$, and $\mu_2 = 0$. At the switching phase I and phase II of blended gains, $\mu_1 = \frac{p_2 - p}{p_2 - p_1}$ and $\mu_2 = \frac{p - p_1}{p_2 - p_1}$. At phase III of the second set of fixed gains, $\mu_1 = 0$, and $\mu_2 = 1$. The PI-D parameter gains can be determined as per Equation 2. The subscript 1 and 2 of

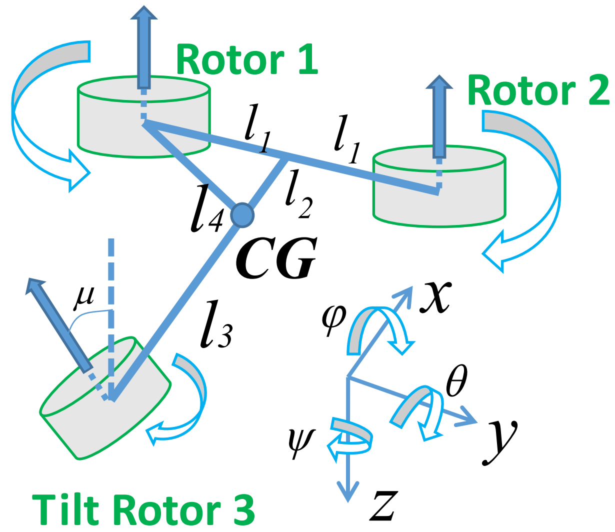
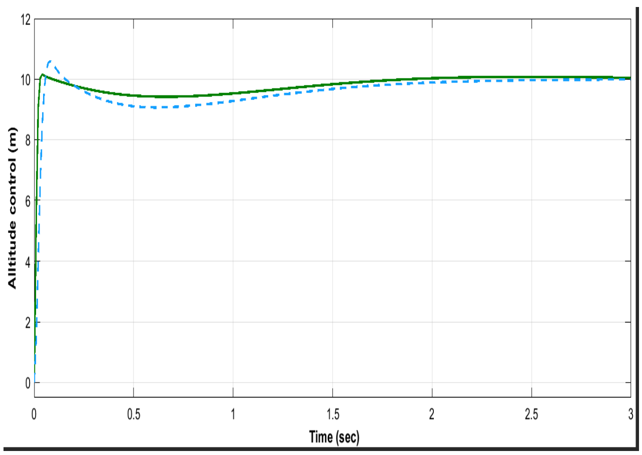
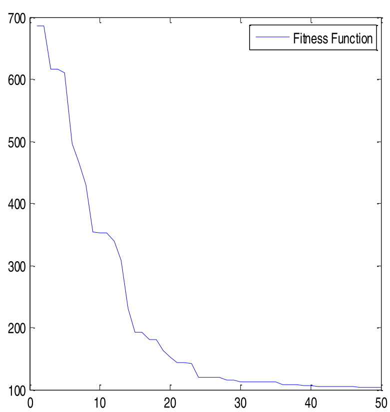


FIGURE 5. The single tilt tricopter UAV pattern.



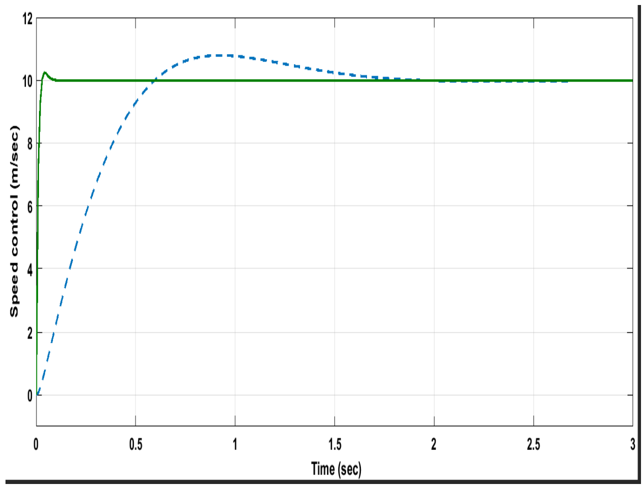
(a)



