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Research Article

Optimization of the Parameters of RISE Feedback Controller Using Genetic Algorithm

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A control methodology based on a nonlinear control algorithm and optimization technique is presented in this paper. A controller called "the robust integral of the sign of the error" (in short, RISE) is applied to control chaotic systems. The optimum RISE controller parameters are obtained via genetic algorithm optimization techniques. RISE control methodology is implemented on two chaotic systems, namely, the Duffing-Holms and Van der Pol systems. Numerical simulations showed the good performance of the optimized RISE controller in tracking task and its ability to ensure robustness with respect to bounded external disturbances.

1. Introduction

Chaos is the complex, unpredictable, and irregular behavior of systems. The response of a chaotic system is sensitive to a change in its initial conditions. Chaos can be found in many applications such as oscillators, biology, chemical reactions, robotics, lasers, and many other applications. For example, Kengne et al. [1] considered the dynamics and synchronization of improved Colpitts oscillators designed to operate in ultrahigh frequency range. Also, two-well Duffing oscillator with nonlinear damping term proportional to the power of velocity was considered in [2]. Novel swarm dynamics and their applications in automated multiagent systems biology were presented [3]. Also, application of chaos theory to the molecular biology of aging was presented [4]. For chemical reactions, Petrov et al. [5] applied map-based, proportional-feedback algorithm to stabilize the behavior in the chaotic regime of an oscillatory chemical system. Gaspard [6] showed that, for different chemical reactions, the reaction rate can be related to the characteristic quantities of chaos. In the field of robotics, Volos et al. [7] experimentally investigated the coverage performance of a chaotic autonomous mobile robot. A smart scheme for chaotic signal generation in a semiconductor ring laser with optical feedback was proposed in [8].

Many studies have been conducted to analyze and control chaotic systems. Chaotic systems are utilized as a benchmark for testing the performance of controller. Different control techniques have been tried to control uncertain nonlinear systems. Shi et al. [9] designed adaptive delay feedback controllers to control and suppress chaos in ultrasonic motor speed control system. In [10], a nonlinear feedback linearization control method combined with a modified adaptive control strategy was designed to synchronize the two unidirectional coupled neurons and stabilize the chaotic trajectory of the slave system to desired periodic orbit of the master system. Sundarapandian [11] proposed explicit state feedback control laws to regulate the output of the Tigan system so as to track constant reference signals. Furthermore, a new state feedback control law to regulate the output of the Sprott-G chaotic system was derived [12]. Also, Yu et al. [13] proposed a fuzzy adaptive control approach based on a modular design for uncertain chaotic Duffing oscillators. In [14], sliding mode adaptive controllers were proposed for synchronization of uncertain chaotic systems. The active backstepping technique was used for synchronization between two Josephson junction systems evolving from different initial conditions [15].

Fuzzy logic has been largely employed in the last decade for control and identification of nonlinear systems. A fuzzy adaptive controller combined with state observer was used for nonlinear discrete-time systems with input constraint [16]. Adaptive fuzzy control was employed to control unknown nonlinear dynamical systems [17]. Fuzzy adaptive inverse compensation method was proposed for a tracking control problem of uncertain nonlinear systems with generalized actuator dead zone [18]. A control method based on a neural network adaptive leader-following consensus control for second-order nonlinear multiagent systems was proposed in [19]. Fuzzy neural network-based adaptive control for a class of uncertain nonlinear stochastic systems was proposed [20].

A controller for uncertain nonlinear systems called the "robust integral of the sign of the error" (RISE) was proposed in [21]. This method utilizes a continuous control signal to compensate for bounded external disturbances and uncertainties of dynamic system. This robust controller is suitable for nonlinear systems whose dynamics have continuous derivative [22]. The RISE control method differs from the first-order sliding mode control by the use of the integral of the signum of the error. This idea enables an asymptotic tracking and eliminates chattering that is a problem in conventional sliding mode controllers. The RISE controller has been applied to different types of systems, such as autonomous flight control [23], control of an autonomous underwater vehicle [24], control of special classes of multiple input multiple output nonlinear systems [25, 26], and uncertain nonlinear system with unknown state delays [27], and compensates for structured and unstructured uncertainties. An integration of multilayer feedforward neural network with RISE feedback was proposed in [28]. A control method based on RISE feedback and NN feedforward for nonlinear systems with uncertainty was proposed in [29].

