Fuzzy Controller Design by Means of Genetic Optimization and NFN-Based Estimation Technique

Sung-Kwun Oh, Seok-Beom Rho, and Hyun-Ki Kim

Abstract: In this study, we introduce a noble neurogenetic approach to the design of the fuzzy controller. The design procedure dwells on the use of Computational Intelligence (CI), namely genetic algorithms and neurofuzzy networks (NFN). The crux of the design methodology is based on the selection and determination of optimal values of the scaling factors of the fuzzy controllers, which are essential to the entire optimization process. First, tuning of the scaling factors of the fuzzy controller is carried out, and then the development of a nonlinear mapping for the scaling factors is realized by using GA based NFN. The developed approach is applied to an inverted pendulum nonlinear system where we show the results of comprehensive numerical studies and carry out a detailed comparative analysis.

Keywords: Computational Intelligence (CI), estimation algorithm, fuzzy controller, genetic algorithms, neurofuzzy networks (NFN), optimization process, scaling factors.

1. INTRODUCTON

The ongoing challenges we face when designing advanced control systems has resulted in a diversity of underlying methodologies, development platforms and detailed algorithms. In parallel to PID controllers that are regarded nowadays as the standard control constructs of numeric control [1-4], fuzzy controllers have positioned themselves in a similar dominant role at the knowledge-rich end of the entire spectrum of control algorithms. The design goals of PID control and fuzzy control are similar yet the same problem is approached from two different angles. At the final stage of the design phase, one realizes that two different threads are being served. PID controllers are superb when it comes to linear systems or nonlinear systems with an operation mode confined to a small neighborhood around a given set point. The advantages of the fuzzy controllers are situated at opposite ends of the scale as we envision their full strength in the setting of nonlinear systems (as these controllers are nonlinear mappings in the first place) and when dealing with high deviations from the set point. These advantages of fuzzy controllers stem directly from the nonlinear type of characteristics of the linguistic rules and the associated membership functions used in the description of linguistic terms.

The intent of this study is to develop, optimize and experiment with the fuzzy controllers (fuzzy PD controller or fuzzy PID controller) when developing a general design scheme of Computational Intelligence. One of the difficulties in the construction of the fuzzy controller is to derive a set of optimal control parameters of the controller such as linguistic control rules, scaling factors, and membership functions of the fuzzy controller. In the application of the conventional design method, a control expert proposes some linguistic rules and decides upon the type and parameters of the associated membership functions. With an attempt to enhance the quality of the control knowledge conveyed by the expert (and this usually applies to the matter of calibration of such initial domain knowledge), genetic algorithms (GAs) have already started playing a pivotal role. More specifically, considering a vast number of parameters of the fuzzy controller, they are instrumental in carrying out a global search in the overall parameter space. One should stress however that evolutionary computing (such as GAs) is computationally intensive and this may be a point of concern when dealing with the amount of time available for such search. For instance, when controlling a nonlinear plant such as an inverted pendulum of which initial states vary in each case, the search time required by GAs could be prohibitively high when dealing with dynamic systems. As a consequence, the parameters of the fuzzy controller cannot be easily adapted to the

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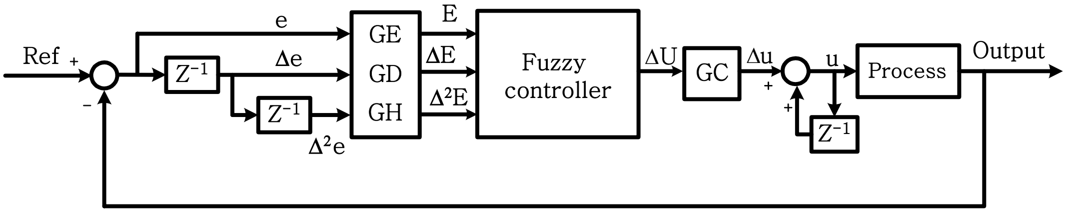


Fig. 1. An overall architecture of the fuzzy PID controller.

changing initial states of this system such as an angular position and an angular velocity of the pendulum. To alleviate this shortcoming, we introduce a nonlinear mapping from the initial states of the system and the corresponding optimal values of the parameters. With anticipation of the nonlinearity residing within such transformation, in its realization we consider GA-based NFN. Bearing this in mind, the development process consists of two main phases. First, using genetic optimization we determine optimal parameters of the fuzzy controller for various initial states (conditions) of the dynamic system. Second, we build up a nonlinear model that captures a relationship between the initial states of the system and the corresponding genetically optimized control parameters. The paper includes the experimental study dealing with the inverted pendulum having the initial states changed. We carry out experimentation with several categories of the controllers such as PID controller, fuzzy PD controller, and fuzzy PID controller. The performance of systems under control is evaluated and compared from the viewpoint of ITAE (Integral of the Time multiplied by the Absolute value of Error), overshoot and rising time [1].

2. THE FUZZY CONTROLLER

The block diagram of a fuzzy PID controller is shown in Fig. 1. We confine ourselves to the following notation: e denotes the error between reference and response (output of the system under control), Δe is the first-order difference of error signal while Δ^2e is the second-order difference of the error. Note that the input variables to the fuzzy controller are transformed by the scaling factors (GE, GD, GH, and GC) whose role is to allow the fuzzy controller to properly “perceive” the external world to be controlled.

The above fuzzy PID controller consists of rules of the following form, cf. [5,6] R_j: if E is A_{1j} and ΔE is A_{2j} and Δ^2E is A_{3j} then ΔU_j is D_j The capital letters existing in the rule (R_j) denote fuzzy variables (linguistic terms) whereas D is a numeric value (singleton) of the control action. In each control rule, a level of its activation is computed in a standard fashion given by (1). Subsequently, the inferred value of consequence part is converted into numeric values with the aid of (2a) [7].

$$\omega_i = \min\{\mu_{A_i}(E), \mu_{B_i}(\Delta E), \mu_{C_i}(\Delta^2 E)\}, \qquad (1)$$

$$\Delta U^* = \frac{\sum_{i=1}^{n}\omega_i D_i}{\sum_{i=1}^{n}\omega_i}, \qquad (2a)$$

$$\Delta u(k) = \Delta U^*(k) \cdot GC. \qquad (2b)$$

An overall operation of a fuzzy PID controller can be described in the format so that the resulting control is formed incrementally based on the previous control

$$u(k) = u(k-1) + \Delta u(k). \qquad (3)$$

Here the input variables are denoted by *E* and *ΔE* while their membership functions are as follows.
NB: Negative Big, NM: Negative Medium, NS: Negative Small, ZO: Zero, PS: Positive Small, PM: Positive Medium, and PB: Positive Big. When dealing with the three input variables of the fuzzy controller, namely E, ΔE, and Δ^2E, the membership functions are denoted as follows N: Negative, Z: Zero, and P: Positive.

The membership functions of the output variable of the controller, that is, the changes of control are NB(-m3), NM(-m2), NS(-m1), ZO(0), PS(m1), PM(m2) and PB(m3). The initial parameters of these membership functions are equal to m1, m2, and m3, respectively. The collection of the rules is shown in Table 1.

We use triangular membership functions defined in the input and output spaces; see Figs. 2 and 3. Here these spaces are normalized to the [-1, 1] interval.

3. AUTO-TUNING OF THE FUZZY CONTROLLER BY GAs

Genetic algorithms (GAs) are the search algorithms inspired by nature in the sense that we exploit a fundamental concept of a survival of the fittest as being encountered in selection mechanisms among species. In GAs, the search variables are encoded in bit strings called chromosomes. They deal with a

Table 1. Fuzzy control rules.

(a) 2 input variables.

		ΔE						
		NB	NM	NS	ZO	PS	PM	PB
E	NB	$-m_3$	$-m_3$	$-m_3$	$-m_3$	$-m_2$	$-m_1$	0
	NM	$-m_3$	$-m_3$	$-m_3$	$-m_2$	$-m_1$	0	m_1
	NS	$-m_3$	$-m_3$	$-m_2$	$-m_1$	0	m_1	m_2
	ZO	$-m_3$	$-m_2$	$-m_1$	0	m_1	m_2	m_3
	PS	$-m_2$	$-m_1$	0	M_1	m_2	m_3	m_3
	PM	$-m_1$	0	m_1	M_2	m_3	m_3	m_3
	PB	0	m_1	m_2	M_3	m_3	m_3	m_3

(b) 3 input variables.

