Stabilization of an Inverted Robot Arm Using Neuro-controller

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Abstract :

Many systems exist in real control applications whose characteristics are difficult to be mathematically modeled, therefore performing the design of an adequate controller is a computationally complex task using the classical methods. Alternatively, neural networks prove to be a good tool in control systems design which can be used without the need to know the exact model. This paper aims at designing a neuro-controller that combines both supervised and adaptive neuro-control schemes. The supervised scheme mimics the classical PID controller off-line; while the adaptive scheme can adapt to the system uncertainty on-line, which could eliminate the need for an exact model. The objective of the proposed neural control system is to stabilize a robot arm and the resulting robot arm angles. However, an experimental set-up of an inverted pendulum rig mounted on a cart is used as the test-bed. The simulation results prove that the proposed adaptive neuro-control scheme successfully maintained the pendulum in an upright position at steady-state.

Keywords— ***supervised neural control, PID control, adaptive neural control, back\ propagation neural networks, robot arm control, inverted pendulum stabilization problem, system modeling, dynamic system analysis and control***

استقرار لذراع روبوت معكوس باستخدام وحدة التحكم العصبية

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الخلاصة:

في تطبيقات السيطرة الحقيقيه هنالك انظمه كثيره يصعب نمذجة خصائصها رياضيا مما يجعل استخدام الطرق التقليديه في تنفيذ تصميم مسيطر مناسب عمليه معقده حسابيا ،لذا استخدام الشبكات العصبيه عن كبديل ذلك يعتبر وسيله جيدة في تصميم انظمة السيطرة حيث يمكن استخدامها من دون الحاجه الى معرفة النموذج الرياضي الدقيق للنظام . يهدفهذا البحث الى تصميم مسيطر عصبي يدمج نمطي كلا من السيطره العصبيه الاشرافيه والمتكيفه (supervised and adaptive) معا . النمط ان حيث الاشرافي يحاكي مسيطر PID التقليدي الغير مباشر off-line، في حين النمط المتكيف يتكيف مع غموض النظام on-line مباشر بشكل وعليه يمكن الغاء الحاجه بذلك

الى نموذج رياضي دقيق للنظام . ان هدف نظام السيطره المقترح هو تحقيق استقرار ذراع روبوت مع زاويةالذراع الناتجه . لكنه عمليا لاجراء هذا البحث تم استخدام منصة بندول مقلوب مثبت على عربه متحركه. اثبتت نتائج المحاكاةعلى اساس ان نظام السيطره المقترح التكيف العصبي و على التحكم قادر الحفاظ بنجاح على البندول في وضع رأسي في حالة الاستقرار.

I. Introduction

Intelligent control using neural networks has been applied to various control problems in the literature [1][2][3]. This type of control is known to be effective in many situations, especially when the controlled system exhibits uncertainties. On the other hand, PID controller has been used as a major control method for real control problems. The simple structure of the PID controller contributes to reasonable robustness against noise and parameter variations. However, due to process uncertainty the PID controller may fail in performing the required control. Thus, it is desirable to combine the intelligent control approach with the traditional PID controller structure.

In this paper, an alternative neuro-control scheme is proposed. The proposed scheme is based on combing both supervised neural control and adaptive neural control schemes. A back-propagation neural network is trained off-line first to mimic a PID control action using supervised control scheme where the PID works as the teacher in this case. The neural controller can then be placed on-line in an adaptive scheme where it will continuously update its weights.

The proposed neuro-controller is used to stabilize an inverted robot arm and has shown its effectiveness through Simulink simulations where the stabilization is determined by solving the standard inverted pendulum problem. The dynamics of inverted pendulum simulates the dynamics of robotic arm in the condition when the center of pressure lies below the centre of gravity for the arm so that the system is also unstable, and hence robotic arm behaves very much like inverted pendulum under this condition.

II. The Inverted Pendulum Problem

As a nonlinear and unstable system with unknown and/or varying parameters, inverted pendulum on a cart poses a challenging control problem. The system, which is shown in **Figure.(1)**, consists of an inverted pole hinged to a cart and free to fall in the plane, in a roughly vertical orientation by moving the cart horizontally in the plane while keeping the cart within some maximum distance of its starting position. This classical system, which is variously known as the inverted pendulum problem, pole-balancing, or broom-balancing, seems to have been one of the attractive tools for testing linear and non-linear control laws. The problem was originally investigated in a neural network context in [4] and [5], and quickly became a classic object of study in both system dynamics and control systems theory, and in

the theory of control systems-learning, as well. Subsequently, numerous papers in the literature used inverted pendulum problem as a testing benchmark for the developed controllers due to its high nonlinearity, uncertainty, and lack of stability. This testing approach was also extended to test the robot arm
ability to interact with its environment in [6], [7] and [8].