Many optimization techniques were introduced to optimize the controller parameters of continuous time nonlinear systems. For example, adaptive parameter control was presented for nonlinear parameter systems in many research studies [30–35]. Furthermore, nonlinear systems with completely unknown dynamic were optimized by using intelligent control-based adaptive design such as the fuzzy control system [17, 36–39] and the neural network control systems [19, 40–45]. On the other hand, the adaptive control of discrete-time nonlinear systems was also built in many other studies by utilizing the fuzzy logic systems [16, 46–48] and the neural networks [49–52]. Liu et al. [48] have presented an adaptive fuzzy controller for nonlinear discrete-time systems with unknown functions and bounded disturbances. Liu and Tong [38] have extended the previous work for a class of multi-input-multioutput (MIMO) problem. Moreover, an adaptive fuzzy controller design for a specific division of nonlinear MIMO systems in an interconnected form was explored by Liu and Tong [17]. Furthermore, Li et al. [53] presented a study for the menace of fuzzy control for nonlinear networked control systems with packet dropouts and uncertainties in parameters based on the interval type 2 fuzzy model based approach. Finally, model identification and adaptive control design are performed on Denavit-Hartenberg model of a humanoid robot. The study focused on the modeling of the 6-degree-of-freedom upper limb of the robot using recursive Newton-Euler formula for the coordinate frame of each joint. It also utilized the particle swarm optimization method to optimize the trajectory of each joint [54].

The aim of this study is to test the performance of the RISE controller in controlling chaotic systems. The RISE controller requires only the error (the difference between the reference set point and the output of the system). To obtain the first needed derivative of the error, a real time differentiator is used. Genetic algorithm (GA) is utilized to obtain the optimum controller parameters. The fitness function used is a combination of the integral of the absolute error and the integral of absolute of the control signal. The remaining structure of this paper is as follows. In the next section, the basics of RISE controller are explained. In Section 3, the characteristics of the GA are given. In Section 4, the simulation results from the application of the controller are presented and discussed. Finally, Section 5 concludes this paper.

2. RISE Controller

Uncertain nonlinear systems can be described as [55]

$$\begin{aligned} \dot{x}_i(t) &= x_{i+1}(t), \quad i = 1, \dots, n-1, \\ \dot{x}_n(t) &= f(X,t) + \Delta f(X,t) + u(t) + \delta(t), \end{aligned} \tag{1}$$

where $X(t) = [x_1(t), x_2(t), \dots, x_n(t)] = [x(t), \dot{x}(t), \dots, x^{(n-1)}(t)] \in R^n$ is the state vector, $f(X,t) \in R$ is a given nonlinear function and $t, u(t) \in R$ is the control input, $\Delta f(X,t)$ being the unmodeled dynamics of the system, and $\delta(t)$ is the varying external disturbance with time. The superscript n denotes the order of differentiation. $u(t)$ is a control signal.

In general, the parameter uncertainty $\Delta f(X,t)$ and the external disturbance $\delta(t)$ are assumed to be bounded.

The objective of the control problem is to ensure that in spite of the external disturbances and modeling uncertainties the state x_1 will follow a desired reference signal in the state space. The output tracking error is given by

$$e_1 = x_1 - x_r, \tag{2}$$

where $x_r(t) \in \mathbb{R}$ represent the reference trajectory which is assumed to be bounded continuous time derivatives. The main control objective is to ensure that the output tracking error converges asymptotically to zero; that is, $|e_1| \to 0$ as $t \to 0$ by designing a continuous robust control law.

To facilitate the control design, auxiliary error signals, denoted as $e_i \in \mathbb{R}$, $i = 1, \dots, n$, are defined in the following manner [21]:

$$\begin{aligned} e_2 &\triangleq \dot{e}_1 + e_1, \\ e_n &\triangleq \dot{e}_{n-1} + e_{n-1} + e_{n-2}. \end{aligned} \tag{3}$$

For a second-order system, the auxiliary error signal is given by [21]

$$e_2 = \dot{e}_1 + ce_1. \tag{4}$$

The RISE controller to control system (1) for $n = 2$ is as follows [23]:

$$u(t) = (k_s + 1)\, e_2(t) - (k_s + 1)\, e_2(0) + \int_0^t \left[(k_s + 1)\,\alpha e_2(\tau) + \beta \operatorname{sign}(e_2(\tau))\right] d\tau, \tag{5}$$

where β, α, k_s, and e_1 are the controller parameters, all the parameters are constant and positive, and sign$(\cdot)$ is the known sign function, which can be defined as

$$\operatorname{sign}(\sigma) = \begin{cases} +1 & \sigma > 0 \\ -1 & \sigma < 0. \end{cases} \tag{6}$$

The first derivative of the error $\dot{e}_1$ can be calculated in real time by a differentiator. A recommended real time differentiator for industrial application can be defined by its transfer function as follows:

$$\frac{\dot{f}(s)}{f(s)} = \frac{s}{\tau s + 1}, \tag{7}$$

where τ is a time constant and $f(s)$, $\dot{f}(s)$ are the signal and its derivative, respectively. To attenuate high-frequency noises, the differentiator has a low pass filter (LPF) $(1/(1 + \tau s))$. An accurate estimation can be obtained by choosing a small τ in the noise-free case.