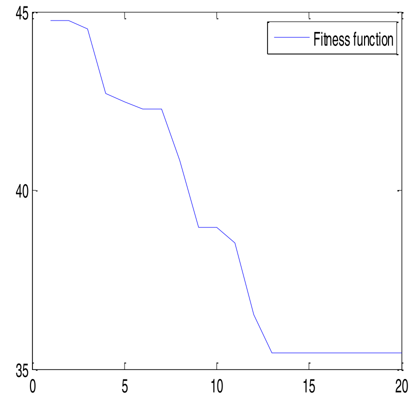
(b)

FIGURE 6. Altitude control. (a) Optimal adaptive control (solid line) – fuzzy gain scheduling (dashed line). (b) Continuous GA fitness function.

the tuning PI-D gains as shown in Figure 2b corresponds to membership I and II, respectively. In the above fuzzy logic rules, the desired position is considered. The block diagram of



(a)



(b)

FIGURE 7. DC Rotor speed control. (a) Optimal adaptive control (solid line) – fuzzy gain scheduling (dash line). (b) Continuous GA fitness function.

the proposed adaptive fuzzy gain scheduling-PID (FGS-PID) controlled system is shown in Figure 3.

$$\begin{cases} K_P = \sum_i \mu_i \cdot K_{P,i} \\ K_I = \sum_i \mu_i \cdot K_{I,i} \\ K_D = \sum_i \mu_i \cdot K_{D,i} \end{cases} \tag{2}$$

III. GENETIC ALGORITHM TO OPTIMIZE THE PARAMETERS

A. CONTINUOUS GENETIC ALGORITHM

The genetic algorithm (GAs) was introduced in 1975 by Holland [20] based on the concept of the Darwinian hypothesis. This optimization technique inspired by the natural evolution has been successfully applied to complex real-world issues, such as optimal structure of steel [17], face recognition [18], and controller design [21], [22]. During the GA

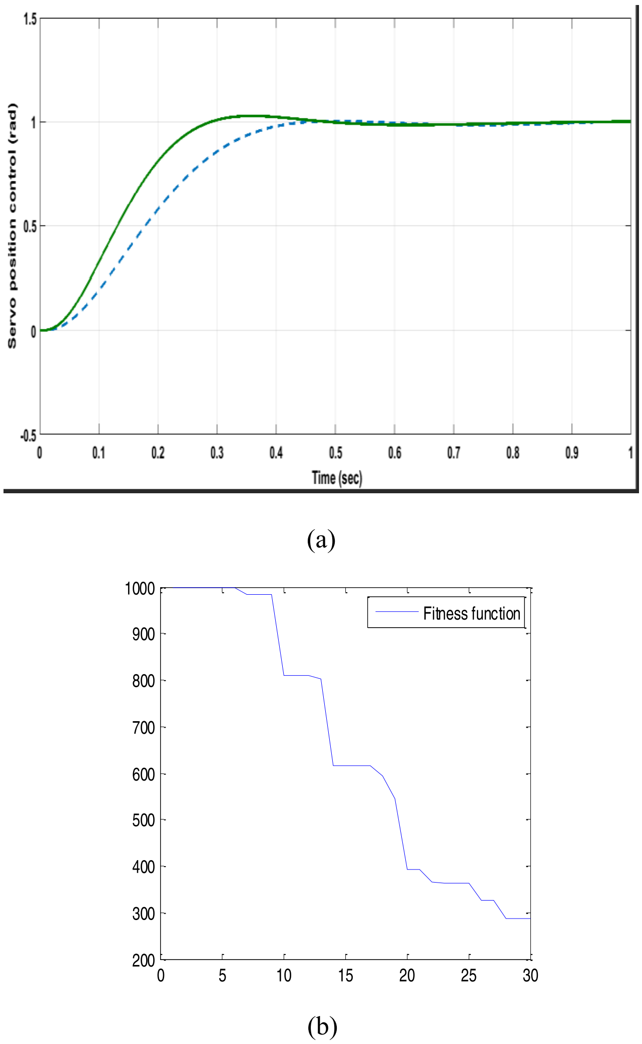


FIGURE 8. Servo motor position control. (a) Optimal adaptive control (solid line) – Fuzzy gain scheduling (dashed line). (b) Continuous GA fitness function.

