

Evolved Algorithm and Vibration Stability for Nonlinear Disturbed Security Systems

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Abstract: In this paper, a method sustaining system stability after decomposition is proposed. Based on the stability criterion derived from the energy function, a set of intelligent controllers is synthesized which is used to maintain the stability of the system. The sustainable stability problem can be reformulated as a Linear Matrix Inequalities (LMI) problem. The key to guaranteeing the stability of the system as a whole is to find a common symmetrically positive definite matrix for all subsystems. Furthermore, the Evolved Bat Algorithm (EBA) is employed to replace the pole assignment method and the conventional mathematical methods for solving the LMI. The EBA is utilized to find feasible solutions in terms of the energy equation. The experimental results show that the EBA is capable of providing proper solutions, which satisfy the sustainability and stability criteria, after a short period of recursive computing.

Keywords: Fuzzy energy equation; swarm intelligence; evolved bat algorithm

1 Introduction

The Linear Matrix Inequality (LMI) theory is a useful analytical tool for analyzing the sustainability and stability of a system. Many problems in system and control theory can be reformatted as a few standard convex or quasiconvex optimization problems with LMI. The result is that the complex system behavior becomes more straightforward and easier to analysis. The control system characteristics can be transformed into optimization problems that can be easily solved with numerical computation or swarm intelligence algorithms. Stability is another essential property of a control system and has thus been widely investigated in the literature on fuzzy dynamic systems [1,2,7,8,9,12,14,25,32,39,44]. Many monographs regarding the stability analysis of fuzzy control systems have been published, such as those by Cao and Frank (2001) [4], Yi and Heng (2002) [42], Li et al. (2004) [19], Tian and Peng (2006) [35], Liu and Zhang (2008) [24]. Cao and Frank [3-4] first considered using T-S based fuzzy control to present nonlinear time-delay systems. In 2002, Zhang and Pheng [43] proposed using an LMI-based approach for the stability analysis of fuzzy control systems with bounded uncertain delays.

Swarm intelligence is another popular field gaining much interest from researchers. In swarm intelligence methods, algorithms can not only be utilized to solve optimization problems, but can also be employed to simulate the behavior of a system or to provide solutions for scheduling, manufacturing, and logistics in engineering and business. For example, Panda et al. (2011) utilized Cat Swarm Optimization (CSO) to develop a population based learning rule for an Infinite Impulse Response (IIR) system [26]; Tsai et al. (2012) proposed the Enhanced Parallel Cat Swarm Optimization (EPCSO) method and used it to solve

the aircraft schedule recovery problem [37]; Pardhan and Panda (2012) used CSO to solve multiobjective problems [27]; and Wang et al. (2012) utilized CSO to optimize information hiding results [40]. In addition, the Interactive Artificial Bee Colony (IABC) has been employed by Tsai et al. (2012) to assist in a continuous authentication system [36], while Temel et al. (2013) used CSO with the Wavelet Transform method to compose a deployment plan for wireless sensors on 3D Terrain [34]. Chang et al. (2013) used IABC for both constructing a stock portfolio [6] and forecasting the exchange rate [5]; Saha et al. (2013) employed CSO for optimizing the design of a linear phase FIR filter [28]. The fast development of swarm intelligence algorithms amply demonstrates that it that they are useful and powerful tools for finding solutions in different knowledge domains.

In this study, we focus on finding solutions for fuzzy control security systems under the stability criteria derived by the Lyapunov function. To achieve this goal, the T-S fuzzy model with a PDC scheme is first used to decompose the whole nonlinear system. Subsequently, the LMI conditions obtained via the Lyapunov function approach are utilized to construct an analytical model for defining the stability criteria for the designed fuzzy controller. Finally, a newly developed swarm intelligence algorithm, called the Evolved Bat Algorithm (EBA) (Tsai et al., 2012) [38], is employed to find the feasible solutions for the designed fuzzy controller. Finally, some conclusions are drawn based on the experiments.