The saturation block imposes upper and lower limits on the control signal. Output the signal, but only up to some limited magnitude, and then cap the output to a value of T. The saturation function is an odd function. The saturation function is given by

$$f(e) = \begin{cases} T & \text{if } e > T \\ e & \text{if } -T \le e \le T \\ -T & \text{if } e < -T. \end{cases} \tag{8}$$

Figure 1 shows a flow chart detailing the implementation of the above described procedures of the closed loop control system.

Note that, from the above equations, to design a controller, all of its parameters including k_s, β, α, $e(0)$, and the parameter c need to be determined. To obtain the optimum controller parameters a minimization problem can be defined as follows:

$$\text{min:} \quad J(k_s, \beta, \alpha, e(0), c) = \mu J_1 + J_2, \tag{9}$$

where J_1 and J_2 are given as

$$J_1 = \int_0^T |e(t)|\, dt, \tag{10}$$

$$J_2 = \int_0^T |u(t)|\, dt. \tag{11}$$

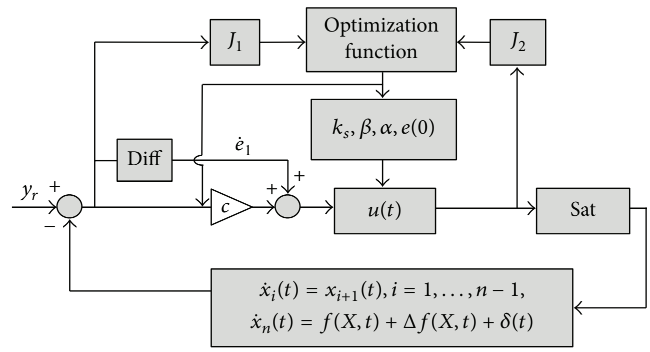

Figure 1: Schematic diagram of the closed loop control system.

To find the optimal parameters of the controller, GA is used in this research. The next section describes briefly the basics of GA.

3. Genetic Algorithms

The GA [56] is a search method based on natural genetics and fittest theory of selection. Individuals in some environment have a higher probability of reproducing if their fitness is high. The basic element of GA that possesses the genetic information is the chromosome. For a given solution, chromosome can be coded using binary or real string. The three basic operations of GA are selection, combination, and mutation. The application of the three basics operators results in new offspring better than their parents. These steps are repeated for a predefined generation. The algorithm stops when the optimum offspring that represent the solution to the problem are obtained. As shown in Figure 2, GA applies by using the following steps:

(i) *Initialization*: it is a random generation of initial population of candidate chromosomes for the search domain.

(ii) *Evaluation*: obtain the fitness value of each chromosome in the population.

(iii) *Selection*: select two parent chromosomes from a population based on obtained fitness value.

(iv) *Recombination*: apply the crossover operator to the selected parents to form new offspring with a crossover probability.

(v) *Mutation*: obtain new offspring with preselected mutation probability.

(vi) *Replacement*: use the new offspring to generate new population for the next run of the algorithm.

(vii) If the stopping criterion is satisfied, stop and return the best solution in the current population.

The evaluation step (step (ii) above) consists of calculating the fitness value of each individual. The fitness function is selected based on the problem. Based on the fitness value, the best and the worst individuals in the population are determined. The best individuals in each generation are the