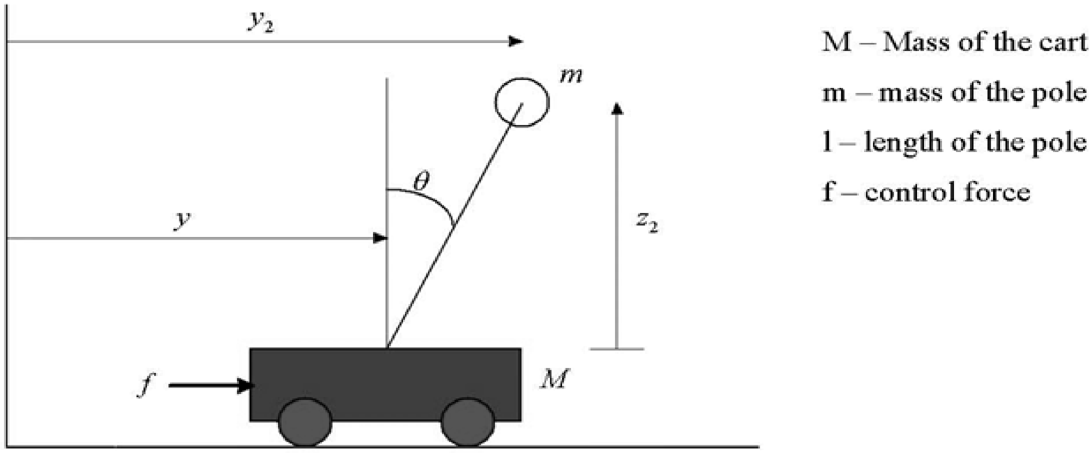

Fig. (1). Free body diagram of the inverted pendulum system

The main task here is to design a controller which keeps the pendulum system stabilized. There are important points to remember when designing such controller. One point is that standard linear PID controllers cannot be used for this system because they cannot map the complex nonlinearities in the pendulum process. In contrast, neural networks have shown that they are capable of identifying complex nonlinear systems and hence they are well suited for generating the complex internal mapping between inputs and control actions. Another point is that PID controller can operate correctly only if the system operates around a certain point and fail if any sort of uncertainty in form of disturbance or change in system parameters may occur. On the contrary, neural networks will adapt to such uncertainty by adjusting the weights and maintain controlling the system. Also a neural network can approximate data on which it has never been trained.

Two steps are carried out in this work to design this neuro-controller. The first step is to derive the mathematical model of the inverted pendulum system (this will be given in section IV). The second step is to develop a neural network controller which determines the correct control action to stabilize this model.

III. Neuro-control of the inverted pendulum

In the literature on neural networks architecture for control systems applications, a large number of control structures have been proposed and used. In this paper, however, a particular emphasis is given on two of these structures which can be used to stabilize the inverted pendulum. These two neuro-control structures are namely; the neuro-supervised control structure and the neuro-adaptive control structure.

In supervised control the neural network uses an existing controller, PID in this case, to learn the control action. Supervised control proceeds with a teacher providing the control output for the neural network to learn. The simplest approach to this method is to teach the network off-line; subsequently the neural network is placed in the feedback loop as in **Figure.(2)**. The main disadvantage of this scheme is the developed neuro-controller is based on a control law which can only effectively control a specific model for the inverted pendulum under certain operating conditions. If these model parameters are slightly changed or if the model was subjected to unknown disturbance then this controller would fail to keep the pendulum stable.

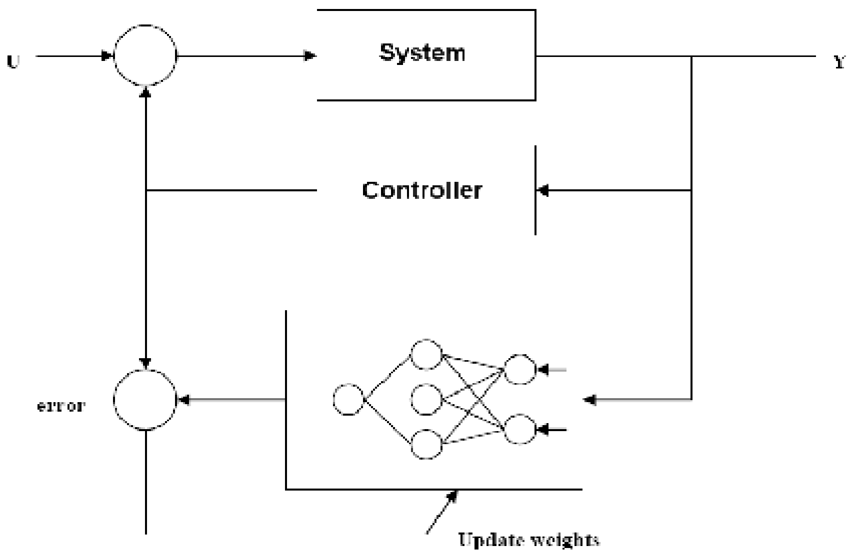

Fig. (2). Supervised control using existing controller

Figure. (2) shows the adaptive control scheme which has the ability to adapt on-line. This is achieved by presenting the neuro-controller with an error signal which is calculated by subtracting the actual output from the desired output. Subsequently this error is used to adjust the neural network weights on-line. However, the existing algorithms to perform adaptive adjusting are slow and have very low convergence rates. In these algorithms, the criterion to be minimized presents a quadratic of higher order which implies the existence of local minima. Moreover, online training allows neither multiple session optimization, nor employment of global optimization methods. Therefore, the probability of finding and getting stuck on a poor local minimum is high. Also, on-line adaptation of all the network weights does not intelligently use available, large data sets, and because it does not give priority to identify the system dynamics (or some specific operation points of the system); the resulting network is not a good approximation of the system to be modeled. With these drawbacks this scheme cannot cope with the uncertainty, instability and non-linearity involved in the inverted pendulum.