Δ^2E=N

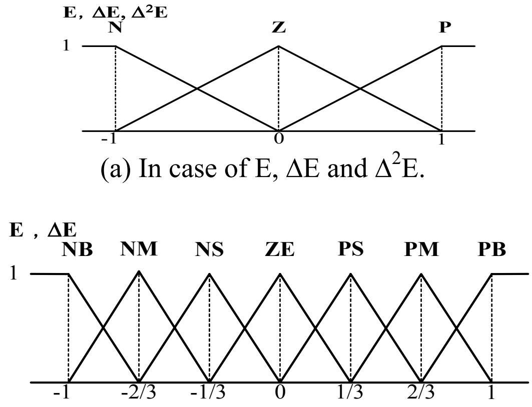
		ΔE		
		N	Z	P
E	N	$-m_3$	$-m_3$	$-m_2$
	Z	$-m_2$	$-m_1$	0
	P	0	m_1	m^3

Δ^2E = Z

		ΔE		
		N	Z	P
E	N	$-m_3$	$-m_3$	$-m_2$
	Z	$-m_2$	$-m_1$	0
	P	0	m_1	m_3

Δ^2E =P

		ΔE		
		N	Z	P
E	N	$-m_3$	$-m_3$	$-m_2$
	Z	$-m_2$	$-m_1$	0
	P	0	m_1	m^3



(a) In case of E, ΔE and Δ^2E.

(b) In case of E and ΔE.

Fig. 2. Membership functions of the premise input variables.

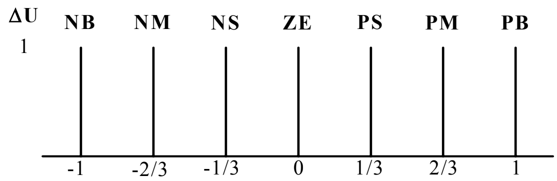


Fig. 3. Membership functions (singletons) defined in the consequence variable, ΔU.

population of chromosomes with each representing a possible solution for a given problem. Each chromosome has a fitness value that indicates how good a solution represented by it is. In control applications, the chromosome represents the controller's adjustable parameters and the fitness value is a quantitative measure of the performance of the controller.

In general, the population size, number of bits used for binary coding, crossover rate, and mutation rate are essential parameters whose values are specified in advance. The genetic search is guided by reproduction, mutation, and crossover. Each of these phases comes with a set of specific numeric parameters characterizing the phase. In this study, the number of generations is set at 100, crossover rate is equal to 0.6, while the mutation rate is taken as 0.1. The number of bits used in the coding is equal to 10.

Fig. 4 portrays an overall auto-tuning scheme. Let us recall that this involves tuning of the scaling factors and a construction of the control rules. These are genetically optimized. We set the initial individuals of GAs using three types of parameter estimation modes such as a basic mode, contraction mode and expansion mode. In the case of the basic mode (BM), we use scaling parameters that normalize error between reference and output, one level error difference and two level error difference by [-1, 1] for the initial individuals in the GA. In the contraction mode (CM), we use scaling parameters reduced by 25% in relation to the basic mode. In the expansion mode (EM), we use scaling parameters enlarged by 25% from a basic mode. The standard ITAE expressed for the reference and the output of the system under control is treated as a fitness function [2].

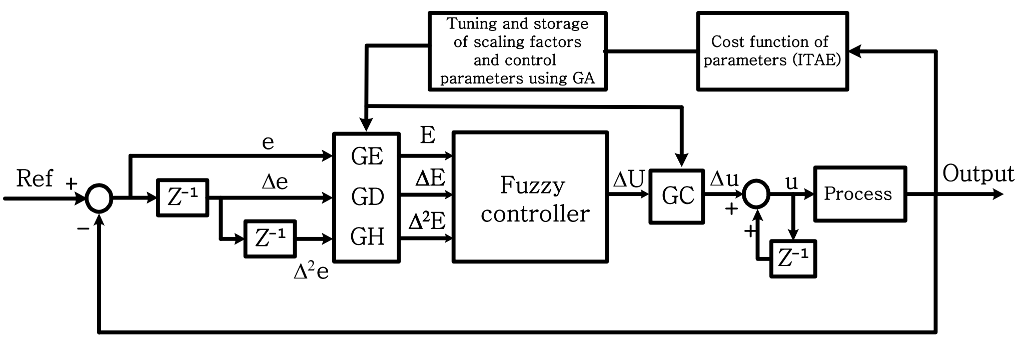


Fig. 4. The scheme of auto-tuning of the fuzzy PID controller involving estimation of the scaling factors.

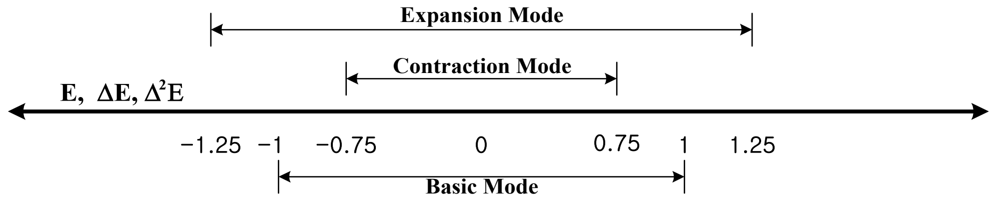


Fig. 5. Three types of estimation modes for the scaling factors: basic, expansion, and contraction.

The overall design procedure of the fuzzy PID controller realized by means of GAs is illustrated in Fig. 4. It consists of the following steps.

[Step 1] Select the general structure of the fuzzy controller according to the purpose of control and dynamics of the process. In particular, we consider architectural options. (PID, FPD (Fuzzy PD), and FPID (Fuzzy PID) controller)

[Step 2] Define the number of fuzzy sets for each variable and set up initial control rules. Refer to Figs. 2 and 3.

[Step 3] Form a collection of initial individuals of GAs. We set the initial individuals of GAs for the scaling factors of the fuzzy controller. The scaling factors can be described as normalized coefficients. Each scaling factor is expressed by (4).

Fig. 5 illustrates three types of estimation modes of the scaling factors being used in setting the initial individuals of GAs describing the fuzzy controller.

$$E(kT) = e \times GE, \tag{4a}$$

$$\Delta E(kT) = [e(kT) - e((k-1)T)] \times GD, \tag{4b}$$

$$\Delta^2 E(kT) = [e(kT) - 2e((k-1)T) + e((k-2)T)] \times GH, \tag{4c}$$

$$U(kT) = U((k-1)T) + \Delta U(kT) \times GC. \tag{4d}$$

[Step 4] Here, all the control parameters such as the scaling factors GE, GD, GH and GC are tuned simultaneously.

4. THE ESTIMATION ALGORITHM BY MEANS OF GA-BASED NEUROFUZZY NETWORKS (NFN)

Let us consider an extension of the network with the fuzzy partition realized by fuzzy relations. Fig. 6 visualizes the architecture of two-input and one-output NFNs, where each input assumes three membership functions. The circles denote processing units of the NFN. The node indicated $\prod$ denotes a Cartesian product, whose output is the product of all the incoming signals. N denotes the normalization of the membership grades.

