TOWARD A QUANTUM PID CONTROLLER DESIGN BASED ON QUANTUM INFERENCE: KNOWLEDGE BASE SELF-ORGANIZION FROM TWO K-GAINS OF CLASSICAL PID CONTROLLER

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A new problem – a Quantum PID controller design based on quantum inference (QI) from two K-gains (K_1 and K_2) of classical PID (with constant K-gains) controllers is investigate.

<u>Keywords</u>: PID controller tuning, quantum fuzzy inference, intelligent control, simulation of robust knowledge.

ПРОЕКТИРОВАНИЕ РОБАСТНОГО ПИД-РЕГУЛЯТОРА НА ОСНОВЕ ПРИМЕНЕНИЯ КВАНТОВОГО НЕЧЕТКОГО ВЫВОДА: САМООРГАНИЗАЦИЯ БАЗ ЗНАНИЙ НА ОСНОВЕ КОЭФФИЦИЕНТОВ УСИЛЕНИЯ ДВУХ КЛАССИЧЕСКИХ ПИД-РЕГУЛЯТОРОВ

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Рассматривается проектирование квантового ПИД-регулятора, основанное на применении квантового нечеткого вывода для постоянных коэффициентов управления двух классических ПИД-регуляторов.

<u>Ключевые слова</u>: ПИД регулятор, квантовый нечеткий вывод, интеллектуальное управление, моделирование робастной базы знаний.

Introduction: General problem of design

General problem of intelligent PID-controllers are considered in [1–5]. In this article we are considered the case of optimal robust PID controller with constants parameters that is very important for engineering applications.

On Fig. 1, the general structure of control system with quantum PID controller in the presence of external stochastic noise, sensor's time delay and noise in sensor system is shown.

Consider main ideas of *Quantum Inference based on two PID gains* [1–5]. We have the following computing steps.

First of all, for two teaching conditions we will design two *K*-gains , K_1 and K_2, by using genetic algorithm (GA) (a so called PID tuning based on GA): $K_1 = \left[k_P^1 \ k_D^1 \ k_I^1 \right]$ and $K_2 = \left[k_P^2 \ k_D^2 \ k_I^2 \right]$.

By using artificial stochastic noise disturb obtained *K*-gains as follows:

$$K_{1,2}(t) = \begin{bmatrix} k_P + G_P \cdot \xi(t) \\ k_D + G_D \cdot \xi(t) \\ k_I + G_I \cdot \xi(t)] \end{bmatrix}, \text{where} \, \xi(t) - stochastic \text{ noise with amplitude 1}$$

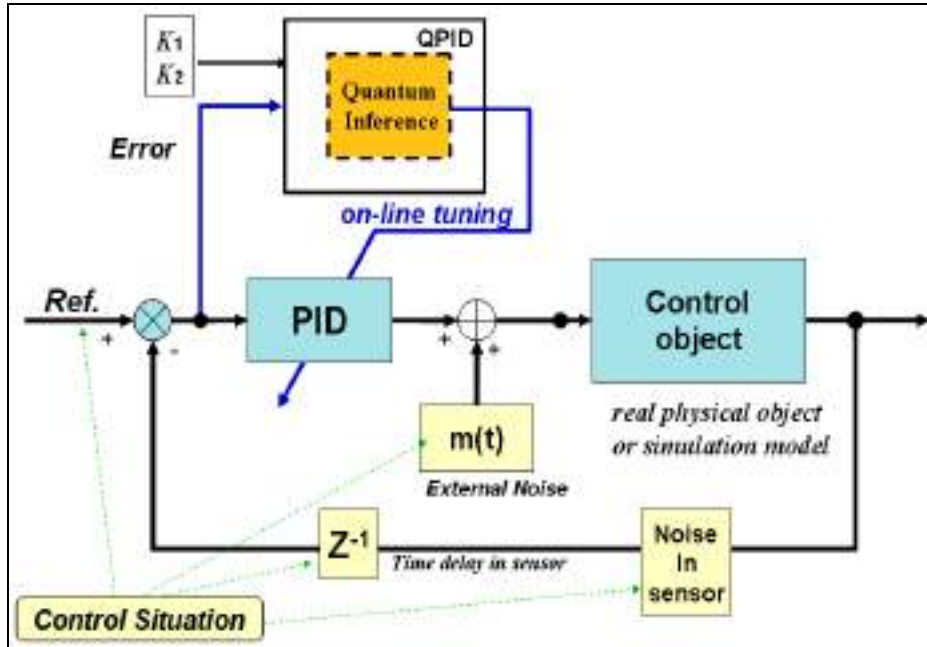and G_P, G_D, G_I are increasing/decreasing coefficients that can be chosen manually.

Figure 1. General structure of QPID based on two K-gains of classical PID and quantum inference

In two teaching conditions, simulate control object motion with new disturbed *K*-gains and design two probability distributions of *K*- signals for design of states $|0\rangle$ and $|1\rangle$ in quantum inference.

Realize quantum inference process with the following steps [3–5].

Step 1: Coding.

Preparation of all normalized states $|0\rangle$ and $|1\rangle$ for current values of disturbed control signals K_1 and K_2 including:

(a) calculation of probability amplitudes α_0, α_1 of states $|0\rangle$ and $|1\rangle$ from histograms;

(b) by using α_1 calculation of normalized value of state $|1\rangle$.

Step 2: Choose quantum correlation type for preparation of entangled state.

Consider the following quantum correlation (spatial):

$$e_1 e_2 k_P^{1,2} k_D^{1,2} \to k_P^{new} \cdot gain_P;$$
$$\dot{e}_1 \, \dot{e}_2 \, k_D^{1,2} k_I^{1,2} \to k_D^{new} \cdot gain_D;$$
$$Ie_1 \, Ie_2 \, k_I^{1,2} k_P^{1,2} \to k_I^{new} \cdot gain_I;$$

where $e, \dot{e}, Ie$ – are control error, derivative and integral of control error and $gain_{P(D,I)}$ – are QI scaling factors that can be obtained by GA. So, a quantum state $|a_1 a_2 a_3 a_4 a_5 a_6\rangle = |e_1 e_2 k_P^1(t) k_D^1(t) k_P^2(t) k_D^2(t)\rangle$ is considered as entangled state.

Step 3: Superposition and Entanglement.

According to the chosen quantum correlation type construct superposition of entangled states.

Step 4: Interference and measurement.

Choose a quantum state $\left| a_1 a_2 a_3 a_4 a_5 a_6 \right\rangle = \left| e_1(t) e_2(t) k_P^1(t) k_D^1(t) k_P^2(t) k_D^2(t) \right\rangle$ with maximum amplitude of probability $A = \sqrt{P_{e_1}} \cdot \sqrt{P_{e_2}} \cdot \sqrt{P_{k_P^1}} \cdot \sqrt{P_{k_D^1}} \cdot \sqrt{P_{k_P^2}} \cdot \sqrt{P_{k_D^2}}$. Choose subvector $\left| k_P^1(t) k_D^1(t) k_P^2(t) k_D^2(t) \right\rangle$.

Step 5: Decoding.

Calculate normalized output as a norm of subvector of the chosen quantum state as follows:

$$k_P^{new}(t) = \frac{1}{\sqrt{2^{n-2}}} \sqrt{\left\langle a_3...a_n \mid a_3...a_n \right\rangle} = \frac{1}{\sqrt{2^{n-2}}} \sqrt{\sum_{i=3}^{n} (a_i)^2} \ .$$

Step 6: Denormalization.

Calculate final (denormalized) output result as follows:

$$k_P^{output} = k_P^{new}(t) \cdot gain_P, \quad k_D^{output} = k_D^{new}(t) \cdot gain_D, \quad k_I^{output} = k_I^{new}(t) \cdot gain_I.$$

Step 6a: find robust QI scaling gains $\{gain_P, gain_D, gain_I\}$ based on GA and a chosen fitness function.

Let us choose one benchmark of control object and investigate robustness and self-organization properties of proposed QPID controller based on developed QI algorithm. In simulation results demonstrated below we describe first, preliminary, simulations. More deep study of proposed QPID model is the aim of further future investigations.

Quantum PID based smart control design: example of benchmark simulation results

The geometrical model of control object as «cart-pole system» is shown in Fig. 2.
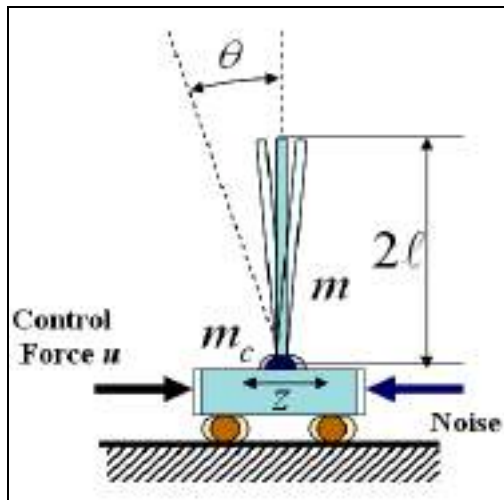

Figure 2. Geometrical model of cart-pole system

The inverted pendulum (called also a pole) problem control is described by second-order differential equations for calculating the force to be used for moving the cart:

$$\ddot{\theta} = \frac{g \sin\theta + \cos\theta \left(\dfrac{+(u+\xi(t)) + \{+a_1\dot{z} + a_2 z\} - ml\dot{\theta}^2 \sin\theta}{m_c + m} \right) - k\dot{\theta}}{l\left(\dfrac{4}{3} - \dfrac{m\cos^2\theta}{m_c + m} \right)},$$

$$\ddot{z} = \frac{u + \xi(t) + \{-a_1\dot{z} - a_2 z\} + ml(\dot{\theta}^2 \sin\theta - \ddot{\theta}\cos\theta)}{m_c + m},$$

where z and θ are generalized coordinate; g is the acceleration due to gravity (usually $9.8\,m/\sec^2$), m_c is the mass of the cart, m is the mass of inverted pendulum (called also as a pole), l is the half-length of the pendulum, k and a_1 are friction coefficients in z and θ correspondingly, a_2 is a spring force in cart , $\xi(t)$ is external stochastic noise and u is the applied control force in Newton's.

PID controller is connected with a cart. In this case for the pole stabilization ($\theta = 0$) we introduce a new reference signal for z as follows: z_{ref} (a reference signal for z) is a projection on axis z of the center of gravity of the pole. It must be 0 for stabilization the pole motion.

We can represent z_{ref} as follows: $z_{ref} = -w \cdot l \cdot \sin\theta,$ where w is some scaling parameter. If $\theta \to 0; z_{ref} \to 0$. We also introduce limitations on the center of gravity projection: $\left| z_{ref} \right| \le 1$ and on applied control force: $\left\lfloor u \right\rfloor \le 5\,(N)$.

Teaching conditions for PID tuning

In Table 1 model parameters for the chosen control object are described.

Table 1. Cart-Pole System: Model Parameters

m_C [kg]	m [kg]	l [m]	Damping in q, k	Damping in z, a2	Spring force coefficient in dz,a1
1.0	0.1	0.5	0.4	0.1	5.0

We also take the following Cart-Pole initial conditions:

The pole angle θ = [10 ; 0.1] in degrees; cart position z =[0; 0] in m.

Constraints: Cart position: $-1.0 < z < 1.0$ [m]; Control Force: $-5.0 < u < 5.0$ [N] .

Sensor's delay time = 0.001 sec.

We will use two stochastic external noises (shown on Fig. 3) for two teaching conditions with different probability distribution density functions: Gaussian noise (symmetric probability distribution density function) and Rayleign noise (with nonsymmetrical probability distribution density function).
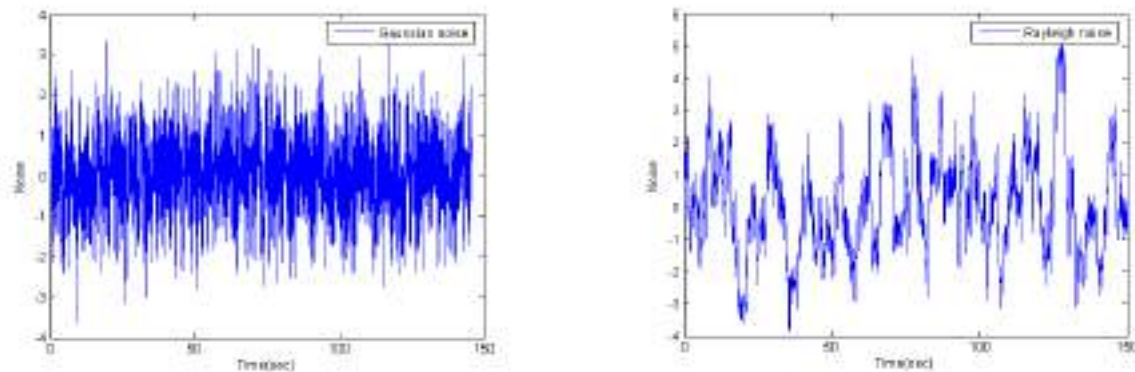
Figure 3. External stochastic noises in teaching control situations

According to description of QI algorithm above at first stage let us find for two teaching conditions two K-gains K_1 and K_2 by using GA.

PID tuning based on GA

Search space for PID gains K = [100 100 100] is defined from preliminary simulations with PID control. We will use the following Fitness Function (y) for GA tuning:

$$y = -\sum_t \theta^2 - \sum_t \dot{\theta}^2 .$$

In *Matlab*, fitness function is represented as follows:

$$y = -sum(\text{simoutX}(:,1).^2) / \text{Norm} - sum(\text{simoutX}(:,2).^2) / \text{Norm}$$

where simoutX(:,1) is a vector of angle values; simoutX(:,2) is a vector of angular velocity values and Norm is a length of these vectors.

Teaching conditions 1 *with Gaussian noise* (named as TS1). As result of GA tuning we obtained the following $K_1 = [82.7 \ 13.6 \ 9.4]$. We will call PID with K_1 as PID1.

Teaching conditions 2 *with Rayleigh noise* (named as TS2). As result of GA tuning we obtained $K_2 = [92.2 \ 14.9 \ 7.84]$. We will call PID with K_2 as PID2.

Now consider the motion of our control object under disturbed *K*-gains as shown below:

1. TS1 control situation

$$K_1(t) = \begin{bmatrix} k_p + gain_p \cdot \xi(t) \\ k_d + gain_d \cdot \xi(t) \\ k_i + gain_i \cdot \xi(t)] \end{bmatrix} = \begin{bmatrix} 82.7 + 20 \cdot \xi(t) \\ 13.6 + 10 \cdot \xi(t) \\ 9.4 + 5 \cdot \xi(t)] \end{bmatrix}, \text{where } \xi(t) - G\text{aussian noise with amplitude 1.}$$

(a) Pole motion with constant K   (b) Pole motion with variable K
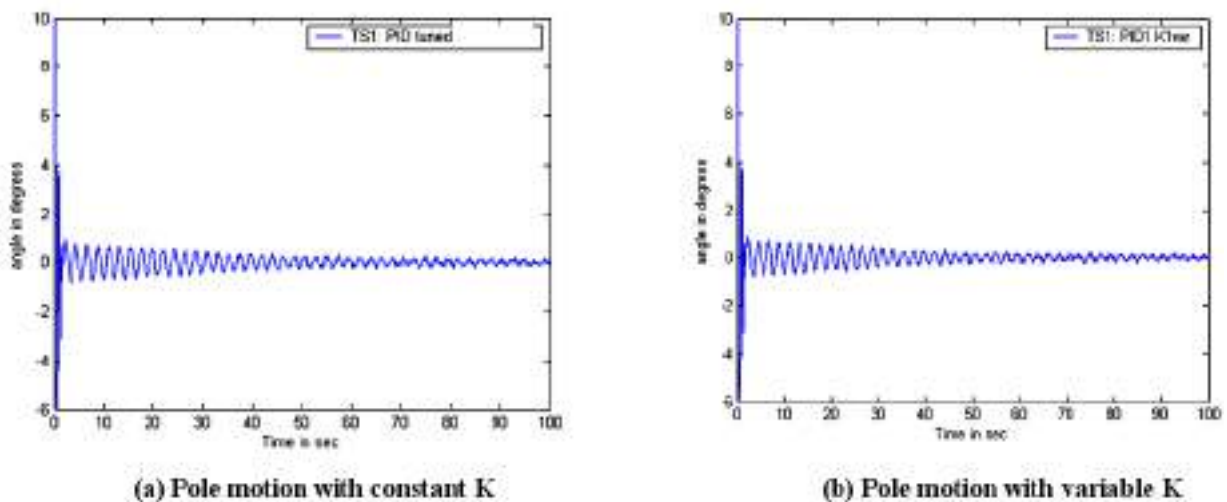
Figure 4. Teaching conditions 1: Pole motion with constant and disturbed K-gains of PID1

Simulation results show that the pole motion is stable in both cases.