The remainder of this paper is structured as follows: a brief review of the T-S fuzzy model, which is combined with the PDC scheme to construct a global fuzzy logic controller, and of the stability analysis of a nonlinear system is given in Section 2; the stability conditions derived by LMI with the Lyapunov function (Yeh et al., 2008) [41] are reviewed in Section 3. Subsequently, a short introduction to the employed EBA is given in Section 4, and the experimental design and results obtained with our proposed approach are described in Section 5, followed by the presentation of conclusions in Section 6.

2 System Description

Consider a nonlinear system represented as follows:

$$\dot{x}(t) = f(x(t), u(t)) + \phi(t), \quad (1)$$

where $\dot{x}(t)$ denotes a derivative of $x(t)$ which is the state vector; f is the nonlinear vector-valued function; t stands for the time; $\phi(t)$ represents the external disturbance; and $u(t)$ is the input vector.

Definition 1 (Khalil, 1992) [18]. It can be said that solutions for a dynamic system are uniformly ultimately bounded (UUB) if there exist positive constants β and k , and there is a positive constant $T = T(\delta)$ for every $\delta \in (0, k)$, such that $\|x(t_0)\| < \delta \Rightarrow \|x(t)\| \leq \beta \forall t \geq t_0 + T$.

When using the concept of T-S fuzzy modeling (Takagi and Sugeno, 1985) [29] to describe the nonlinear system listed above, a set of fuzzy IF-THEN rules are utilized to compose the system. Each rule stands for the local linear input-output relation of the nonlinear system, and has the following form:

$$\text{If } z_1(t) \text{ is } M_{i_1} \text{ and } \dots \text{ and } z_g(t) \text{ is } M_{i_g}; \quad (2)$$

$$\text{Then } \dot{X}(t) = A_i X(t) + B_i U(t) + \phi(t), \quad (3)$$

where $i = 1, 2, \dots, r$; and an unknown disturbance is defined as $\phi(t)$ with a known upper bound. In addition, A_i and B_i are constant matrices with appropriate dimensions; $z_1(t) \sim z_g(t)$ are the premise variables; M_{i_p} ($p = 1, 2, \dots, g$) indicates the fuzzy set.

Since the premise components for the PDC controller are the same as those for the T-S fuzzy model, the i th linear control rule can be derived based on Eq. (2) as follows:

$$\text{If } z_1(t) \text{ is } M_{i_1} \text{ and } \dots \text{ and } z_g(t) \text{ is } M_{i_g}; \quad (4)$$

$$\text{Then } U(t) = -F_i X(t), \quad i = 1, 2, \dots, r. \quad (5)$$

The final control can be inferred from the Sum-Product reasoning method, formulated as in Eq. (4):

$$U(t) = - \frac{- \sum_{i=1}^r w_i(t) F_i X(t)}{\sum_{i=1}^r w_i(t)}; \quad (6)$$

$$w_i(t) = \prod_{p=1}^g M_{ip}(z_p). \quad (7)$$

Finally, the closed-loop controlled system of the nonlinear system listed in Eq. (1) is now able to be represented as in Eq. (6) according to the T-S fuzzy model and the PDC scheme mentioned above:

$$\dot{X}(t) = \sum_{i=1}^r \sum_{l=1}^r h_i(t) h_l(t) \{ (A_i - B_i F_l) X(t) \} + \phi(t). \quad (8)$$

3 LMI Conditions Obtained Through the Lyapunov Function Approach

Equations and mathematical expressions must be inserted into the main text. Two different types of styles can be used for equations and mathematical expressions. They are: in-line style, and display style [20, 39, 15].