In the language of the rule-based systems, the structure is equivalent to the following collection of rules

$$R^1 : If \ x_1 \ is \ A_{11} \ and \ \cdots \ x_k \ is \ A_{1k} \ then \ y_1 = w_1$$
$$\vdots \quad \vdots$$
$$R^j : If \ x_1 \ is \ A_{j1} \ and \ \cdots \ x_k \ is \ A_{jk} \ then \ y_j = w_j$$
$$\vdots \quad \vdots$$
$$R^n : If \ x_1 \ is \ A_{n1} \ and \ \cdots \ x_k \ is \ A_{nk} \ then \ y_n = w_n. \tag{5}$$

The fuzzy rules in equation (5) constitute the overall networks of modified NFNs such as are shown in Fig. 6. The output f_i of each node generates a final output $\hat{y}$ of the form

$$\hat{y} = \sum_{i=1}^{n} f_i = \sum_{i=1}^{n} \bar{\mu}_i \cdot w_i = \sum_{i=1}^{n} \frac{\mu_i \cdot w_i}{\sum_{i=1}^{n} \mu_i}. \tag{6}$$

The learning of the NFN is realized by adjusting connections of the neurons and as such it follows a standard Back-Propagation (BP) algorithm. In this study, we use the Euclidean error distances

$$E_p = (y_p - \hat{y}_p)^2, \tag{7}$$

$$E = \sum_{p=1}^{N} (y_p - \hat{y}_p)^2, \tag{8}$$

where E_p is an error measure for the *p-th* data, y_p is the *p-th* target output data, $\hat{y}_p$ stands for the *p-th* actual output of the model for this specific data point, N is total input-output data pairs, and E is a sum of the errors. As far as learning is concerned, the

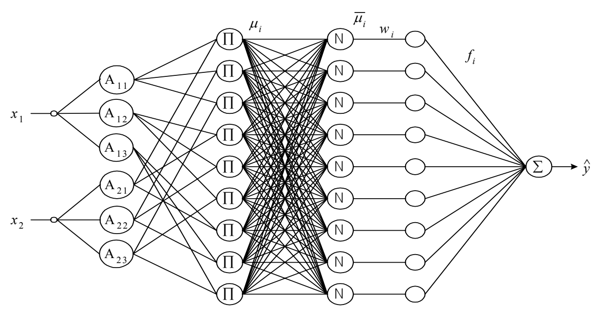


Fig. 6. NFN structure by means of the fuzzy space partition realized by fuzzy relations.

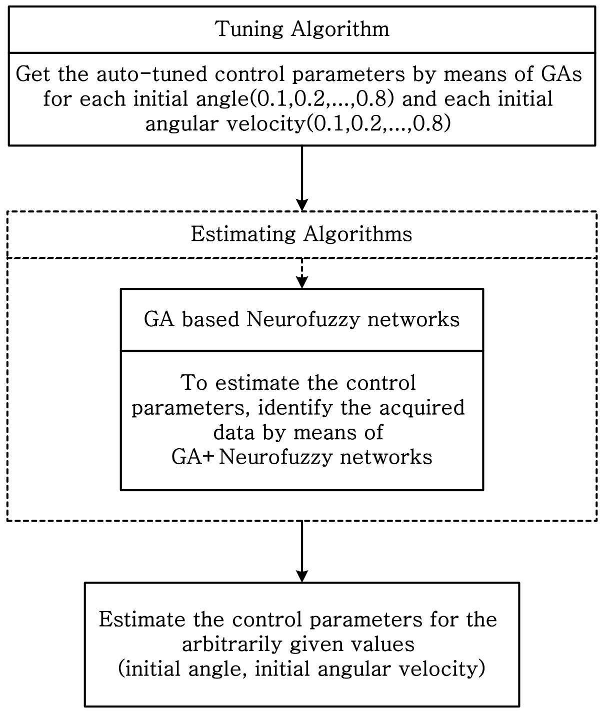


Fig. 7. Overall organization of the optimization process.

connections change as follows

$$w(new) = w(old) + \Delta w \,, \tag{9}$$

where the update formula follows the gradient descent method

$$\begin{aligned} \Delta w_{ij} &= \eta \cdot \left(-\frac{\partial E_p}{\partial w_i} \right) = -\eta \cdot \frac{\partial E_p}{\partial \hat{y}_p} \cdot \frac{\partial \hat{y}_p}{\partial f_i} \cdot \frac{\partial f_i}{\partial w_i} \\ &= 2 \cdot \eta \cdot (y_p - \hat{y}_p) \cdot \overline{\mu}_i \end{aligned} \tag{10}$$

with η being a positive learning rate.

Quite commonly to accelerate convergence, a momentum term is being added to the learning expression. Combining (10) and a momentum term, the complete update formula merging the already discussed components is

$$\Delta w_{ij} = 2 \cdot \eta \cdot (y_p - \hat{y}_p) \cdot \mu_i + \alpha (w_{ij}(t) - w_{ij}(t-1)). \tag{11}$$

(Here the momentum coefficient, α, is constrained to the unit interval).

In this algorithm, to optimize the learning rate, we use the genetic algorithm for the momentum term and fuzzy membership function of the above NFN. We use 100 generations, 60 populations, 10 bits per string, crossover rate equal to 0.6, and mutation probability equal to 0.1. Fig. 7. depicts the detailed flowchart of the overall optimization process.

5. EXPERIMENTAL STUDIES

The proposed control scheme can be applied to a variety of control problems. In this section, we demonstrate the effectiveness of the fuzzy PD/PID controller by applying it to the inverted pendulum system. The inverted pendulum system is composed of a rigid pole and a cart on which the pole is hinged [4,8]. The cart moves on the rail tracks to its right or left, depending on the force exerted on the cart. The pole is hinged to the car through a frictionless free joint such that it has only one degree of freedom. The control goal is to balance the pole starting from nonzero conditions by supplying appropriate force to the cart. In this study, the dynamics of the inverted pendulum system are characterized by two state variables: θ (angle of the pole with respect to the vertical axis), $\dot{\theta}$ (angular velocity of the pole). The behavior of these two state variables is governed by the following second-order equation.

The dynamic equation of the inverted pendulum comes in the form

$$\ddot{\theta} = \frac{g \sin\theta + \cos\theta \left(\dfrac{-F - ml\dot{\theta}^2 \sin\theta}{m_c + m} \right)}{l \left(\dfrac{4}{3} - \dfrac{m \cos^2\theta}{m_c + m} \right)}, \tag{12}$$

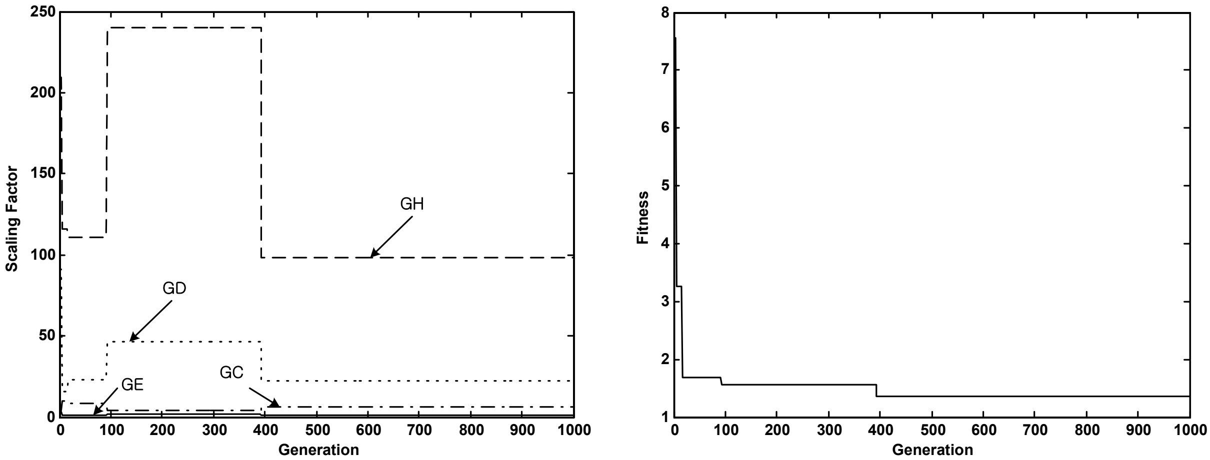
where g (acceleration due to gravity) is $9.8 m/s^2$, m_c (mass of cart) is $1.0 kg$, m (mass of pole) is $0.5 kg$, and F is the applied force expressed in Newtons.

Our control goal here is to balance the pole without regard to the cart's position and velocity, and we compare the fuzzy PID controller and the fuzzy PD controller with the conventional PID controller under identical conditions to validate the fuzzy PID controller and the fuzzy PD controller.