On Fig. 5 the disturbed K-gains of PID1 (called as control laws) are shown.
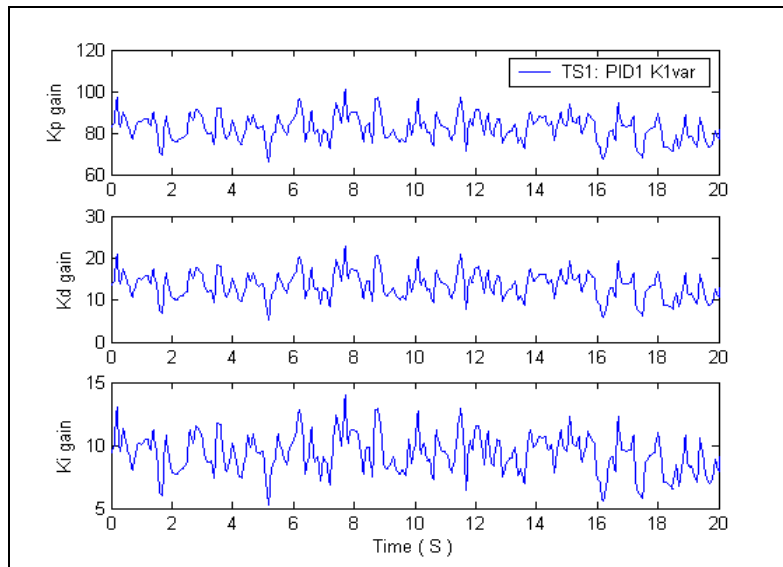
Figure 5. Teaching conditions 1: Control laws

Remark. On Fig. 6 and all others below we will denote pole angle θ as *x*.

2. TS2 control situation

$$K_2(t) = \begin{bmatrix} k_p + gain_p \cdot \xi(t) \\ k_d + gain_d \cdot \xi(t) \\ k_i + gain_i \cdot \xi(t)] \end{bmatrix} = \begin{bmatrix} 92.2 + 20 \cdot \xi(t) \\ 14.9 + 10 \cdot \xi(t) \\ 7.84 + 5 \cdot \xi(t)] \end{bmatrix}, \text{ where } \xi(t) - \text{gaussian noise with amplitude 1.}$$

(a) Pole motion with constant K

(b) Pole motion with variable K
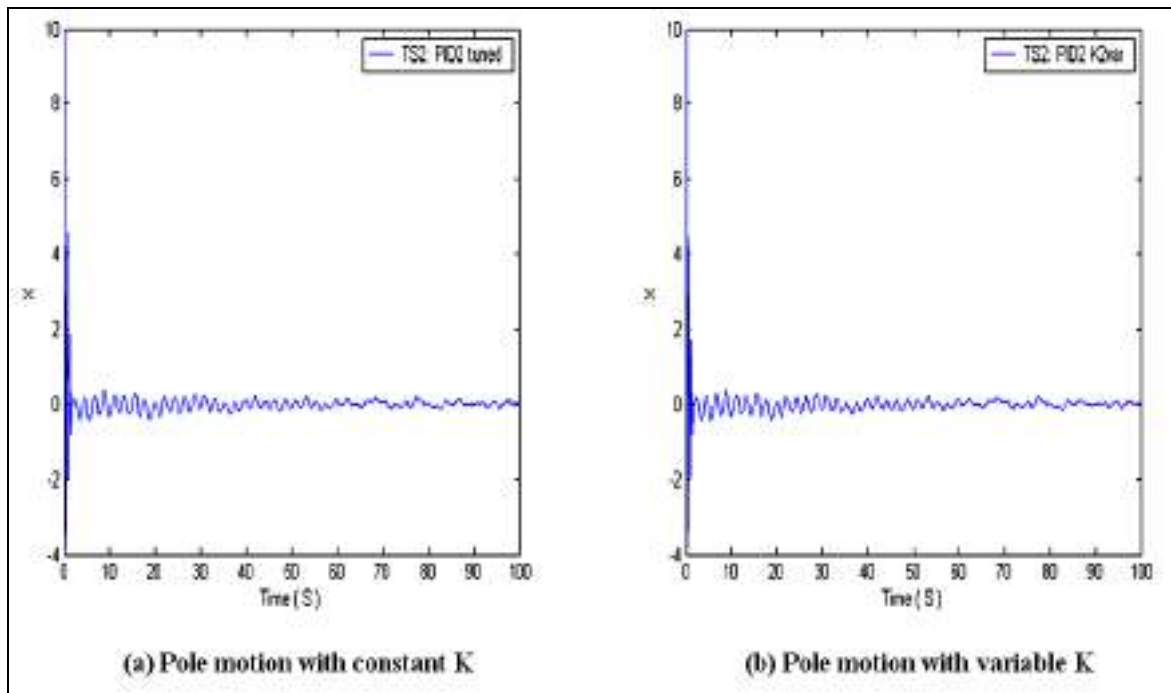
Figure 6. Teaching conditions 2: Pole motion with constant and disturbed K-gains of PID2

In this case also simulation results show that the pole motion is stable in both cases.
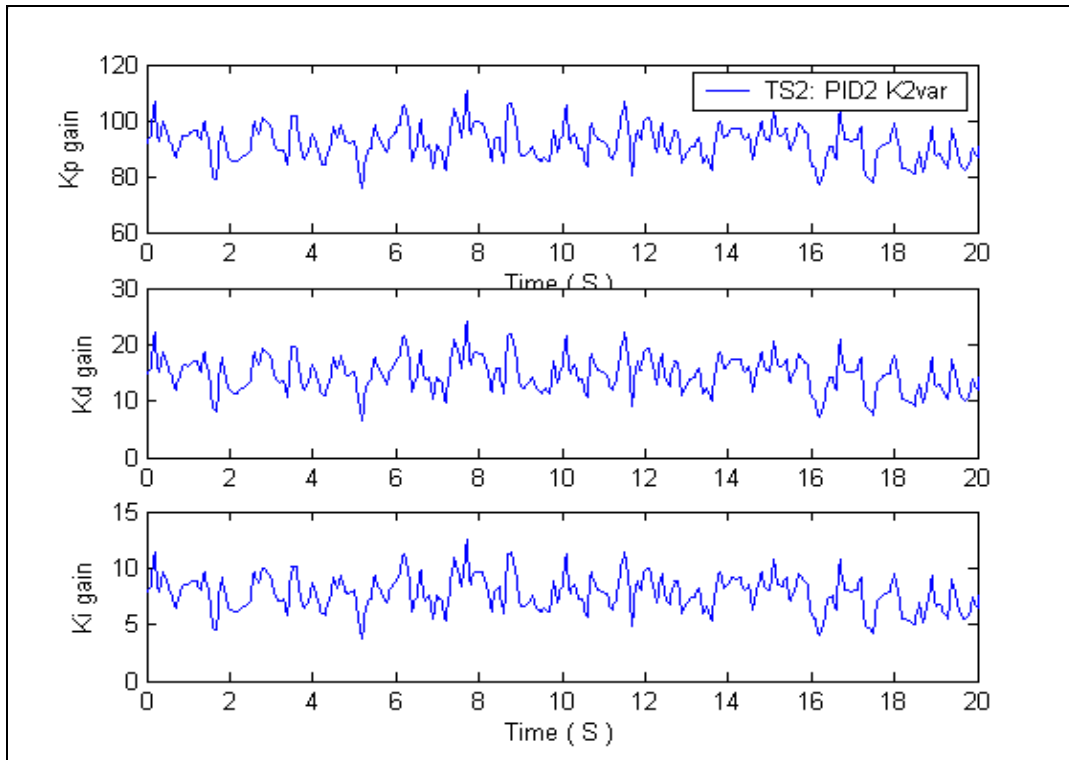
Figure 7. Teaching conditions 2: Control laws

Conclusion: simulation results show that the pole motion is stable in both cases. It means that we can use disturbed *K*-values for further calculations.

QPID controller based on new type of computing

As we have said above, we developed special tools for Quantum Fuzzy and Quantum PID inference based on QC optimizer.

QC optimizer tools allow to control as physical system and mathematical model of control object as shown on Fig. 8.
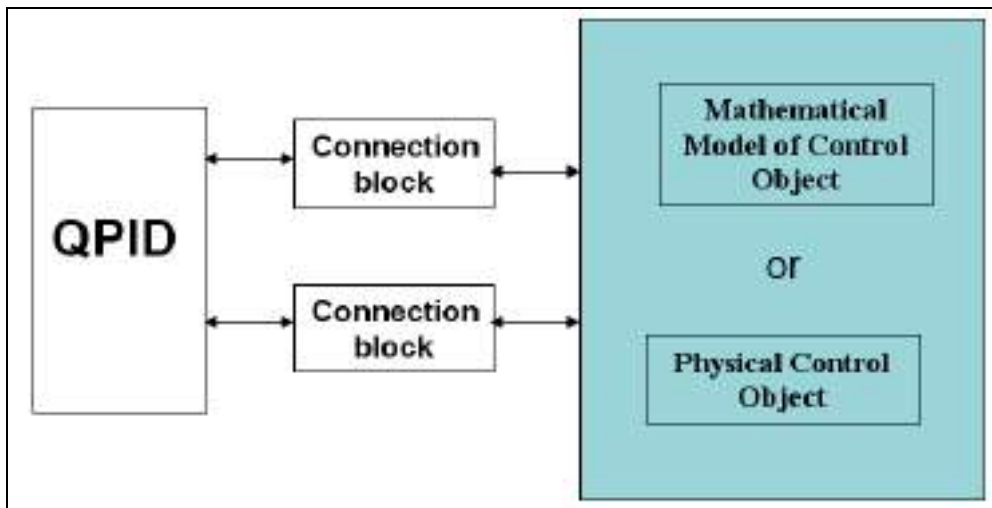
Figure 8. QPID controller connected with control object

We will work with mathematical model of control object represented in Matlab/Simulink version 6.5. Control loop with QPID is shown on Fig. 9.
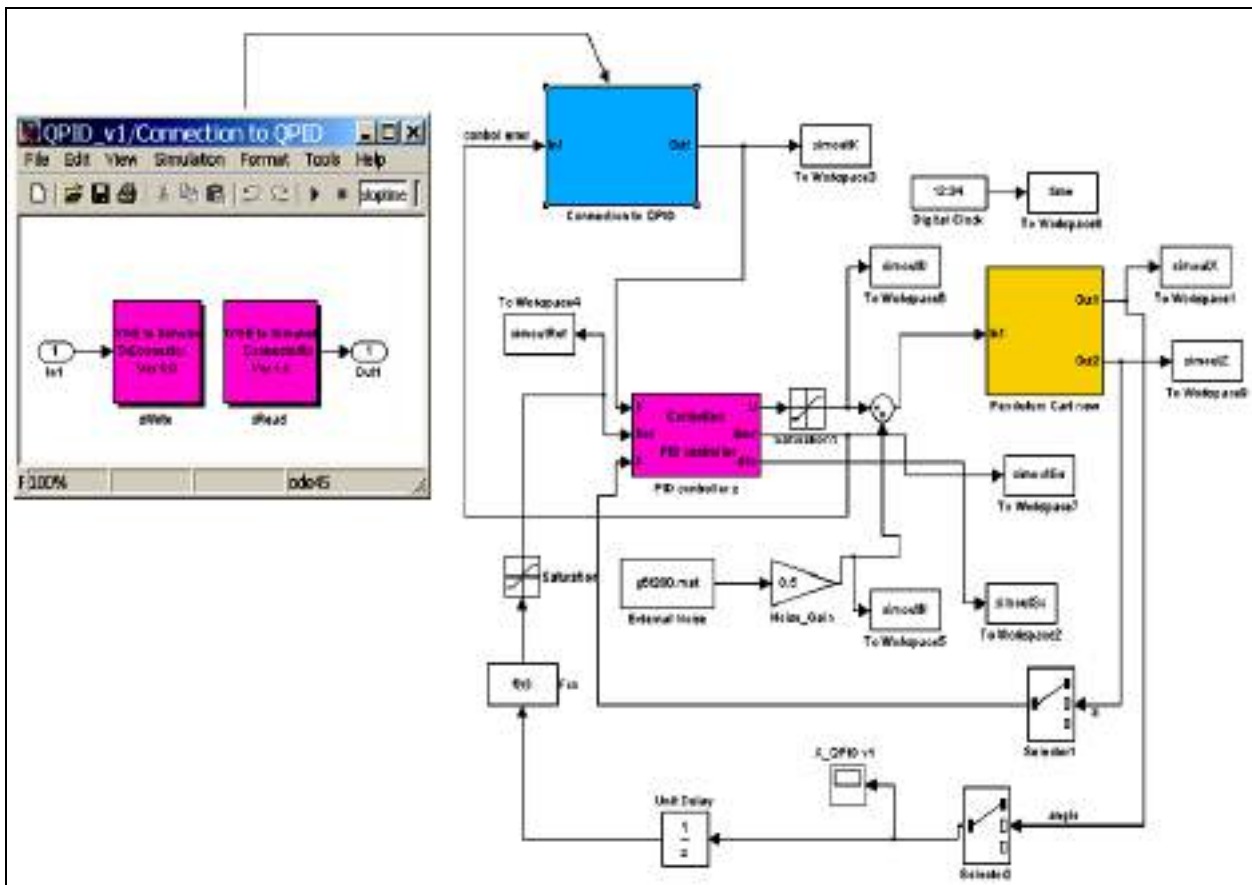
Figure 9. Matlab/Simulink model of control object with control loop based on QPID

Calculations corresponding to Quantum Inference based (QI) on two *K*-gains are realized in the block QPID by QC Optimizer tools.