Lemma 2 shows a sufficient condition, which is able to ensure the asymptotic stability of the closed-loop fuzzy system. Yeh et al. (2008) have derived the following stability conditions based on the above inequalities:

Theorem 1 (Yeh et al., 2008) [41]. There exists a fuzzy H^∞ controller where the closed-loop T-S fuzzy system is largely stable, if there exists a symmetric and common positive definite matrix $P \in R^{n \times n}$, a positive constant η , and the feedback gains K_i such that the following inequality is satisfied:

$$(A_i - B_i K_i)^T P + P(A_i - B_i K_i) + \frac{1}{\eta^2} P P + Q < 0, \quad (9)$$

where $P = P^T > 0$ and $i, j = 1, 2, \dots, r$. (10)

Since the stability criteria are known from previous studies in the literature, the key to insuring that the fuzzy control system is stable in the large is simplified into the problem of finding the common positive definite matrix P and the control force K_i .

4 Review of the Evolved Bat Algorithm (EBA)

The EBA (Tsai et al., 2012) [38] is a newly developed swarm intelligence algorithm inspired by bat echolocation in the natural world. The computational speed of the EBA is fast because its structure is designed with simple and light computations. Unlike other swarm intelligence algorithms (e.g., Particle Swarm Optimization (PSO) (Eberhart and Kennedy, 1995) [13], Artificial Bee Colony (ABC) optimization (Karaboga, 2005) [16-17], or Cat Swarm Optimization (Chu et al., 2006) [10-11]), there is only one major variable which should be determined before using EBA, i.e., the medium for sound waves. The chosen medium determines the step size of the movement of the artificial agent in the solution space. In general, the step size has a direct influence on the search result. When the chosen step size overlarge, the artificial agents in the solution space jump rapidly from one coordinate to another meaning it is quite possible to fly over the coordinates where a global optimum exists, without paying attention to them. In contrast, when the step size is too small, the artificial agents are easily trapped in the local optimum. According to experiments carried out by Tsai et al., the chosen medium is air, based on the natural environment where bats live.

The operation of EBA contains the following 4 steps:

Initialization: The artificial agents are spread throughout the solution space by randomly assigning the coordinates to them.

Movement: The artificial agents are moved by Eqs. (11)-(12). A random number is generated and then it is checked whether it is greater than the fixed pulse emission rate. If the result is positive, the artificial agent is moved using the random walk process, as defined by Eq. (13).

$$D = 0.17 \cdot \Delta T, \quad (11)$$

where D denotes the distance; and ΔT indicates the time cost between sending the sound wave and receiving the echo.

$$x_i^t = x_i^{t-1} + D, \quad (12)$$

where x_i indicates the coordinate of the i th artificial agent; and t is the iteration number.

$$x_i^{tR} = \beta \cdot (x_{best} - x_i^t), \quad \beta \in [0,1], \quad (13)$$

where β is a random number; x_{best} indicates the coordinate of the near best solution found so far over all artificial agents; and x_i^{tR} represents the new coordinates of the artificial agent after the operation of the random walk process.

Evaluation: The fitness of the artificial agents is calculated by the user defined fitness function and updated to the stored near best solution.

Termination: The termination conditions are checked to decide whether to go back to Step 2 or terminate the program and output the near best solution.

5 Experimental Design and Experimental Results

In this section, we discuss an experimental example, an inverted pendulum on a cart [33]. The nonlinear system is first described by the T-S fuzzy model with the PDC scheme. Subsequently, the LMI conditions obtained through the Lyapunov function approach are utilized to construct the analytical model for defining the stability criteria of the designed fuzzy controller. In addition, based on the conditions derived in the previous step, the fitness function is designed for later employment in EBA. Finally, EBA is utilized to find feasible solutions under the stability criteria for the fuzzy control system.

