Soft Computing based smart control design: example of benchmark simulation results

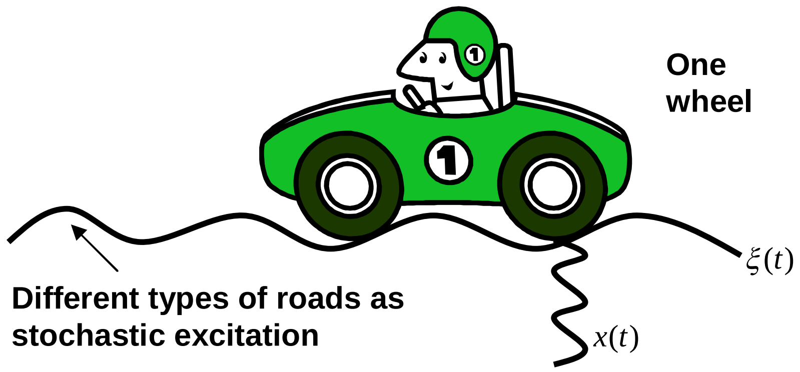
Fuzzy inference

GA optimization

FNN learning

Control Object

Car's suspension control system design (simplified illustrative example)



Simplified version of car suspension system for one wheel may be considered as a *nonlinear oscillator with sizable nonlinear dissipative components* that can be described by the following equations:
of motion:

$$\ddot{x} + \left[2\beta + a\dot{x}^2 + k_1 x^2 - 1\right]\dot{x} + kx = \xi(t) + u(t)$$

and

of entropy production rate:

$$\frac{dS}{dt} = \left[2\beta + a\dot{x}^2 + k_1 x^2 - 1\right]\dot{x}\cdot\dot{x},$$

where $\xi(t)$ is a given stochastic excitations with an appropriate probability density function, $u(t)$ is a control force and S is an entropy production of the given dynamic object.

Model parameters: $\beta = \{0.1; -0.1; 0.5\}; \alpha = 0.3; k_1 = 0.2; k = 5.$

Initial conditions: $[x_0][\dot{x}_0] = [2.5]\,[0.1]$.

In Fig.1 and Fig.2, free motion (dynamic and thermodynamic behavior) of control object with the given above parameters are shown.

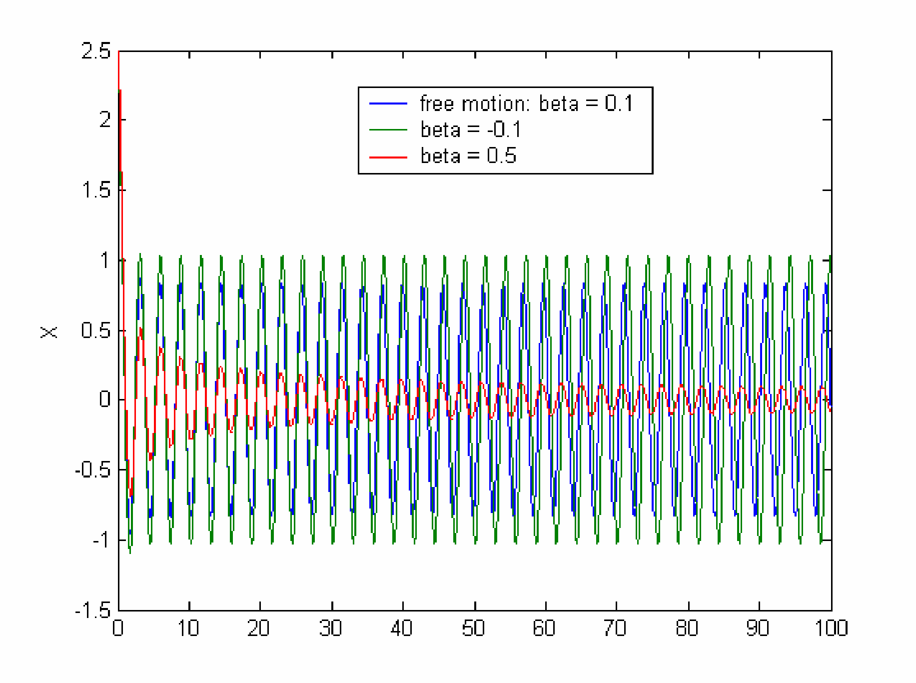


Figure 1. Nonlinear oscillator. Free motion

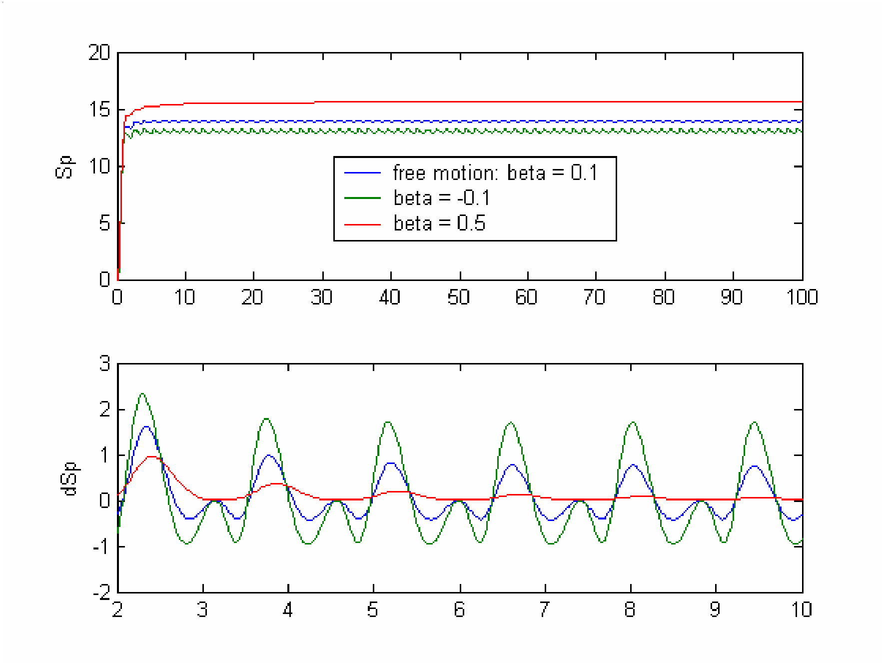


Figure 2: Nonlinear oscillator. Free motion. Thermodynamic behavior

On Fig. 2 you can see that for model parameters $\beta = 0.1$ and $\beta = -0.1$ entropy production rate $\frac{dS}{dt} \le 0$ for some temporal points. So, simulation results show that the given control object (CO) is a *locally* un*stable in Lyapunov sense dynamic system*.

Stochastic external excitations

Consider behaviour of this control object under two different types of stochastic excitations (Gaussian and Rayleigh noises) shown in Fig.3.

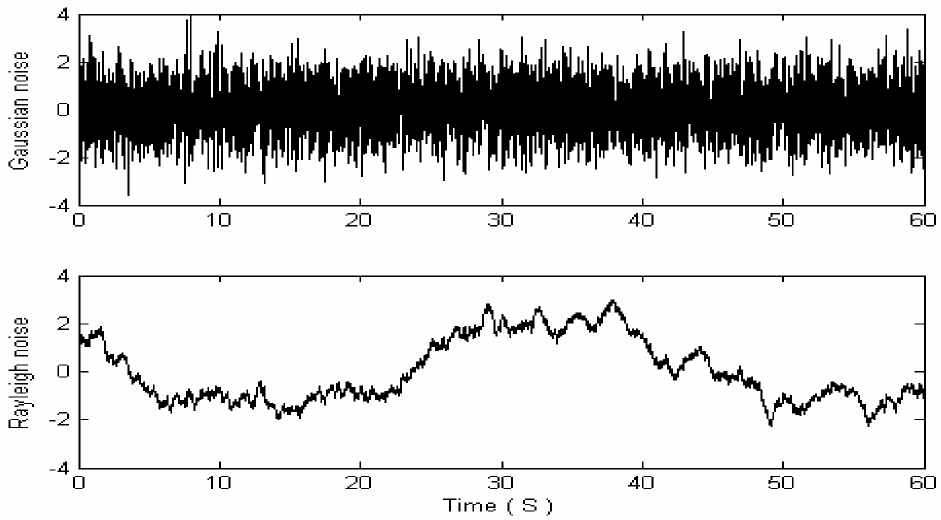


Figure 3. Stochastic noises: Gaussian (top) and Rayleigh (below)

In Figures 4, 5 and 6 dynamic and thermodynamic motion of CO under stochastic noises is shown.

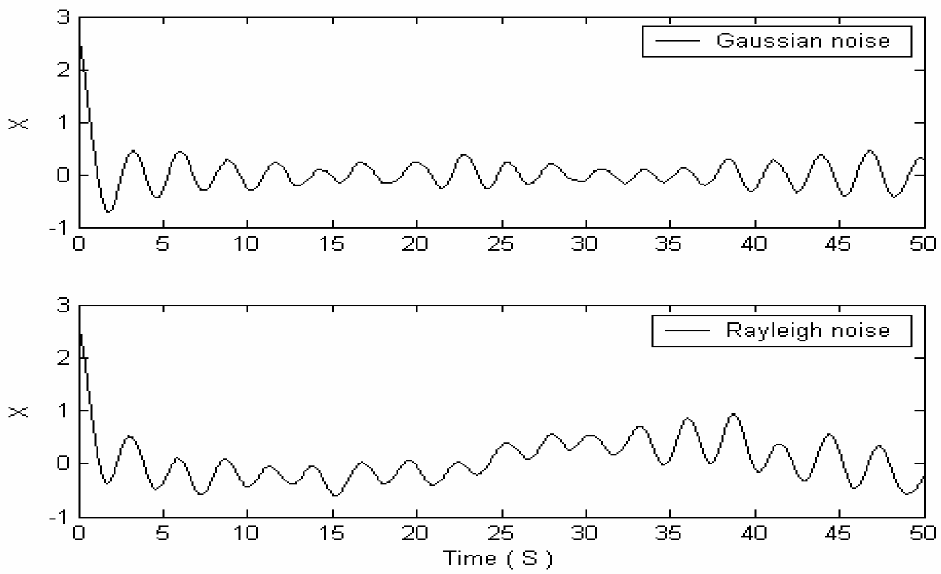


Figure 4. Nonlinear oscillator. Stochastic motion

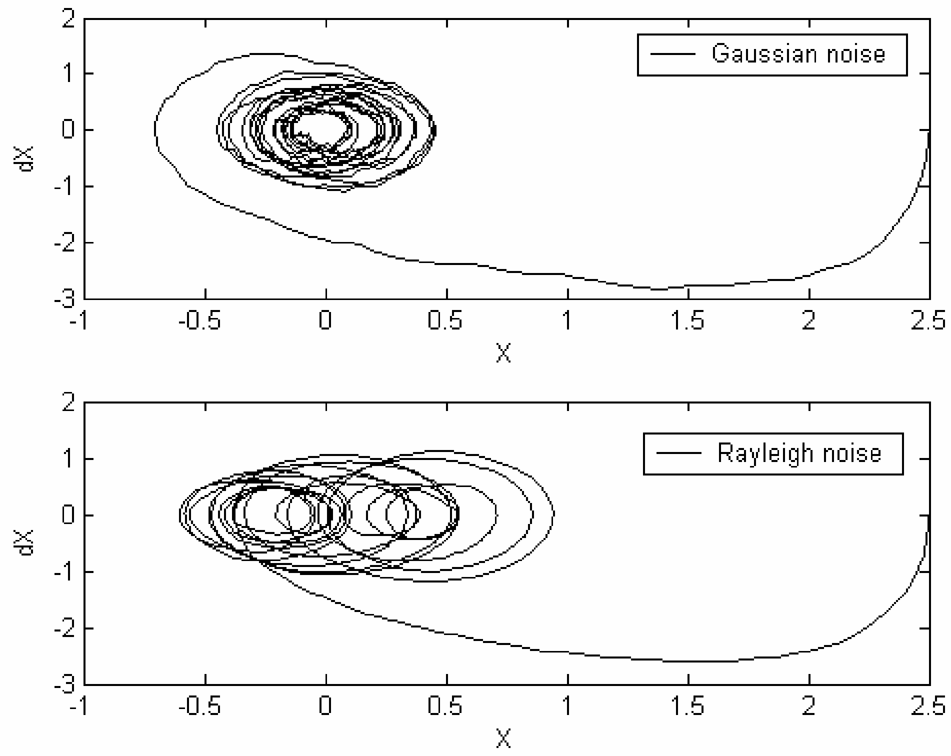


Figure 5. Nonlinear oscillator. Stochastic motion. Phase portraits

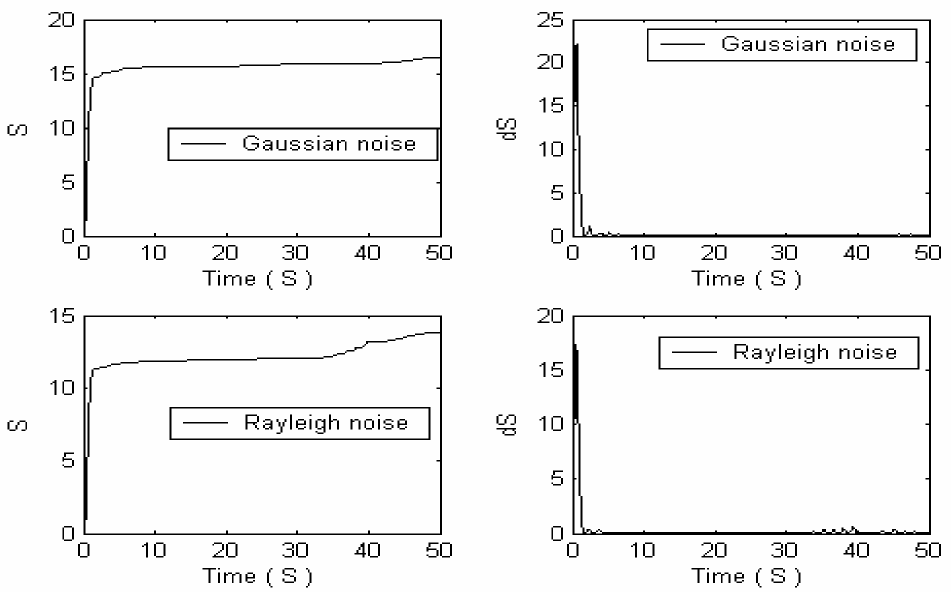


Figure 6. Nonlinear oscillator. Stochastic motion. Thermodynamic behavior

Simulation results show that CO dynamic behavior under Rayleigh excitation is more complicated.