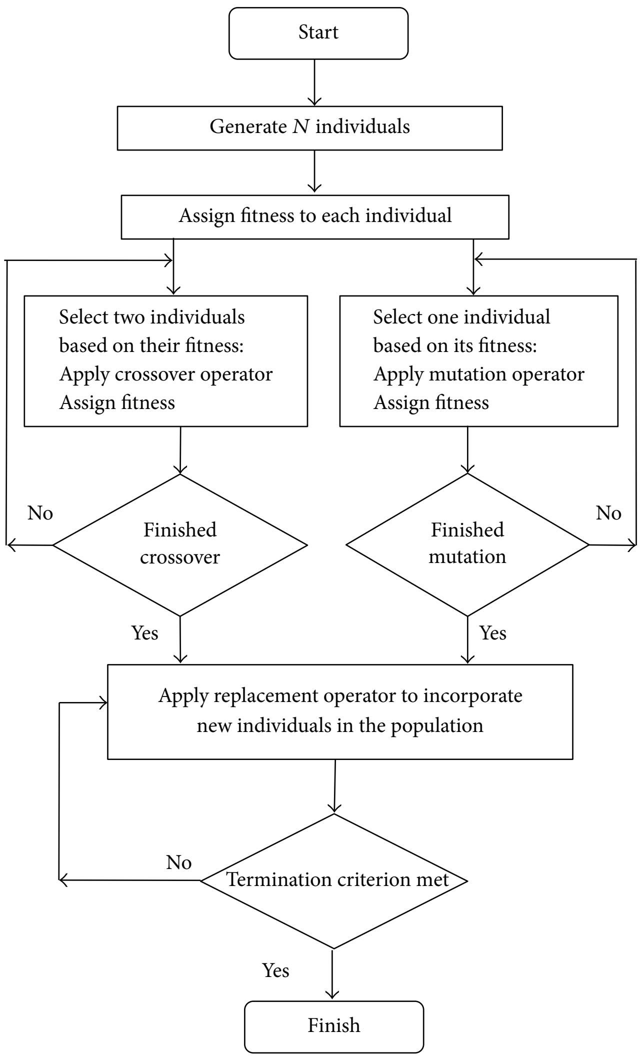

Figure 2: Genetic algorithm flow chart.

optimal parameters of the optimization process. A generation is a complete run which consists of the generation population, applying the genetic operators, and evaluation of finally the population members (solutions), and lastly when the stopping criterion is satisfied the iterative run is finished.

4. Simulations Results and Discussions

In this section, simulation results are given to show the effectiveness of the proposed control methodology using two application examples.

4.1. Simulation Example for Duffing-Holmes Forced Oscillation System. Duffing equation describes the dynamics of nonlinear mechanical oscillator. This system has a cubic stiffness term to describe the hardening spring effect observed in many mechanical oscillators. In this paper, we consider a modified Duffing equation named Duffing-Holmes described as [57]

$$m\ddot{x} + p_0\dot{x} + p_1 x + p_2 x^3 - q\cos(\omega t) = 0, \tag{12}$$

where x is the oscillation displacement, p_0 is the damping constant, p_1 is the linear stiffness constant, p_2 is the cubic stiffness constant, q is the excitation amplitude, and ω is excitation frequency. By defining the states of (11), $x_1 = x$, and $x_2 = \dot{x}$. In addition to adding a plant uncertainty representing the unmodeled dynamics or structural variation of the system $\Delta f(x_1, x_2, t)$ and external disturbance $\delta(t)$ the time-varying disturbance equation (11) can be rewritten as two first-order ordinary differential equations:

$$\begin{aligned}\dot{x}_1(t) &= x_2(t),\\ \dot{x}_2(t) &= x_1(t) - 0.25x_2(t) - x_1^3(t)\\ &\quad + 0.3\cos(t) + \Delta f(x_1, x_2, t) + \delta(t) + u(t),\\ y(t) &= x_1(t).\end{aligned} \tag{13}$$

Abounded uncertainty $\Delta f(x_1, x_2, t)$, for simulation purposes, is modeled as

$$\Delta f(x_1, x_2, t) = 0.1\sin(t)\sqrt{x_1^2 + x_2^2} \tag{14}$$

and a bounded external disturbance $\delta(t)$ is given by

$$\delta(t) = 0.1\sin(t). \tag{15}$$

To show the behavior of uncontrolled chaotic system we simulate Duffing-Holmes system (DHS) with the following values of parameters: $p_0 = 1$, $p_1 = 0.25$, $p_2 = 1$, $q = 0.3$, and $\omega = 1$ rad/sec. Figure 3 shows the response of DHS for the initial conditions $x_{10} = 0.3$ and $x_{20} = 0.1$.

To demonstrate the performance of the RISE controller, we present the results of the numerical simulations obtained using MATLAB/Simulink. The RISE controller is used in tracking problem. The tracking problem can be stated as follows: for any bounded reference trajectory x_r with its bounded and continuous derivatives $\dot{x}_r$ and $\ddot{x}_r$ in the interval $[0, \infty]$. Design a controller $u(t, \dot{x}, x)$ that forces the output $x_1(t)$ to track x_r in finite time for any initial states $(x(t_0), \dot{x}(t_0)) \in \mathbb{R}$.