Consider the problem of an inverted pendulum on a cart [33] formulated as follows:

$$\dot{x}_1 = x_2, \quad (14)$$

where x_1 denotes the radius of the pendulum vertically; and x_2 is the first-order differential results of x_1 .

$$\dot{x}_2 = \frac{1}{l(4 - 3ma \cos^2 x_1)} (3g \sin x_1 - 3a \cos x_1 [u + d(t) + mlx_2^2 \sin x_1]) \quad (15)$$

where l is defined as half the length of the pendulum in meters; $g = 9.8 \text{ (m/s}^2\text{)}$ indicates the gravity constant; $a = 1/(m + M)$, and m and M are the mass of the pendulum and the cart, respectively; u denotes the input; and $d(t)$ is related to the external disturbances, which may be caused by the frictional force.

$$\dot{x}_3 = x_4, \quad (16)$$

where x_3 represents the displacement of the cart; and x_4 is the first-order differential results of x_3 .

$$\dot{x}_4 = -\frac{1}{4 - 3ma \cos^2 x_1} (1.5mag \sin 2x_1 - 4a[u + d(t) + mlx_2^2 \sin x_1]) \quad (17)$$

where \dot{x}_4 is the first-order differential results of x_4 .

Assume that $m = 1 \text{ (kg)}$, $M = 9 \text{ (kg)}$, l is equal to 1 meter; and $d(t)$ is bounded by $|d(t)| \leq \rho_0 + \rho_1 \|x\|$, where ρ_0 and ρ_1 are known constants. The temporary status of the nonlinear system

can be described by a fuzzy IF-THEN rule; by combining a set of fuzzy IF-THEN rules it is possible to approximate the whole nonlinear system. Similar operations can be found in previous studies (see [30-34,41,21-23]). Hence, the T-S fuzzy model approximated inverted pendulum on a cart nonlinear system can be described as follows:

$$\text{Rule 1: If } x_1 \approx 0, \text{ THEN } \dot{x} = A_1x + B_1[u + h(t, x)]. \quad (18)$$

$$\text{Rule 2: If } x_1 \approx \pm \frac{\pi}{3} \text{ (rad), THEN } \dot{x} = A_2x + B_2[u + h(t, x)], \quad (19)$$

$$\text{where } A_1 = \begin{bmatrix} 0 & 1 & 0 & 0 \\ 7.9459 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 \\ -0.7946 & 0 & 0 & 0 \end{bmatrix}, \quad A_2 = \begin{bmatrix} 0 & 1 & 0 & 0 \\ 6.1945 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 \\ -0.3097 & 0 & 0 & 0 \end{bmatrix}, \quad B_1 = \begin{bmatrix} 0 \\ -0.0811 \\ 0 \\ 0.1081 \end{bmatrix}, \quad B_2 = \begin{bmatrix} 0 \\ -0.0382 \\ 0 \\ 0.1019 \end{bmatrix},$$

$$h(t, x) = d(t) + x_2^2 \sin x_1,$$

So far, the nonlinear system of the inverted pendulum on a cart can be approximated by the T-S fuzzy model in Eqs. (18-19). Considering the LMI criteria from the Lyapunov function approach, as described in Section 3, theorem 1 provides a useful criterion in Eq. (10) to ensure that the system is stable in the large. According to theorem 1, finding the common positive definite matrix P and the control force K_i is the main problem to be dealt with. By finding the proper P and K_i , a stable T-S fuzzy controller system is achieved. Hence, in this study, we utilize EBA to find the proper solutions.

Utilizing swarm intelligence algorithms to solve problems in engineering, the first thing to do is to design the fitness function. Moreover, the characteristic of the system stability problem is that the solutions found by the algorithms can be dichotomized into feasible and infeasible solutions. This implies that it is more suitable and simpler to design the fitness function as a binary operation form to use in this application field. In this study, the fitness function is designed based on the stability criteria derived from the LMI conditions via the Lyapunov function approach, as noted above. In order to produce the binary classification results on the discovered solutions, the AND logical operation is employed in the fitness function for examining the solutions. The fitness function we design for this application is formulated as follows:

$$F = \alpha \times \beta, \quad (20)$$

where F denotes the fitness value; and \times stands for the AND operation in Boolean logic; α and β are the binary logical results, which are operated by Eqs. (21) and (22).