Control problem

Consider the following *control task* for this example: in the presence of Rayleigh noise maintain motion of CO at the given reference signal $x_{ref} = 0$.

Let us design intelligent Fuzzy Control (FC) system for the given above control problem by using our Knowledge Base (KB) FC design tools and compare results with traditional PID Controller.

Key points of Application of Soft Computing methods in Control Engineering

- PID Gain coefficient schedule (control laws) is described in the form of a Knowledge Base (KB) of a Fuzzy Inference System (realized in a Fuzzy Controller (FC))
- Genetic Algorithm (GA) with complicated Fitness Function is used for KB FC forming
- FC KB optimization is based on Fuzzy Neural Networks tuning by using error back propagation algorithm (step 1 technology)

Simulink structure of PID control system for the given control object is shown on Fig.7.

Matlab Simulink structure of PID control

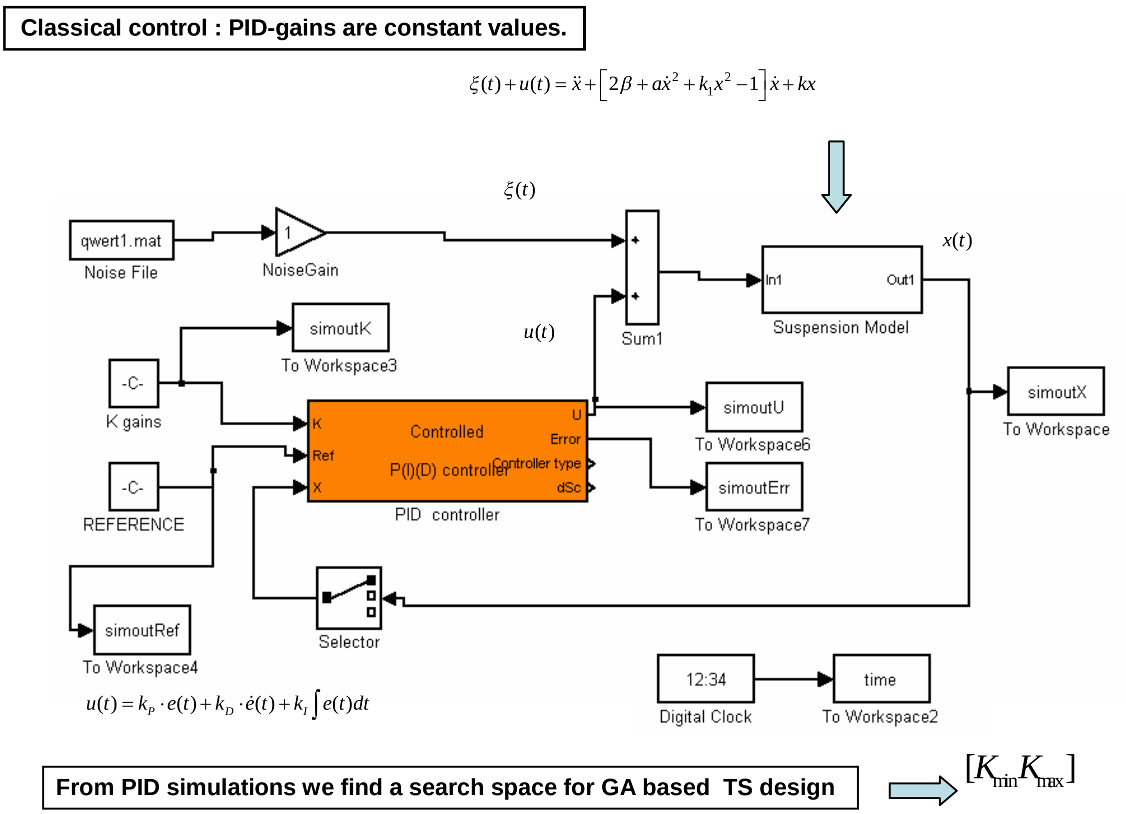


Figure 7.

Smart control design

We will design a FC-PID controller (Fig.8) with three input variables to FC and three output variables of FC.

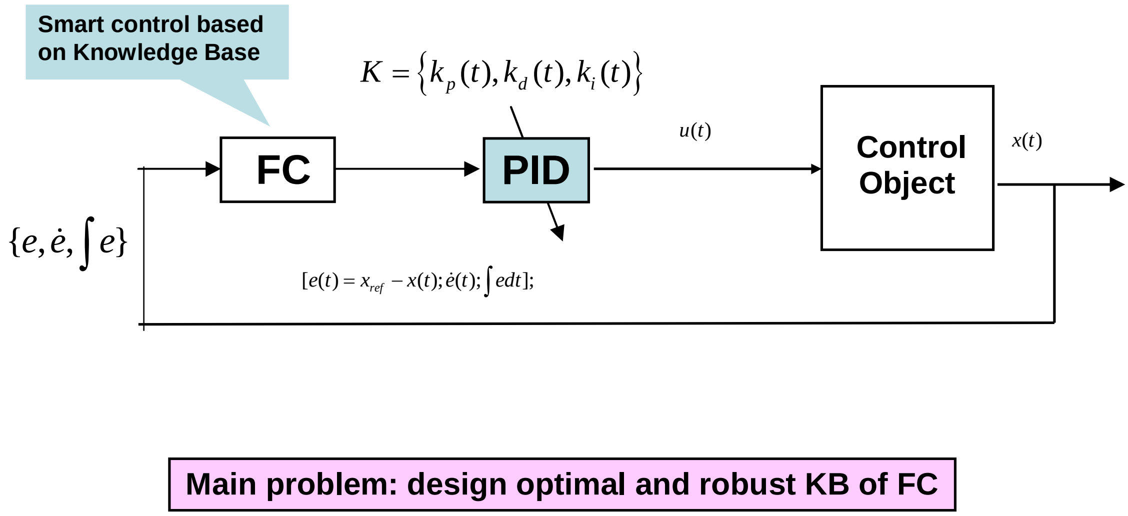


Figure 8.

GA-based Teaching Signal design

At this step we design a *teaching signal* (TS) of optimal control based on the given control quality criterion as a GA Fitness Function (FF). The structure of GA–PID controller is shown on Fig.9 below.

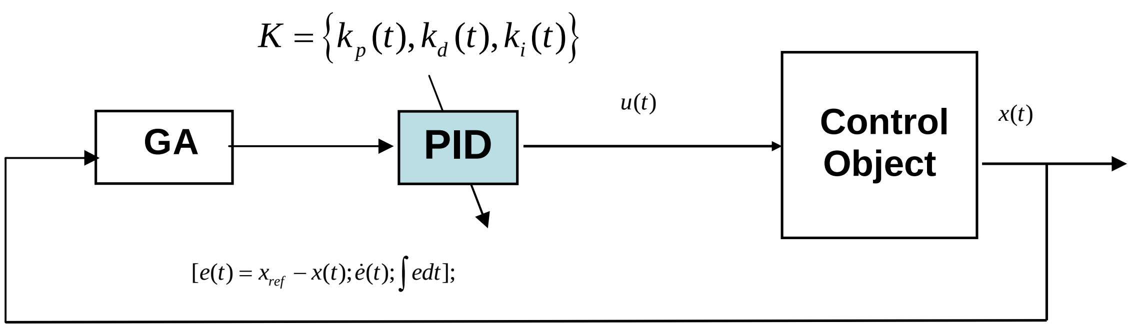


Figure 9.

Teaching conditions

We have the following TS control situation:

- Model Parameters: $\beta = 0.5; \alpha = 0.3; k_1 = 0.2; k = 5.$

- Initial conditions: [2.5] [0.1]; Reference signals: $x_{ref} = 0$
- Rayleigh noise shown in Fig.10 below.

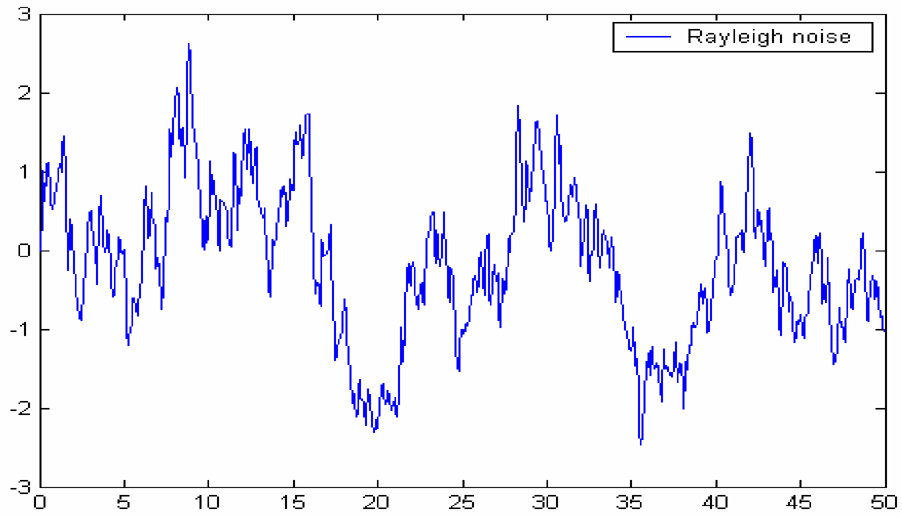


Figure 10 . Rayleigh noise used in teaching situation

For this case we will use the following GA parameters:

- GA parameters: search space for K-gains parameters: [0,10];
- GA FF: minimum of " control error".

In Fig.11 the comparison of motion under GA-PID and conventional PID control with PID gains K = [10 10 10] is shown. You can see that GA-PID control is more accurate than classical one.

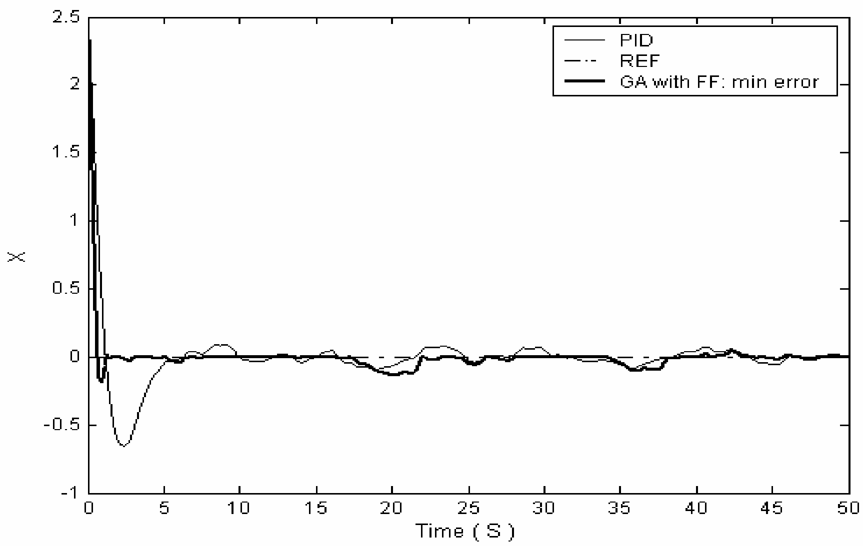


Figure 11. Nonlinear oscillator. GA- PID control

In practice, **it is difficult to realize physically control laws obtained by GA**. Moreover, TS doesn't contain knowledge information in direct form. Therefore, we need in one more step: an extraction of KB FC from TS obtained by GA. KB extraction task is equivalent to the task of TS approximation by corresponding FNN.

