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Research Article

An Improved Approach of Neural Network to Non-Linear Inverted Pendulum System

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ABSTRACT

This paper introduced a best approach techniques for control the non linearity of the inverted pendulum (IP) by using Artificial Neural Network (ANN). In A Artificial Neural network type is Feed-Forward Network (FFN).Training is done by "Trainlm" network function that is use to updates weight and bias states according to Levenberg Marquardt (LM) back-propagation algorithm. This technique is focused on how to solve non linear behaviour the of "parameter modification" such as angle and position of inverted pendulum. We use controllers(like conventional controller) to compare their response with Neural network controller to find their linear behaviour with improve accuracy and precious time by using MATALAB simulation. The method is applied to the Nonlinear IP model with the application of some precariousness, and the experimental results show that the system responds very well to handle those precariousness.

Keywords-Inverted pendulum (IP); Artificial Neural network(ANN); Feed-Forward Network(FFN);Control Law; Levenberg Marquardt(LM).

I. INTRODUCTION

The inverted pendulum problem is a unique example of an nonlinear dynamic system. Therefore, much awareness has been given to investigate a better solution for it and further, to solve other similar control problems. Nonlinear framework control presently possesses an inexorably significant situation in the territory of cycle control designing as reflected by the enormous expansion in the quantity of exploration papers distributed here. Artificial neural network proved to be a useful tool in dealing with applications such as pattern recognition, signal processing, image processing and various complex control and mapping problems etc. Neural networks are applied successfully to spot and control of dynamic systems due to their learning capacity and skill to tolerate incorrect or noisy data[1]. The universal estimation skills of the multilayer perceptron make it a esteemed choice for modeling nonlinear systems and for implementing general-purpose nonlinear controllers. A conventional controller which is proposed in [2] is employed to gather the training data to develop Neural Network controller for a inverted pendulum system. Multilayer neural network consists of single layer each for inputs and outputs and one or more hidden layers, each layer can have one or more no's of neurons. The linking weights are updated by the back-propagation algorithm. It can control different arrangement through quick learning process and has perfect accomplishment. Ni(1996) proposed a method for identification and control of nonlinear dynamic system a recurrent model was applied as identifier[3]. Gupata(1999) presented an improvement to back-propagation algorithm supported the utilization of an independent, adaptive learning rate parameter for every weight with adaptive nonlinear function[4]. LM algorithm is an efficient optimization technique which will guide the load optimization[5]. Neural network has been widely applied for state feedback controller design, nonlinear system control, nonlinear dynamical system identification, optimal control synthesis and three-dimensional medical image [6-10].This paper utilizes the regularized LM calculation to prepare the interfacing of neural organization. The objective of this paper is to build up a neural organization based nonlinear regulator and give a fast, reliable solution for the control algorithm.