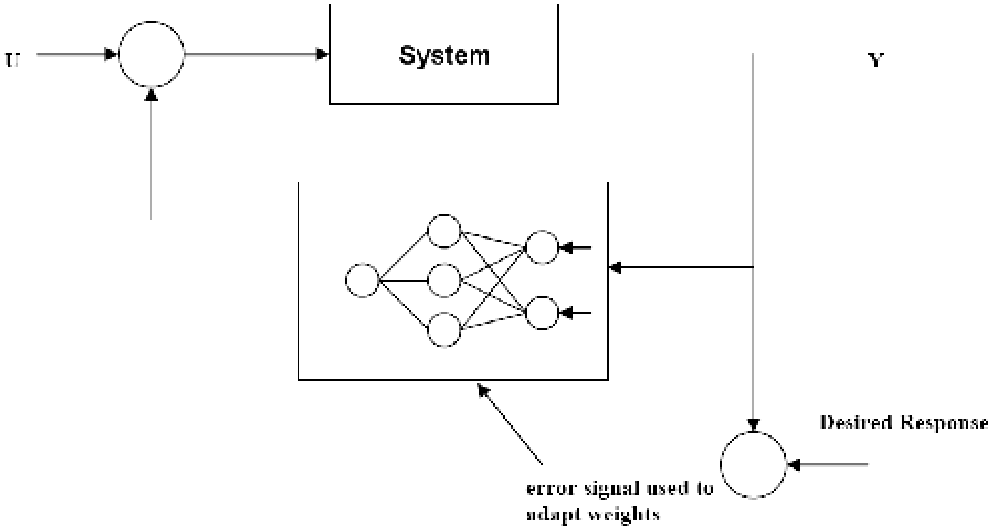

Fig. (3). Adaptive control scheme

The proposed neuro-control scheme overcomes the drawbacks of these two schemes by combing them together. The neural network is trained off-line first to imitate the PID controller, then the PID controller will be replaced by the trained neural network, which will control the system instead, while continues its learning in an adaptive manner to.

IV. Inverted Pendulum Modeling

The free body diagram of the system **Figure.(1)** is used to obtain the system model based on equations of motion. **Figure.(4)** below shows the two parts of this system's free body diagram in details, where the forces acting on the cart are depicted to the left and on the pendulum to the right (the figure's parameters are defined on the next page).

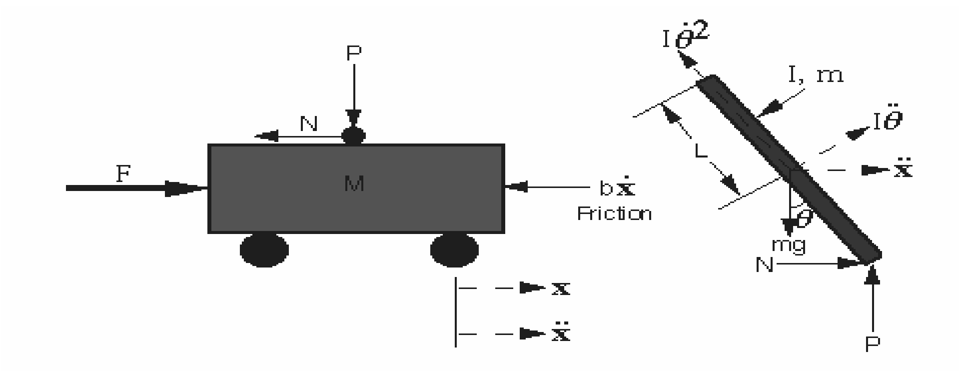

Fig .(4). Detailed free body diagram of the system with the cart (left) and inverted pendulum(right)

Where **Figure's 4** parameters are determined by the following:

M: mass of the cart.

m: mass of the pendulum.

b: friction of the cart.

L: length to pendulum center of mass.

I: inertia of the pendulum.

F: force applied to the cart.

x: cart position coordinates (with its first and second derivatives represent the linear velocity and acceleration, respectively).

θ : pendulum angle from the vertical axis (with its first and second derivatives represent the angular velocity and acceleration, respectively).

g: gravitational acceleration.

P and N: interaction forces between the cart and the pendulum in the vertical and horizontal directions respectively.

As depicted, both the cart and the pendulum have one-degree-of-freedom which is determined by x and θ, respectively. Hence, these two degrees-of-freedom can be mathematically modeled according to the basic Newton's equations as:

$$\ddot{x} = \frac{1}{M}\sum_{Cart} F_{linear} = \frac{1}{M}(F - N - b\dot{x})$$

$$\ddot{\theta} = \frac{1}{I}\sum_{Pendulum} F_{rotational} = \frac{1}{I}(NL\cos\theta + PL\sin\theta)$$

Summing the forces in the free body diagram of the cart in the horizontal direction, the following equation of motion is produced:

$$M\ddot{x} + b\dot{x} + N = F \qquad (1)$$

The sum of forces in the vertical direction is not considered because there is no motion in this direction and that the reaction force of the earth is considered balances all the vertical forces.

The force exerted in the horizontal direction due to the moment on the pendulum is determined as follows:

$$F_{moment} = mL\ddot{\theta} \qquad (1\text{-}1)$$

The component of this force in the direction of N is $mL\ddot{\theta}\cos\theta$.

The component of the centripetal force acting along the horizontal axis is as follows:

$$F_{\mathrm{centripetal}} = mL\dot{\theta}^2 \qquad (1\text{-}2)$$

The component of this force in the direction of N is $mL\dot{\theta}^2\sin\theta$.