Tuning of control parameters and estimation

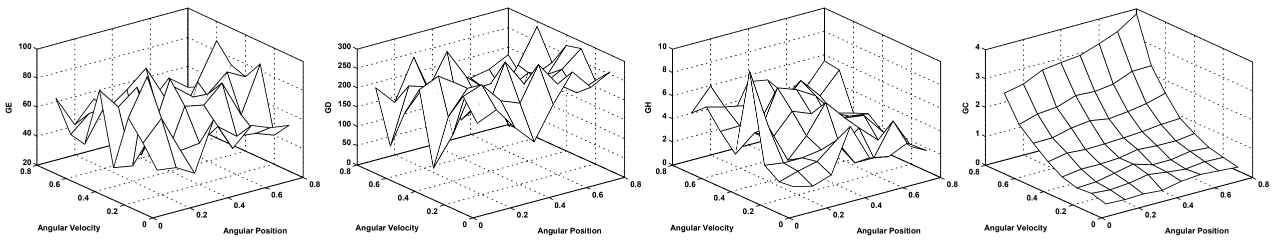
We genetically optimize control parameters (namely GE, GD, GH, and GC) with a clear intent of achieving the best performance of the controller [9]. GAs are powerful nonlinear optimization techniques.

However, their high performance is obtained at the expense of computing time. This essentially rules out the use of GAs in an on-line mode. Rather than that we select a collection of "representative" control scenarios (viz. initial conditions of the pendulum) to off-line genetically optimize the controller and then use these results as a training set to form a nonlinear mapping between the initial conditions of the system and the corresponding scaling factors of the fuzzy controller. The form of the mapping can be experimented



(a) (b)

Fig. 8. (a) fitness function, (b) tuning procedure of scaling factors in successive generations (θ = 0.6 rad and $\dot{\theta}$ =0.4 rad/sec).



(a)GE (b) GD (c)GH (d) GC

Fig. 9. Auto-tuned scaling factors according to the change of initial angles and angular velocity in the fuzzy PID controller (a) GE, (b) GD, (c) GH and (d) GC.

with the help of a GA-based NFN. In the sequel, first we select several initial angular positions and angular velocities and then we obtain the auto-tuned control parameters by means of GAs according to the change of each selected initial angular positions and angular velocities. Next we build a table. Secondly, we use a GA-based NFN to estimate the control parameters, which are explained in the next section [10,11]. Proceeding with the genetic optimization, we consider the ITAE (Integral of the Time multiplied by the Absolute value of Error), overshoot and rising time as the three underlying criteria of the PI (Performance Index) of the controller. We decided to select 0.1 rad., 0.2 rad.,…,0.7 rad., and 0.8 rad. as a collection of initial angular positions and 0.1 rad/sec, 0.2 rad/sec ,…, 0.7 rad/sec, and 0.8 rad/sec as the corresponding family of values of the initial angular velocity. We also tuned (adjust) the control parameters of each controller (fuzzy PID controller, fuzzy PD controller and PID controller).

Table 2 presents the scaling factors of the fuzzy controller tuned by using GAs, ITAE, overshoot and rising time in case that the initial angular position of the inverted pendulum is 0.1 rad, 0.2 rad,…, 0.7 rad, and 0.8 rad and the initial angular velocity is 0.1 rad/sec, 0.2 rad/sec,…, 0.7 rad/sec, and 0.8 rad/sec, respectively. Using these 64 data, the auto-tuned values of scaling factors are obtained by using GAs for estimating control parameters.

Fig. 8 shows (a) the performance of a fitness function in case of θ = 0.6 (rad) and $\dot{\theta}$ =0.4 (rad/sec) and (b) the tuning procedure of scaling factors such as GE, GD, GH and GC according to successive generation with the aid of GAs. Refer to Table 2.

Fig. 9 visualizes the value of the scaling factors treated as a function of initial angular position and angular velocity of the inverted pendulum in the fuzzy PID controller. Evidently there are nonlinear characteristics.

Table 3 summarizes the scaling factors of the fuzzy PD controller that are tuned by using GAs under the same initial condition as those of the fuzzy PID controller, ITAE, overshoot and rising time.

Table 4 shows the control parameters of the PID controller that are tuned by using GAs under the same initial condition as those of the fuzzy PID controller, ITAE, overshoot and rising time.

Table 2. The control parameters, ITAE, overshoot and rising time of the fuzzy PID controller after genetic optimization in the case that the initial angular position of the inverted pendulum is 0.1 rad, 0.2 rad,…, 0.7 rad, and 0.8 rad and the initial angular velocity 0.1 rad/sec, 0.2 rad/sec ,…, 0.7 rad/sec, and 0.8 rad/sec.

θ	$\dot{\theta}$	GE	GD	GH	GC	ITAE	Overshoot (%)	Rising time (sec)
0.100000	0.100000	1.650049	45.161293	215.542511	1.735093	0.097273	0.000255	0.19108
0.100000	0.200000	1.668622	43.108505	236.656891	1.319648	0.074026	1.057175	0.14779
0.100000	0.300000	1.557185	36.070381	177.126099	1.832844	0.074897	0.520979	0.14178
0.100000	0.400000	7.351906	69.208214	127.272728	5.571847	0.031921	0.284381	0.076249
0.100000	0.500000	1.575758	45.747803	211.730194	2.468231	0.177262	0.001417	0.22292
0.100000	0.600000	1.854350	58.651028	281.524933	2.126100	0.220245	0.000361	0.24818
0.100000	0.700000	1.947214	53.372433	229.912018	2.834800	0.181537	0.003848	0.2131
0.100000	0.800000	2.040078	51.319649	256.598236	1.735093	0.138513	0.597917	0.16876
0.200000	0.100000	2.244379	59.237537	268.328430	1.588465	0.220017	0.002452	0.19383
0.200000	0.200000	3.321603	72.434013	283.870972	2.003910	0.176821	0.084697	0.16606
0.200000	0.300000	1.891496	47.214077	229.618759	2.443793	0.233764	0.572674	0.18522
0.200000	0.400000	1.668622	48.680351	210.263931	3.787879	0.358009	0.000340	0.23948
0.200000	0.500000	2.114369	56.598240	297.360718	1.441838	0.253218	0.523023	0.18571
0.200000	0.600000	1.928641	46.334312	232.844574	1.441838	0.194606	0.575528	0.1466
0.200000	0.700000	1.928641	44.868038	197.360718	4.178886	0.262681	0.529929	0.17919
0.200000	0.800000	1.538612	39.882702	216.129044	1.515152	0.243090	0.813163	0.15522
0.300000	0.100000	2.987292	72.140762	198.240479	2.443793	0.194699	0.168146	0.11374
0.300000	0.200000	3.080156	96.774193	257.771271	2.199414	0.228670	0.541496	0.12085
0.300000	0.300000	1.538612	37.536655	184.457474	2.174976	0.335907	0.476415	0.16969
0.300000	0.400000	2.448680	69.501465	299.413483	2.419355	0.491584	0.001374	0.21956
0.300000	0.500000	2.820137	66.862167	229.912018	2.199414	0.278169	0.016132	0.12592
0.300000	0.600000	3.154448	78.299118	214.662750	3.470186	0.276092	0.682007	0.11368
0.300000	0.700000	2.281525	53.079178	241.348969	1.930596	0.392080	0.401829	0.16297
0.300000	0.800000	2.857283	84.750732	281.231659	1.710655	0.343879	0.931851	0.12301
0.400000	0.100000	2.337243	33.137829	47.507332	9.946237	0.344132	0.983603	0.12211
0.400000	0.200000	1.650049	30.791788	119.354843	4.667644	0.445385	0.557061	0.15545
0.400000	0.300000	1.928641	48.973606	223.460419	1.417400	0.439613	0.764274	0.14312
0.400000	0.400000	2.430108	83.577713	226.392960	3.054741	0.457985	0.822324	0.13338
0.400000	0.500000	1.130010	25.219942	102.639297	5.498534	0.596329	0.123811	0.1798
0.400000	0.600000	2.374389	66.275658	229.325516	3.714565	0.533014	0.669856	0.1411
0.400000	0.700000	2.411535	78.005859	210.557175	3.494624	0.522671	0.438267	0.13076
0.400000	0.800000	2.114369	70.967743	272.434021	1.686217	0.612176	0.021387	0.1484
0.500000	0.100000	1.891496	81.818184	234.017593	2.223851	0.636086	0.223738	0.15523
0.500000	0.200000	1.928641	66.862167	255.718475	3.616813	0.747243	0.334514	0.1702
0.500000	0.300000	1.947214	76.832840	222.873901	2.834800	0.703863	0.279617	0.15312
0.500000	0.400000	2.040078	49.266865	154.252197	4.618768	0.723054	0.941279	0.14564
0.500000	0.500000	2.021505	70.087975	158.651016	3.983382	0.753718	0.752549	0.14271
0.500000	0.600000	1.891496	59.530792	179.765396	2.834800	0.795945	0.282009	0.14634
0.500000	0.700000	1.854350	52.785923	189.149551	2.859238	0.870931	0.278803	0.15069
0.500000	0.800000	1.891496	74.486801	210.557175	2.663734	0.911025	0.314776	0.14768
0.600000	0.100000	1.575758	39.882702	153.665680	3.616813	1.044728	0.004459	0.18124
0.600000	0.200000	1.687194	61.583576	211.730194	3.641251	1.066975	0.153832	0.1748
0.600000	0.300000	1.390029	35.483871	175.659821	2.419355	1.219189	0.529370	0.19305
0.600000	0.400000	1.018573	22.287392	98.533730	6.036168	1.291297	0.595427	0.19592
0.600000	0.500000	1.761486	43.695015	127.565987	5.474096	1.181221	0.279334	0.16266
0.600000	0.600000	1.705767	39.589439	129.618774	4.472141	1.260368	0.796205	0.16061
0.600000	0.700000	1.594330	62.170086	200.586517	2.565982	1.358645	0.001934	0.16766
0.600000	0.800000	1.557185	86.803520	287.683289	2.101662	1.556496	0.127577	0.18196
0.700000	0.100000	1.427175	42.228741	53.372433	5.131965	1.465122	1.354618	0.17854
0.700000	0.200000	1.538612	53.079178	195.894424	4.692082	1.647075	0.410465	0.19333
0.700000	0.300000	1.575758	52.785923	172.434021	4.398827	1.707701	0.906766	0.18489
0.700000	0.400000	1.427175	62.463341	258.357788	3.079179	1.947195	0.362886	0.20453
0.700000	0.500000	1.538612	73.900291	179.472153	3.567937	1.900622	0.604560	0.18265
0.700000	0.600000	1.594330	50.733139	136.363647	5.229716	1.982359	0.690369	0.17907
0.700000	0.700000	1.018573	23.460411	112.023460	3.494624	2.255980	0.444391	0.2019
0.700000	0.800000	1.594330	50.733139	136.363647	5.229716	2.274349	1.094785	0.17625
0.800000	0.100000	1.427175	62.756596	185.923752	4.032258	2.319965	0.348073	0.20954
0.800000	0.200000	1.445748	40.762466	136.070389	5.962854	2.451787	0.062809	0.21003
0.800000	0.300000	1.260020	55.131966	239.296188	2.321603	2.768469	0.366498	0.2222
0.800000	0.400000	1.371457	34.310852	125.219940	5.449658	2.848641	0.013807	0.21421
0.800000	0.500000	1.408602	30.205278	88.563049	5.156403	2.930422	1.509672	0.19847
0.800000	0.600000	1.334311	42.228741	145.747803	3.372434	3.164248	0.050040	0.20457
0.800000	0.700000	1.371457	55.425220	154.545456	3.519062	3.402342	0.285634	0.20153
0.800000	0.800000	1.445748	45.454548	180.645172	5.474096	3.833133	1.429595	0.20405