The task: extract KB from TS obtained by GA

KB extraction task is equivalent to the task of TS approximation by corresponding FNN.

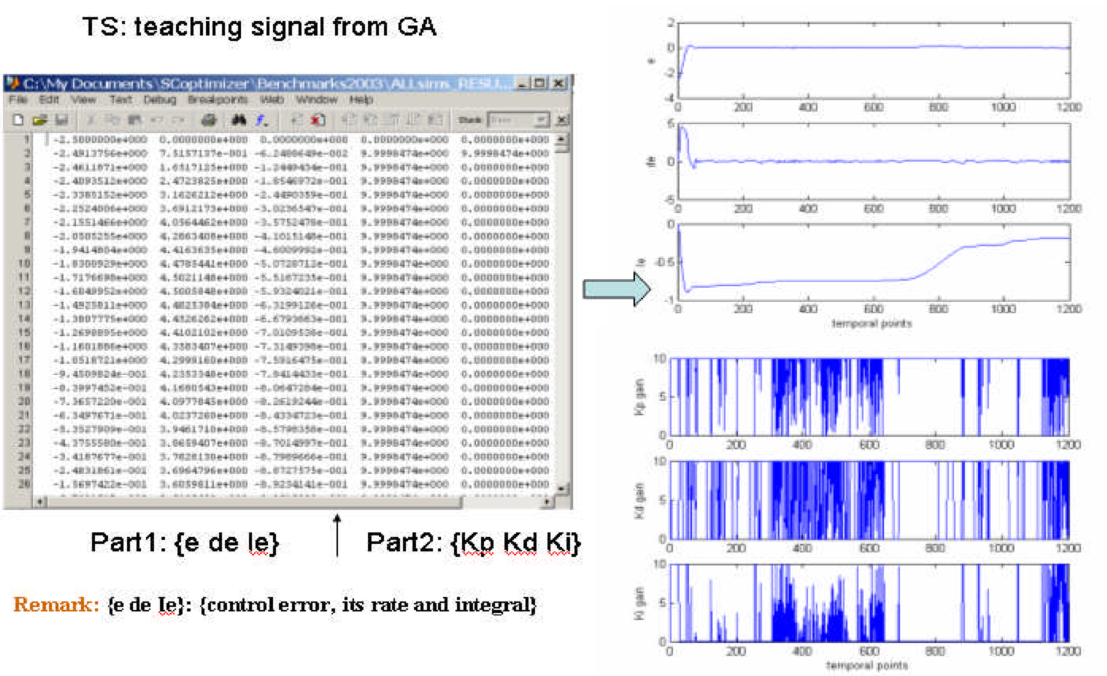


Figure 12.

FNN-based KB FC design process

For the given control task we will design FC-PID controller with three input variables to FC as $\left\{e, \dot{e}, \int edt\right\}$ and three output variables of FC as $\left\{k_p, k_d, k_i\right\}$.

For this aim we will use our developed tools and compare results with AFM-tools developed by STMicroelectronics (see http://eu.st.com/stonline/index.shtml).

AFM based KB design process is described as follows:

- Manual design of numbers of membership functions for each input variables: 5;
- Complete number of fuzzy rules: 5x5x5= 125 rules;
- Number of activated rules in KB**: 125 rules.**

In Fig.13 AFM representation of membership functions for input FC variables is shown.

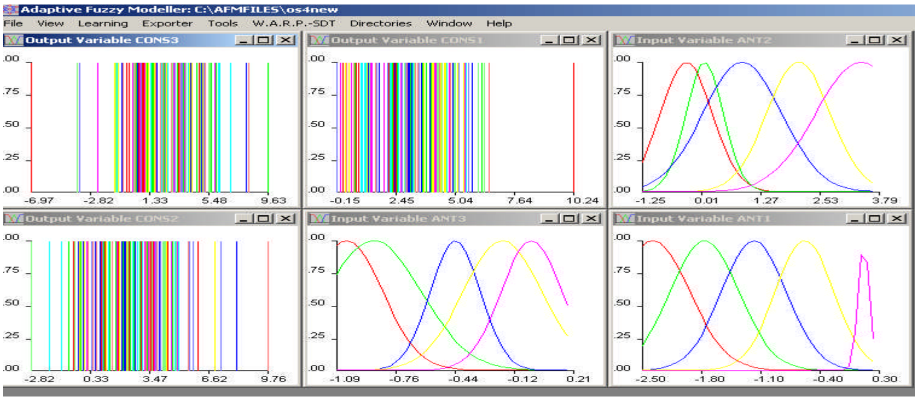


Figure 13. Nonlinear oscillator. AFM based membership functions representation

Remark: full comparison of our benchmark simulation results with AFM based simulation results you may find in published book (see vol 60).

Main disadvantage of traditional soft computing tools working with Fuzzy Neural Networks (FNN) is the following: FNN structure must be given *a priori* (i.e., the number and type of MF must be introduced by a user), but for complex dynamic systems, especially unstable dynamic systems, it is difficult to define the optimal FNN structure manually.

In our tools we define best shape of membership functions and their number (see description of SC Optimizer tools in corresponding place on the site). We define optimal structure of FNN by using GA and different information-thermodynamic criteria.

SC Optimizer-based KB FC design process

The process of KB FC design is described as follows:

- *Creation of linguistic values* by GA1 : number of membership functions for each input variables: 6,8,9 ;
- Complete number of fuzzy rules: 6x8x9 = 432 rules;
- *Rule selection* : with SUM of firing strength criterion (*Number of selected rules = 64)*
- *KB optimization by* GA2:
- *KB learning*: by BP algorithm

In Fig.14 SC Optimizer representation of membership functions and their shapes for third input FC variables is shown.

Remark. In AFM based representation number and MF shapes are selected manually by a user. In SC optimizer for each input variables optimal MF shapes and MF number are defined by GA.

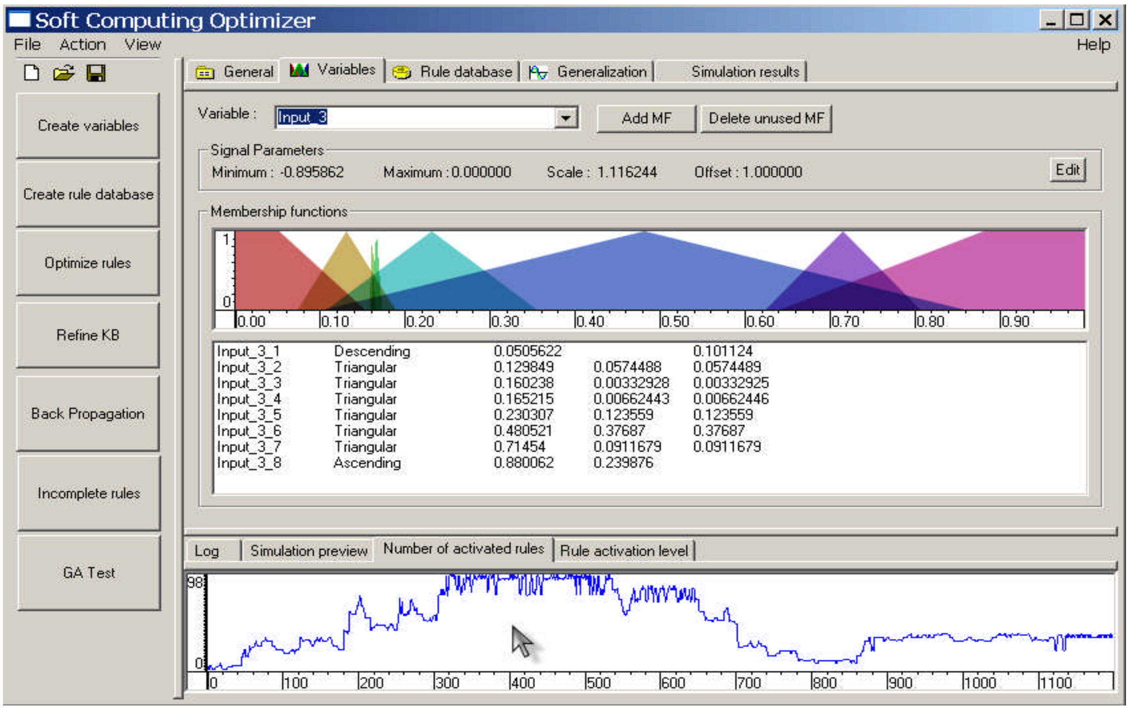


Figure 14. Nonlinear oscillator. SC Optimizer based membership functions representation

FNN design for the given TS

Chose Fuzzy Inference System as follows: Sugeno-0 with Fuzzy AND operation as a product.

KB

IF e is A_{n1} and $\dot{e}$ is B_{n2} and $\int edt$ is L_{n3}

THEN $k_p = C_{11}, k_I = D_{11}, k_d = E_{11}$

Total number of fuzzy rules:

$n_1 \times n_2 \times n_3$

Left parts of rules are designed according to information given in TS Part1.

Right part of rules unknown yet, choose some numbers from [0,1] and design FNN structure.

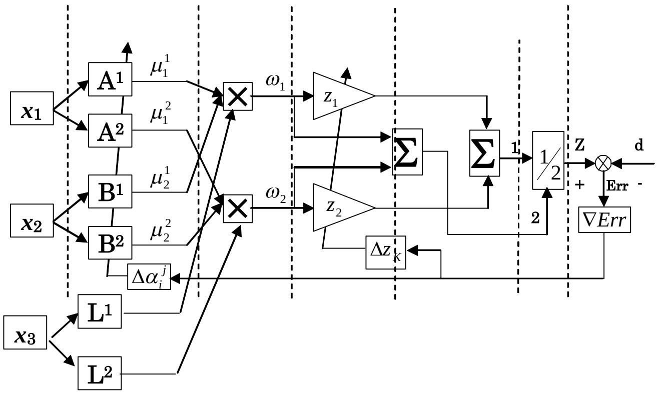


Figure 15.

Next step: Use TS and supervised learning for optimal FNN parameters defining.

FNN designed by SC Optimizer

Input : teaching Signal (TS) obtained at Stage 1 from GA.
Output : robust KB with optimal FNN structure.

Depending of chosen criterion used during KB design we obtain two “good” KBs (and FNN structures correspondingly): KB1 with 64 rules and KB2 with 31 rules.

KB1 representation

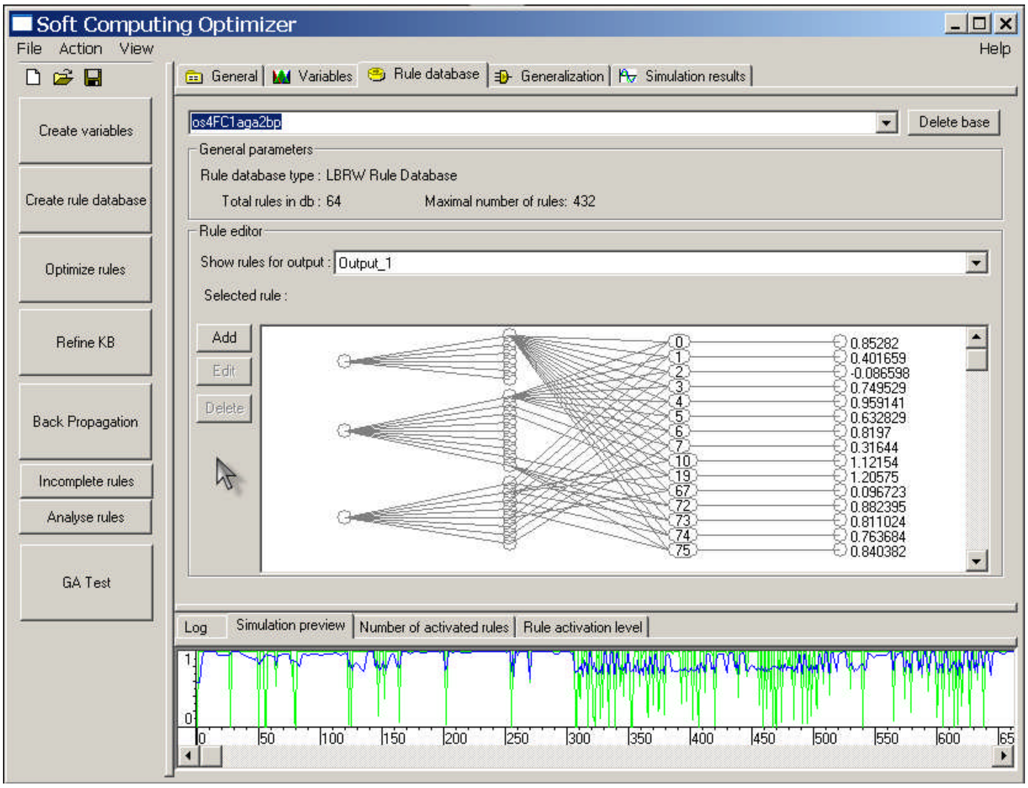


Figure 16 . KB1 with 64 rules

Remark: On Fig. 16 a green line represents a **Teaching signal of control signal;** Blue line – its **FNN approximation**

On Fig.17 dynamic behavior of control object under FC control with KB1 and comparison with PID control with K= [8 6 5] is shown. On Fig.18 control laws (Kp, Kd, Ki gains) are shown.