QPID in terms of QC optimizer tool

On Figs 10a and 10b, internal structure of QPID in terms of our tools is shown.
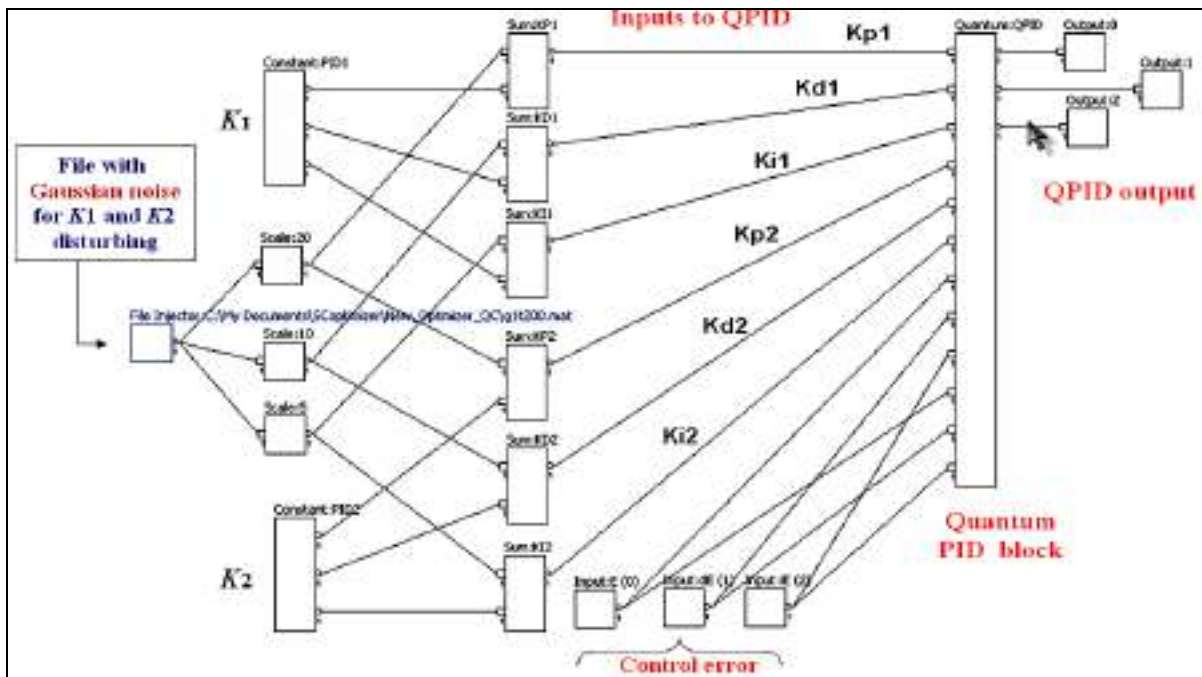
Figure 10a. QPID structure in terms of QC Optimizer tools
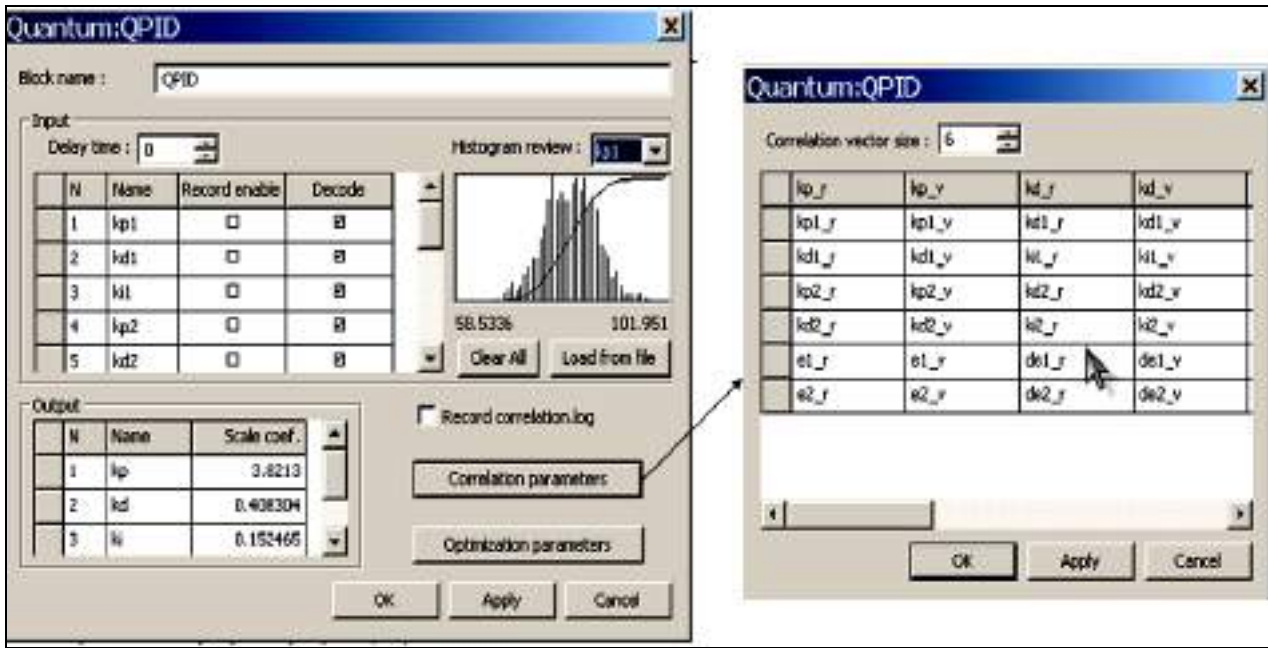
Figure 10b. QPID structure. Internal layer

On Fig. 10b internal structure of QPID block is shown. In this block the following items are described:

- names of input variables $k_{P(D,I)}^{1,2}$, where indexes 1, 2 denotes PID1 and PID2 (or K_1 and K_2; names of output variables $k_{P(D,I)}$;

- histograms for each input variable representing probability distribution of the given input;

- QI scaling coefficients for calculation output values (that is founded by GA for teaching conditions and then used for all control situations);

- knob «correlation parameters» is used for chosen type of quantum correlation description. For example, as follows spatial quantum correlations:

$$e_1 e_2 k_P^{1,2} k_D^{1,2} \to k_P^{new};$$
$$\dot{e}_1 \, \dot{e}_2 \, k_D^{1,2} k_I^{1,2} \to k_D^{new};$$
$$Ie_1 \, Ie_2 \, k_I^{1,2} k_P^{1,2} \to k_I^{new}.$$

By using GA and chosen quantum correlation we obtained the following QI scaling coefficients: Q_A_params =   2.4200   0.3320   0.1000.

Now investigate robustness properties of designed QPID based on QI with *spatial correlations* in different control situations.

Investigation of self-organization capability of Quantum PID Control based on two PID controllers (or two K-gains)

We will consider the following controllers:

- PID1 controller with constant gains K_1 = [82.7 13.6   9.4];

- PID2 controller with constant gains K_2 = [92.2   14.9   7.84];

- QPID controller based on quantum inference with K_1 and K_2.

Consider now behavior of our control object in teaching and modeled unpredicted control situations and investigate robustness property of designed controllers.

Investigation of different types of quantum correlations: *Spatial correlations*.

TS1: Comparison of QPID, PID1 and PID2 control performances.
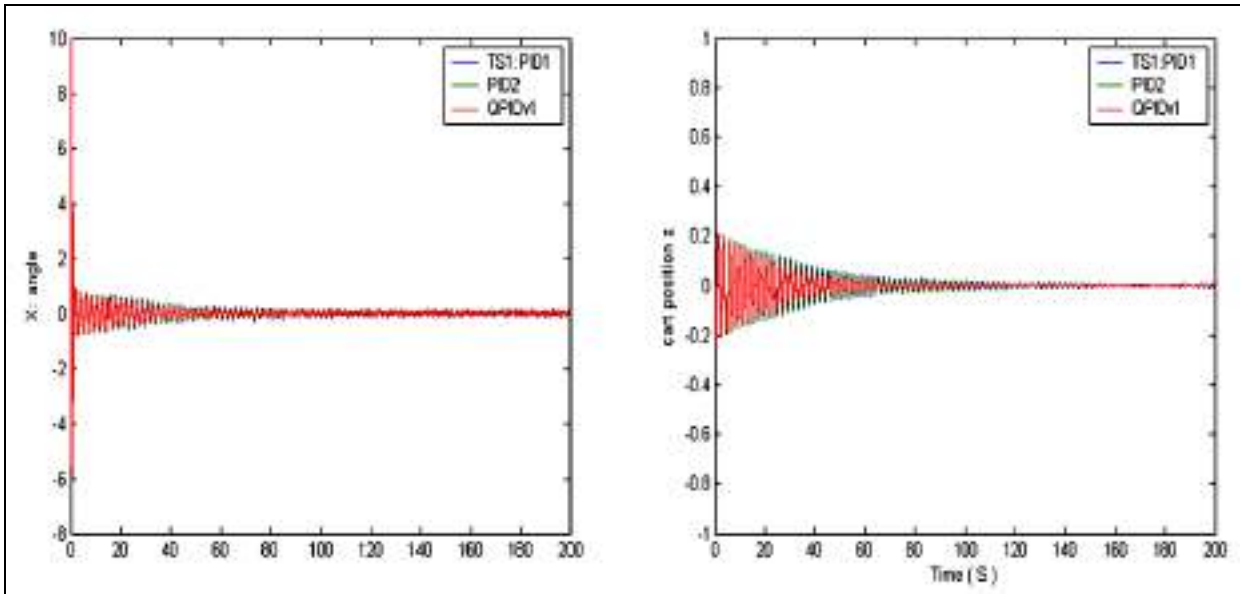
Figure 11. Pole motion (left) and cart motion (right) comparison
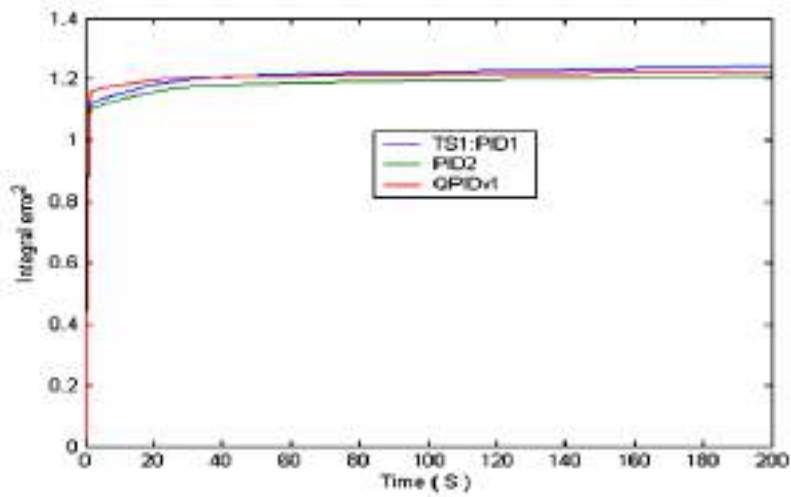
Figure 12. Integral control error
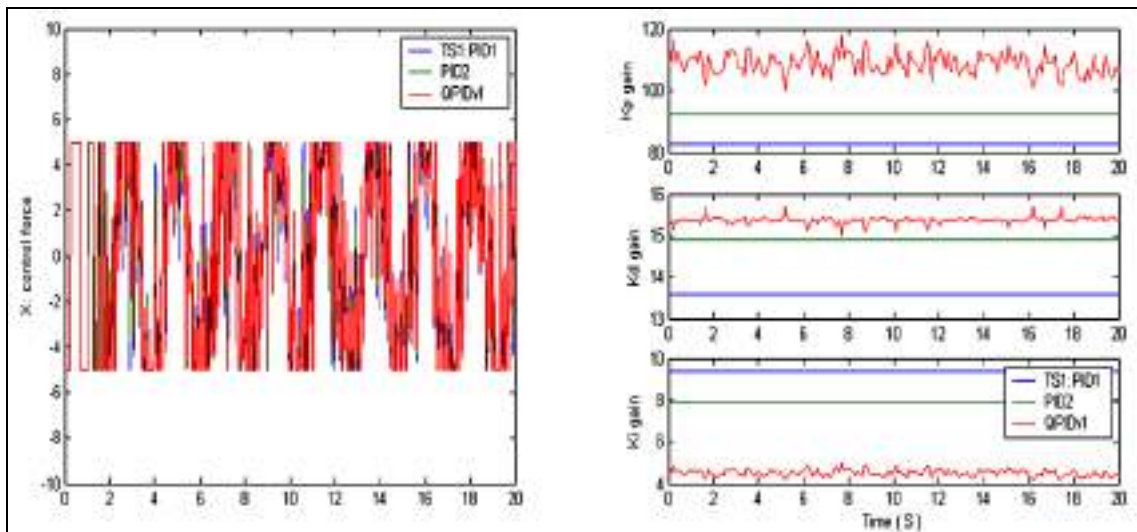
Figure 13. Control force and control laws

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Conclusion: all controllers are successful to balance the Pole in TS1 situation.

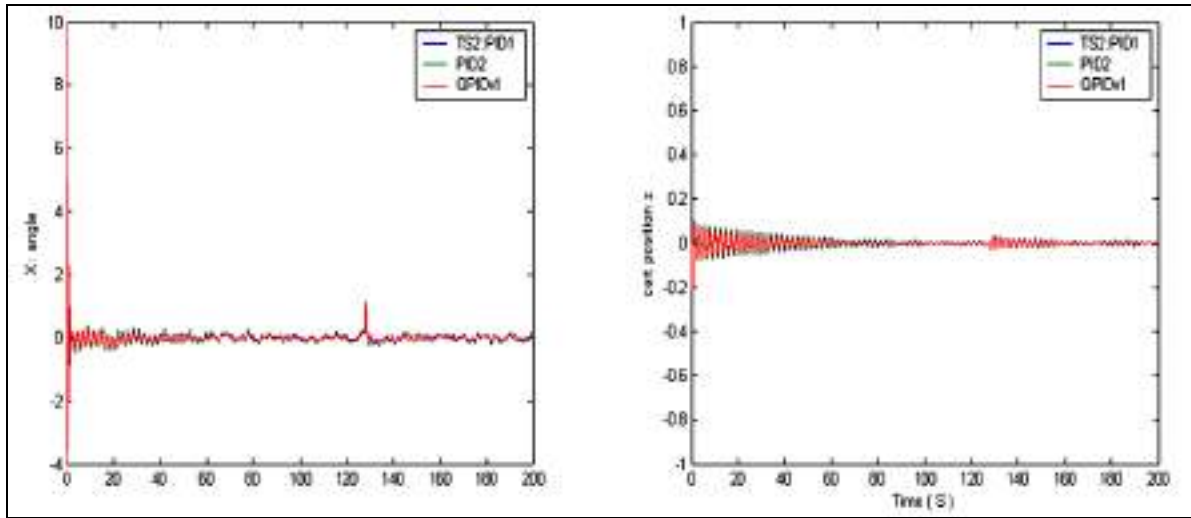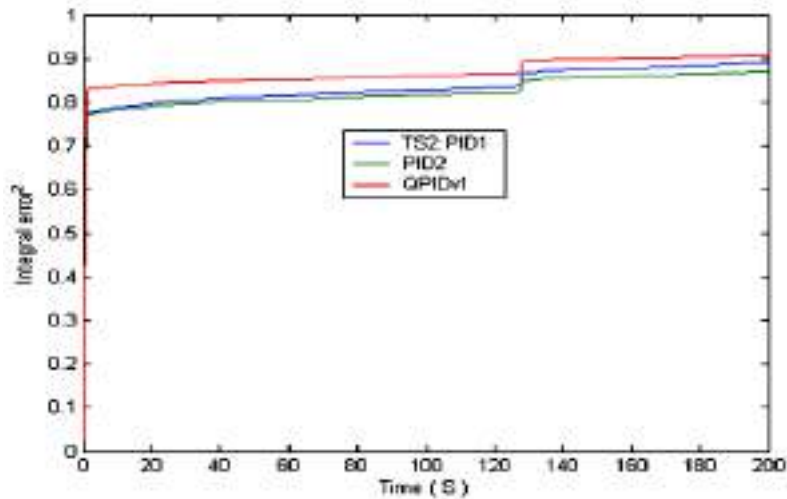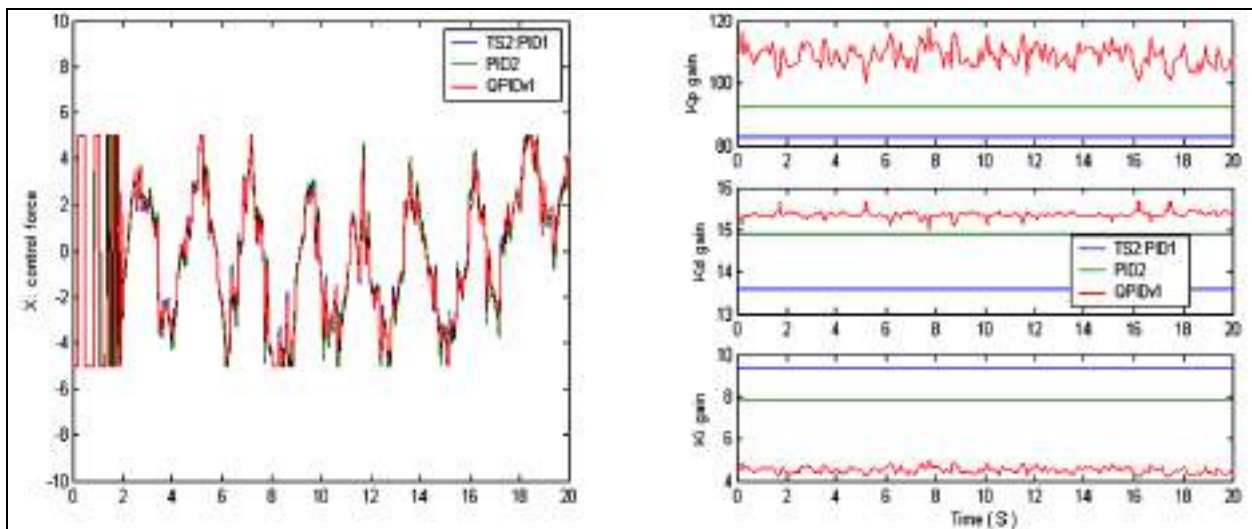**TS2**: Comparison of QPID, PID1 and PID2 control performances.