The DHS is controlled to follow the trajectory given by

$$x_r = 2\cos(t) + \sin(t). \tag{16}$$

The reference trajectory (13) is not one of the embedded orbits of the strange attractors. The parameters of the DHS are chosen as $p_0 = 0.25$, $p_1 = 1$, $p_2 = 1$, $q = 0.3$, and $\omega = 1$ rad/sec and the initial conditions $x_{10} = 2$ and $x_{20} = 3$. The sampling time used in the simulation is equal to 0.001 sec. To obtain the optimized controller parameters, it is important to select the appropriate parameters of GA. They affect the results of the GA minimization. The most important parameters are the population size, mutation constant, and crossover constant, as well as the number of generations. After experimentation with different population size, a population size of 25 individuals and a crossover rate of 0.70 were used. A higher mutation constant is necessary to expand the search space. A mutation constant of 0.05% was used. The optimized RISE controller parameters $c = 1.56$,

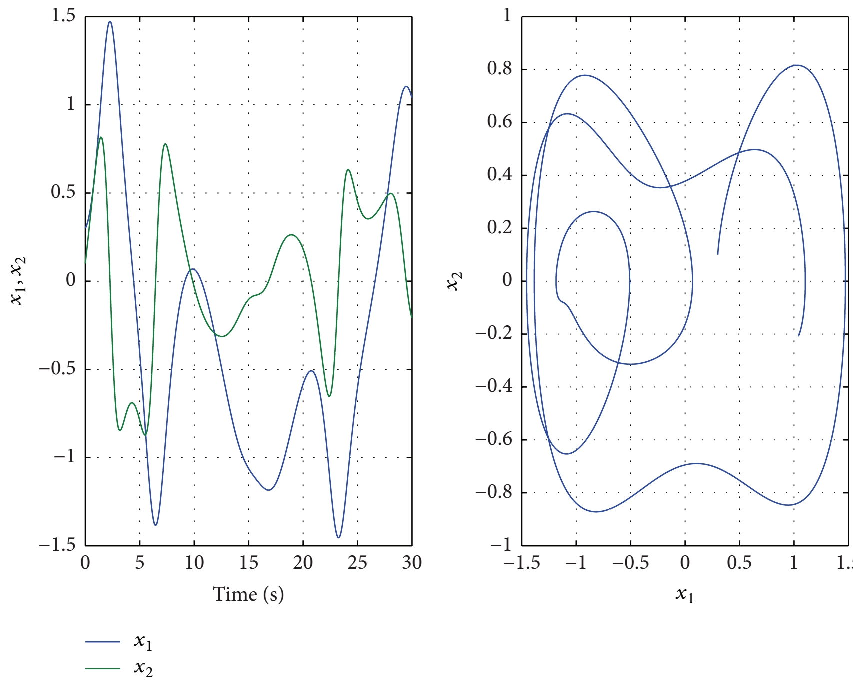

FIGURE 3: Chaotic behavior of the uncontrolled DHS for 30 seconds.

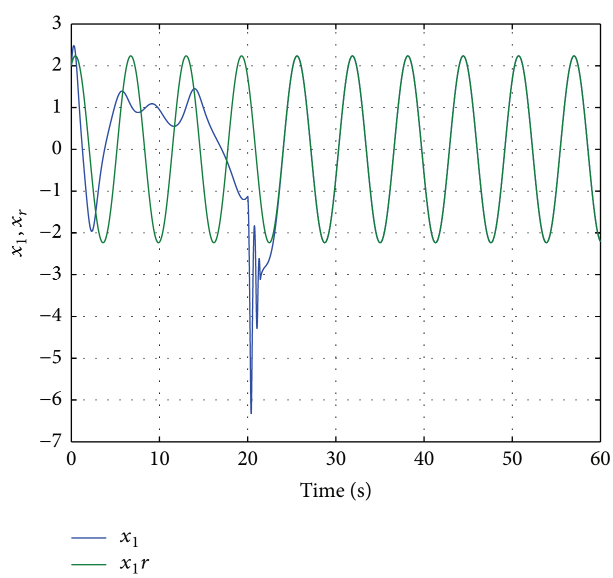

FIGURE 4: Controlled time response of x_1.

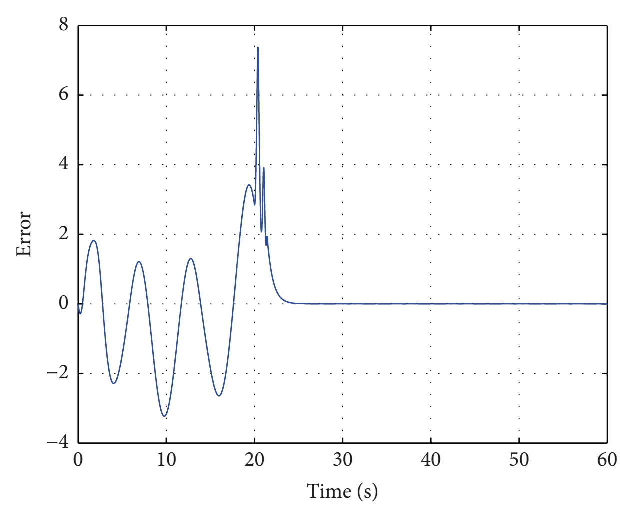

FIGURE 5: The error as function of time.