Summing the forces in the free body diagram of the pendulum in the horizontal direction an equation for the interaction force N can be written as:

$$N = m\ddot{x} + mL\ddot{\theta}\cos\theta - mL\dot{\theta}^2\sin\theta \qquad (2)$$

By substituting equation (2) into equation (1), the first equation of motion for this system is produced:

$$(M+m)\ddot{x} + b\dot{x} + mL\ddot{\theta}\cos\theta - mL\dot{\theta}^2\sin\theta = F \qquad (3)$$

Then by summing the perpendicular forces to the pendulum, the second equation of motion can be provided by:

$$P\sin\theta + N\cos\theta - mg\sin\theta = mL\ddot{\theta} + m\ddot{x}\cos\theta \qquad (4)$$

Also by summing the moments around the centre of pendulum to eliminate P and N in equation (4) which leads to the following equation:

$$-PL\sin\theta - NL\cos\theta = I\ddot{\theta} \qquad (5)$$

Combining equations (4) & (5), the second dynamic equation is set to be:

$$(I+mL^2)\ddot{\theta} + mgL\sin\theta = -mL\ddot{x}\cos\theta \qquad (6)$$

The equations (3) and (6) are completely defining the dynamics of the inverted pendulum system, and they are non linear equations. Since the pendulum is required to be stabilized at an stable equilibrium position ($\theta = 180^0$), it is possible to linearize these equations by approximating:

$\cos\theta = -1$, $\sin\theta = -\phi$ and $\dot{\theta}^2 = 0$

It is assumed that ϕ is kept as a very small angle value from the vertical upward direction of the pendulum. Therefore the equivalent linear system equations are:

$$(M+m)\ddot{x} + b\dot{x} - mL\ddot{\phi} = u \qquad (7)$$

where u represents the input to the control system, and

$$(I+mL^2)\ddot{\phi} - mgL\phi = mL\ddot{x} \qquad (8)$$

To obtain the transfer function of the linearized system equations analytically, the Laplace transform of the system equations is taken. The Laplace transforms are:

$$(M+m)s^2X(s)+bsX(s)-mLs^2\Phi(s)=U(s)$$
$$(I+mL^2)s^2\Phi(s)-mgL\Phi(s)=mLs^2X(s) \qquad (8\text{-}1)$$

When finding the transfer function, initial conditions are assumed to be zero. The transfer function relates the variation from desired position (output) to the force on the cart (input). Since the angle Φ is sought as the output of interest, so:

$$X(s)=[\frac{(I+mL^2)}{mL}-\frac{g}{s^2}]\Phi(s) \qquad (8\text{-}2)$$

Then, substituting into the second equation will yield:

$$(M+m)[\frac{(I+mL^2)}{mL}+\frac{g}{s}]s^2\Phi(s)+b[\frac{(I+mL^2)}{mL}+\frac{g}{s}]s\Phi(s)-mLs^2\Phi(s)=U(s) \qquad (8\text{-}3)$$

By assuming that $q=(M+m)(L+ml^2)-(mL)^2$, and rearranging the equation above then the transfer function will be as :

$$\frac{\Phi(s)}{U(s)}=\frac{mLs}{qs^3+b(l+ml^2)s^2-mgl(M+m)s-bmgL} \qquad (9)$$

The forces that have the most effect on the cart will be its weight, the reaction driving force acting on the cart and the friction. In order to model the motion of the cart mathematically to a reasonable precision friction can be disregarded because the cart is moving at a nominal speed and that the cart is moving on a very well lubricated track.

Thus neglecting the friction in the system, that is, by take the coefficient of friction $b=0$, then:

$$\frac{\Phi(s)}{U(s)}=\frac{K_P}{s^2/A_P{}^2-1} \qquad (10)$$

where :

$$K_P=\frac{1}{(M+m)g} \quad \text{, and} \quad A_P=\pm\sqrt{\frac{(M+m)mgL}{(M+m)(I+mL^2)-(mL)^2}}$$

and thus the linearized approximation transfer function for the inverted pendulum system has been obtained.

In practice the experiment can be carried out using a setup as shown in **Figure.(5)** [9]. As shown in this setup, the pendulum rig consists of a simple cart which runs along a track. The cart is restricted to traveling in the track axis. The position of the cart is controlled by a DC motor and drive belt. A pole with mass on the end is pivoted on the cart and is free to swing in the same axis. The output from this system is the angle of the pendulum measured using optical encoder sensor. The output signal is sent to a control algorithm via a data acquisition card. The control algorithm determines a control action to keep the pendulum inverted. A DC signal controls the speed and magnitude of the motor which determines the position of the cart.

Therefore the actuation mechanism, which consists of the movable cart on track driven by the DC motor via a pulley and belt, its transfer function, can be written as:

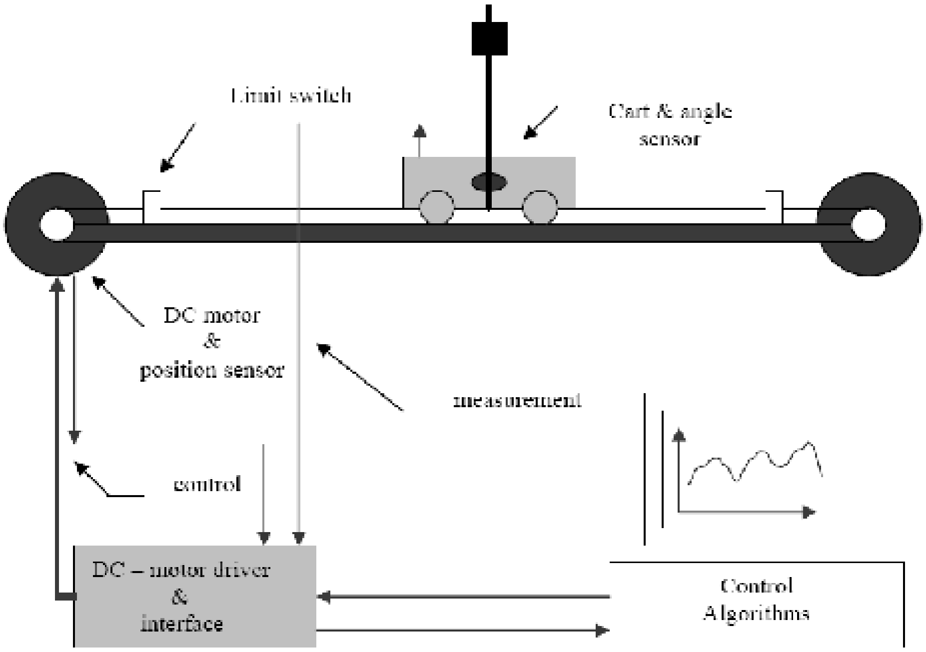

Fig. (5). The experimental set-up of the pendulum rig

$$\frac{U(s)}{E(s)} = K_m \frac{(M+m)rs}{(t_m s+1)} \qquad (11)$$

where K_m and t_m are the system gain and time constant, respectively, and it depends upon the load drive. r is proportional to the force F .

Finally the transfer function for the whole uncontrolled system can be given as:

$$\frac{\Phi(s)}{E(s)} = K \frac{s}{(t_m s+1)(\frac{s^2}{A_P^2}-1)} \qquad (12)$$

where $K = K_F K_P K_M r(M+m)$

$E(s) =$ Error Voltage

$\Phi(s) =$ Angular Position of Pendulum

The above physical parameters of the system prototype may be chosen according to [10] which are given in **Table 1.**

Table 1 : The physical parameters of the system prototype

Symbol	Description	Value
M	Mass of Cart	900 gm
m	Mass of the Pendulum	100 gm
b	Friction of the Cart	0.01 N/m/sec
L	Length of Pendulum to Center of Gravity	23.5 cm
I	Moment of Inertia (Pendulum)	5.3 gm-m^2
R	Radius of Pulley	2.3 cm
t_M	Time Constant of Motor	0.5 sec
$\mathbf{K_m}$	Gain of Motor	17 rad/sec/V
$\mathbf{K_F}$	Gain of Feedback	9/π V/rad/sec

V. Implementation of the Proposed Neuro-controller

The developed neuro-control scheme was implemented using Simulink. As was disused in section III that this scheme results from applying both supervised and adaptive control structures. The first structure uses supervised learning as shown in **Figure.(6**) where there is an existing PID controller in the feed-forward loop. The MLP (multilayer percepetron) back-probagation type neural network will be trained off-line first to imitate this controller. Two different cases of external disturbance subjected on the force on the cart and on Theta are considered. In this case the reference position is assumed to be zero. On the other hand three different types of inputs are subjected at the system input where the system is run free of external disturbances. These inputs are impulse, step, and band limited white noise respectively.

Figure.(7) shows the second structure used afterwards where the PID controller has been removed and replaced by the MLP where it can be trained and adjust its weights on-line. Therefore it can adapt and compensate effectively for any disturbance or uncertainty. The MLP used in this experiment is an add-on for Simulnk and is given by toolbox developed in [11] and inspired by methodologies presented in [12]. The MLP consists of an input, an output and 2 hidden layers and was trained by tuning its perceptions' weights in the off-line training phase such that to maintain a unity system feedback loop gain.