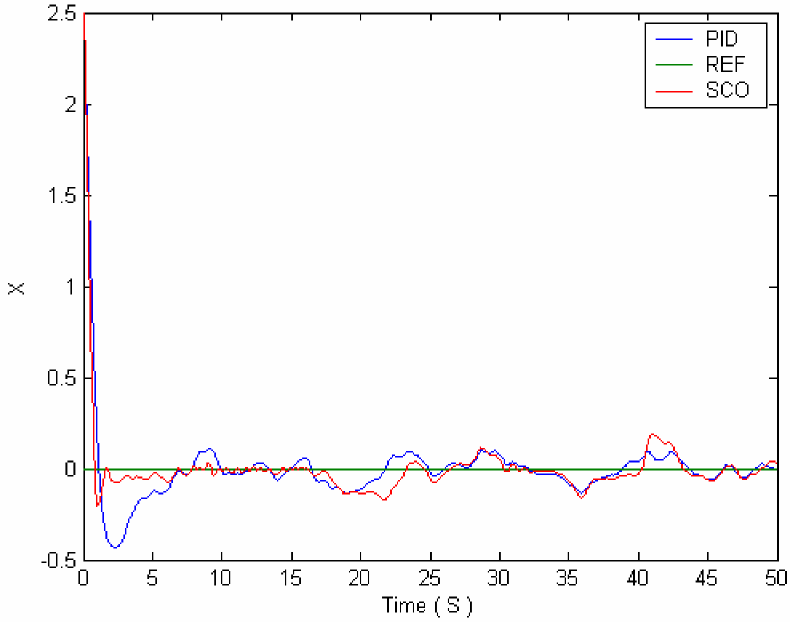


Figure 17. Dynamic motion under FC control with KB1 with 64 rules

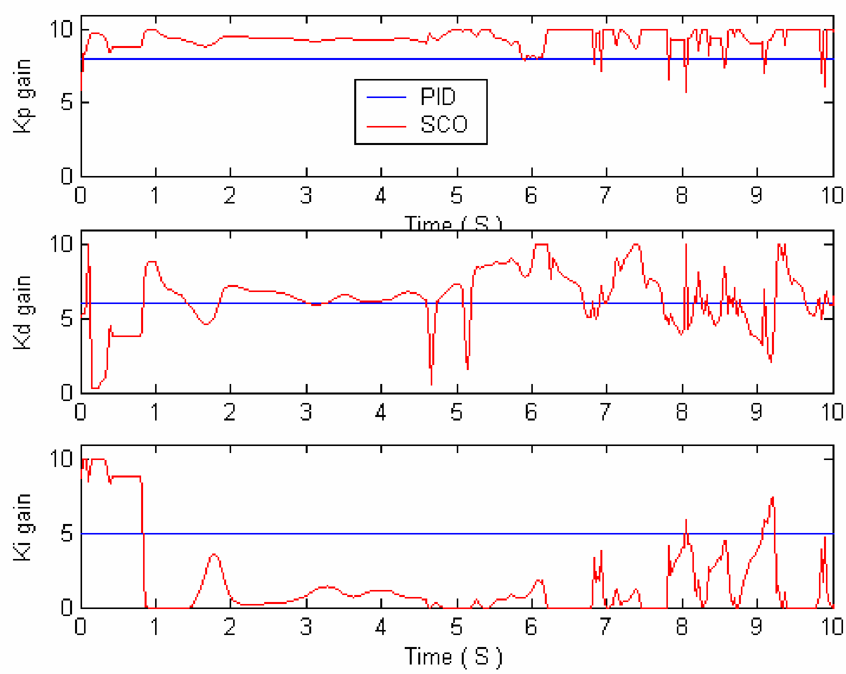


Figure 18. Control laws of FC control with KB1 with 64 rules

KB2 representation

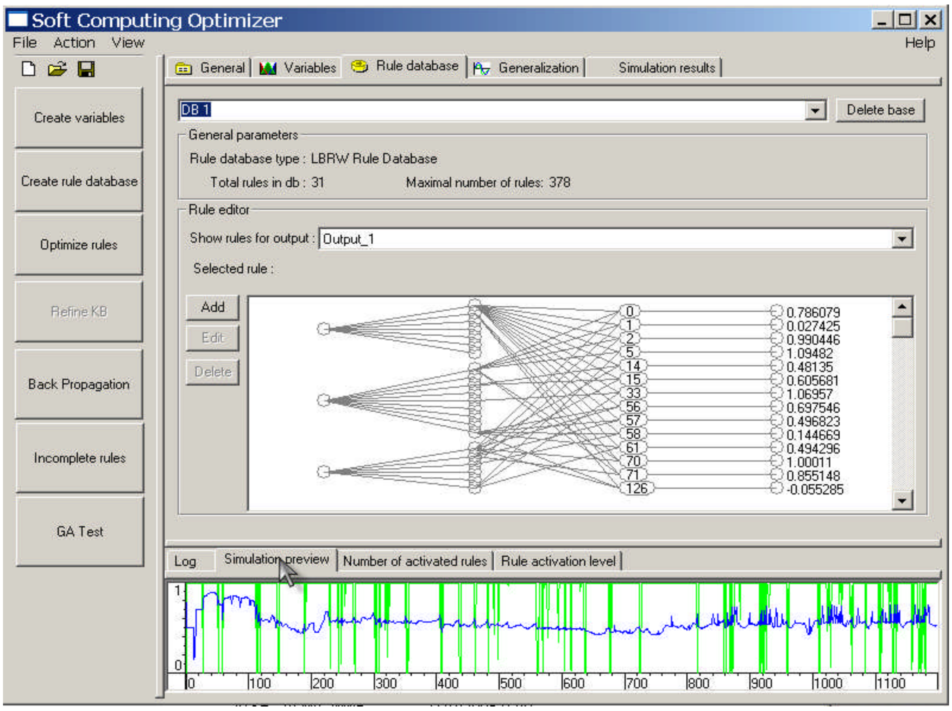


Figure 19. KB2 with 31 rules

Dynamic behavior of control object under FC control with KB2 and comparison with PID K= [7 7 1] is shown on Fig.20 below.

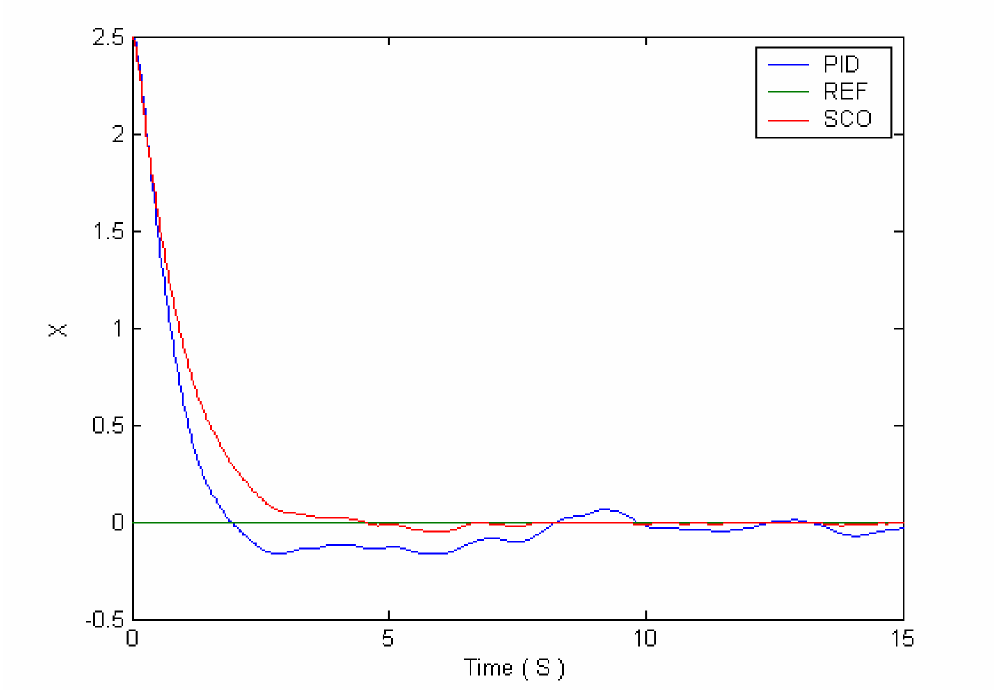


Figure 20. Dynamic motion under FC control with KB2 with 31 rules

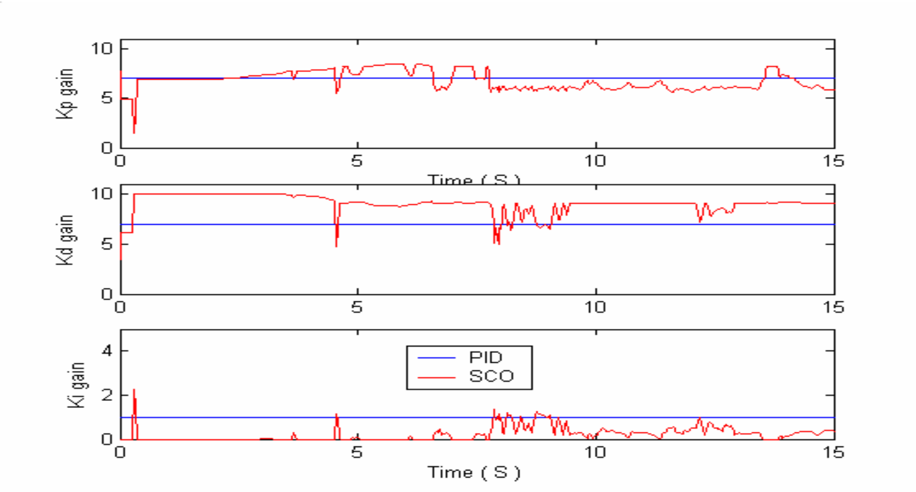


Figure 21. KB2 with 31 rules. Control laws comparison

General comparison of CO dynamic and thermodynamic behavior under there types of control: PID with K= [7 7 1] , FC with KB1 (with 64 rules) and FC with KB2 (with 31 rules) in the case of teaching conditions

On Figures 22 - 27 results of comparison of CO stochastic motion under three types of control are shown. Control laws for TS control situation are shown in Fig.25.