Figure 14. Pole motion (left) and cart motion (right) comparison in TS2 situation

Figure 15. Integral control error

On Figs 14 – 16, behavior of Cart-Pole system in teaching conditions TS2 is shown.

Figure 16. Control force and control laws in TS2 situation

Conclusion: all controllers are successful to balance the Pole in TS2 situation.

Investigation of self-organization capability of chosen QI

In Table 2 modeled unpredicted control situations (Class 1) are shown.

Table 2. Class 1 of modeled unpredicted control situations

New 1 control situation	New 2 control situation	New 3 control situation
(in legend S1)	(in legend S1a)	(in legend S1b)
External noise: *Rayleigh* (TS2 teaching noise);	External noise: *Rayleigh* (TS2 teaching noise);	External noise: *Rayleigh* (TS2 teaching noise);
New sensor's time delay = 0.005 sec;	New sensor's time delay = 0.005 sec;	Sensor's time delay = 0.001 sec;
Internal sensor noise: Gaussian noise with amplitude = 0.015;	Internal sensor noise: Gaussian noise with amplitude = 0.015;	Internal sensor noise: Gaussian noise with amplitude = 0.01;
TS model parameters	*New model parameter a2 = 8*	*New model parameter a2 = 6*

Let us investigate robustness of proposed QPID model in new control environment (Table 2).

New 1 control situation
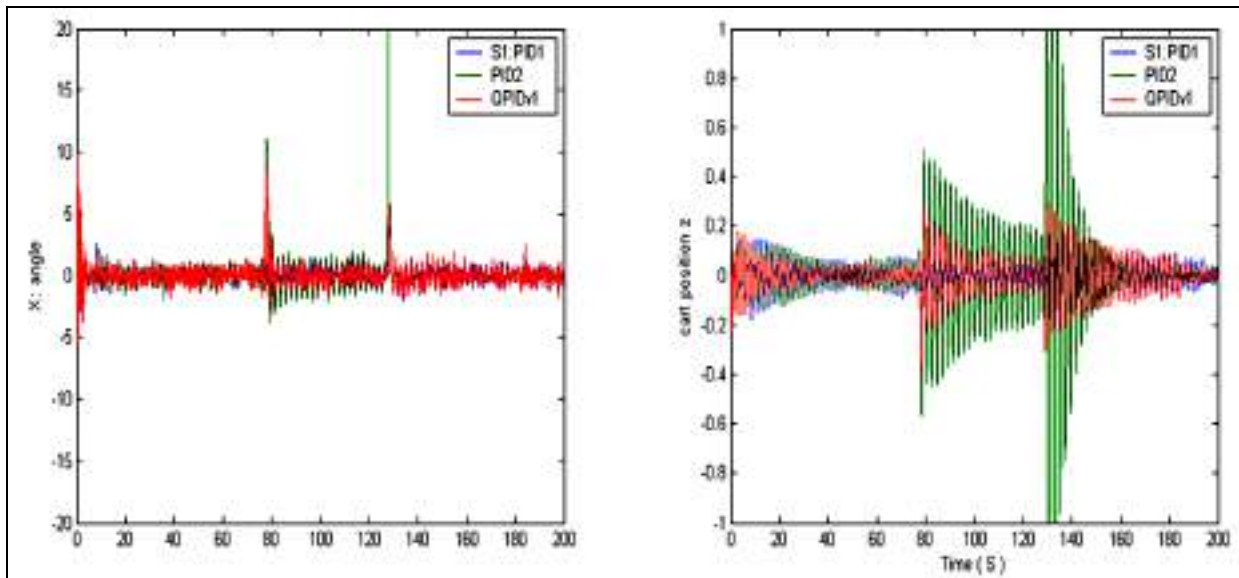
Figure 17. Pole motion (left) and cart motion (right) comparison in New 1 situation
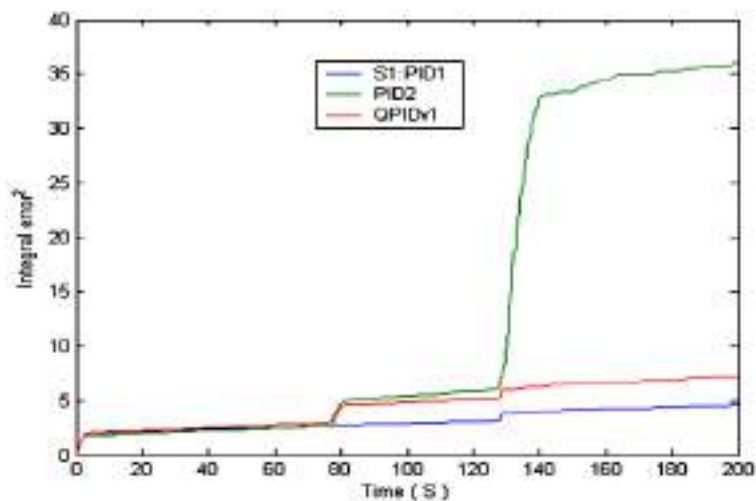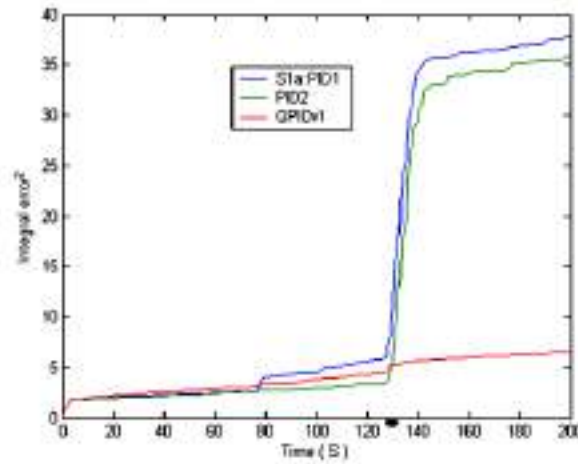

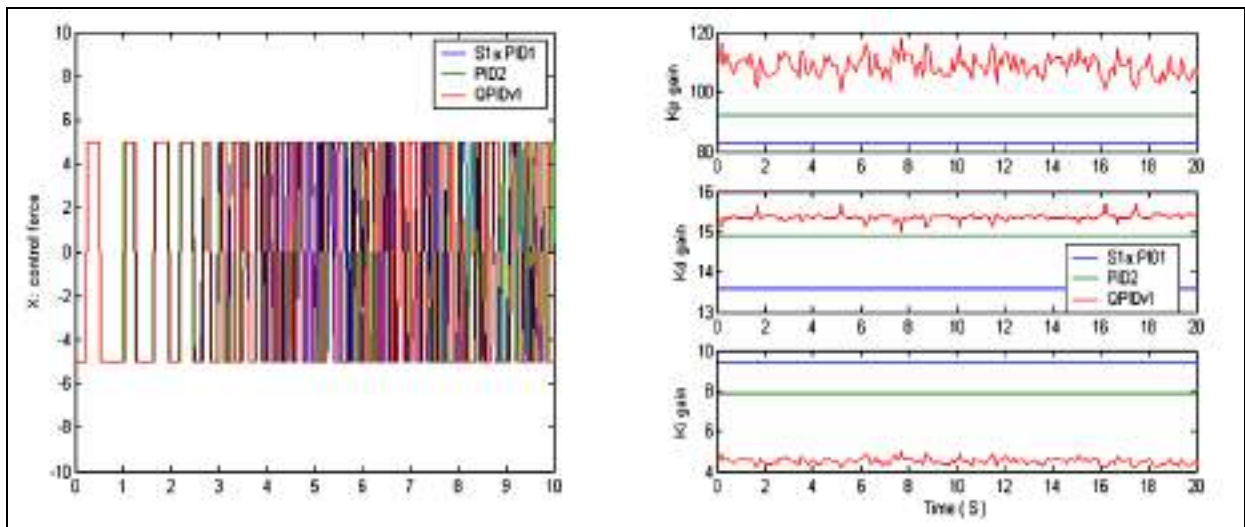*Figure 18. Integral control error in New 1 situation*
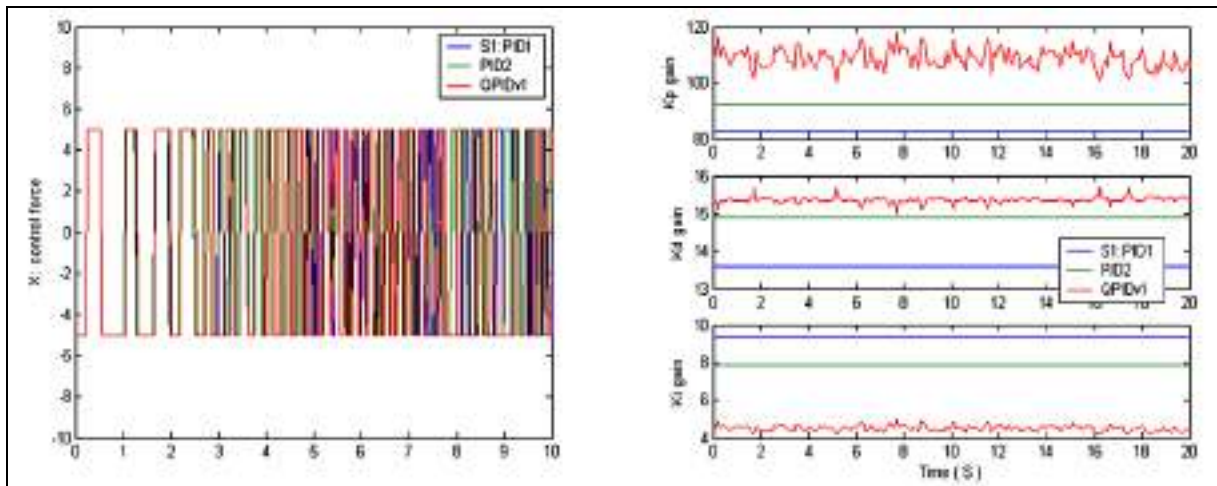
Figure 19. Control force and control laws in New 1 situation

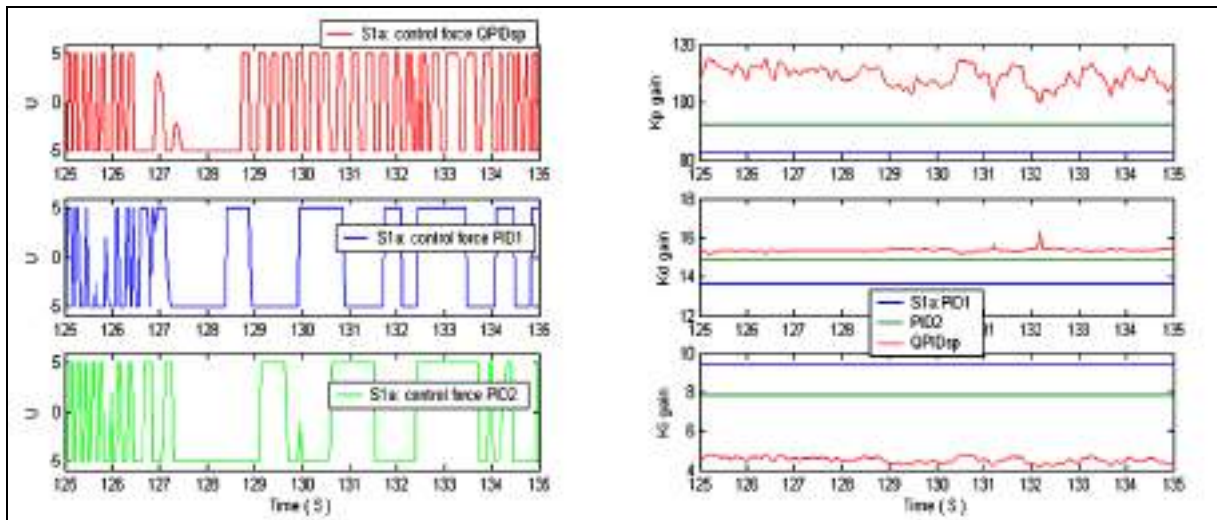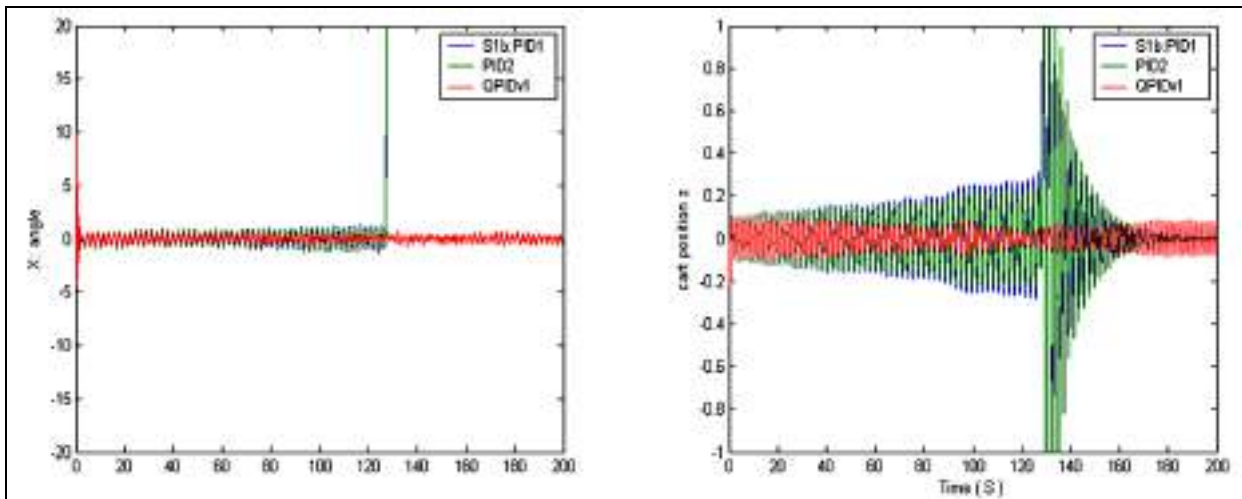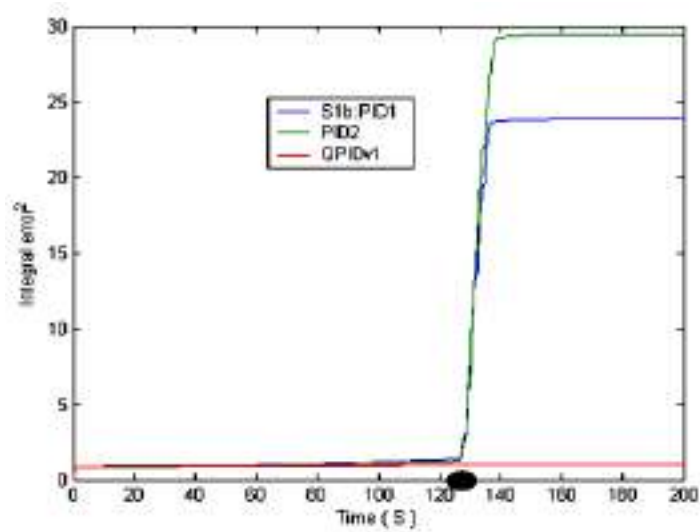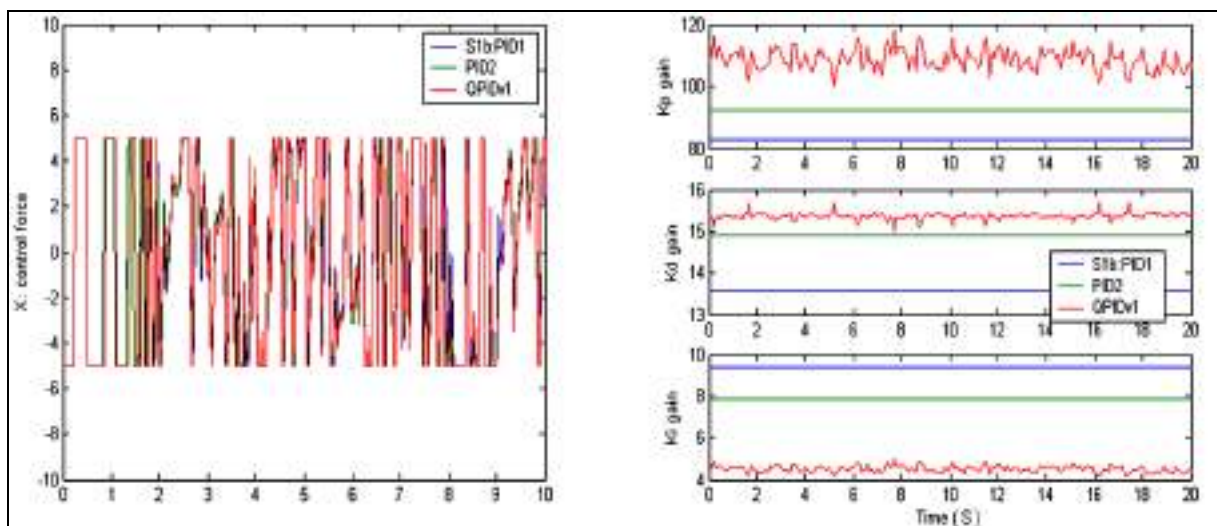Analysis of control laws and control force in point where Pole falls down.
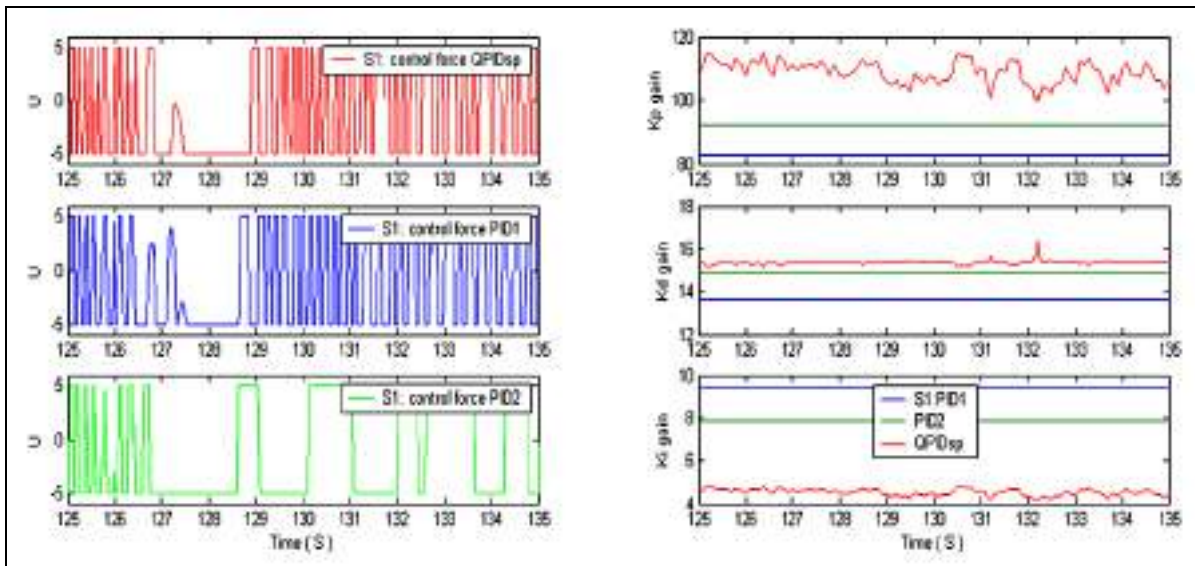
Figure 19a. Control force and control laws in New 1 situation