$k_s = 62.26$, $\alpha = 30.48$, $e(0) = 1.25$, $\beta = 3.64$, $J_1 = 36.80$, and $J_2 = 256.70$ are obtained. Figure 4 shows the time responses of the state variables of the DHS.

Figure 5 represents the time history of the tracking error, where the finite time convergence to zero is clearly presented. Note that the error reached zero in a very short time. Figure 6 shows the control effort required to follow the reference trajectory x_r. A good view of tracking the DHS, the reference trajectory, is shown in phase plane plot depicted in Figure 7, where the beginning and ending points appeared clearly in the figure.

4.2. Simulation Example for Van der Pol System. The RISE controller is used to control the following Van der Pol system [57]:

$$\dot{x}_1 = x_2,$$
$$\dot{x}_2 = -2x_1 + 3\left(1 - x_1^2\right)x_2 + u(t) + \delta(t), \tag{17}$$

where the external disturbance is given by

$$\delta(t) = 2\sin(0.1\pi t) + 3\sin\left(0.2\sqrt{(t+1)}\right) \tag{18}$$

and the desired trajectory is taken as

$$x_r = 2\sin(0.2t). \tag{19}$$

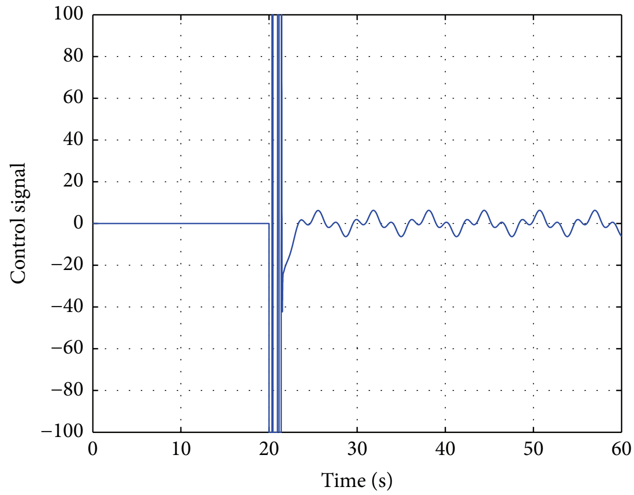

Figure 6: The time response of the control signal $u(t)$.

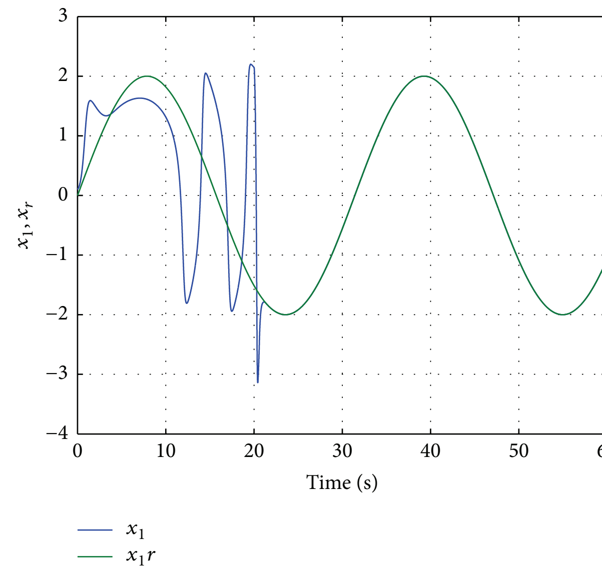

Figure 8: Controlled time response of x_1.

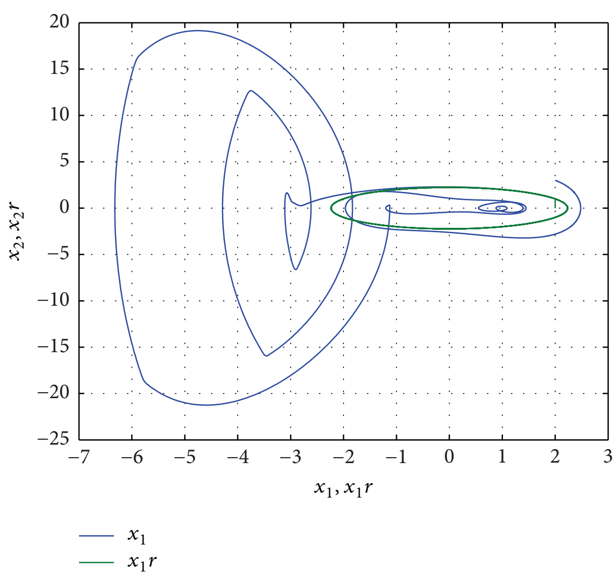

Figure 7: The phase plane plot of controlled DHS.