$$\alpha = \begin{cases} 1, & \text{if } (A_i - B_i K_i)^T P + P(A_i - B_i K_i) < 0 \\ 0, & \text{otherwise} \end{cases}, \quad (21)$$

$$\beta = \begin{cases} 1, & P = P^T > 0 \\ 0, & \text{otherwise} \end{cases}. \quad (22)$$

Employing EBA to find solutions in this application, we need to define what information an artificial agent should carry. Our design aims to find the common positive definite matrix P and the control force K_i , simultaneously. In addition, the nonlinear system given in the example has been approximated by two T-S fuzzy system rules in Eqs. (18-19). Since A_1, A_2 and B_1, B_2 are 4×4 and 4×1 matrices, respectively, it is obvious that, in this case, the common positive definite matrix P must be a 4×4 matrix and the control force K_i is a 1×4 matrix. To further reduce the complexity of using the fuzzy controller, we enact an even more strict condition forcing the fuzzy controller system to share the same control force, i.e., $K_i = K, \forall i$, as insured in our obtained results. Thus, the virtual bat in this application is designed to be a 20 dimensional vector. The matrix P is stretched into a 1×16 vector and is followed by matrix K^T . A control system can be classified as stable even if the final state of the system shows regular oscillation with a fixed amplitude. However, we eliminate the P and K , which cause the control system to demonstrated an oscillation

phenomena in our design. Only the solutions with definitely stable status remain. To achieve this goal, the matrix P is always constrained to be symmetric when adjusting the elements inside it through EBA. Moreover, a boundary condition is given at the initialization process for both matrices P and K . The same range of boundary conditions keeps influencing matrix P , to produce feasible solutions in a suitable range, but not on matrix K , because the total effect contributed to the whole control system by the control force is relatively small. The parameters, which we use in our experiment for EBA, are listed in Tab. 1.

Table 1: Parameters for EBA

Boundary conditions for matrix P	$[-3, 3]$
Initial range for matrix K_t	$[-3, 3]$
Number of runs	30
Number of iterations	500
Media material	Air
Population size	16

Swarm intelligence algorithms find solutions based on specifically designed random search processes. Hence, when employing swarm intelligence algorithms to solve problems in engineering, the same experiment should be repeated several times to ensure that the obtained results are consistent. The number of runs aims to provide a series of experimental results for examining with statistical methods. In addition, the operation of swarm intelligence algorithms requires a lot of recursive calculations. Three different termination criteria are generally used in swarm intelligence algorithms: the first one is a fixed number of iterations, the second is the fixed process time, and the last is the convergence of the fitness value. In this application, we choose a fixed number of iterations as the termination criterion and set it to be 500. As mentioned above, Tsai et al. chose air as the medium for the transmission of the sound wave. The reason for this is that it is the most fitting for the natural environment in which bats live in. However, the design of the EBA allows the user to choose different media in the formula. Different media bring different coefficient values and variation in the step size, which influence the search accuracy and the movement of the artificial agent. In our experiment, for simplicity, we leave the medium untouched and adopt the one chosen by Tsai et al. Moreover, there are always multiple numbers of artificial agents operating at the same time in the solution space in swarm intelligence algorithms. The number of artificial agents is controlled by the parameter called population size. A large population size provides a larger chance for the algorithm to find the near best solutions, while on the other hand, a larger population size requires more memory resource and computation power. There is a trade-off problem in swarm intelligence. In our experiment, we set the population size to be 16, which is not a large number, but is capable of providing satisfactory results. Figure 1 shows the search results of EBA.