Tables 2-4 show the control parameters such as the scaling factors and PID parameter of each controllers obtained from GAs, and the performance indexes (ITAE, overshoot, and rising time) for each controller. In general, fuzzy PD and fuzzy PID controllers are preferred architectures. However, PID controller is also satisfactory in comparison to fuzzy PID controller within a linear range of $\theta < 0.4$, while in case of a nonlinear range of $\theta > 0.6$ fuzzy PID controller architecture is superior to both fuzzy PD and PID controller.

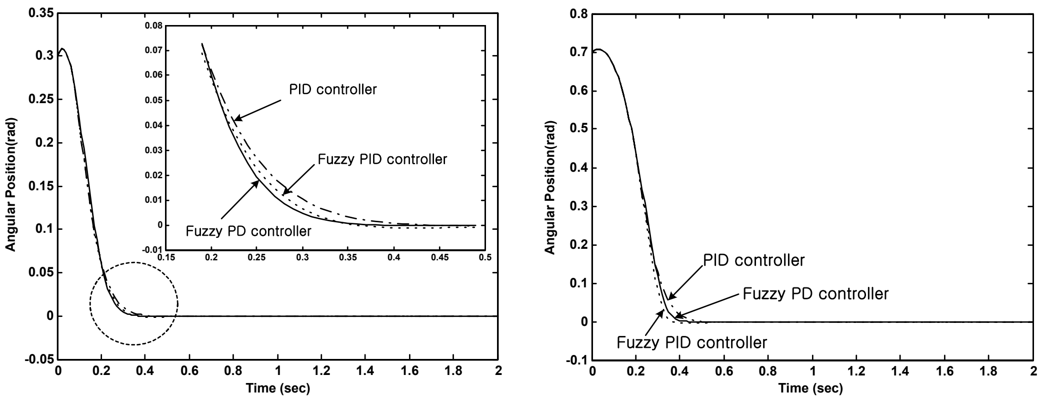
Fig. 10(a) and (b) illustrate the dynamics of output of the system controlled by each controller after genetic optimization in the case of θ = 0.3 (rad), $\dot{\theta}$ =0.7 (rad/sec) and (b) θ = 0.7 (rad), $\dot{\theta}$ =0.5 (rad/sec), respectively.

In Fig. 10, we know that the fuzzy PID controller and fuzzy PD controller are superior to the conventional PID controller from the viewpoint of ITAE, overshoot and rising time.

Now, we consider the case in which the initial angular positions and angular velocities of the inverted pendulum are not included in Tables 2, 3 and 4 (in other words, selected arbitrarily within the given range). Here we show that the control parameters under the arbitrarily selected initial condition are not tuned by the GAs and the control parameters of each

Table 3. The control parameter and performance index (ITAE, overshoot and rising time) of the fuzzy PD controller after genetic optimization in the case of θ = 0.1,…,0.8 (rad) and $\dot{\theta}$ = 0.1,…,0.8 (rad/sec).