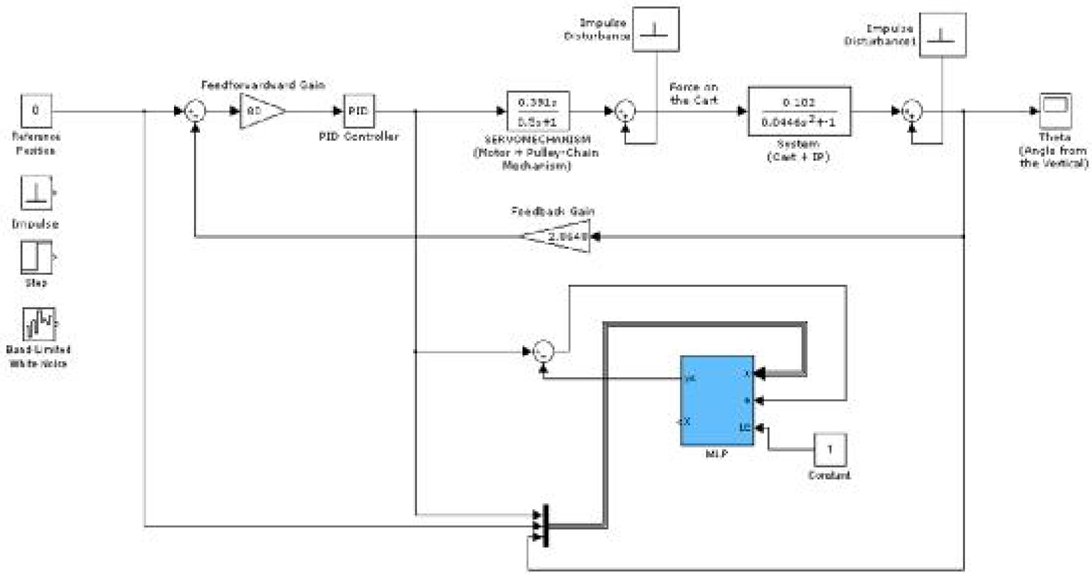

Fig .(6). Simulink implementation using the supervised control structure

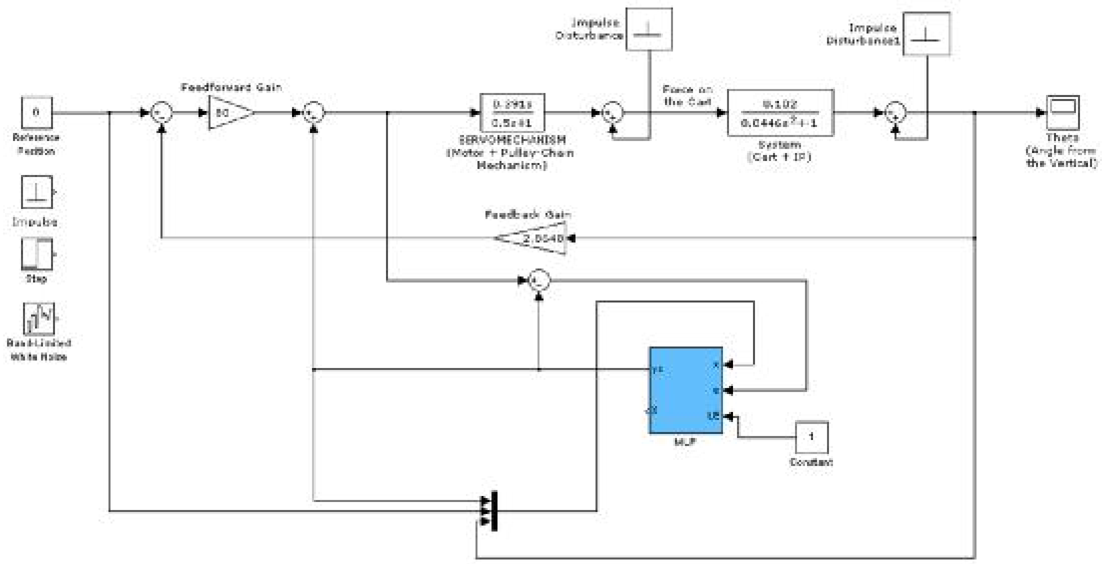

Fig .(7). Simulink implementation using the adaptive control structure

VI. Simulation Results and Neuro-controller Performance

This section demonstrates the testing experimentation results of the proposed adaptive neuro-controller using the Simulink implementation described in the previous section. The supervised learning scheme of **Figure. (6)** is used first to train the neural network. Then this trained neural network will be the core of the proposed adaptive neuro-controller shown **in Figure .(7).**

Figure .(8) shows the response to an impulse disturbance in force subjected on the cart only where the overall feedback adaptive neuro-control system rejects the disturbance due to such force disturbance applied on the cart. Similarly, **Figure .(9)** shows the response to an impulse disturbance on position of the inverted pendulum only where the system rejects the disturbance on the position of the pendulum. In these two test cases the reference position input is kept zero.

Figure. (10) shows the impulse response of the inverted pendulum system to an impulse input subjected on the system input. While **Figure. (11)** shows the step response of the compensated inverted pendulum system to as step input. This Fig shows that the system becomes stable as the output stabilizes and compensates for certain small value of Theta, the angle of the pendulum from the vertical.

Finally, **Figure. (12)** shows the system response to input disturbance of a random noise with variance equals to 0.01.