execution, an individual population is arranged in the optimization space. The standard GA, which has three essential parameters including population size (N), crossover rate (Rc), and mutation rate (Rm), is used to verify the optimal gains of the control system. It should be noted that the chromosomes are not compulsory to decode prior to the evaluation of the cost function. Hence, we proposed the innovative continuous GA implying that the decode chromosome step can be totally neglected. This approach is superior to the standard GA in terms of less storage required and the faster convergence pace [24].

B. OPTIMAL GAIN SCHEDULING PARAMETERS

The purpose of the scheduled gains is to enable the system to reach the precise target and to stabilize as fast as possible. Therefore, the stabilizing time is chosen as the objective function to minimize the control parameters, i.e., P, I, and D gains. It should be noted that applying the GA optimization resulted in significant success in many fields. Hence, the continuous

TABLE 1. The parameters of the tricopter model.

Notation	Parameter (unit)	Notation	Parameter (unit)
I_{xx}	0.0057211 kg.m^2	l_1	0.19 m
I_{yy}	0.073933 kg.m^2	l_2	0.122 m
I_{zz}	0.012545 kg.m^2	l_3	0.23 m
$b_1 = b_2$	0.00013678	l_4	$\sqrt{l_1^2 + l_2^2} = 0.225m$
$d_1 = d_2$	0.000024323	m	0.84 kg

TABLE 2. The tuning results obtained using optimal adaptive FGS-PID.

	Generation	K_P	K_I	K_D
Altitude control (10 m)	50	10.76	0.18	31.52
DC motor speed control (10 m/s)	20	36.08	1.92	22.83
Servo motor position control (1 rad)	30	22.66	2.49	18.51

GA optimized adaptive FGS-PID controller is proposed to achieve an optimal compromise between the easier flight pilot and system stability. In addition, the fitness function ITSE, as described in equation (3), is selected as the minimum error criterion. The optimal algorithm flowchart is illustrated in Figure 4.

$$ITSE = \int_{0}^{\infty} t \cdot e^2(t) \cdot dt \tag{3}$$

IV. SIMULATION RESULTS

The model of the tricopter derived from [33]–[36] has six degrees of freedom (DOF) and is based on the Newton-Euler formulation. The tricopter pattern, as demonstrated in Figure 5, is depicted using the right hand generalized earth coordinate system of axes and a right hand body frame. The positive x-axis points towards the two front rotors (rotor 1 and 2), the positive y-axis towards the right side (rotor 2), and the positive z-axis is directed downwards. The three-angle roll (φ), pitch (θ), and yaw (ψ) of the attitude control are decided by the right handed rotation x, y, and z axes, respectively [33]. The tilt angle μ is measured by the y-z coordinate axis. The tricopter has four input signals: three rotorcraft speeds and one tilt angle created by a servomotor attached in the rear.

The tricopter UAV parameters are summarized in Table 1. The three significant variables of tricopter models used to estimate the efficiency of the proposed method are the following:

- Altitude control (Z motion of the UAV tricopter): $\frac{1}{0.84s^2+0.4286+19.376}$
- Speed control (for three DC rotorcrafts): $\frac{11.4286}{(s+57.14)(s+2.004)}$

- Position control (for the tilting servo system): $\frac{106.7}{s(s+281.8)(s+2.582)}$

In this paper, the PID controller tuning gains are set within the range [0, 100], and the optimal gains are provided in Table 2. The iteration of the continuous GA population for each controller design is as follows: altitude control, speed control, and servo position control, which has the crossover rate Rc = 0.95 and the mutation rate Rm = 0.1, are set 50, 20, and 30, respectively. The response performance estimates of three tricopter models described above are displayed one-by-one in Figure 6, Figure 7, and Figure 8. In summary, the proposed optimal continuous GA applied to the adaptive fuzzy gain scheduling of the three PID control gains allows achieving the faster response with shorter stabilization time, and no overshoot at all since the performances are in range of error. The continuous GA is also superior in terms of updating the number of generations comparing against the standard GA with a hundreds of generation [26], [27].