Conclusion: QPID and PID1 controllers are successful to balance the Pole in New 1 situation. PID2 controller is unsuccessful to balance the Pole in New 1 situation

New 2 control situation
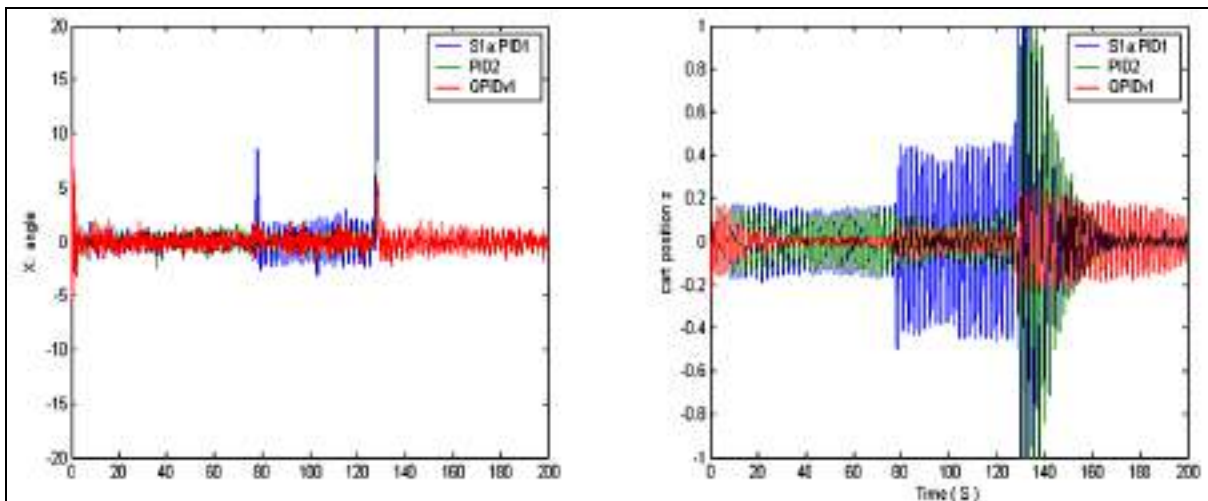
Figure 20. Pole motion (left) and cart motion (right) comparison in New 2 situation

Figure 21. Integral control error in New 2 situation

Figure 22. Control force and control laws in New 2 situation

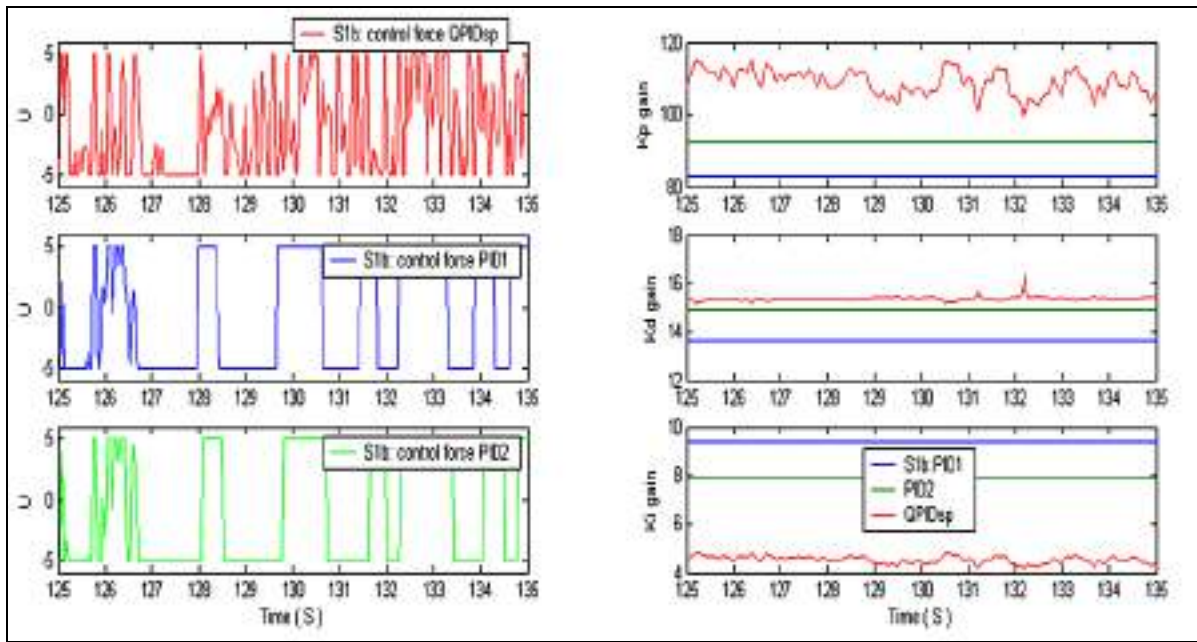Analysis of control laws and control force in point where Pole falls down.

Figure 22a. Control force and control laws in New 2 situation

Conclusion: QPID controller is successful to balance the Pole in **New 2** situation. PID1 and PID2 controllers are unsuccessful to balance the Pole in **New 2** situation.

New 3 control situation

Figure 23. Pole motion (left) and cart motion (right) comparison in New 3 situation

Figure 24. Integral control error in New 3 situation

Figure 25. Control force and control laws in New 3 situation

Analysis of control laws and control force in point where Pole falls down.

Figure 25a. Control force and control laws in New 3 situation

Conclusion: QPID controller is successful to balance the Pole in **New 3** situation. PID1 and PID2 controllers are unsuccessful to balance the Pole in **New 3** situation.

Final conclusions:

- QPID controller is robust in all situations of **class1**;

- PID1 controller is robust in **New 1** situation only;

- PID2 controller is not robust in **class 1** situations;

- QPID based on new type of calculations increases robustness of designed PID controllers.

Investigation of different types of quantum correlations: Temporal correlations

Investigate now robustness of temporal QI correlations and compare with spatial type of QI for the given control object. For QI we consider the following temporal quantum correlations:

$$e_1 e_2 k_P^{1,2} k_P^{1,2} (t - \Delta t) \rightarrow k_P^{new} \cdot gain_P;$$
$$\dot{e}_1 \dot{e}_2 k_D^{1,2} k_D^{1,2} (t - \Delta t) \rightarrow k_D^{new} \cdot gain_D;$$
$$Ie_1 Ie_2 k_I^{1,2} k_I^{1,2} (t - \Delta t) \rightarrow k_I^{new} \cdot gain_I.$$

On Fig. 26, cart-pole dynamic motion in TS1 situation is shown for different values of time correlation parameter $\Delta t = 0.25$ sec and 0.05 sec.
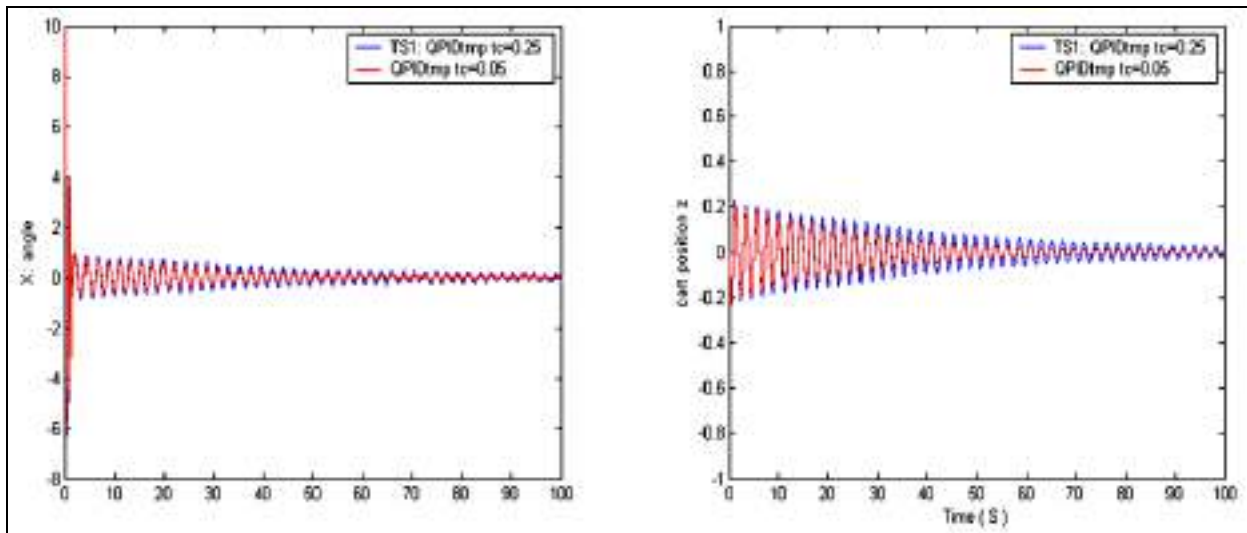
Figure 26. Pole motion (left) and cart motion (right) comparison in TS1 situation – Temporal quantum correlations

Check now robustness of temporal correlations.

On Fig. 28, cart-pole dynamic motion in **New 1** control situation (in legend S1) is shown for different values of time correlation parameter $\Delta t = 0.25$ sec and 0.05 sec.
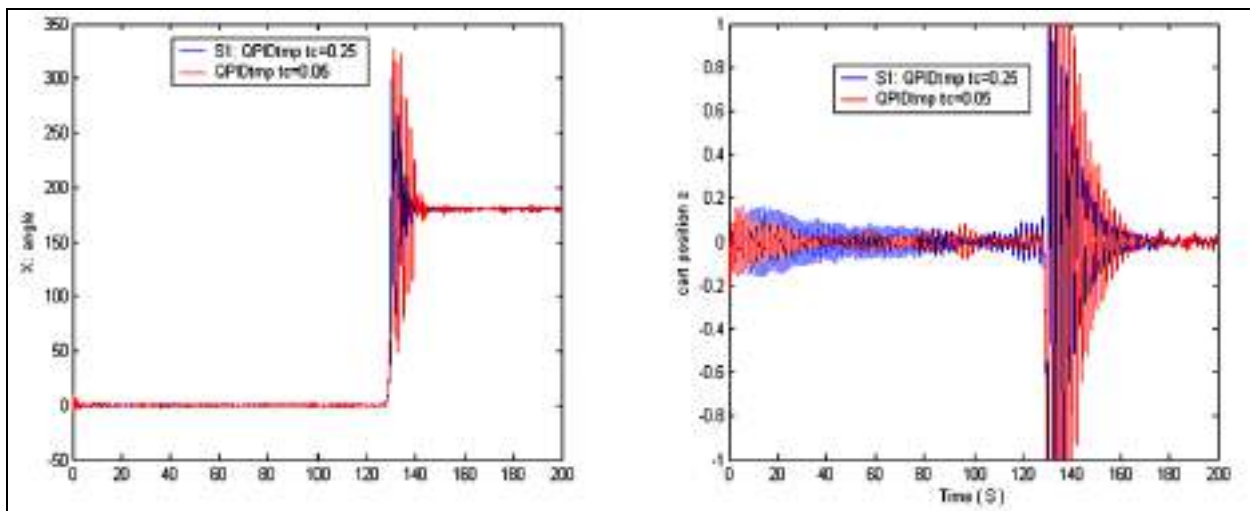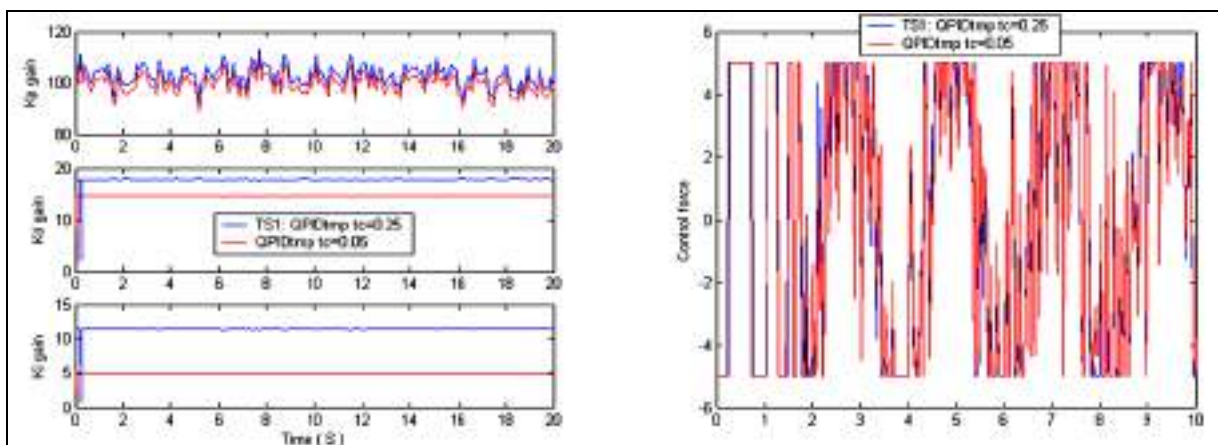