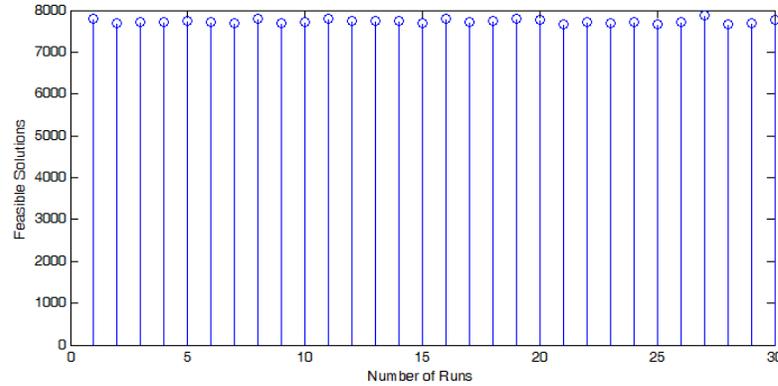


Figure 1: Number of feasible solutions found by EBA in 30 runs

As shown in Fig. 2, EBA produces a similar number of feasible solutions in 30 runs with different random seeds. Tab. 2 gives the statistical information of the EBA produced solutions.

Table 2: Statistical information of solutions produced by EBA

Maximum of feasible solutions	7,868
Mean of feasible solutions	7,735
Minimum of feasible solutions	7,673
Standard deviation (STD)	47

During the experiments, EBA produces 7,735 feasible solutions, on average, and at least 7,673 feasible solutions in each run. Assuming that every artificial agent successfully allocates a feasible solution in all iterations, the maximum number of feasible solutions that can be found in one run is 8,000. This implies that the success rate for utilizing the EBA to find feasible solutions is at least 95.51% and is 96.69%, on average. The solutions found by the EBA are said to be feasible if the eigen values from Eq. (8) are negative, because the negative eigen values result in the control system staying stable in the large.

6 Conclusions

In this study, a T-S fuzzy control system is utilized to decompose the nonlinear system via the PDC technique. The stability criteria derived from LMI conditions through the Lyapunov function approach reform the stability analysis problem into an inequality equation; and the problem is thus converted into finding a common symmetric positive definite matrix and the control force matrix. The stability criteria are then used to construct the fitness function for employing the EBA in order to find the feasible solutions which insure that the fuzzy control system is stable in the large. An inverted pendulum on a cart is taken as an example of the nonlinear system in our experiment. An even more strict condition is given in our design, which ensures uniformity of the system control force, making it equal. EBA is employed in the experiment. There are 500 iterations and 30 runs to provide the data for statistical analysis. The experimental results indicate that the EBA with our proposed fitness function presents a 96.69% success rate on average for finding the feasible solutions under the additional constraint criterion on the system control force.

References

1. Cao, S. G., Rees, N. W., Feng, G. (1996). Stability analysis and design for a class of continuous-time fuzzy control systems. *International Journal of Control*, 64(6), 1069-1087.
2. Tsai, P. W., Alsaedi, A., Hayat, T., Chen, C. W. (2016). A novel control algorithm for interaction between surface