V. CONCLUSION

In this article, the fuzzy logic rules based on the trapezoidal membership function design are applied to the error tracking of the controller design through tuning the parameters in each of scheduled gains. The proposed control method is able to function properly during the whole operation time period, and the system performance in terms of response time is appropriate. In addition, the continuous GA optimization method, which neglects the decode chromosome step, is utilized to update and improve the controller gains. The proposed GA adaptive fuzzy gain scheduling controller was implemented to control the following parameters of the single tilt tricopter UAV device: DC motor speed, DC servo motor position, and the altitude of the tricopter. From the results, it can be concluded that the proposed controller achieves high effectiveness in terms of required saving the operation time, robustness, and reliability.

COMPETING INTERESTS

The authors declare that they have no competing interests.

REFERENCES

[1] Electro-Craft Corporation, *DC Motors, Speed Controls, Servo Systems: An Engineering Handbook*. New York, NY, USA: Pergamon, 1977.
[2] Z.-Y. Zhao, M. Tomizuka, and S. Isaka, "Fuzzy gain scheduling of PID controllers," *IEEE Trans. Syst., Man and*, vol. 23, no. 5, pp. 1392–1398, Sep. 1993.
[3] D. J. Leith and W. E. Leithead, "Survey of gain-scheduling analysis and design," *Int. J. Control*, vol. 73, no. 11, pp. 1001–1025, 2000.
[4] K. J. Astrom and B. Wittenmark, *Adaptive Control*, 2nd ed. Reading, MA, USA: Addison-Wesley, 1994.
[5] G. Orelind, L. Wozniak, J. Medanic, and T. Whittemore, "Optimal PID gain schedule for hydrogenerators-design and application," *IEEE Trans. Energy Convers.*, vol. EC-4, no. 3, pp. 300–307, Sep. 1989.
[6] R. W. Beaven, M. T. Wright, S. D. Garvey, M. I. Friswell, and D. R. Seaward, "The application of setpoint gain scheduling to high-speed independent drives," *Control Eng. Pract.*, vol. 3, no. 11, pp. 1581–1585, 1995.
[7] E. H. Mamdani, "Application of fuzzy algorithms for control of simple dynamic plant," *Proc. Inst. Elect. Eng.*, vol. 121, no. 12, pp. 1585–1588, Dec. 1974.
[8] P. J. King and E. H. Mamdani, "The application of fuzzy control systems to industrial processes," *Automatica*, vol. 13, no. 3, pp. 235–242, 1977.
[9] S. Tan, C.-C. Hang, and J.-S. Chai, "Gain scheduling: From conventional to neuro-fuzzy," *Automatica*, vol. 33, no. 3, pp. 411–419, 1997.
[10] J.-P. Su and C.-C. Wang, "Fuzzy gain-scheduled integral control and its application to a twin rotor system," *Int. J. Fuzzy Syst.*, vol. 2, no. 3, pp. 205–219, 2000.
[11] T. P. Blanchett, G. C. Kember, and R. Dubay, "PID gain scheduling using fuzzy logic," *ISA Trans.*, vol. 39, no. 3, pp. 317–325, 2000.
[12] T.-Y. Huang and H. K. Tran, "Optimization of setpoint-based fuzzy gain scheduling and its application to a linear stage," in *Proc. 7th IEEE Conf. Ind. Electron. Appl.*, Singapore, Jul. 2012, pp. 2106–2111.
[13] A. I. Dounis, P. Kofinas, C. Alafodimos, and D. Tseles, "Adaptive fuzzy gain scheduling PID controller for maximum power point tracking of photovoltaic system," *Renew. Energy*, vol. 60, pp. 202–214, Dec. 2013.
[14] K. R. M. V. Chandrakala, S. Balamurugan, and K. Sankaranarayanan, "Variable structure fuzzy gain scheduling based load frequency controller for multi source multi area hydro thermal system," *Int. J. Elect. Power Energy Syst.*, vol. 53, pp. 375–381, Dec. 2013.