Figure 27. Pole motion (left) and cart motion (right) comparison in New 1 situation: Temporal quantum correlations

Figure 28. Control force and control laws: Temporal quantum correlations
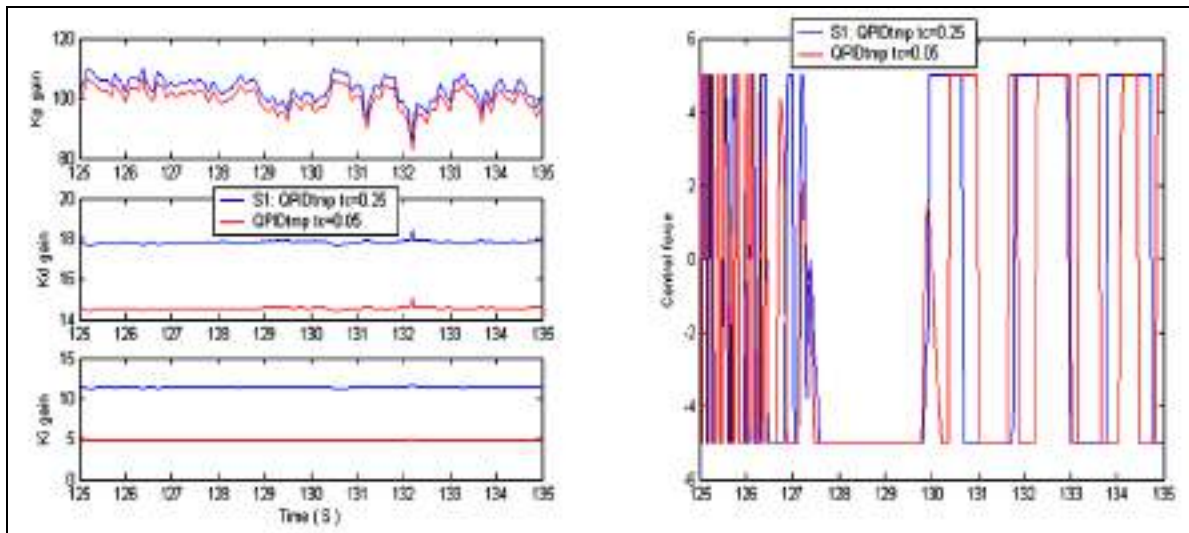
Figure 29. Control force and control laws in points where Pole falls down: Temporal quantum correlations

Comparison QPID control performance under spatial and temporal correlations

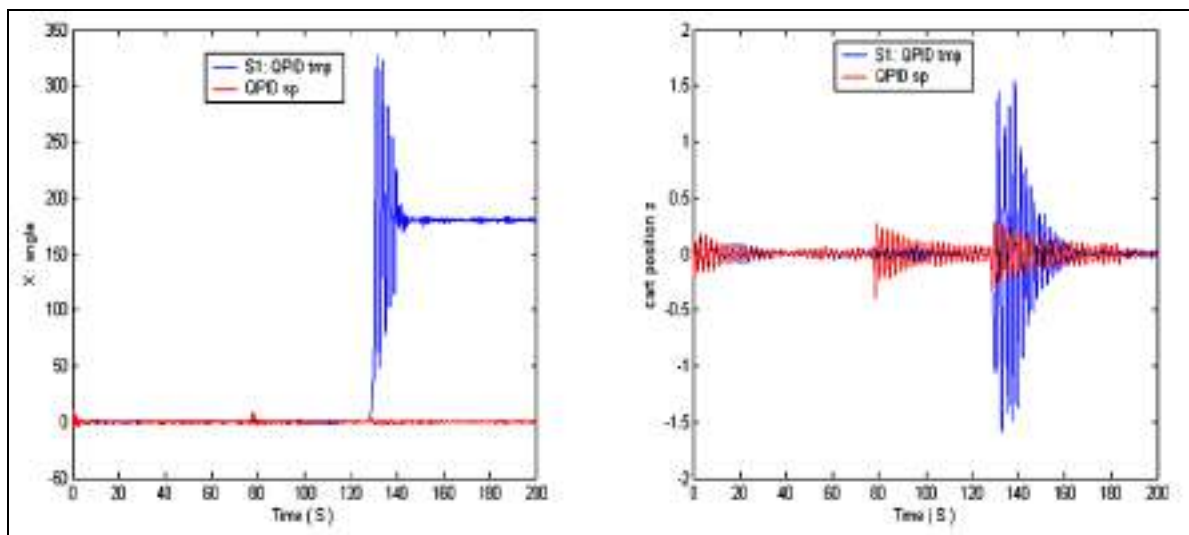Consider dynamic motion and control laws comparison (around the point, where the Pole falls down).

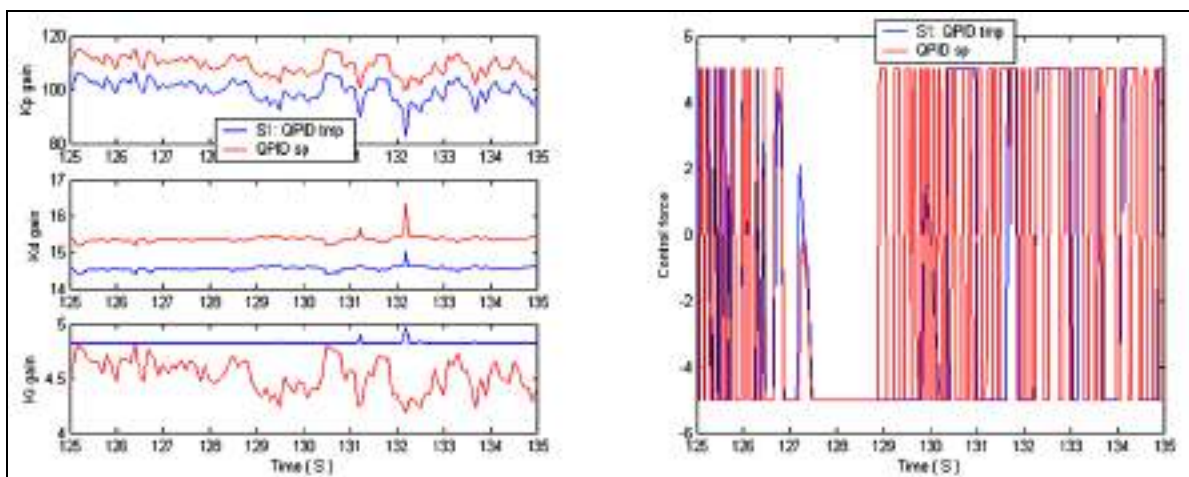*Figure 30. Pole motion (left) and cart motion (right) comparison*

Figure 31. Control force and control laws – QPID with spatial and temporal correlations comparison

Conclusion: QPID with temporal correlations is not robust in **New 1** situation. So, choose spatial QI as best for robust QPID control realization.

Consider now a new class of modeled unpredicted control situations (**Class 2**) shown in Table 3. For the new control situations (**New 6** and **New 7**) the external uniform noise is used (Fig. 32).
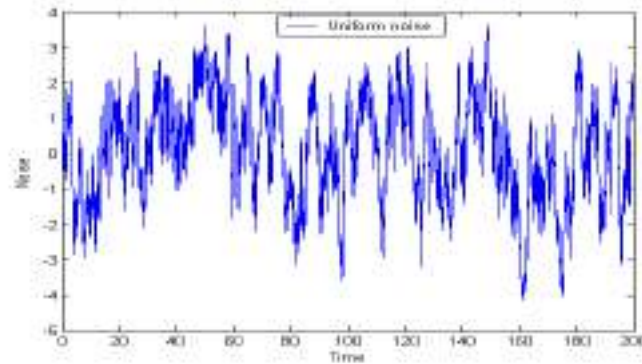

Figure 32. External Uniform noise applied in New 6 and New 7 control situations

Table 3. Class 2 of modeled unpredicted control situations

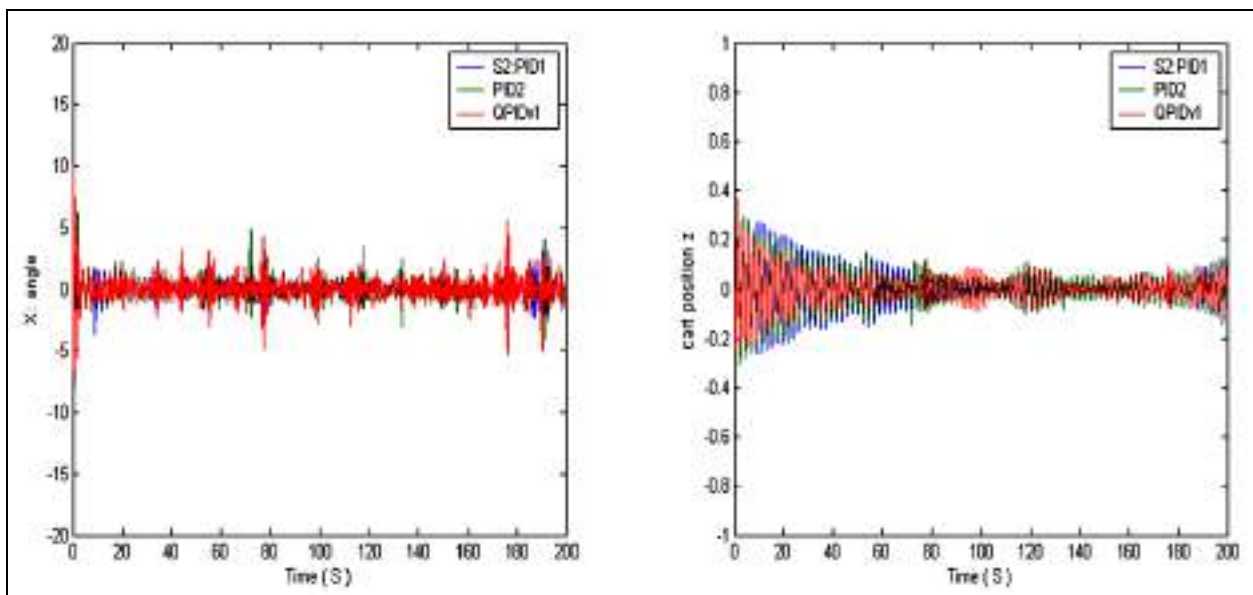| **New 4 control situation**	**New 5 control situation**
(in legend **S2**)	(in legend **S2a**)
External noise: G*aussian* (TS1 teaching noise);	External noise: G*aussian* (TS1 teaching noise);
New sensor's time delay = 0.004 sec;	New sensor's time delay = 0.004 sec;
Internal sensor noise: Gaussian noise with	Internal sensor noise: Gaussian noise with
amplitude = 0.015;	amplitude = 0.015;
TS model parameters	*New model parameter a2 = 8*
New 6 control situation	**New 7 control situation**
(in legend **S3**)	(in legend **S3b**)
New external noise: *Uniform* (Fig.13.32);	New external noise: *Uniform* (Fig.13.32);
New sensor's time delay = 0.005 sec;	New sensor's time delay = 0.005 sec;
Internal sensor noise: Gaussian noise with	Internal sensor noise: Gaussian noise with
amplitude = 0.015;	amplitude = 0.015;
TS model parameters	*New model parameter a2 = 8*

New 4 control situation

Figure 33. Pole motion (left) and cart motion (right) comparison in New 4 situation
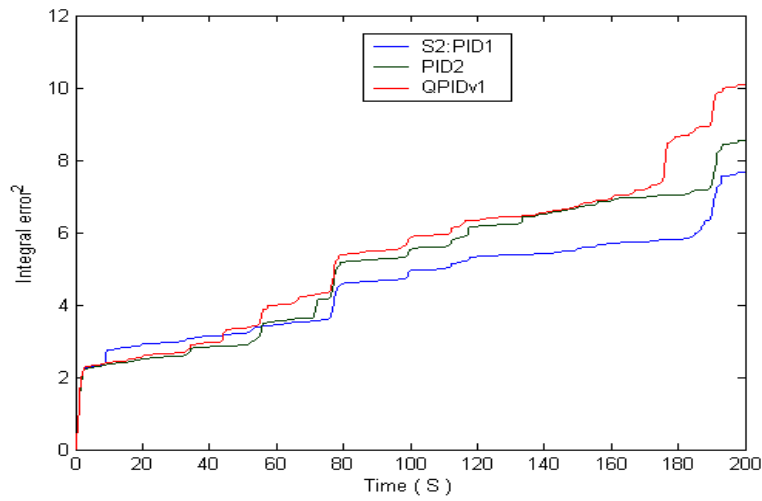
Figure 34. Integral control error in New 4 situation

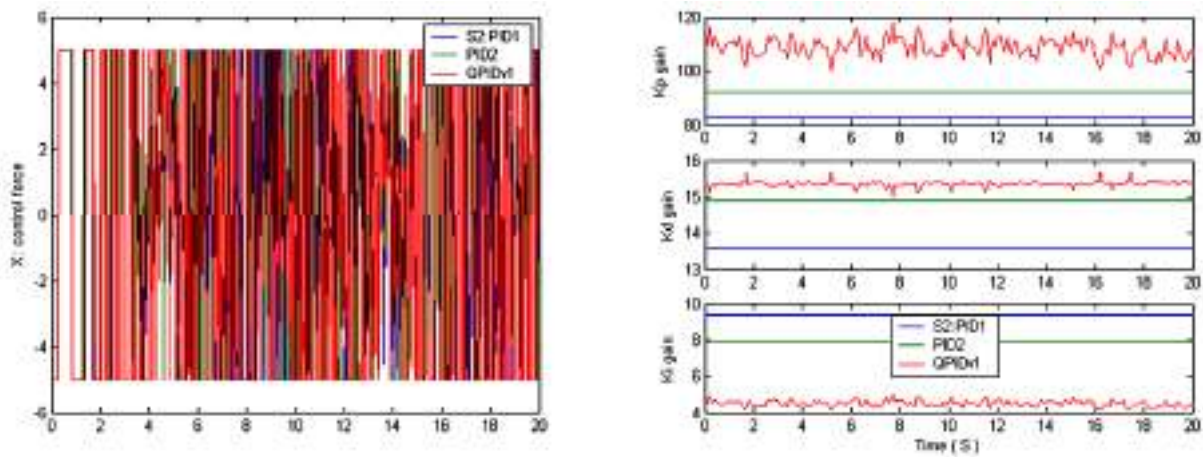*Figure 35. Control force and control laws in New 4 situation*

Conclusion: All controllers are successful to balance the Pole in New 4 situation.
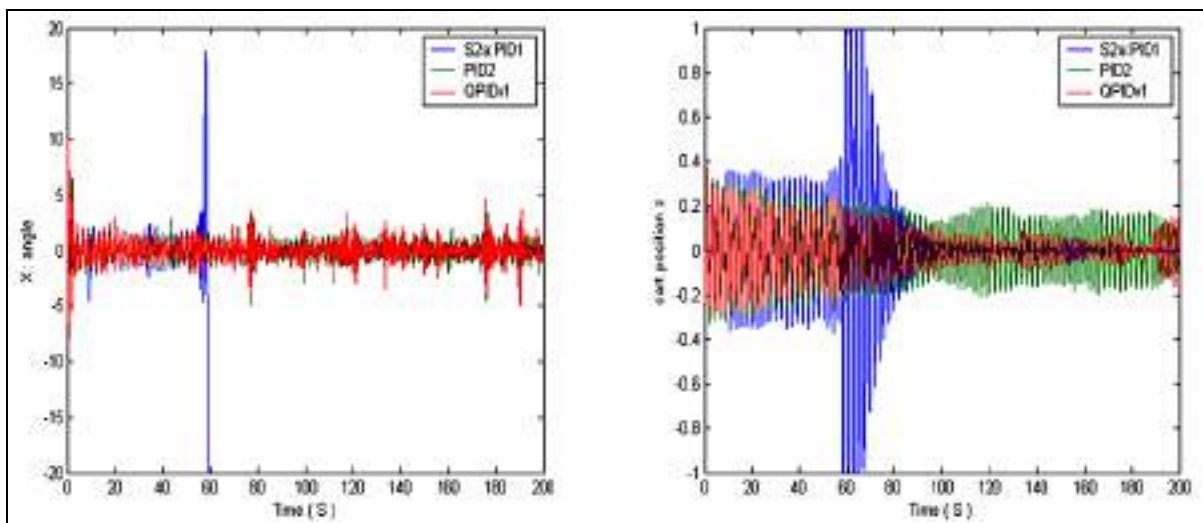
New 5 control situation