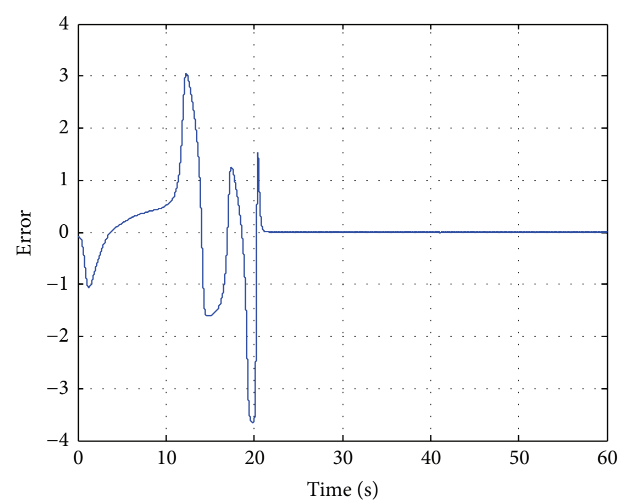

Figure 9: The error as function of time.

The simulation and genetic algorithm parameters are the same as in the previous example.

The optimized controller parameters are $c = 16.10$, $k_s = 65.40$, $\alpha = 5.40$, $e(0) = 96.32$, $\beta = 45.11$, $J_1 = 19.69$, and $J_2 = 226.70$. Figure 8 shows the good performance of the proposed control methodology for the Van der Pol system. Figure 9 shows the time history of the tracking error, where the fast convergence to zero can be observed. Figure 10 shows the control signal with saturation values is given by $u_{\max} = 100$ and $u_{\min} = -100$. Figure 11 shows the phase plane plot of controlled Van der Pol system.

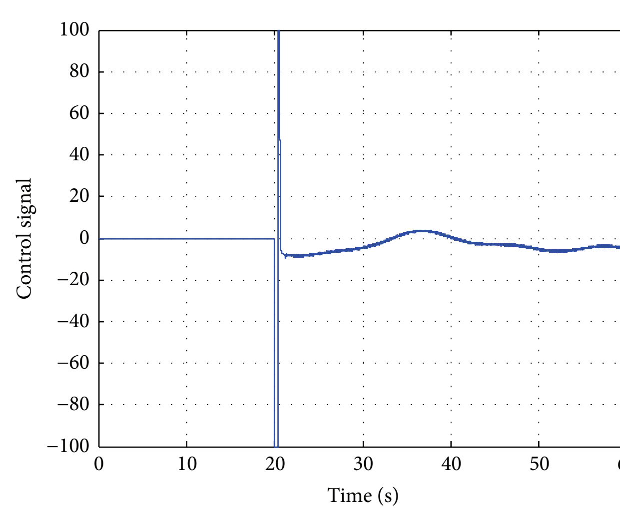

Figure 10: The time response of the control signal $u(t)$.

5. Conclusions

In this paper, the RISE controller was applied to chaotic systems. The performance of the controller was verified on two chaotic systems. The parameters of the controller were found

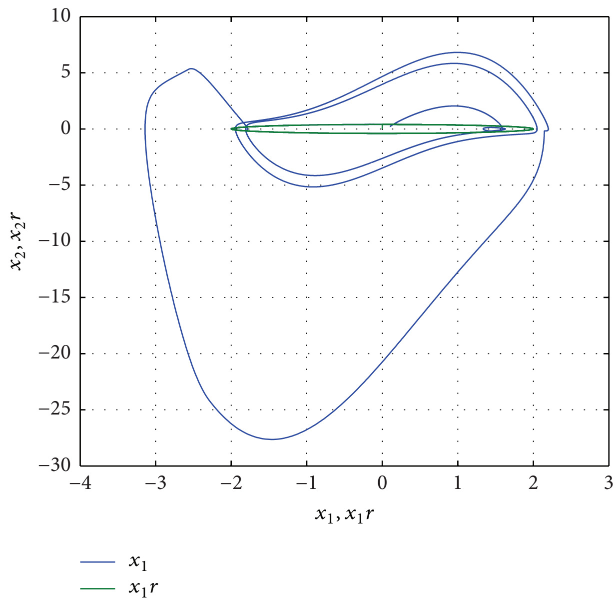

FIGURE 11: The time response of the control signal $u(t)$.