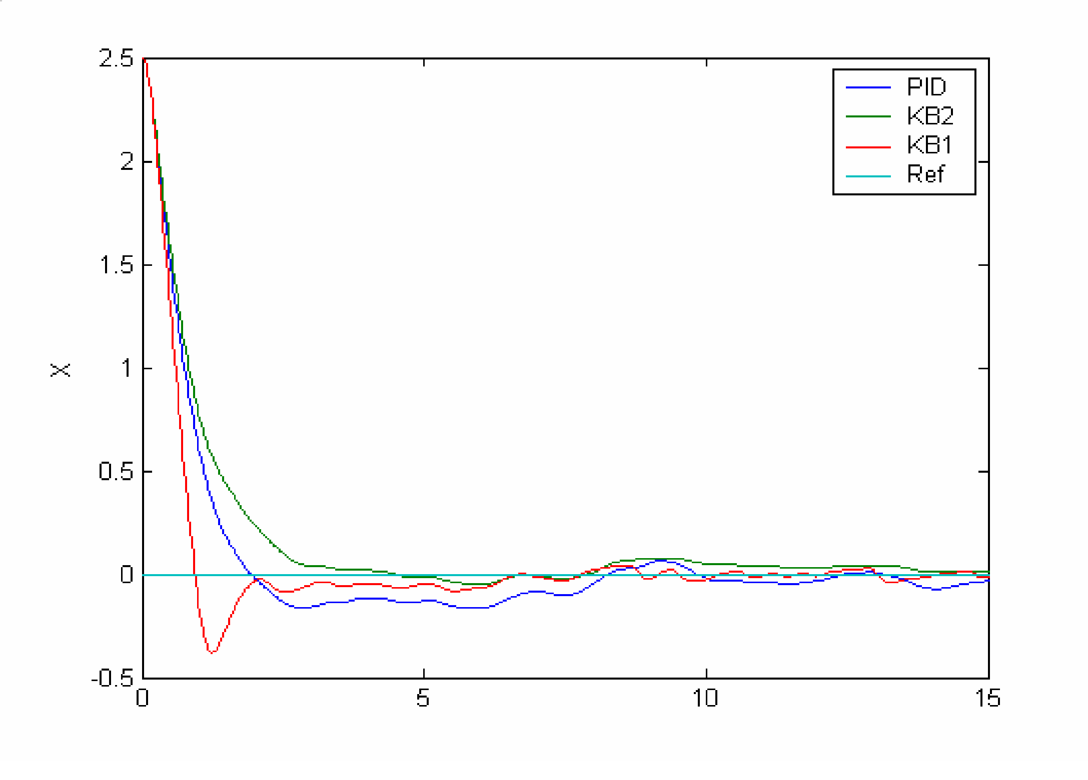


Figure 22. Dynamic motion under FC-KB1, FC-KB2 and PID

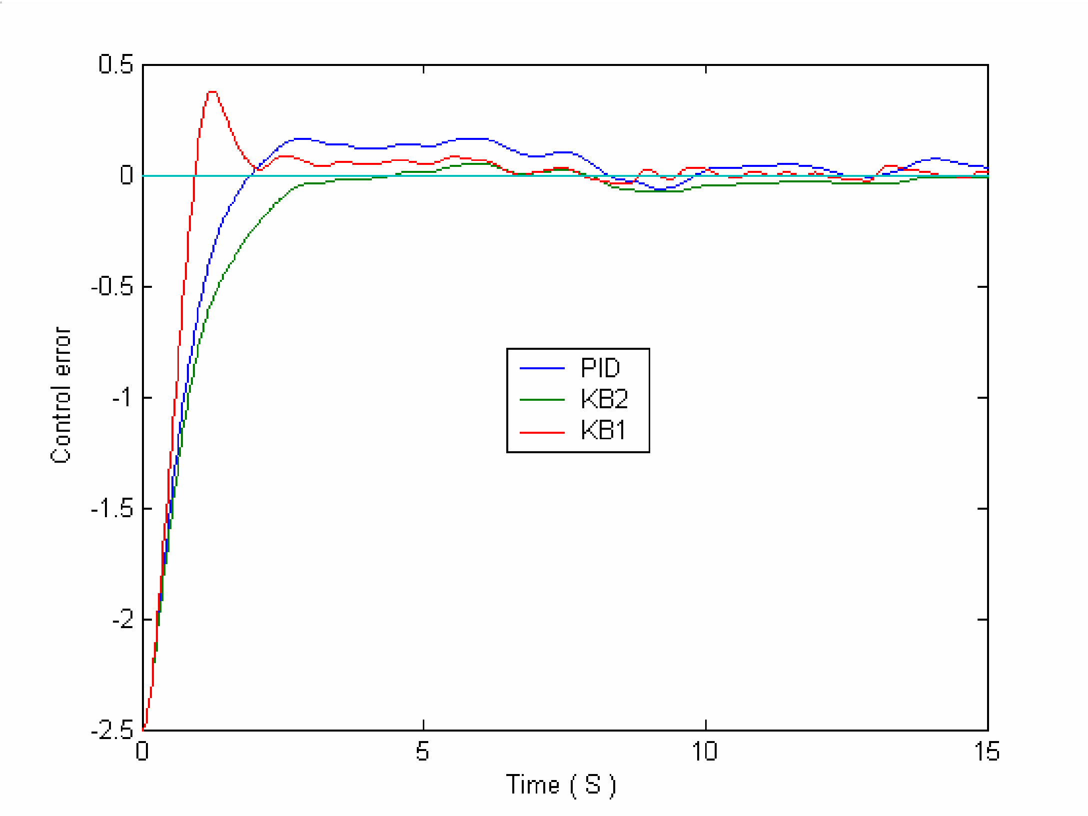


Figure 23. Control error comparison

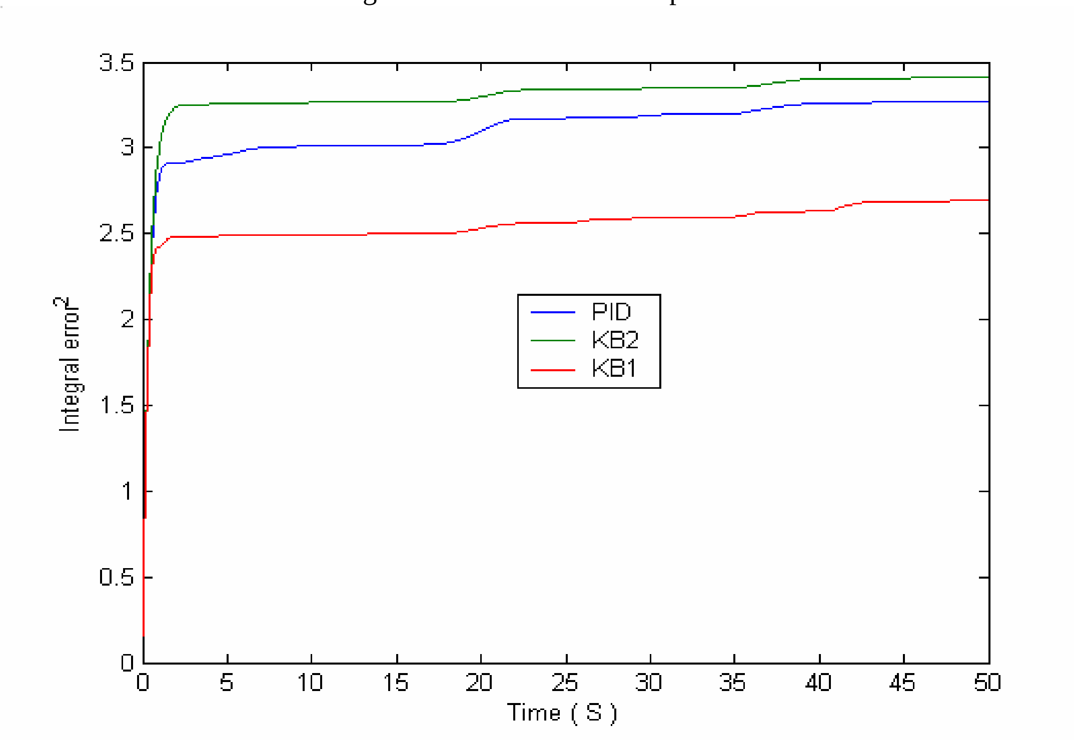


Figure 24. Integral of squared control error comparison

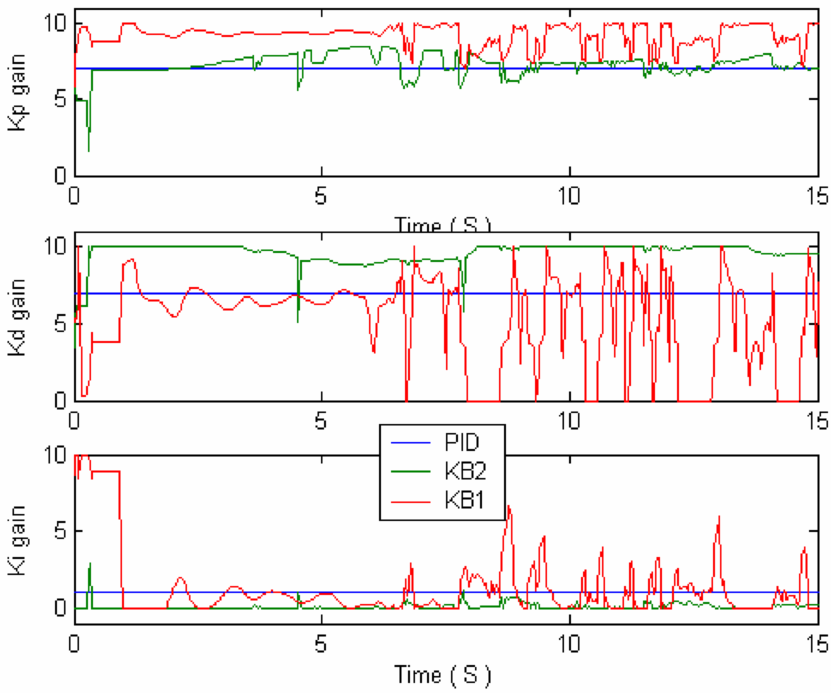


Figure 25. Control laws comparison

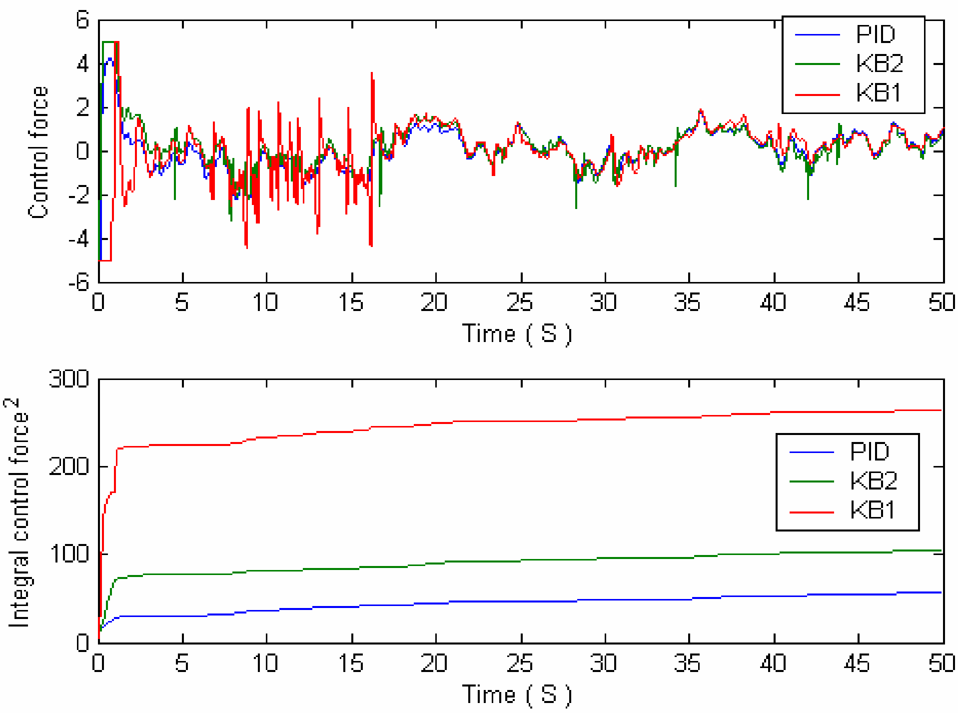


Figure 26. Control forces.