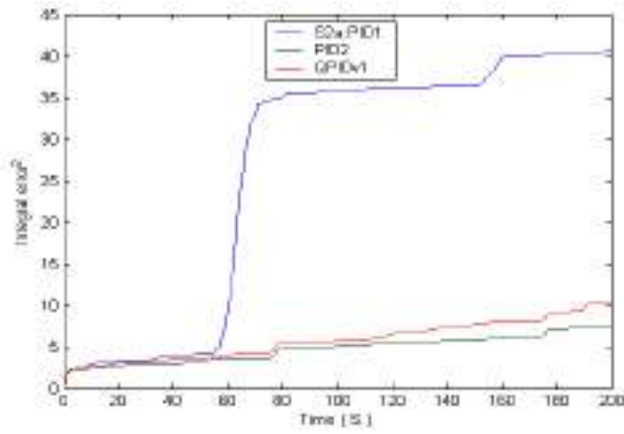*Figure 36. Pole motion (left) and cart motion (right) comparison in New 5 situation*

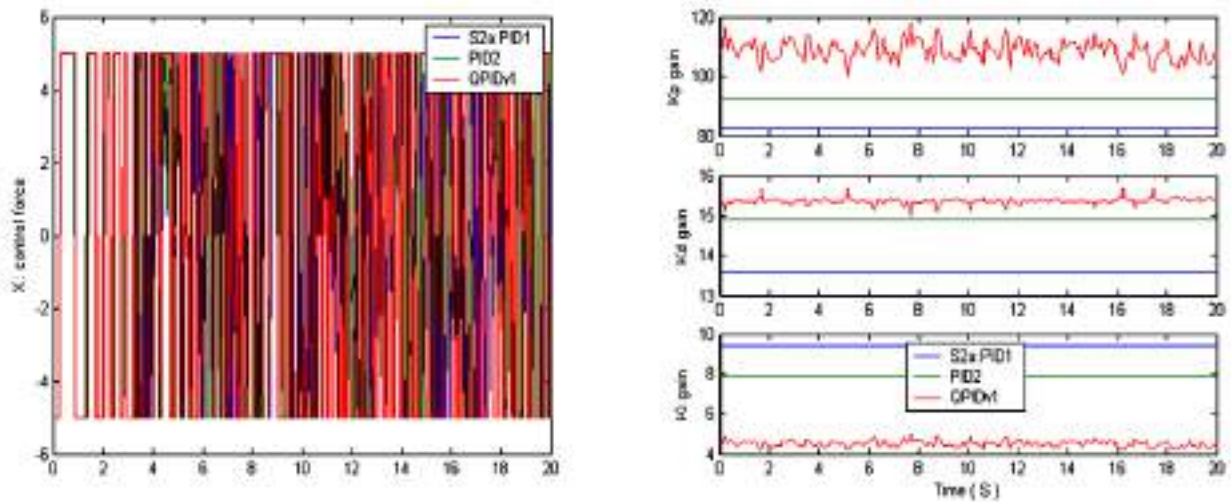*Figure 37. Integral control error in New 5 situation*

Figure 38. Control force and control laws in New 5 situation

Conclusion: QPID controller and PID2 controllers are successful to balance the Pole in **New 5** situation. PID1 controller is unsuccessful to balance the Pole in **New 5** situation.

Analysis of control laws and control force in point where Pole falls down.
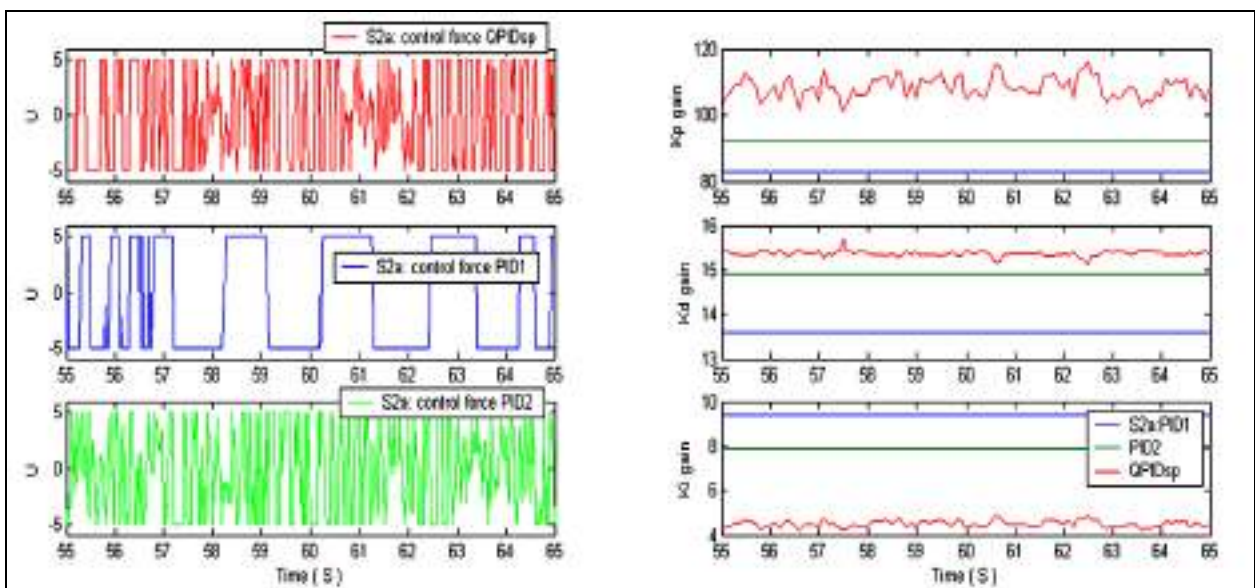

Figure 39. Control force and control laws in New 2 situation

New 6 control situation

- New external noise: *Uniform* (Fig.13.32);

- New sensor's time delay = 0.005 sec;

- Internal sensor noise: Gaussian noise with amplitude = 0.015;
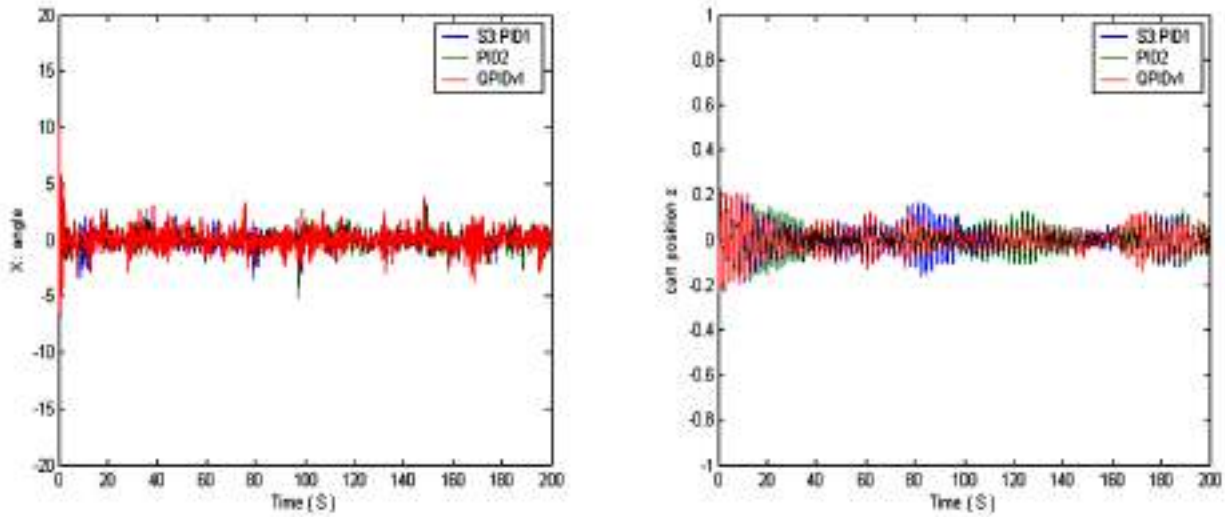
- TS model parameters.

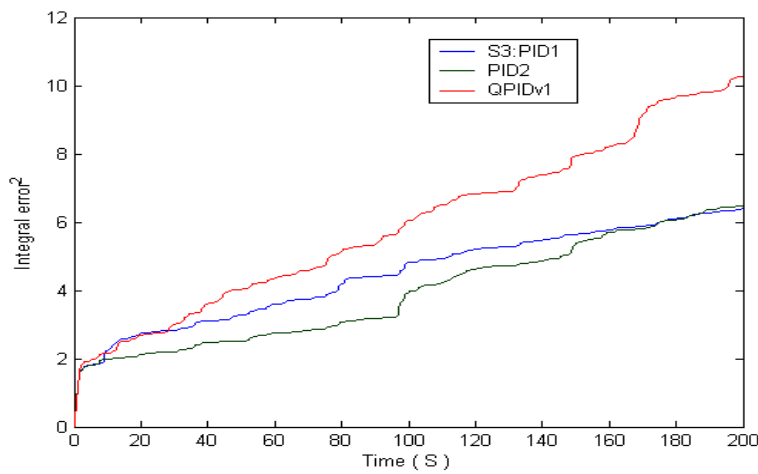*Figure 40. Pole motion (left) and cart motion (right) comparison in New 6 situation*

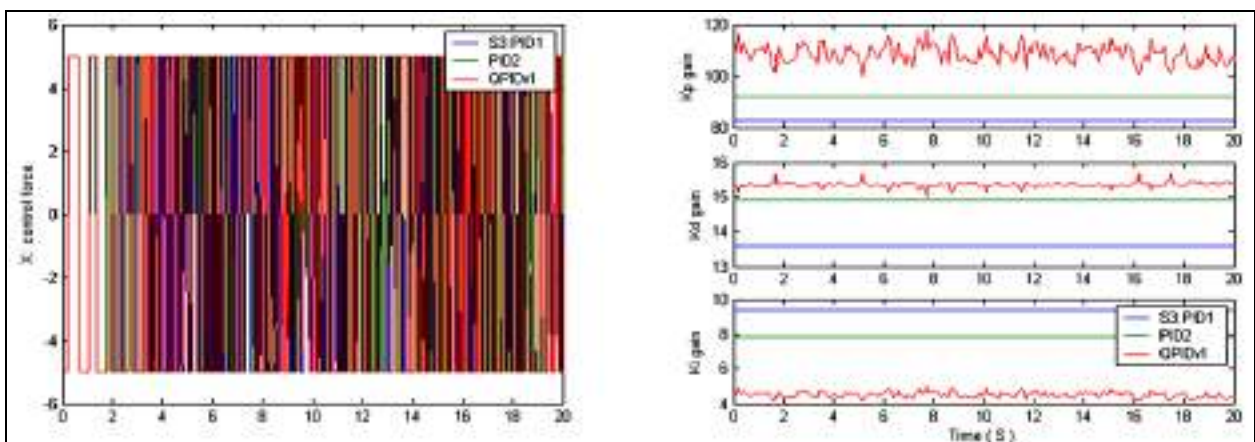*Figure 41. Integral control error in New 6 situation*

Figure 42. Control force and control laws in New 6 situation

Conclusion: All controllers are successful to balance the Pole in **New 6** situation.

New 7 control situation

- New external noise: Uniform (Fig.13.32);

 - New sensor's time delay = 0.005 sec;

- Internal sensor noise: Gaussian noise with amplitude = 0.015;
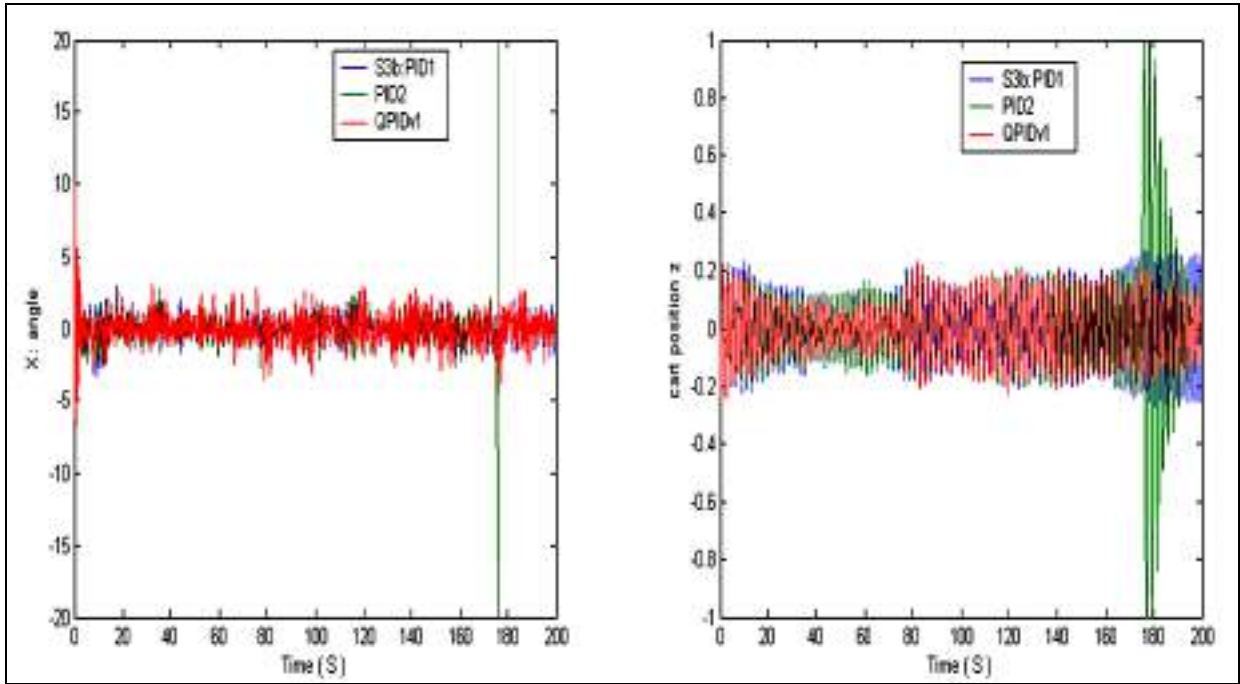
- New model parameter a2 = 8.