[15] N. Kanagasabai and N. Jaya, "Fuzzy gain scheduling of PID controller for a MIMO Process," *Int. J. Comput. Appl.*, vol. 91, no. 10, pp. 13–20, 2014.
[16] P. Thrift, "Fuzzy logic synthesis with genetic algorithm," in *Proc. 4th Int. Conf. Genetic Algorithms*, San Diego, CA, USA, 1991, pp. 509–513.
[17] K. C. Sarmaand and H. Adeli, "Fuzzy genetic algorithm for optimization of steel structures," *J. Struct. Eng.*, vol. 126, no. 5, pp. 596–604, 2000.
[18] M. Xue, W. Liu, and X. Liu, "A novel weighted fuzzy LDA for face recognition using the genetic algorithm," *Neural Comput. Appl.*, vol. 2, nos. 7–8, pp. 1531–1541, 2013.
[19] C. Chen, M. Li, J. Sui, K. Wei, and Q. Pei, "A genetic algorithm-optimized fuzzy logic controller to avoid rear-end collisions," *J. Adv. Transp.*, vol. 50, np. 8, pp. 1735–1753, 2016.
[20] J. H. Holland, *Adaptation in Natural and Artificial Systems: An Introductory Analysis With Applications to Biology, Control, and Artificial Intelligence*. Ann Arbor, MI, USA: Univ. Michigan Press, 1975.
[21] J. J. Grefenstette, "Optimization of control parameters for genetic algorithms," *IEEE Trans. Syst., Man, Cybern.*, vol. SMC-16, no. 1, pp. 122–128, Jan. 1986.
[22] D. E. Goldberg, *Genetic Algorithms in Search, Optimization, and Machine Learning*. Reading, MA, USA: Addison-Wesley, 1989.
[23] M. Srinivas and L. M. Patnaik, "Adaptive probabilities of crossover and mutation in genetic algorithms," *IEEE Trans. Syst., Man, Cybern.*, vol. 24, no. 4, pp. 656–667, Apr. 1994.
[24] R. L. Haupt and S. E. Haupt, *Practical Genetic Algorithms*, 2nd ed. Hoboken, NJ, USA: Wiley, 2004.
[25] J. Zhang, H. S.-H. Chung, and W.-L. Lo, "Clustering-based adaptive crossover and mutation probabilities for genetic algorithms," *IEEE Trans. Evol. Comput.*, vol. 11, no. 3, pp. 326–335, Jun. 2007.
[26] A. P. Antunes and J. L. F. Azevedo, "Studies in aerodynamic optimization based on genetic algorithms," *J. Aircr.*, vol. 51, no. 3, pp. 1002–1012, 2014.
[27] J. Tang, J. Zhang, Z. Wu, Z. Liu, T. Chai, and W. Yu, "Modeling collinear data using double-layer GA-based selective ensemble kernel partial least squares algorithm," *Neurocomputing*, vol. 219, pp. 248–262, Jan. 2017.
[28] S. Skogestad, "Simple analytic rules for model reduction and PID controller tuning," *J. Process Control*, vol. 13, no. 4, pp. 291–309, Jun. 2003.
[29] F. G. Martins, "Tuning PID controllers using the ITAE criterion," *Int. J. Eng. Educ.*, vol. 21, no. 5, pp. 867–873, 2005.
[30] W. Tan, J. Liu, T. Chen, and H. J. Marquez, "Comparison of some well-known PID tuning formulas," *Comput. Chem. Eng.*, vol. 30, pp. 1416–1423, Jul. 2006.
[31] Y.-T. Juang, Y.-T. Chang, and C.-P. Huang, "Design of fuzzy PID controllers using modified triangular membership functions," *Inf. Sci.*, vol. 178, no. 5, pp. 1325–1333, 2008.
[32] E. N. Sanchez, H. M. Becerra, and C. M. Velez, "Combining fuzzy, PID and regulation control for an autonomous mini-helicopter," *Inf. Sci.*, vol. 177, pp. 1999–2022, May 2007.
[33] J.-S. Chiou, H.-K. Tran, and S.-T. Peng, "Attitude control of a single tilt tri-rotor UAV system: Dynamic modeling and each channel's nonlinear controllers design," *Math. Problems Eng.*, vol. 2013, Aug. 2013, Art. no. 275905.
[34] H.-K. Tran and J.-S. Chiou, "PSO-based algorithm applied to quadcopter micro air vehicle controller design," *Micromachines*, vol. 7, no. 6, p. 168, 2016.