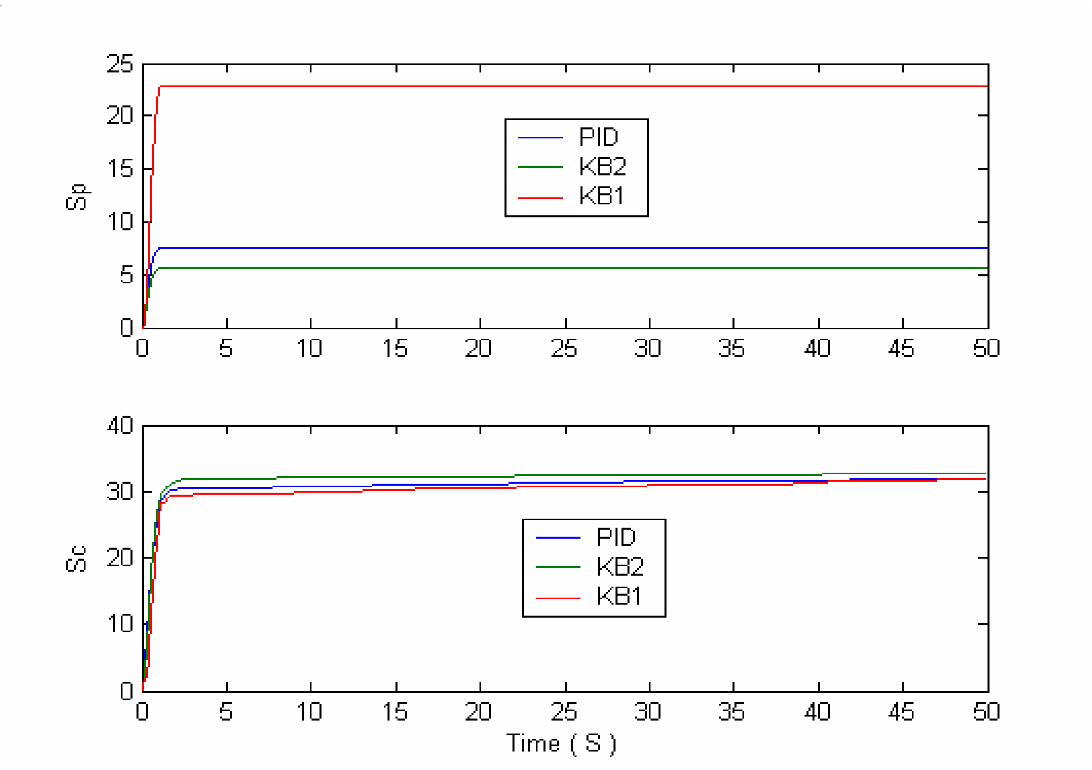


Figure 26. Thermodynamic behavior comparison

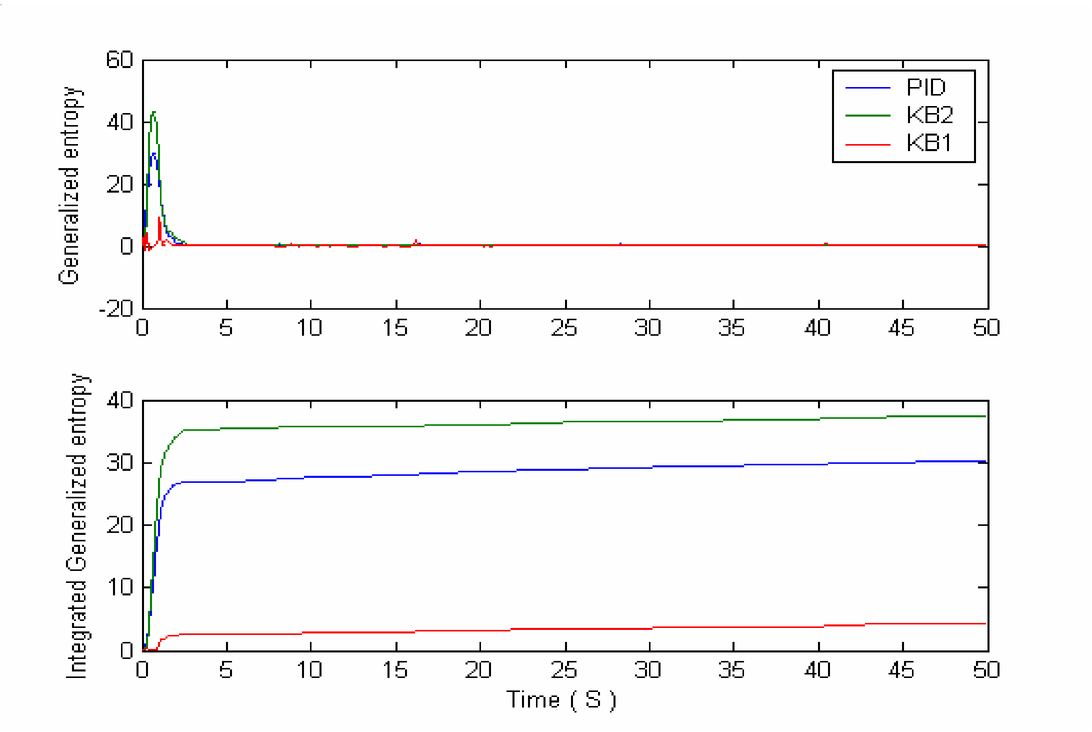


Figure 27. Thermodynamic behavior comparison

Main conclusions:
- by using SC and developed dools we can design a lot of optimal KBs satisfiing selected control quality criterion and chosen criteria of KB design;

From given above general comparison you can see that:
- KB1 is best KB from minimum of control error and generalized entropy production criteria;
- KB2 is best from a minimum of CO entropy production criterion;
- The given PID is best from integral control force criterion.

But main criterion of designed KBs is their robustness. Let's check this property and finally choose the best controller.

Robustness investigation of KB FC designed for the chosen teaching control conditions

Investigation of SC based FC controllers robustness region

1) *Simulated* ***new 1*** *control situation*
Let us take FC_SCO and PID with chosen k= [7 7 1] developed for the teaching conditions and use them in a *new control situation*, where

- new model parameters: $\beta = 0.1`; \alpha = 0.3; k_1 = 0.2; k = 5.$
- new type of noise: Gaussian (see Fig.28 below);

are considered.

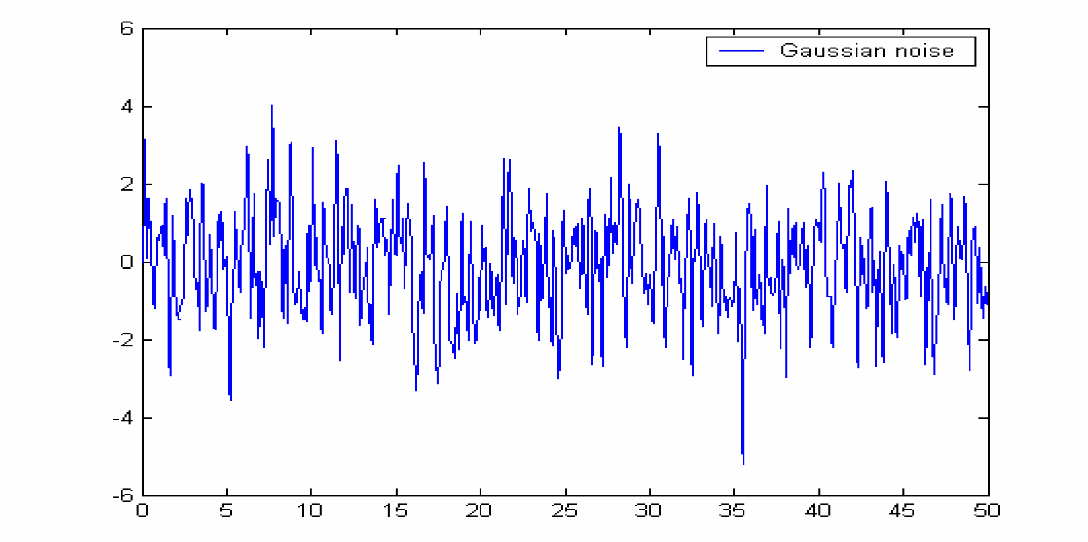
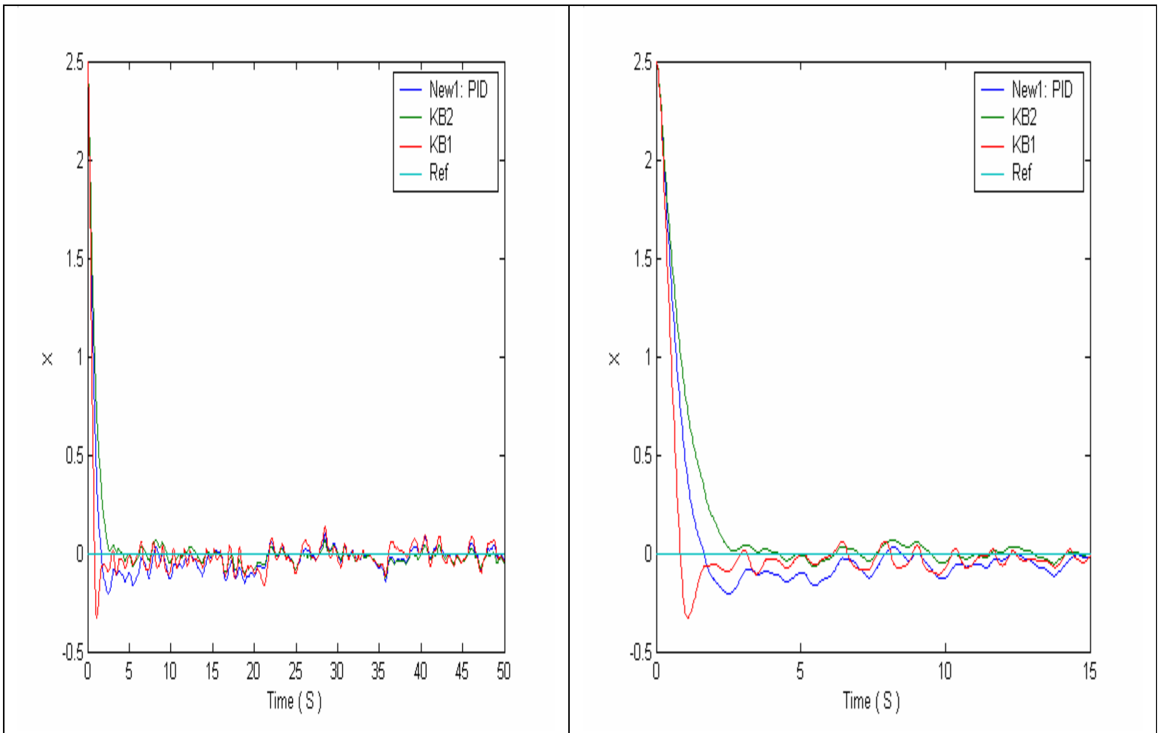


Figure 28.

In Fig. 29 and results of comparison of CO stochastic motion under three types of control in the new 1 control situation are shown.



CO dynamic motion | CO dynamic motion at transit stage

Figure 29. *New 1* control situation. Dynamic motion under FC-KB1, FC-KB2 and PID