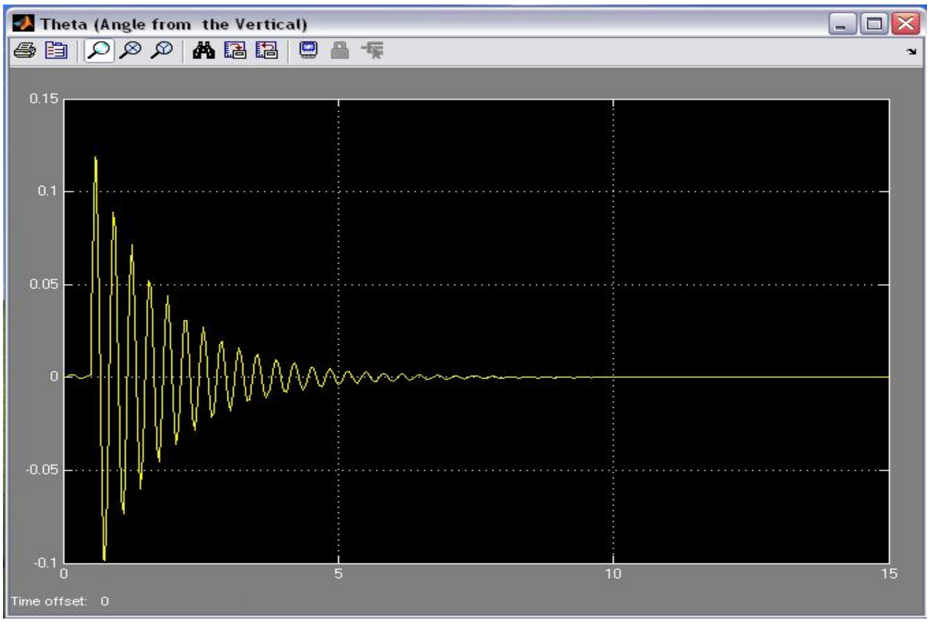

Fig .(8). System response to disturbance in force subjected on the cart

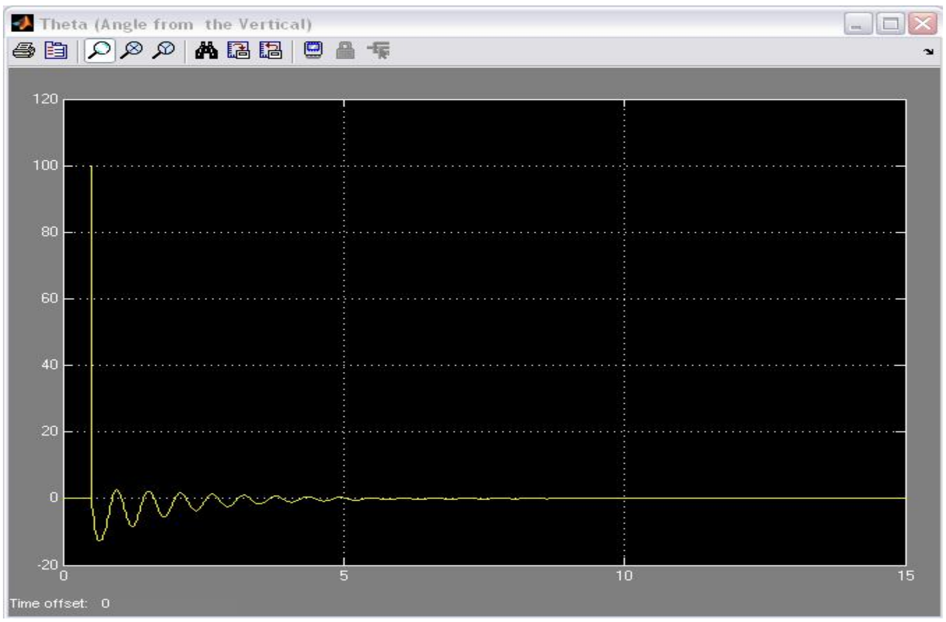

Fig .(9). System response to disturbance on position of the inverted pendulum

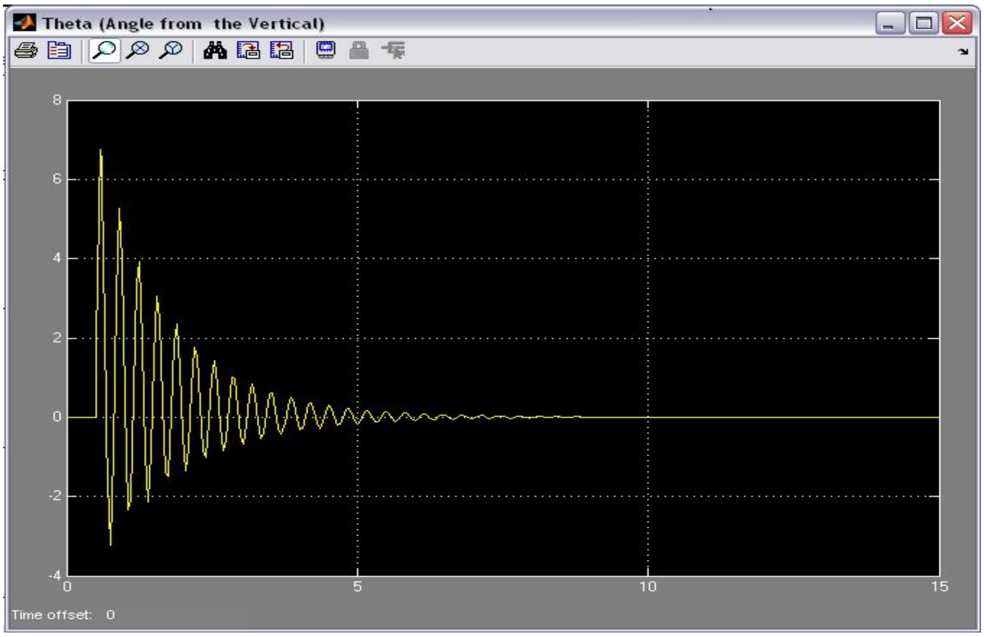

Fig .(10). System impulse response to an impulse input

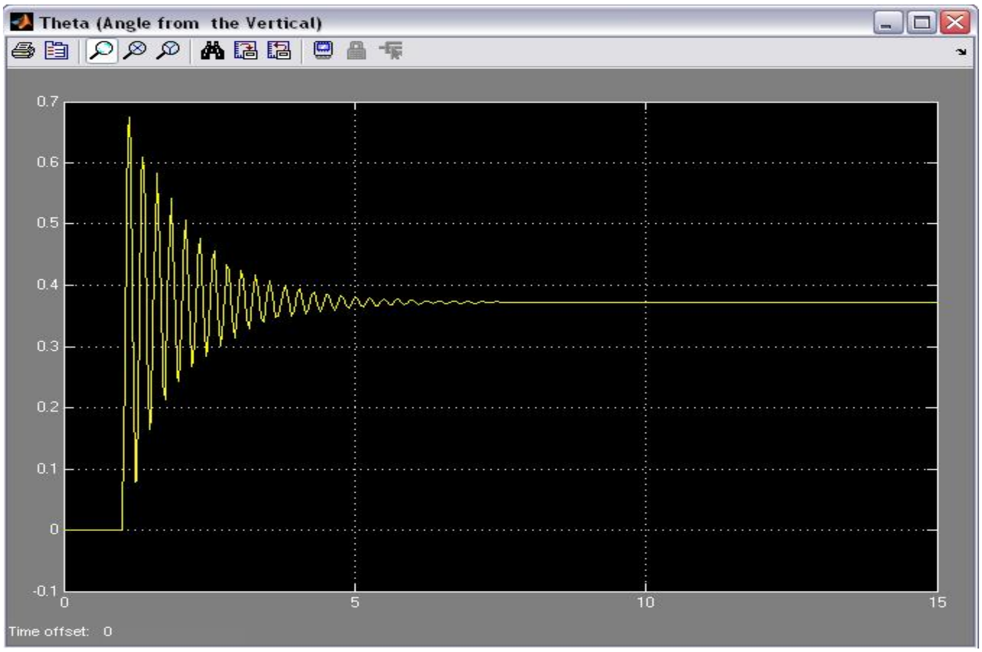

Fig .(11). System step response to a step input

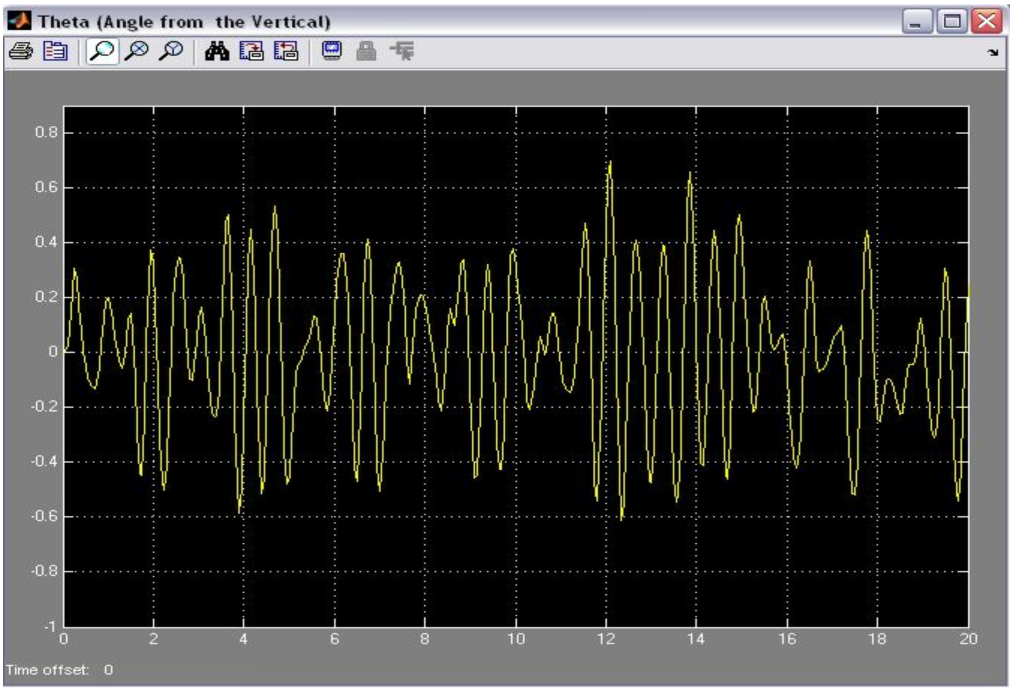

Fig .(12). System response to an input disturbance of a random noise with variance equals to 0.01

In all the test cases mentioned above except for the step input **Figure. (11)** the inverted pendulum is initially at vertical zero position then the system has become stable as Theta returns back to zero. For the step input case **Figure. (11)** the inverted pendulum is initially at vertical zero position then the system stabilizes at small value of the vertical angle Theta slightly beyond zero.

As illustrated by the results of **Figure. (8)** and **Figure.(9)** that the proposed adaptive neuro-control algorithm rejects properly and robustly the two different types of impulse disturbances imposed on the force (on the cart) and on the position (on pendulum). While from the results of **Figure. (10)** and **Figure. (11)**, it is obvious that the overall feedback control system respond successfully and follows the required two deterministic inputs, impulse input and step input. In addition, **Figure .(12)** shows that the overall feedback control system is responding successfully to an input disturbance sequence of a random noise with variance equals to 0.01 by stabilizing the vertical value of Theta to be always around zero value despite this random noise.