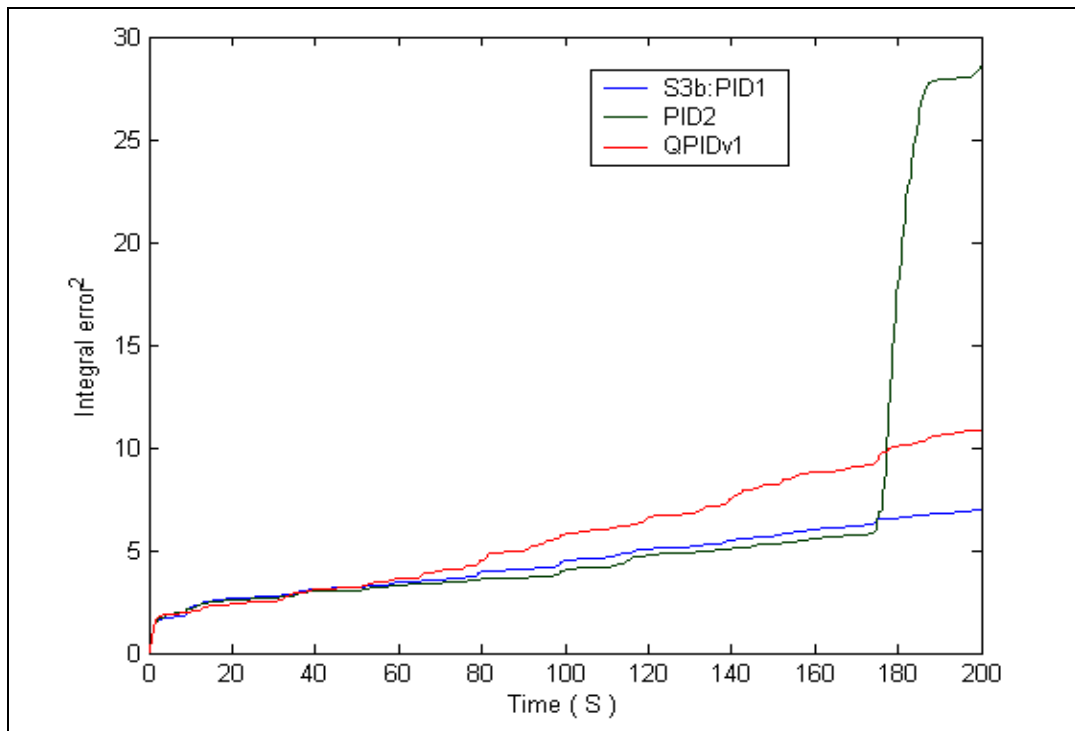*Figure 43. Pole motion (left) and cart motion (right) comparison in New 7 situation*

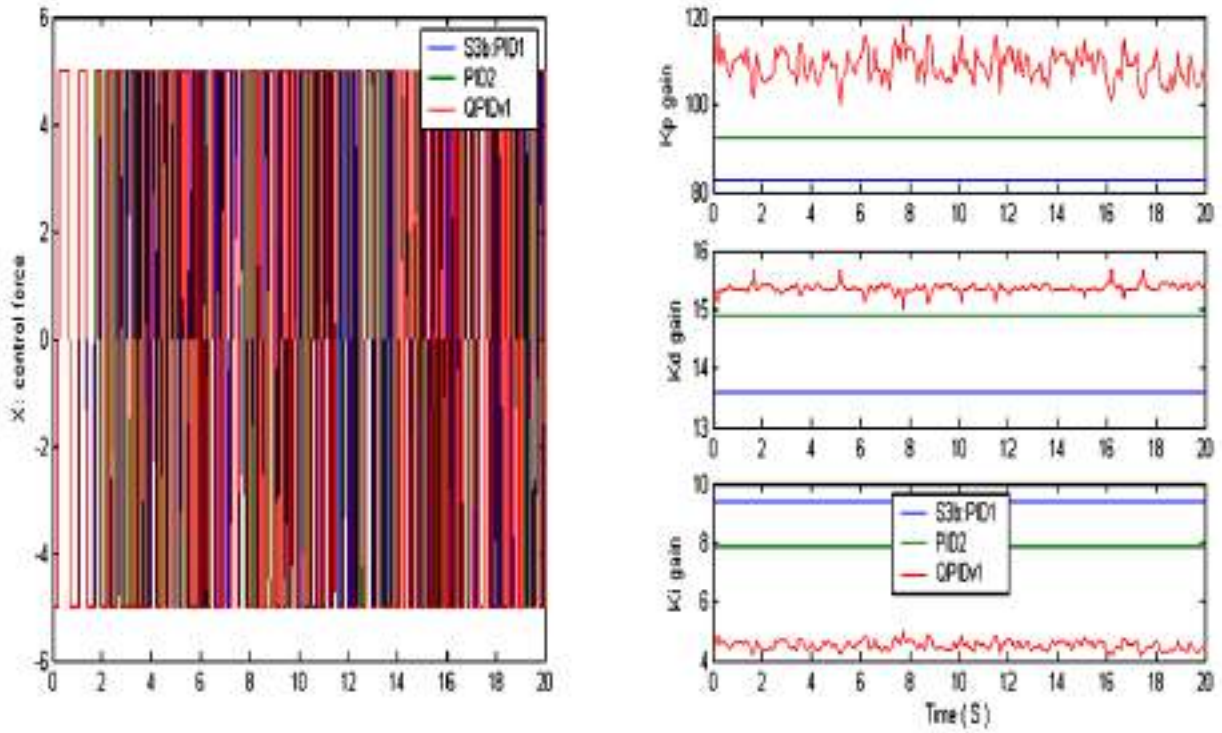*Figure 44. Integral control error in New 7 situation*

Figure 45. Control force and control laws in New 7 situation

Analysis of control laws and control force in point where Pole falls down.
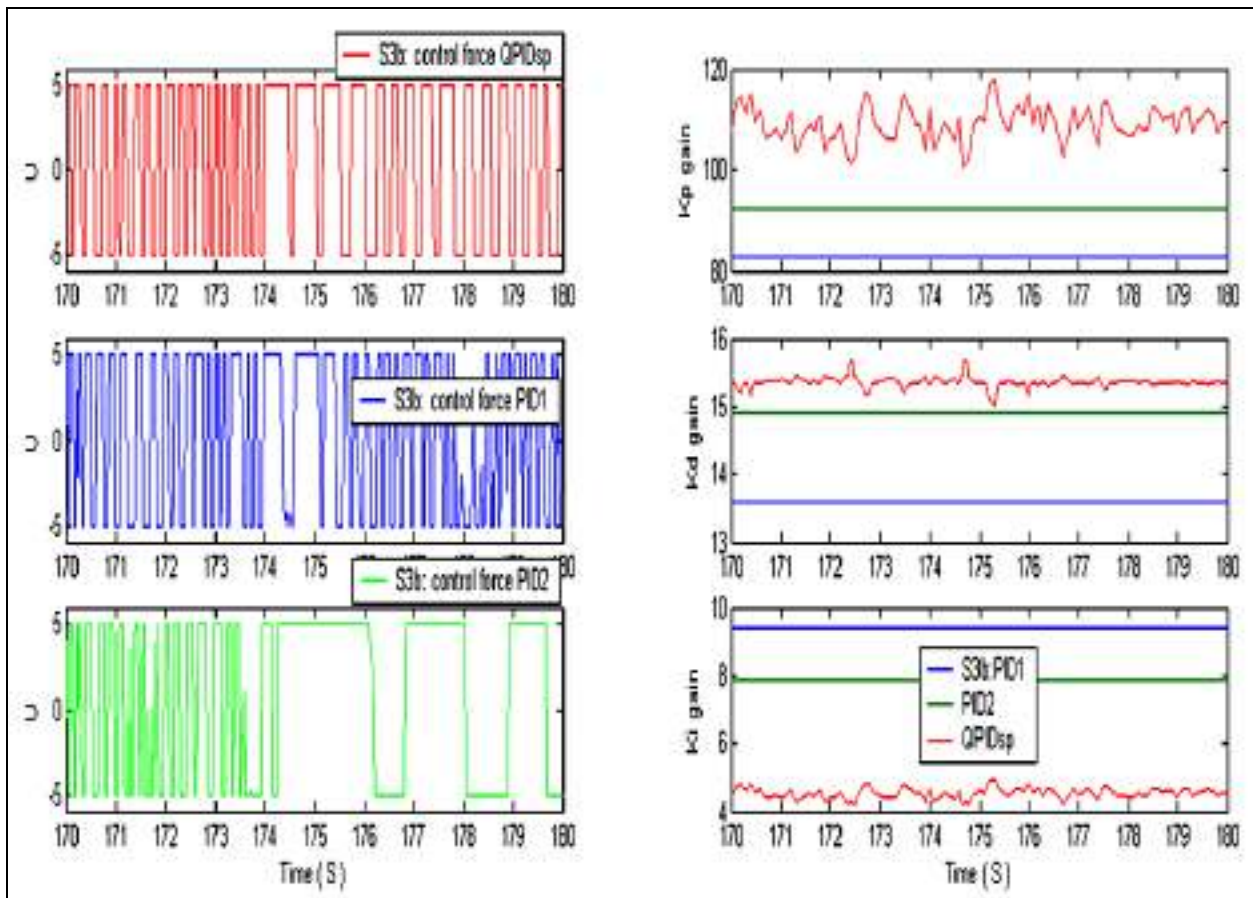

Figure 46. Control force and control laws in New 7 situation

Conclusion: QPID and PID1 controllers are successful to balance the Pole in **New 7** situation. PID2 controller is unsuccessful to balance the Pole in **New 7** situation.

Some important remarks. As shown on Fig. 47 and Fig. 48 below, control laws of QPID in teaching conditions and in new control situations are the same.
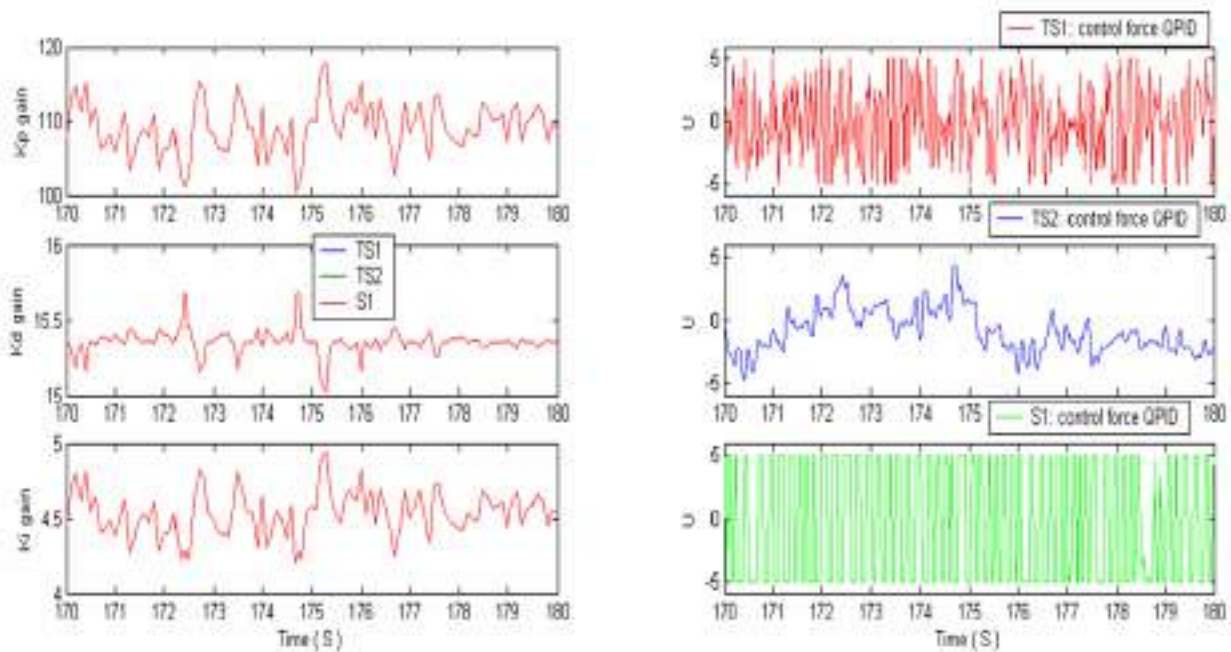

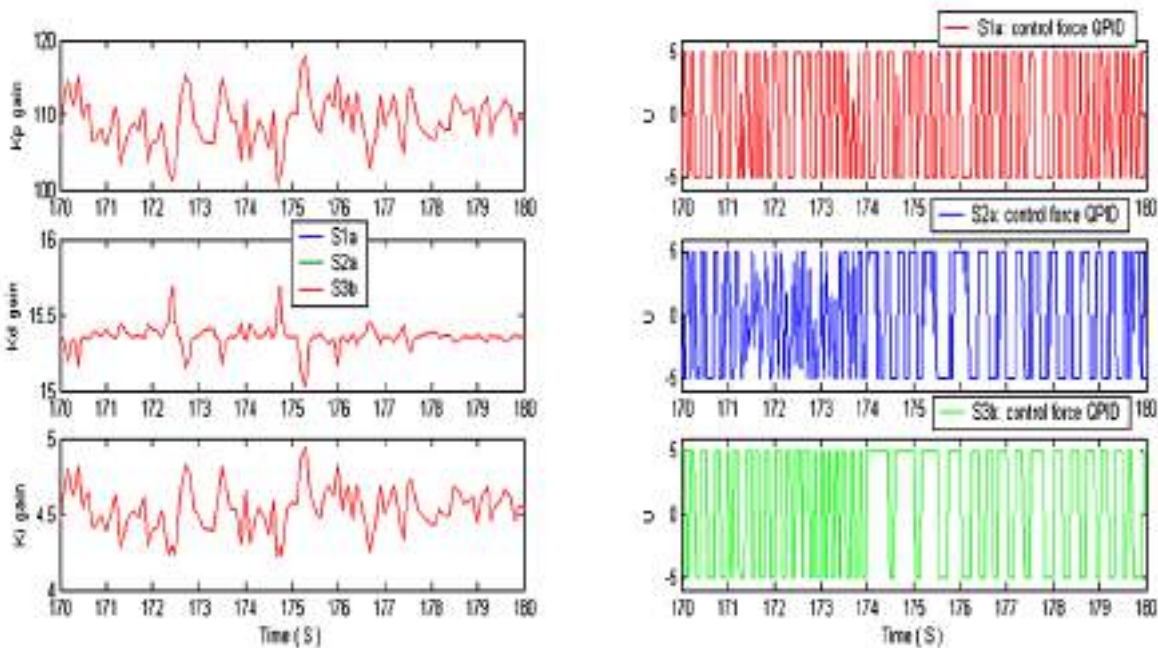*Figure 47. Control laws and control forces in teaching conditions (TS1 and TS2) and in New 1 situation*

Figure 48. Control laws and control forces in New 2, New 5, New 7 situations

Thus we have used *constant values* K_1 and K_2 of classical PID in order to obtain *variable K*-gains of QPID. Constant K_1 and K_2 of classical PID are not changed when control situation is changed, variable QPID *K*-gains also is not changed when control situation is changed. If so, let us take average values from obtained QPID *K*-gains. By this way we can receive new PID that we will call as PID-average.

If we take $K = \max_t K_{QPID}$, then we obtain new controller named as PID-max.

Let us check robustness of new obtained controllers in chosen control situation (**New 2** or in legend **S1a**).
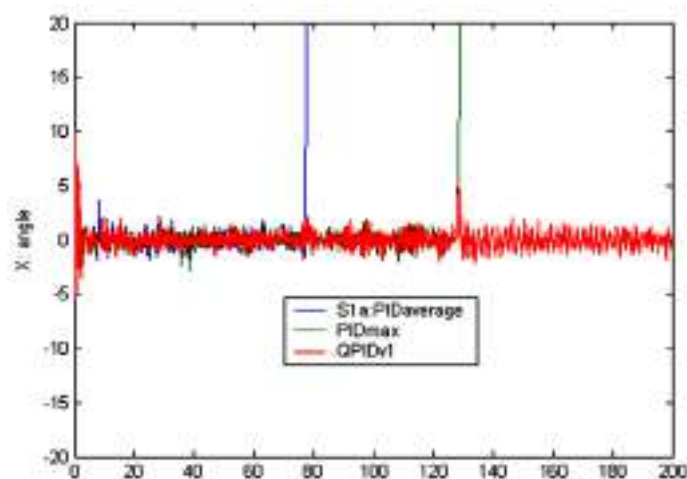
Figure 49. Pole motion under three types of control

On Fig.13.49 comparison of cart-pole motion under three types of control:

- QPID with variable (time dependent) K-gains obtained by on-line QI process;

- PID-average with constant gains K= [108.8507   15.3634   4.5209];

- PID-max with constant gains K= [119.2325   16.3510   5.1046].

Simulation results show that PID-average and PID-max controllers with constant gains are incapable to balance a Pole in the chosen control situation.

We have seen that constant *K*-gains obtained from quantum inference cannot control pendulum motion in the new situation. But *variable* K-gains can do it!

Thus we have principally new calculation process.

Conclusions

- For practical applications, when we have deal only with PID controllers, we may increase robustness of control system by using quantum inference block.

- In this case only two sets of PID constant *K*-gains are needed.

- Simulation results show good robustness properties of QPID based on quantum inference block.

- Further investigations of different QPID models are considered as useful and important.

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