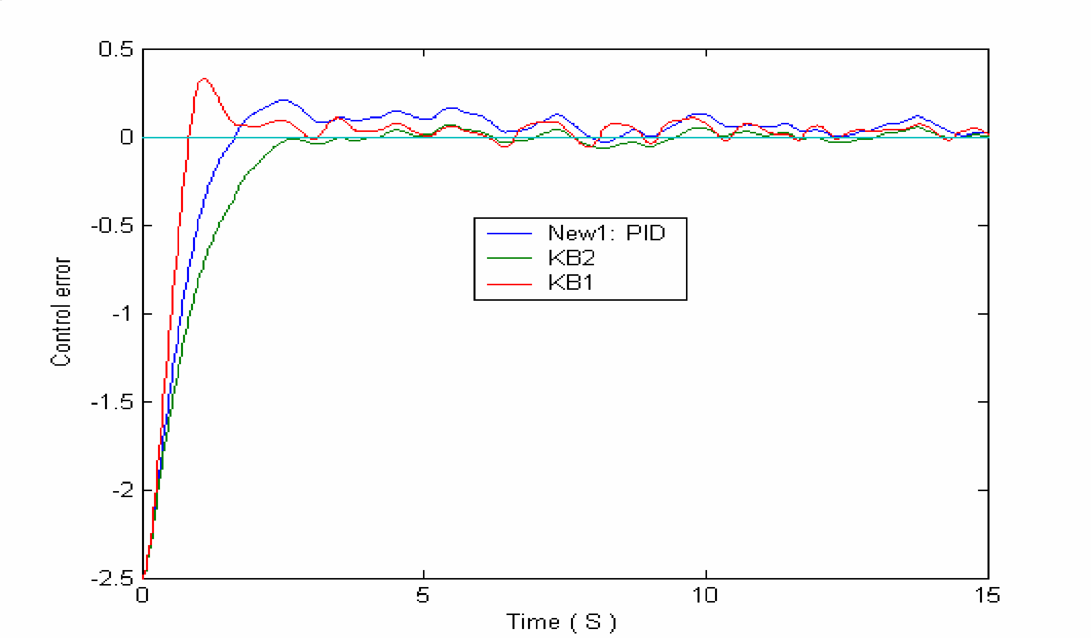


Figure 30. *New 1* control situation.Control error comparison

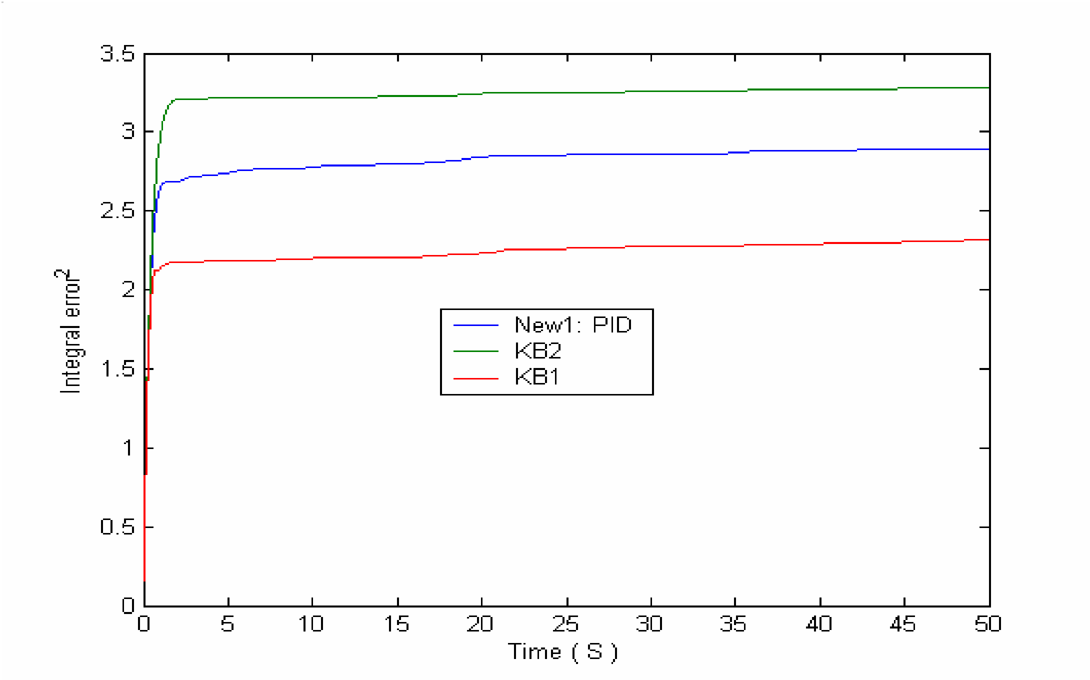


Figure 30. *New 1* control situation. Integral control error

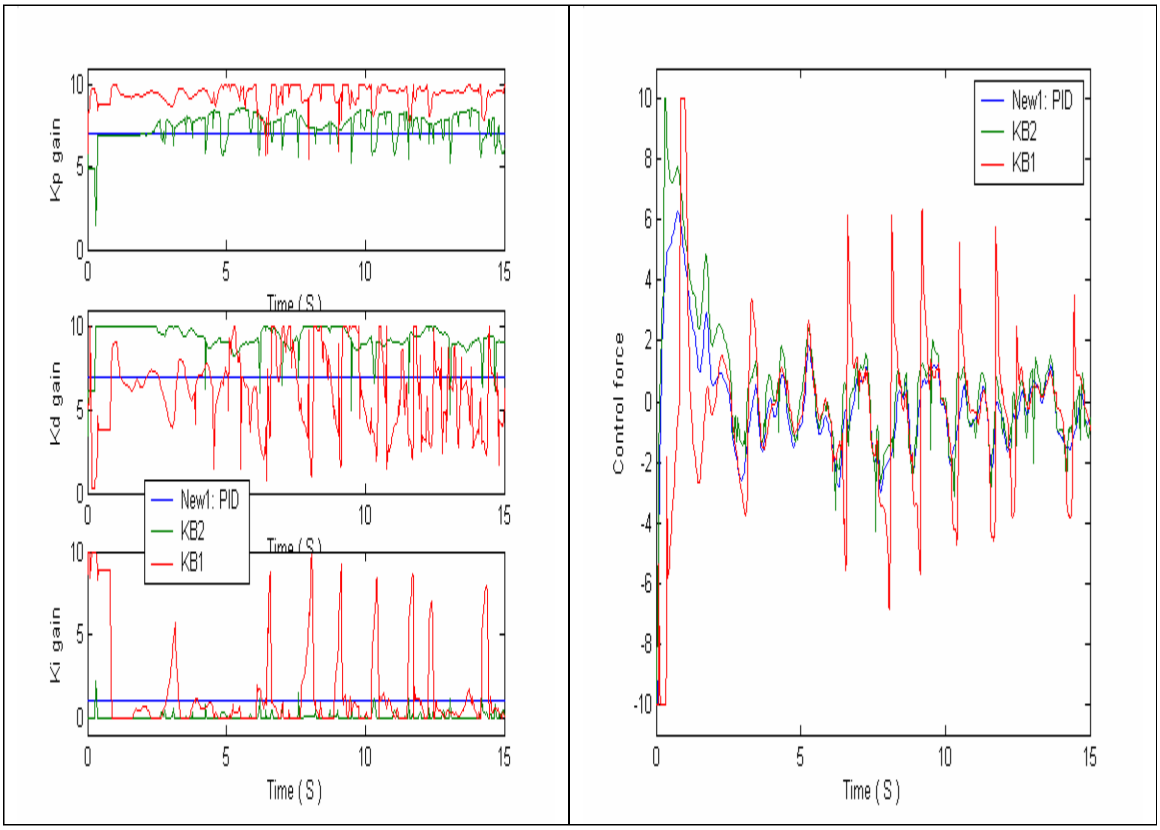


Figure 31. *New 1* control situation. Control laws and control forces

2) *Simulated* ***new 2*** *control situation*

Let us take FC_SCO and PID with chosen k= [7 7 1] developed for the teaching conditions and use them in a *new control situation*, where

- new model parameters: $\beta = -0.5`; \alpha = 0.3; k_1 = 0.2; k = 5.$
- new type of noise: Uniform (see Fig.32 below);

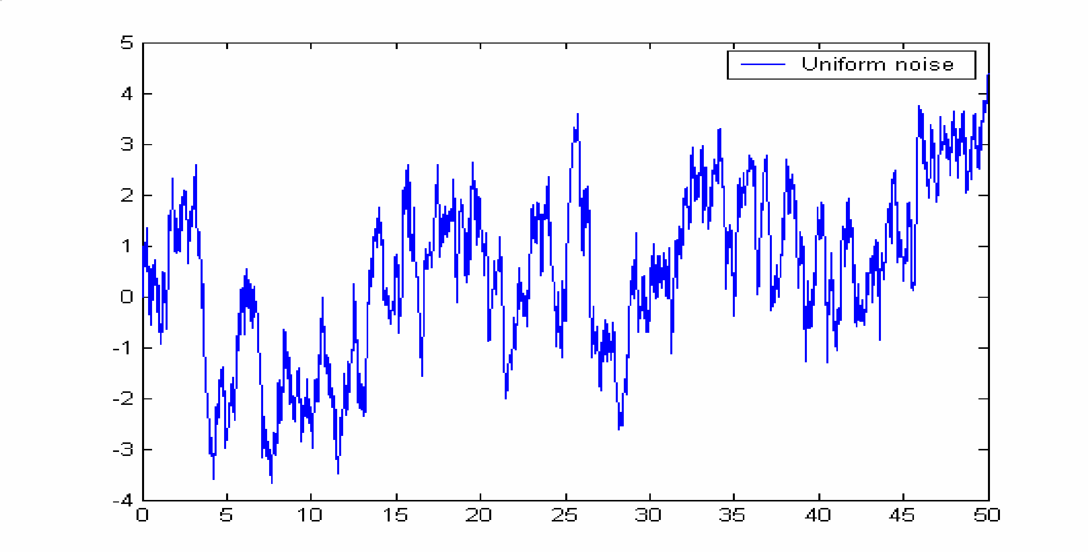


Figure 32.