[35] G. D. Padfield, *Helicopter Flight Dynamics: The Theory and Application of Flying Qualities and Simulation Modeling*. Reston, VA, USA: AIAA, 1996.

[36] B. L. Stevens and F. L. Lewis, *Aircraft Control and Simulation*. Hoboken, NJ, USA: Wiley, 1992.

HUU KHOA TRAN received the Ph.D. degree in mechatronics technology from the Southern Taiwan University of Science and Technology (STUST), Tainan, Taiwan, in 2015. He is currently an Assistant Professor with the National Taiwan University of Science and Technology (NTUST), Taipei, Taiwan. He has over 15 research articles. His research interests include artificial intelligence, autonomous robot (UAV, AGV), decision and control, optimization algorithms, big data, and the Internet of Things.

JUING-SHIAN CHIOU received the B.S. degree from the Department of Electrical Engineering, Feng Chia University, Taiwan, in 1986, and the M.S. degree from the Department of Electrical Engineering, National Central University, Taiwan, 1990, and the Ph.D. degree from the Department of Electrical Engineering, National Cheng Kung University, Tainan, Taiwan, in 2000.

In 2000, he joined the Department of Electrical Engineering, Southern Taiwan University of Science and Technology, Tainan, where he is currently a Distinguished Professor and the Vice-President of the Taiwan Association for Academic Innovation, and Review Committee of the Ministry of Science and Technology, Taiwan. He has over 60 articles. His research interests include artificial intelligence, fuzzy control, unmanned aerial vehicles, algorithm, large-scale systems, and hybrid systems.

NGUYEN THANH NAM received the B.S. and M.S. degrees in mechanical engineering, in 1984, and the Ph.D. degree in mechanical engineering from the Technical University, Sofia, Bungaria, in 1991.

Since 1986, he has been a Lecturer with the Faculty of mechanical engineering, Ho Chi Minh City University of Technology, VNU-HCM. From 2004 to 2016, he was the Deputy Director of the Department of Science and Technology, VNU-HCM. Since 2008, he has been the Director of the National Key Laboratory of Digital Control and System Engineering (DCSELAB). He is also the author of three books, more than 83 articles, and more than seven inventions. His research interests include UAV advanced design, robotic and automation, fabrication (ISF technology, 3D printing), product design and development, and aerodynamics and hydrodynamics (CFD, two-phase current).

VO TUYEN received the Ph.D. degree in mechanical engineering from the Ho Chi Minh City University of Technology, in 2014. From 2005 to 2011, he was the Dean of mechanical engineering with the Ho Chi Minh City University of Food Industry (HUFI), where he has been a Vice Rector, since 2011. He is the author more than 20 articles and more than five inventions. His research interests include UAV advanced design, robotic and automation, and aerodynamics and hydrodynamics (CFD, two-phase current).