The overall performance of this proposed adaptive neuro-control scheme seems to be promising where the controller successfully maintained the pendulum in an upright position at steady-state. However, further adjustments and modifications are required to improve the system stability during the transit response period and/or stabilizing the system at larger values of Theta, the angle of the pendulum from the vertical.

VII.Conclusions

In this paper an alternative neuro-control scheme is proposed. This scheme is based on combing the well-known supervised learning and adaptive control schemes together in order to obtain their better features. The supervised learning control scheme is used to train the neural network to mimic PID control action off-line, and then the neural network is used to control the system while the network continues its training on-line to compensate for any uncertainty or disturbance.

The proposed neuro-controller is used to stabilize an inverted robot arm and show its effectiveness through simulation. The stabilization will be determined by solving the standard inverted pendulum problem which is perhaps the most widely used benchmarking study to assess the effectiveness of emerging control design techniques.

The back-propagation learning method is used to train the multilayer perceptron neural network to control the pendulum which is free to pivot on a cart. The goal of the neural controller is to maintain the inverted pendulum balanced. The neural network has been implemented with Simulink and the experimental results show the effectiveness of the used adaptive neuro-control technique as the network is able to balance the pendulum.

This proposed adaptive neuro-control scheme is open to future development to achieve substantial improvements in the system stability during the transit response period and/or stabilizing the system at larger values of Theta, the angle of the pendulum from the vertical.

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