by incorporating the genetic algorithm in the closed loop control. An appropriate error function was selected to solve the tracking problem. The results of the application examples verified the performance of the controller in providing the convergence of the tracking error in a very short time. From the simulation results, it is concluded that the suggested scheme can effectively solve the control problem of chaotic systems with disturbances and uncertainties. It has been observed that a proper selection of the control parameters influences the control effort and the tracking error. As a future study, the RISE controller will be used for synchronization of chaos.

Competing Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

Acknowledgments

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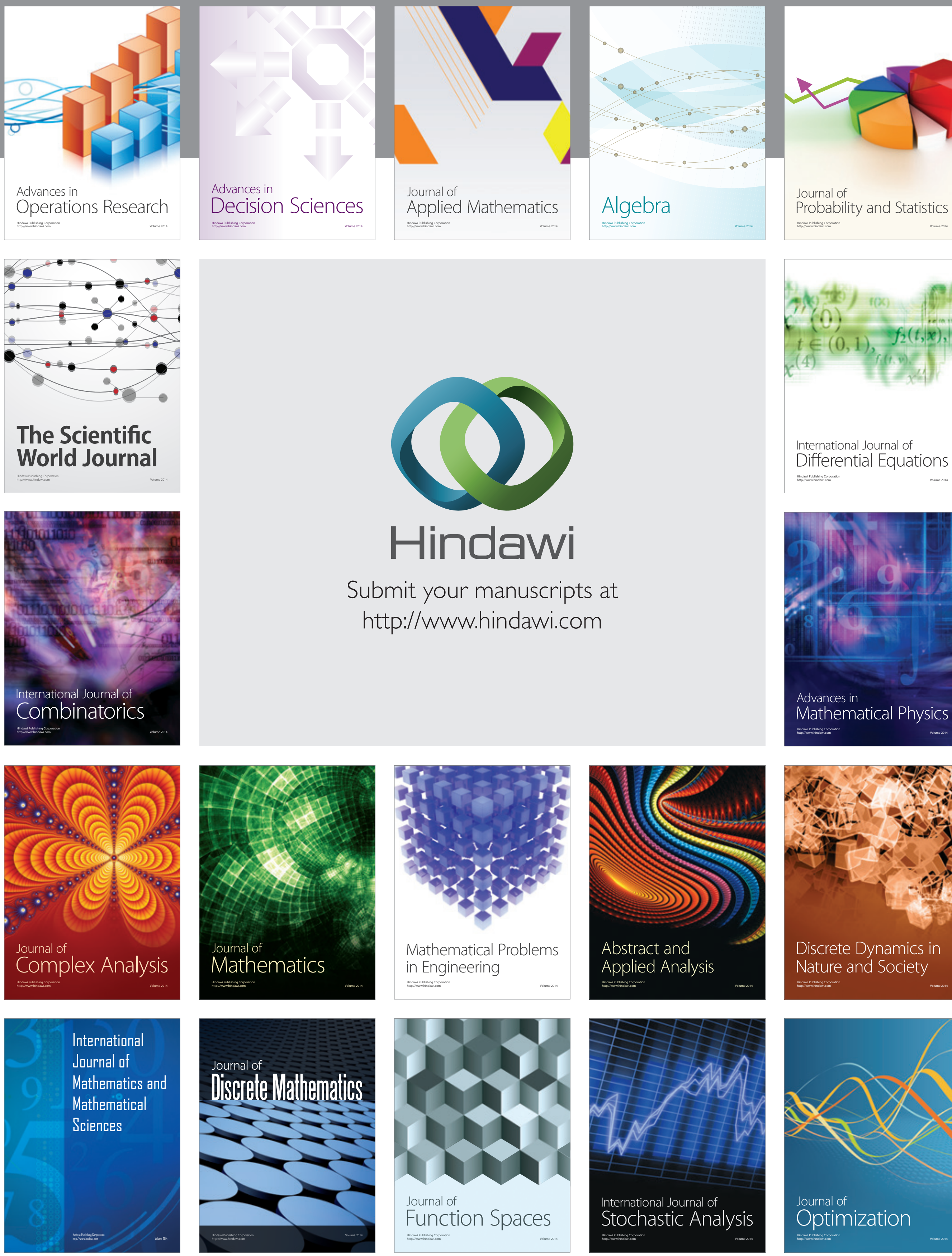
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