θ	$\dot{\theta}$	GE	GD	GC	ITAE	Overshoot(%)	Rising time (sec)
0.100000	0.100000	14.93646	0.899866	1.185454	0.034373	0.000092	0.09920
0.100000	0.200000	10.26392	0.802163	1.052545	0.045998	0.100769	0.11809
0.100000	0.300000	6.549364	0.622390	1.287091	0.073581	0.000000	0.15279
0.100000	0.400000	17.12610	1.046420	0.978273	0.049569	0.026306	0.10701
0.100000	0.500000	7.820137	0.765036	0.927455	0.087333	0.076760	0.15233
0.100000	0.600000	3.734115	0.247211	3.831909	0.047277	0.134572	0.09530
0.100000	0.700000	9.716520	0.675150	1.377000	0.054430	0.073070	0.09997
0.100000	0.800000	13.43108	0.911590	1.033000	0.065572	0.073025	0.10502
0.200000	0.100000	4.672532	0.305833	3.151727	0.095997	0.077961	0.10776
0.200000	0.200000	9.638318	0.626298	1.549000	0.127201	0.051684	0.12571
0.200000	0.300000	5.571847	0.454341	1.810909	0.135217	0.074449	0.13046
0.200000	0.400000	5.337244	0.426984	1.955546	0.139306	0.074474	0.12701
0.200000	0.500000	10.45943	0.661471	1.517727	0.158252	0.018422	0.12827
0.200000	0.600000	5.298142	0.374225	2.448091	0.139665	0.072501	0.11224
0.200000	0.700000	6.392962	0.462157	1.932091	0.153668	0.101304	0.11511
0.200000	0.800000	6.295210	0.626298	1.111182	0.248850	0.081654	0.16335
0.300000	0.100000	3.069404	0.256981	3.128273	0.242936	0.076407	0.14274
0.300000	0.200000	6.920821	0.460203	2.065000	0.252706	0.060785	0.13752
0.300000	0.300000	6.001955	0.395719	2.428545	0.241516	0.055312	0.12708
0.300000	0.400000	6.510263	0.442617	2.139273	0.276194	0.037955	0.13542
0.300000	0.500000	3.558162	0.256981	3.511364	0.267076	0.064160	0.12602
0.300000	0.600000	4.437928	0.380087	2.096273	0.325881	0.054341	0.14534
0.300000	0.700000	6.451612	0.512963	1.631091	0.392499	0.056445	0.15815
0.300000	0.800000	5.591398	0.342960	2.956273	0.299164	0.044844	0.11366
0.400000	0.100000	7.526882	0.499284	1.912545	0.538816	0.036244	0.1821
0.400000	0.200000	3.753666	0.335144	2.287818	0.469680	0.059967	0.16405
0.400000	0.300000	3.343109	0.303879	2.487182	0.486880	0.062577	0.16267
0.400000	0.400000	4.320626	0.305833	2.964091	0.445922	0.080275	0.13948
0.400000	0.500000	3.460411	0.282384	2.925000	0.498048	0.055342	0.14933
0.400000	0.600000	4.633431	0.399628	1.963364	0.616099	0.060080	0.17118
0.400000	0.700000	3.734115	0.294108	2.854636	0.545544	0.080466	0.1447
0.400000	0.800000	4.985337	0.305833	3.296364	0.533104	0.070599	0.12827
0.500000	0.100000	5.767351	0.423076	2.104091	0.842767	0.036113	0.1983
0.500000	0.200000	4.242424	0.337098	2.487182	0.749735	0.049547	0.17579
0.500000	0.300000	4.281525	0.288246	3.296364	0.690006	0.043878	0.15353
0.500000	0.400000	3.323558	0.253073	3.390182	0.733171	0.084664	0.15592
0.500000	0.500000	1.779081	0.180773	3.573909	0.899276	0.270279	0.18419
0.500000	0.600000	4.907136	0.319511	3.038364	0.843915	0.038558	0.15806
0.500000	0.700000	3.910069	0.286292	3.104818	0.877988	0.060032	0.15613
0.500000	0.800000	3.304008	0.243303	3.652091	0.902420	0.058428	0.15031
0.600000	0.100000	4.496579	0.307787	3.030545	1.048746	0.044971	0.18273
0.600000	0.200000	2.697947	0.217900	3.769364	1.045987	0.078194	0.17535
0.600000	0.300000	4.261975	0.272614	3.401909	1.075930	0.422543	0.16773
0.600000	0.400000	3.479961	0.262844	3.312000	1.171544	0.052938	0.17489
0.600000	0.500000	2.795699	0.229625	3.577818	1.240273	0.049336	0.17577
0.600000	0.600000	2.287390	0.221808	3.237727	1.407169	0.052847	0.19181
0.600000	0.700000	2.717498	0.239395	3.214273	1.425942	0.071779	0.18084
0.600000	0.800000	3.538612	0.258935	3.468364	1.456570	0.037791	0.16951
0.700000	0.100000	3.753666	0.268706	3.358909	1.552194	0.048066	0.19662
0.700000	0.200000	4.320626	0.282384	3.409727	1.645655	0.055660	0.19666
0.700000	0.300000	4.750733	0.290200	3.628637	1.741531	0.010769	0.19666
0.700000	0.400000	2.521994	0.227671	3.308091	1.860775	0.070872	0.20154
0.700000	0.500000	4.535679	0.288246	3.421455	1.966259	0.052065	0.1963
0.700000	0.600000	4.125122	0.290200	3.186909	2.134502	0.026069	0.20084
0.700000	0.700000	2.033236	0.200314	3.476182	2.282319	0.086637	0.20661
0.700000	0.800000	2.248289	0.221808	3.151727	2.432745	0.075062	0.20607
0.800000	0.100000	3.577713	0.253073	3.636455	2.346170	0.042356	0.21543
0.800000	0.200000	2.209189	0.200314	3.773273	2.528666	0.053902	0.22109
0.800000	0.300000	2.971652	0.223762	3.914000	2.592028	0.079453	0.20856
0.800000	0.400000	2.404692	0.225717	3.296364	2.927830	0.033023	0.22568
0.800000	0.500000	2.306940	0.204222	3.753727	3.045240	0.064020	0.21653
0.800000	0.600000	3.792766	0.264798	3.476182	3.301775	0.045469	0.21634
0.800000	0.700000	3.010753	0.235487	3.605182	3.490056	0.045494	0.21136
0.800000	0.800000	2.404692	0.204222	3.914000	3.748619	0.046755	0.20982



(a) (b)

Fig. 10. The dynamics of output of the system controlled by each optimized controller in the case of (a) θ = 0.3 (rad), $\dot{\theta}$ =0.7 (rad/sec) and (b) θ = 0.7 (rad), $\dot{\theta}$ =0.5 (rad/sec).

Table 4. The control parameter and performance index (ITAE, overshoot and rising time) of the PID controller after genetic optimization in the case of $\theta = 0.1,\ldots,0.8$ (rad) and $\dot{\theta} = 0.1,\ldots,0.8$ (rad/sec).

θ	$\dot{\theta}$	K	Ti	Td	ITAE	Overshoot (%)	Rising time (sec)
0.100000	0.100000	166.177917	168.670975	0.105460	0.094016	0.076108	0.17165
0.100000	0.200000	168.670578	161.195160	0.104877	0.098847	0.080049	0.17077
0.100000	0.300000	167.174973	168.670975	0.105655	0.105030	0.078796	0.17169
0.100000	0.400000	168.172043	167.341934	0.106239	0.111790	0.080387	0.17288
0.100000	0.500000	167.174973	165.348389	0.105849	0.116218	0.085414	0.17029
0.100000	0.600000	168.670578	165.348389	0.104099	0.117358	0.096094	0.16486
0.100000	0.700000	170.000000	164.850006	0.105849	0.128590	0.090310	0.1688
0.100000	0.800000	168.338226	165.182266	0.106822	0.137882	0.094369	0.16985
0.200000	0.100000	167.839691	165.680649	0.104488	0.207465	0.086079	0.1716
0.200000	0.200000	168.504395	159.035477	0.104682	0.218555	0.088015	0.17226
0.200000	0.300000	169.335297	167.508072	0.104488	0.225252	0.085342	0.17157
0.200000	0.400000	169.833817	168.006454	0.103515	0.230809	0.095161	0.16843
0.200000	0.500000	169.501465	170.000000	0.105655	0.251252	0.085611	0.17366
0.200000	0.600000	167.507339	169.501617	0.105655	0.261690	0.090230	0.17212
0.200000	0.700000	167.839691	169.335480	0.105460	0.273272	0.093410	0.17106
0.200000	0.800000	165.180847	169.335480	0.105266	0.284905	0.104905	0.16889
0.300000	0.100000	169.002930	167.840332	0.104099	0.362849	0.092720	0.17604
0.300000	0.200000	169.501465	161.029037	0.104099	0.379521	0.096959	0.17575
0.300000	0.300000	168.172043	169.501617	0.103904	0.391446	0.102306	0.17478
0.300000	0.400000	169.169113	159.201614	0.104293	0.414550	0.102718	0.17535
0.300000	0.500000	167.673508	168.670975	0.104488	0.430043	0.103205	0.17497
0.300000	0.600000	169.501465	161.195160	0.104099	0.451165	0.108161	0.17388
0.300000	0.700000	169.002930	168.006454	0.103126	0.461775	0.122959	0.17047
0.300000	0.800000	168.836761	157.041931	0.104488	0.498353	0.116110	0.17307
0.400000	0.100000	169.833817	164.850006	0.103126	0.571272	0.112191	0.18146
0.400000	0.200000	169.667648	167.674194	0.102932	0.592150	0.117532	0.18075
0.400000	0.300000	170.000000	168.837097	0.103126	0.618764	0.114223	0.18098
0.400000	0.400000	167.008804	168.172577	0.102932	0.642883	0.144168	0.17913
0.400000	0.500000	170.000000	169.501617	0.103904	0.681876	0.110402	0.18173
0.400000	0.600000	167.839691	165.182266	0.104099	0.715386	0.122198	0.18081
0.400000	0.700000	167.174973	169.003220	0.102932	0.736046	0.151878	0.17733
0.400000	0.800000	169.501465	169.501617	0.101764	0.763473	0.167841	0.17431
0.500000	0.100000	169.002930	169.169357	0.104099	0.868561	0.111528	0.1929
0.500000	0.200000	167.507339	166.511292	0.103515	0.901292	0.131474	0.19141
0.500000	0.300000	169.335297	165.348389	0.103710	0.945491	0.122725	0.19163
0.500000	0.400000	168.005859	168.837097	0.103126	0.979462	0.140650	0.18977
0.500000	0.500000	169.667648	166.677429	0.101375	1.009529	0.181248	0.18561
0.500000	0.600000	169.833817	162.358063	0.102932	1.078726	0.143894	0.18844
0.500000	0.700000	167.341156	163.354828	0.104099	1.140496	0.141993	0.18926
0.500000	0.800000	169.335297	164.351608	0.102348	1.179671	0.166694	0.18525
0.600000	0.100000	168.670578	167.175812	0.103904	1.273187	0.128207	0.20418
0.600000	0.200000	167.507339	168.837097	0.102932	1.318895	0.154512	0.20204
0.600000	0.300000	167.507339	168.670975	0.104099	1.394525	0.136399	0.20372
0.600000	0.400000	168.670578	169.335480	0.102153	1.440542	0.172079	0.19977
0.600000	0.500000	169.501465	166.012909	0.101181	1.505114	0.202769	0.19719
0.600000	0.600000	168.172043	169.501617	0.102153	1.589511	0.185255	0.19793
0.600000	0.700000	168.504395	167.840332	0.101375	1.666328	0.215378	0.19575
0.600000	0.800000	167.673508	168.504837	0.103321	1.778220	0.169083	0.19828
0.700000	0.100000	169.002930	168.006454	0.104293	1.861877	0.138084	0.21974
0.700000	0.200000	163.519058	170.000000	0.104293	1.942323	0.168098	0.21785
0.700000	0.300000	169.169113	163.188705	0.102543	2.035579	0.174166	0.21553
0.700000	0.400000	164.017593	169.335480	0.103515	2.144568	0.193269	0.21567
0.700000	0.500000	167.673508	167.009674	0.101570	2.243018	0.225348	0.21206
0.700000	0.600000	166.842621	167.674194	0.104099	2.406587	0.170850	0.21563
0.700000	0.700000	169.002930	163.188705	0.102348	2.529273	0.200558	0.21162
0.700000	0.800000	166.842621	169.003220	0.101959	2.665989	0.235506	0.20932
0.800000	0.100000	165.845551	165.016129	0.102543	2.707035	0.212035	0.23376
0.800000	0.200000	170.000000	168.172577	0.100792	2.839842	0.227844	0.23121
0.800000	0.300000	167.341156	160.862900	0.102153	3.038635	0.223635	0.23243
0.800000	0.400000	168.836761	164.850006	0.100792	3.202980	0.257897	0.22947
0.800000	0.500000	169.335297	167.840332	0.102153	3.427777	0.210568	0.23097
0.800000	0.600000	166.344086	169.833878	0.103126	3.665044	0.216031	0.23096
0.800000	0.700000	168.338226	162.856445	0.101375	3.906416	0.264730	0.22702
0.800000	0.800000	169.833817	168.837097	0.100986	4.178266	0.262563	0.22532