- waves and a permeable floating structure. *China Ocean Engineering*, 30(2), 161-176.
3. Cao, Y. Y., Frank, P. M. (2000). Analysis and synthesis of nonlinear time-delay systems via fuzzy control approach. *IEEE Transactions on Fuzzy Systems*, 8(2), 200-211.
 4. Cao, Y. Y., Frank, P. M. (2001). Stability analysis and synthesis of nonlinear time-delay systems via linear Takagi-Sugeno fuzzy models. *Fuzzy Sets and Systems*, 124, 213-229.
 5. Chang, J. F., Hsiao, C. T., Tsai, P. W. (2013). Using interactive artificial bee colony to forecast exchange rate. *Proceedings of the 2nd International Conference on Robot, Vision and Signal Processing*, 133-136.
 6. Chang, J. F., Yang, T. W., Tsai, P. W. (2013). Applying interactive artificial bee colony to construct the stock portfolio. *Proceedings of the 2nd International Conference on Robot, Vision and Signal Processing*, 129-132.
 7. Chen, C. W., Chiang, W. L., Hsiao, F. H. (2004). Stability analysis of T-S fuzzy models for nonlinear multiple time-delay interconnected systems. *Mathematics and Computers in Simulation*, 66(6), 523-537.
 8. Chen, C. W. (2006). Stability conditions of fuzzy systems and its application to structural and mechanical systems. *Advances in Engineering Software*, 37, 624-629.
 9. Chen, C. W., Lin, C. L., Tsai, C. H., Chen, C. Y., Yeh, K. (2007). A novel delay-dependent criteria for time-delay T-S fuzzy systems using fuzzy Lyapunov Method. *International Journal on Artificial Intelligence Tools*, 16(3), 545-552.
 10. Chu, S. C., Tsai, P. W., Pan, J. S. (2006). Cat swarm optimization. *Proceedings of Trends in Artificial Intelligence, 9th Pacific Rim International Conference on Artificial Intelligence*, 854-858.
 11. Chu, S. C., Tsai, P. W. (2007). Computational intelligence based on behaviors of cats. *International Journal of Innovative Computing, Information & Control*, 3(1), 163-173.
 12. Cuesta, F., Gordillo, F., Aracil, J., Ollero, A. (1999). Stability analysis of nonlinear multivariable Takagi-Sugeno fuzzy control systems. *IEEE Trans. on Fuzzy Systems*, 7(5), 508-520.
 13. Eberhart, R., Kennedy, J. (1995). A new optimizer using particle swarm theory. *Proceedings of the 6th International Symposium on Micro Machine and Human Science*, 39-43.
 14. Feng, G., Cao, S. G., Rees, N. W., Chak, C. K. (1997). Design of fuzzy control systems with guaranteed stability. *Fuzzy Sets and Systems*, 85(1), 1-10.
 15. Hsiao, F. S., Chen, C. W., Liang, Y. W., Xu, S. D., Chiang, W. L. (2005). T-S fuzzy controllers for nonlinear interconnected systems with multiple time delays. *IEEE Transactions on Circuits and Systems I*, 52(9), 1883-1893.
 16. Karaboga, D. (2005). An idea based on honey bee swarm for numerical optimization. *Technical Report-TR06*, Erciyes University.
 17. Karaboga, D., Basturk, B. (2008). On the performance of artificial bee colony (ABC) algorithm. *Applied Soft Computing*, 8(1), 687-697.
 18. Khalil, H. K. (1992). Nonlinear systems. *Macmillan*, London, UK.
 19. Li, C., Wang, H., Liao, X. (2004). Delay-dependent robust stability of uncertain fuzzy systems with time-varying delays. *IEE Proceedings of Control Theory Applications*, 151(4), 417-421.
 20. Li, X., de Souza, C. E. (1997). Criteria for robust stability and stabilization of uncertain linear systems with state delay. *Automatica*, 33(9), 1657-1662.
 21. Liu, S. C., Lin S. F. (2012). LMI-based robust sliding control for mismatched uncertain nonlinear systems using fuzzy models. *International Journal of Robust and Nonlinear Control*, 22(16), 1827-1836.
 22. Liu, S. C., Lin S. F. (2012). LMI-based robust adaptive control for mismatched uncertain nonlinear time-delay systems using fuzzy models. *Proceedings of 2012 International symposium on Computer, Consumer and Control*, 552-555.
 23. Liu, S. C., Lin, S. F. (2013). Robust sliding control for mismatched uncertain fuzzy time-delay systems using linear matrix inequality approach. *Journal of the Chinese Institute of Engineers*, 36(5), 589-597.
 24. Liu, X., Zhang, H. (2008). Delay-dependent robust stability of uncertain fuzzy large-scale systems with time-varying delays. *Automatica*, 44(1), 193-198.
 25. Margaliot, M., Langholz, G. (2003). A new approach to fuzzy modeling and control of discrete-time systems. *IEEE Transactions on Fuzzy Systems*, 11(4), 486-494.
 26. Panda, G., Pardhan, P. M., Majhi, B. (2011). IIR system identification using cat swarm optimization. *Expert*