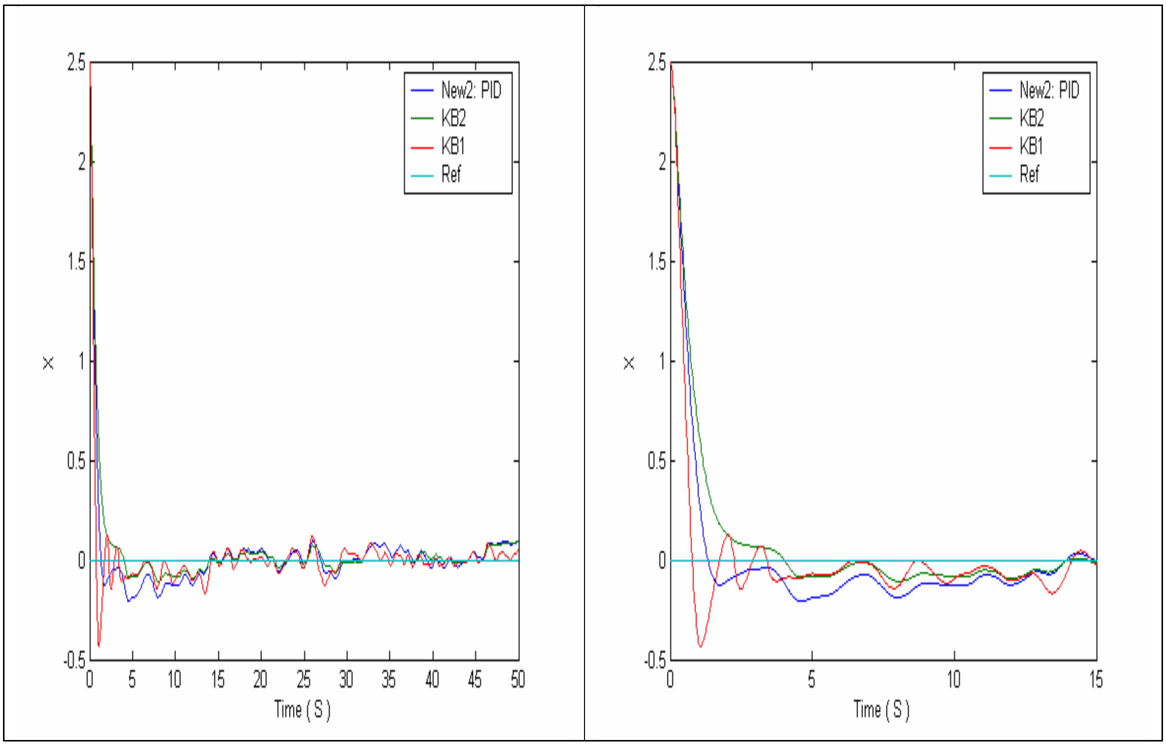


Figure 33. *New 2* control situation. Dynamic motion

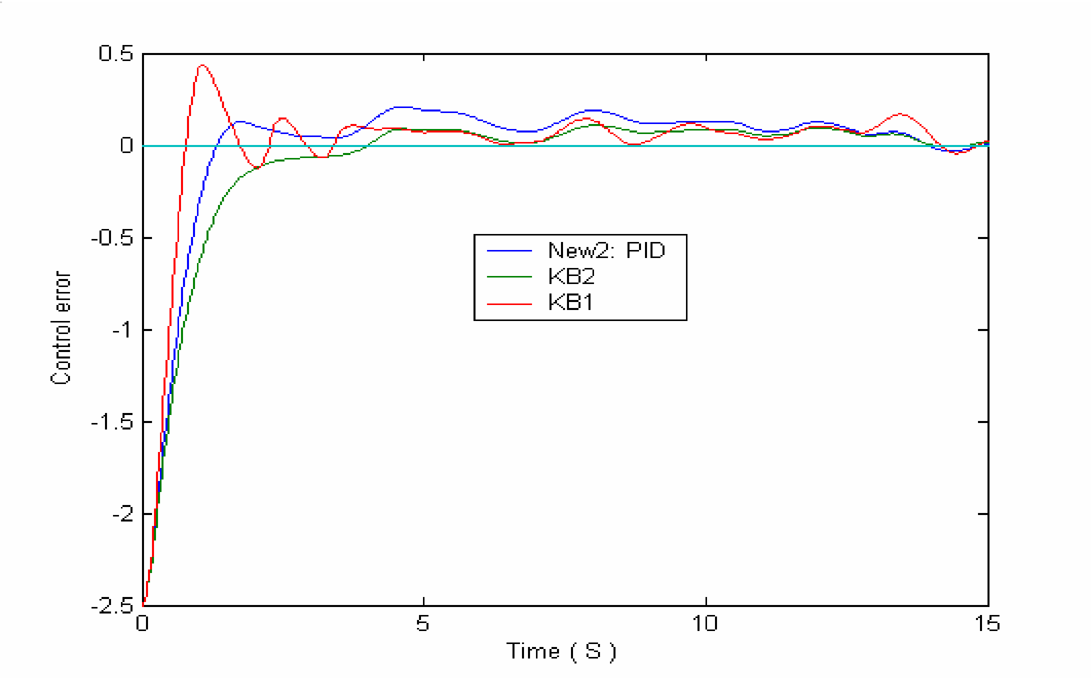


Figure 34. *New 2* control situation. Control error comparison

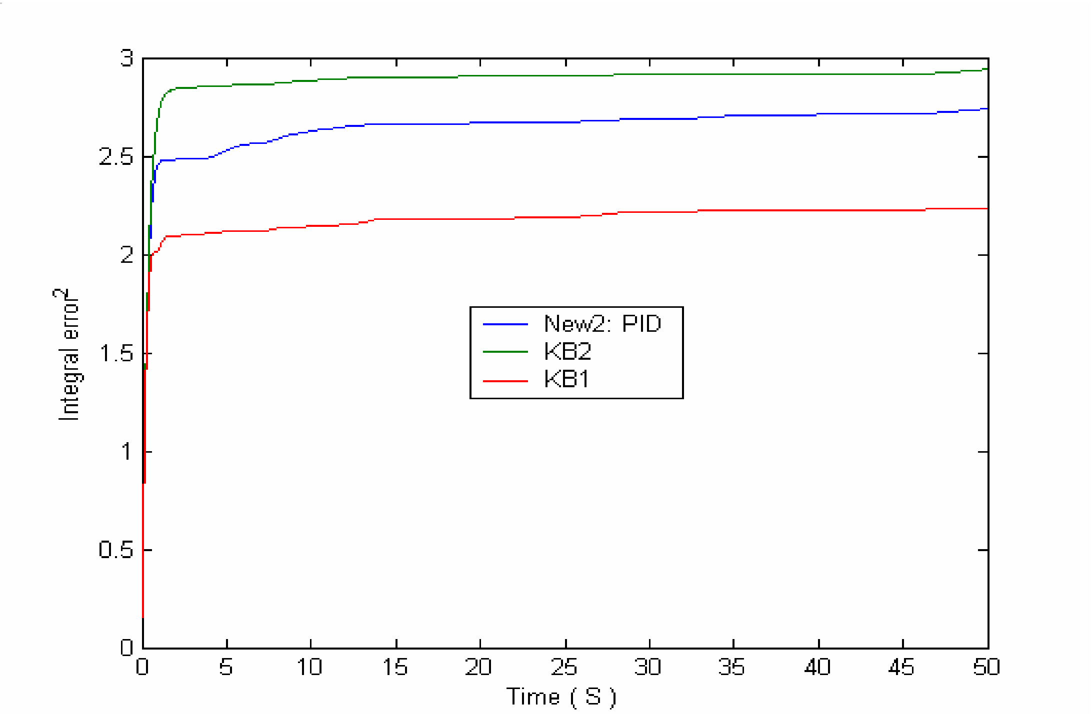


Figure 35. *New 2* control situation. Integral control error comparison

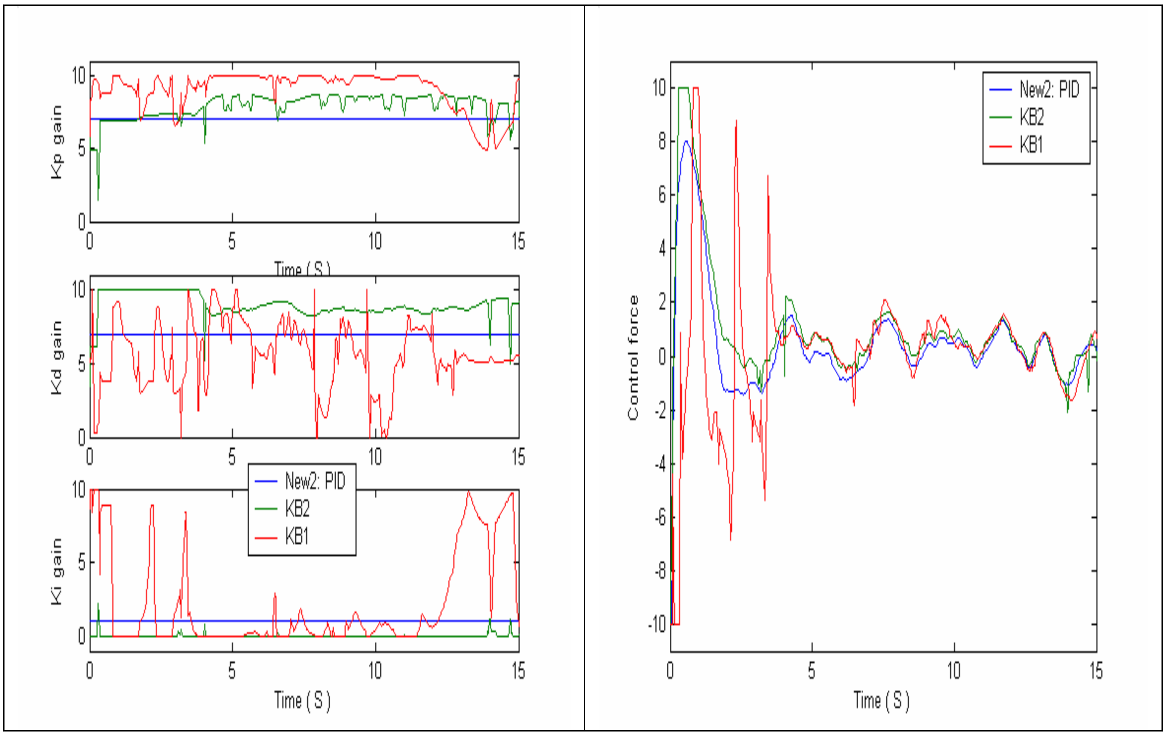


Figure 36. *New 2* control situation. Control laws and control forces

In real practical applications of FC controllers we have encounter with noises and time delay in sensors system. Let's introduce in control system loop time delay for a sensor system which measures the position *x* in our model. In Fig.37 below this control situation is shown.

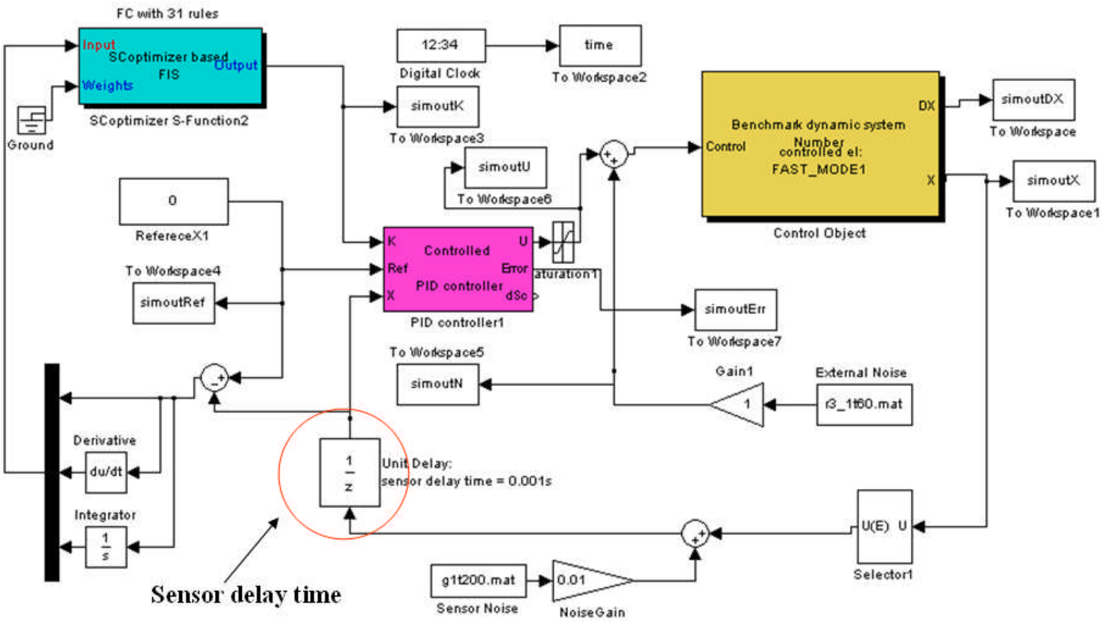


Figure 37.

3) *Simulated new 3 control situation*

Sensor time delay = 0.001 and force control limitation U<=10 (N) ; rest as in teaching conditions $\beta = 0.1`; \alpha = 0.3; k_1 = 0.2; k = 5.$

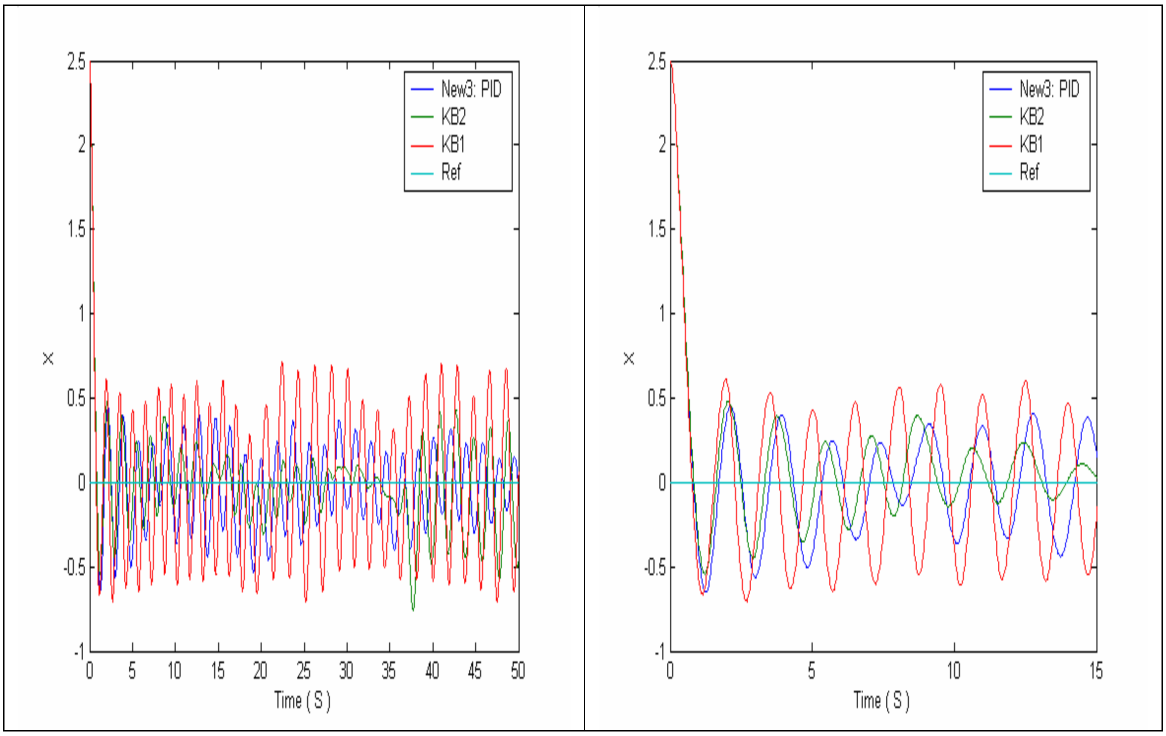


Figure 38. *New 3* control situation. Dynamic motion

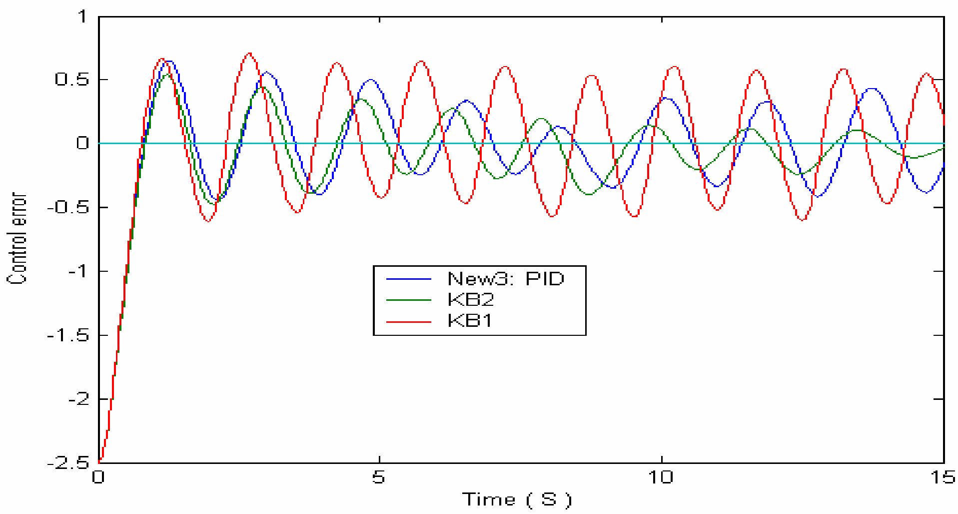


Figure 39. *New 3* control situation. Control error comparison

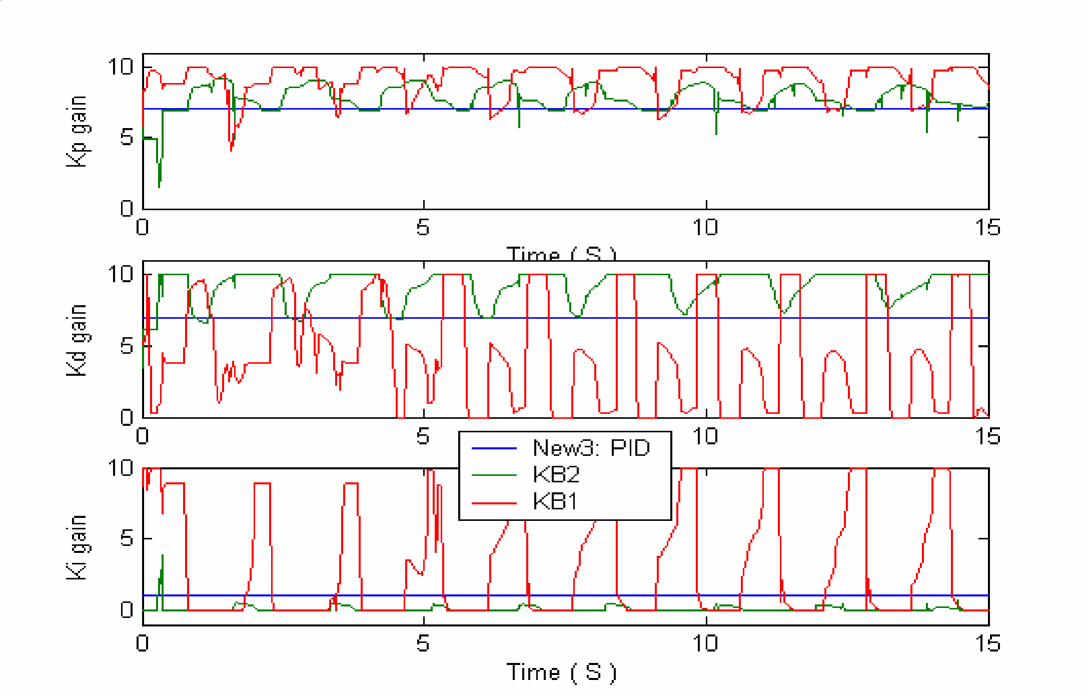


Figure 40. *New 3* control situation. Control laws

Main conclusions:

- PID and designed KB of FC controllers are not robust in the new 3 control situation;
- Simulation results for New3 situation show that PID and designed KB of FC controllers are very sensitive to a such factor as a sensor's time delay.
- Soft Computing technology has limitations on robustness property. SC based controllers may lose robustness property in complicated real and unpredicted control situations.