controller are estimated by using the estimation algorithm of the GA-based NFN. We implement the optimal neurofuzzy networks for parameter estimation using GAs. In this algorithm, we adjust the learning rates, momentum coefficient, and apexes of the membership function of neurofuzzy networks by using GAs.

Table 5 shows the estimated scaling factors of the fuzzy PID controller and describes the performance index (ITAE, overshoot and rising time) of the fuzzy PID controller with the estimated scaling factors in the case of $\theta = 0.22, 0.45, 0.78$ (rad) and $\dot{\theta} = 0.22, 0.45, 0.78$ (rad/sec), respectively.

In the case of the fuzzy PD controller, the estimated scaling factors and performance index are shown in Table 6 when the initial angular position is 0.22 (rad), 0.45 (rad), or 0.78 (rad) and the initial angular velocity is 0.22 (rad/sec), 0.45 (rad/sec), or 0.78 (rad/sec), respectively.

In the case of the PID controller, the estimated scaling factors by means of the GA-based NFN are presented in Table 7 when the initial angular position is 0.22 (rad), 0.45 (rad), or 0.78 (rad) and the initial angular velocity is 0.22 (rad/sec), 0.45 (rad/sec), or 0.78 (rad/sec), respectively.

Fig. 11 demonstrates (a) pole angle (b) pole angular velocity for initial angle $\theta = 0.22$ (rad) and initial angular velocity $\dot{\theta} = 0.22$ (rad/sec) (Case 1).

Table 5. The estimated parameters by means of the GA-based NFN and performance index (ITAE, overshoot and rising time) of the fuzzy PID controller in the case of θ = 0.22, 0.45, 0.78 (rad) and $\dot{\theta}$ = 0.22, 0.45, 0.78 (rad/sec).

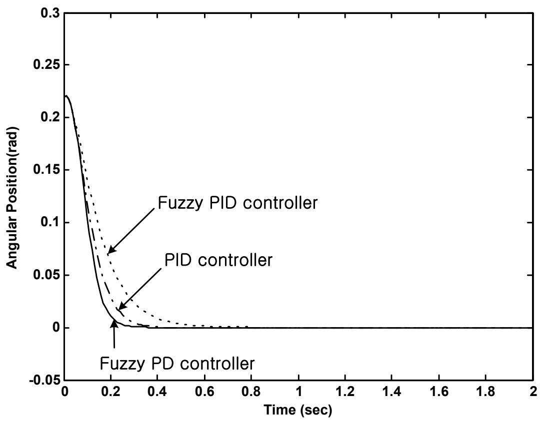
Case	Initial angle (rad)	Initial angular velocity	GE	GD	GH	GC	ITAE	Overshoot (%)	Rising time (sec)
1	0.22	0.22	2.032828	61.545998	237.387817	3.706272	0.419737	0.000000	0.26105
2	0.22	0.45	2.117639	61.290897	242.742706	3.047558	0.398423	0.000000	0.24208
3	0.22	0.78	2.185512	60.583847	250.425781	1.442666	0.363320	0.000000	0.20613
4	0.45	0.22	1.818810	57.950821	222.710297	4.021980	0.923726	0.000000	0.23562
5	0.45	0.45	1.868329	58.781029	228.355225	3.553186	0.898830	0.000000	0.21048
6	0.45	0.78	1.907958	61.082088	236.454498	2.411014	0.855770	0.000000	0.16716
7	0.78	0.22	1.372258	47.819809	174.743240	4.474953	2.432061	0.000000	0.21519
8	0.78	0.45	1.348141	51.708344	181.336151	4.278651	2.911324	0.000000	0.21672
9	0.78	0.78	1.328839	62.486092	190.795532	3.800384	3.726972	0.000000	0.21093

Table 6. The estimated parameters by means of the GA-based NFN and performance index (ITAE, overshoot and rising time) of the fuzzy PD controller in the case of θ = 0.22, 0.45, 0.78 (rad) and $\dot{\theta}$ = 0.22, 0.45, 0.78 (rad/sec).

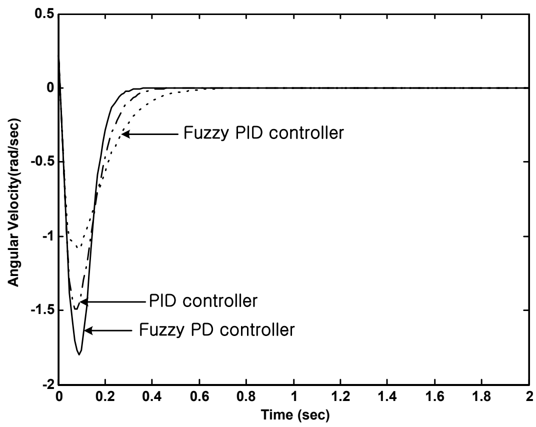
Case	Initial angle (rad)	Initial angular velocity	GE	GD	GC	ITAE	Overshoot (%)	Rising time (sec)
1	0.22	0.22	7.437843	0.529057	1.854648	0.149772	0.000000	0.12902
2	0.22	0.45	7.003085	0.508195	2.066092	0.173872	0.000000	0.13051
3	0.22	0.78	6.693032	0.492697	2.270946	0.216222	0.000000	0.13200
4	0.45	0.22	4.914640	0.333972	2.715822	0.546678	0.155587	0.15296
5	0.45	0.45	4.470177	0.317409	2.791710	0.609271	0.133525	0.15100
6	0.45	0.78	4.153202	0.305104	2.865232	0.728531	0.102153	0.14932
7	0.78	0.22	3.597757	0.247494	3.913758	2.270186	0.026860	0.20643
8	0.78	0.45	3.148229	0.232836	3.801080	2.617699	0.076634	0.20401
9	0.78	0.78	2.827642	0.221947	3.691914	3.304682	0.140848	0.20195

Table 7. The estimated parameters, ITAE, overshoot and rising time of the PID controller in the case of θ = 0.22, 0.45, 0.78 (rad) and $\dot{\theta}$ = 0.22, 0.45, 0.78 (rad/sec).