- Systems with Applications*, 38, 12671-12683.
27. Pardhan, P. M., Panda, G. (2012). Solving multiobjective problems using cat swarm optimization. *Expert Systems with Applications*, 39, 2956-2964.
 28. Saha, S. K., Ghoshal, S. P., Mandal, D. (2013). Cat Swarm Optimization algorithm for optimal linear phase FIR filter design. *ISA Transactions*, 52, 781-794.
 29. Takagi, T., Sugeno, M. (1985). Fuzzy identification of systems and its applications to modeling and control. *IEEE Transactions on Systems, Man, and Cybernetic*, 15(1), 116-132.
 30. Tsai, P. W., Chen, C. W. (2014). A novel criterion for nonlinear time-delay systems using LMI fuzzy Lyapunov method. *Applied Soft Computing*, 25, 461-472.
 31. Chen, C. W. (2014). A criterion of robustness intelligent nonlinear control for multiple time-delay systems based on fuzzy Lyapunov methods. *Nonlinear Dynamics*, 76, 23-31.
 32. Chen, C. W. (2014). Interconnected TS fuzzy technique for nonlinear time-delay structural systems. *Nonlinear Dynamics*, 76, 13-22.
 33. Teixeira, M. C. M., Zak, S. H. (1999). Stabilizing controller design for uncertain nonlinear systems using fuzzy models. *IEEE Trans. on Fuzzy Systems*, 7(2), 133-142.
 34. Temel, S., Unaldi, N., Kaynak, O. (2013). On deployment of wireless sensors on 3-D terrains to maximize sensing coverage by utilizing cat swarm optimization with wavelet transform. *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, 44(1), 111-120.
 35. Tian, E., Peng, C. (2006). Delay-dependent stability analysis and synthesis of uncertain T-S fuzzy systems with time-varying delay. *Fuzzy Sets and Systems*, 157, 544-449.
 36. Tsai, P. W., Khan, M. K., Pan, J. S., Liao, B. Y. (2014). Interactive artificial bee colony supported passive continuous authentication system. *IEEE Systems Journal*, 8(2), pp. 395-405.
 37. Tsai, P. W., Pan, J. S., Chen, S. M., Liao, B. Y. (2012). Enhanced parallel cat swarm optimization based on the Taguchi method. *Expert Systems with Applications*, 39(7), 6309-6319.
 38. Tsai, P. W., Pan, J. S., Liao, B. Y., Tsai, M. J., Vaci, I. (2012). Bat algorithm inspired algorithm for solving numerical optimization problems. *Applied Mechanics and Materials*, 148-149, 134-137.
 39. Wang, H., Tanaka, O. K., Griffin, M. F. (1996). An approach to fuzzy control of nonlinear systems: stability and design issues. *IEEE Transactions on Fuzzy Systems*, 4(1), 14-23.
 40. Wang, Z. H., Chang, C. C., Li, M. C. (2012). Optimizing least-significant-bit substitution using cat swarm optimization strategy. *Information Sciences*, 192, 98-108.
 41. Yeh, K., Chen, C. Y., Chen, C. W. (2008). Robustness design of time-delay fuzzy systems using fuzzy Lyapunov method. *Applied Mathematics and Computation*, 205, 568-577.
 42. Yi, Z., Heng, P. A. (2002). Stability of fuzzy control systems with bounded uncertain delays. *IEEE Transactions on Fuzzy Systems*, 10(1), 92-97.
 43. Zhang, Y., Pheng, A. H. (2002). Stability of fuzzy control systems with bounded uncertain delays. *IEEE Transactions on Fuzzy Systems*, 10(1), 92-97.
 44. Yan, B.; Zhang, S.; Zhang, X.; Wang, C.; Wu, C. (2017) Self-powered electromagnetic energy harvesting for the low power consumption electronics: design and experiment. *International Journal of Applied Electromagnetics and Mechanics*, 54, 1-11+33.