Case	Initial angle (rad)	Initial angular velocity	K	Ti	Td	ITAE	Overshoot (%)	Rising time (sec)
1	0.22	0.22	168.686066	164.717194	0.104505	0.247020	0.087829	0.17247
2	0.22	0.45	168.680069	164.879379	0.104704	0.273436	0.092216	0.17193
3	0.22	0.78	168.661194	164.987473	0.104988	0.319242	0.100283	0.16993
4	0.45	0.22	168.392883	166.310638	0.103440	0.742116	0.122528	0.18613
5	0.45	0.45	168.420395	166.041107	0.103302	0.819175	0.131957	0.18468
6	0.45	0.78	168.506943	165.861481	0.103104	0.953855	0.147016	0.18185
7	0.78	0.22	167.593369	167.404816	0.102826	2.674119	0.187619	0.23005
8	0.78	0.45	167.712250	166.838821	0.102493	3.051612	0.208242	0.22797
9	0.78	0.78	168.086258	166.461639	0.102016	3.762012	0.241529	0.22332

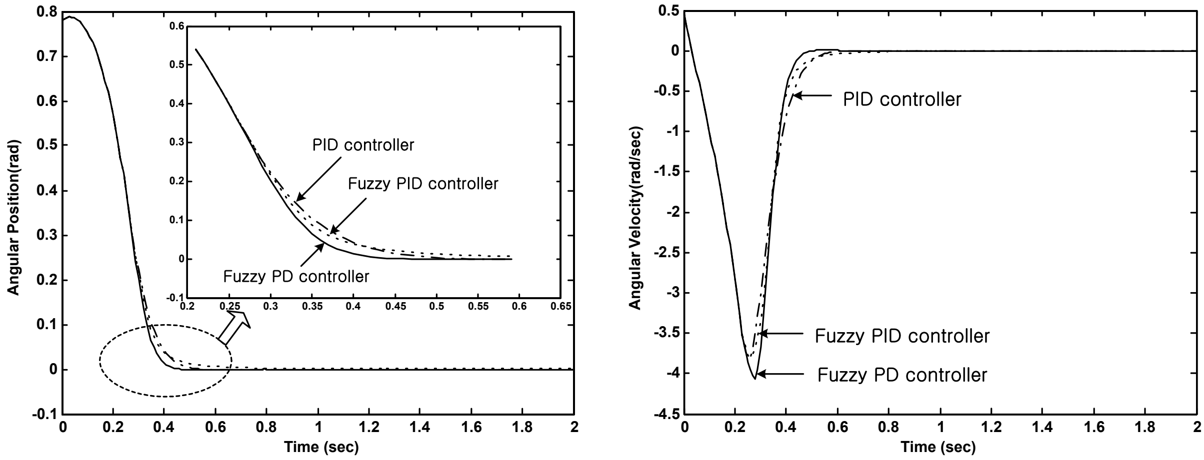


(a)



(b)

Fig. 11. (a) pole angle, (b) pole angular velocity for initial angle θ = 0.22 (rad) and initial angular velocity $\dot{\theta}$ =0.22 (rad/sec) (Case 1).



(a) (b)

Fig. 12. (a) pole angle, (b) pole angular velocity for initial angle θ = 0.78 (rad) and initial angular velocity $\dot{\theta}$ =0.45 (rad/sec) (Case 8).

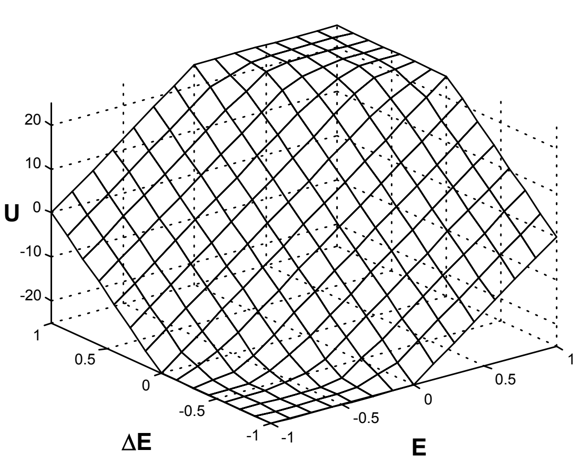


Fig. 13. The input-output relation of the fuzzy PD controller (GE, GD, GC = 1).

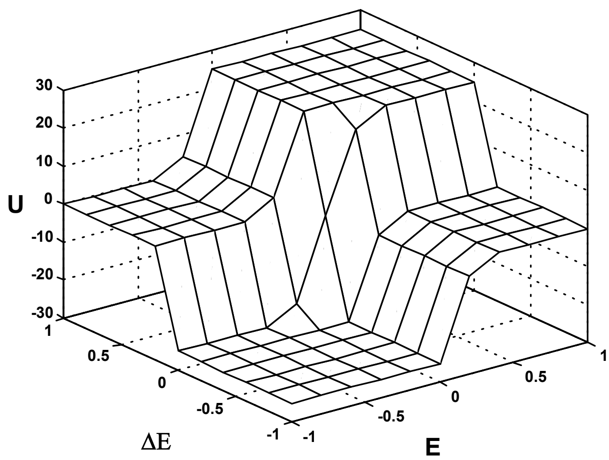


Fig. 14. The input-output relation of fuzzy PD controller (Case 6).

Fig. 12 demonstrates (a) pole angle (b) pole angular velocity for initial angle θ = 0.78 (rad) and initial angular velocity $\dot{\theta}$ =0.45 (rad/sec) (Case 8).

From the above Figs. 11 and 12, we know that the fuzzy PD and fuzzy PID effectively control the inverted pendulum system. The proposed estimation algorithm such as GA-based NFN generates the preferred model architectures. The output performance of the fuzzy controllers such as the fuzzy PD and the fuzzy PID controller including nonlinear characteristics are superior to that of the PID controller, especially in a nonlinear range of θ>0.45 when using the nonlinear dynamic equation of the inverted pendulum. While in case of a linear range θ<0.45, the PID controller is also satisfactory in comparison to the fuzzy PID controller. In particular the fuzzy PD controller is the most preferred one among the controllers when using NFN-based estimation techniques. Fig. 13 depicts the nonlinear characteristic of the fuzzy PD controller in cases where GE, GD, and GC are equal to 1.

Fig. 14 visualizes the input-output relation of the fuzzy PD controller when using Case 6. Note that the fuzzy PD comes with a significant nonlinear mapping between the inputs and the output.

6. CONCLUSIONS

In this paper, we have proposed a two-phase optimization scheme of the fuzzy PID and PD controllers. The parameters under optimization concern scaling factors of the input and output variables of the controller that are known to exhibit an immense impact on its quality. The first phase of the design of the controller employs genetic computing that aims at the global optimization of its scaling factors where they are optimized with regard to a finite collection of initial conditions of the system under control. In the second phase, we construct a nonlinear mapping between the initial conditions of the system and the corresponding values of the scaling factors. Based on the simulation studies, using genetic optimization by scaling factor estimation modes and the estimation algorithm of the GA-based neurofuzzy networks model, we demonstrated that the fuzzy PD/PID controller effectively controls the inverted pendulum system, particularly in a nonlinear range of θ. While the study showed the development of the controller in the experimental framework of control of a specific dynamic system (inverted pendulum), this methodology is general and can be directly utilized to any other system. Similarly, one can envision a number of modifications that are worth investigating. For instance, a design of systems exhibiting a significant level of variability could benefit from the approach pursued in this study.

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