II. MODELLING OF INVERTED PENDULUM

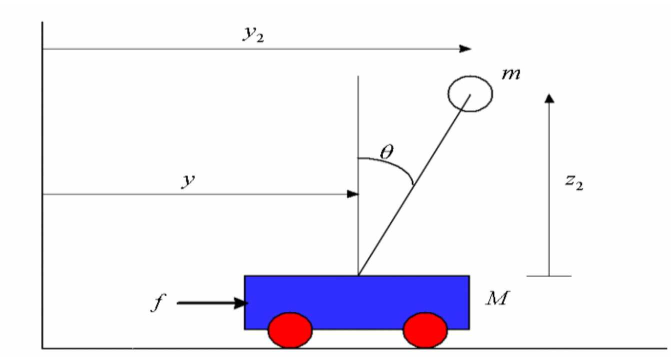


Fig.1. Inverted pendulum system

Where,

M = Mass of the cart

m = Mass of the pole

l= Length of the pole

f=control force

The inverted pendulum system, as shown in Fig.1, is composed of a rigid pole and a cart on which the pole is hinged [11]. The cart moves on the rail track 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 is 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. The displacement of the cart can be measured by a sensor installed on both sides of the rail track, and the angle signal can be measured by a coaxial angle sensor installed in the bearing which articulates the pendulum to the cart. On one side of the rail track a DC permanent magnetic direct torque motor is mounted which drives the cart to move on the rail track using a driving belt. When the cart moves left and right, torque acts on the pendulum to keep the whole system in stable condition. Masked values of system plant parameters are used so that it can be easily varied to check the performance of the proposed controller with different system parameters. The cart mass is M, the pendulum mass is m, its length is 2L. The cart is restricted to move within a fixed range. The reference position for x is 0 meter, when cart is in the center of the rail track and for θ is π radians, when the pendulum is at a natural stable downward position.

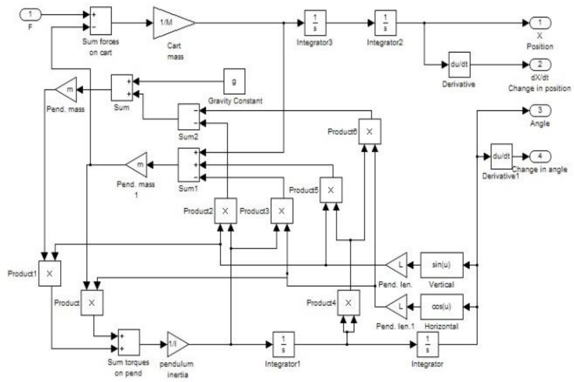


Fig.2. simulation model of nonlinear inverted pendulum system

A. Mathematical model of inverted pendulum The dynamic equations of the system can be found with help of the Euler-Lagrange equation as[2]:

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

$$(I + mL^2)\ddot{\theta} + mgL\sin\theta = -mL\ddot{x}\cos\theta \quad \ldots\ldots\ldots \qquad (1)$$

Now by using the above equations the nonlinear model of IP system is developed in Matlab simulation which is shown in Fig.2.

B. Feedback control law for Inverted Pendulum System To provide the supervised training data for the neural network controller we use the direct adaptive control technique described in [2]. Based on the equation (1) the following equations are a control law developed for the inverted pendulum controller. The first four equations (2-5) are entered into the main equation. The main equation (6) calculates the required force, u to keep the pendulum stable.

$$h_1 = \frac{3}{4L} g sin\theta \qquad (2)$$

$$h_2 = \frac{3}{4L} cos\theta \qquad (3)$$

$$f_1 = m\left(Lsin\theta\dot{\theta}^2 - \frac{3}{8} g sin2\theta\right) \qquad (4)$$

$$f_2 = M + m\left(1 - \frac{3}{4} cos^2\theta\right) \qquad (5)$$

$$u = \frac{f_2}{h_2}\left[h_1 + k_1(\theta - \theta_d) + k_2\dot{\theta} + c_1(x - x_d) + c_2\dot{x}\right] - f_1 \qquad (6)$$

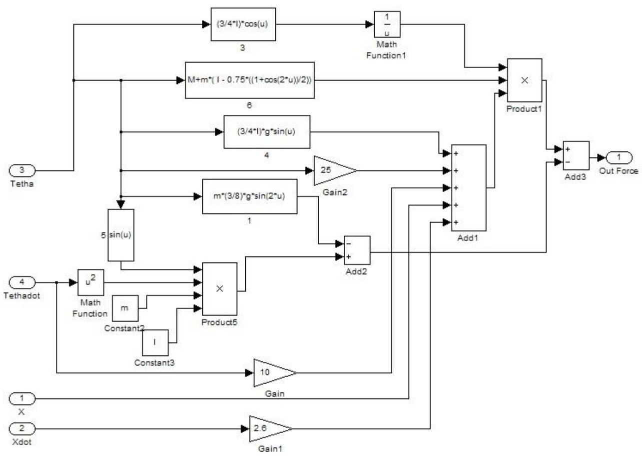


Fig.3. Simulink model of nonlinear control law

For the simulation M , m , L , g are set to the values of the pendulum model. The following numeric values are used: M=1.096 Kg, m=0.109 Kg, L=0.25 m, g=9.81 m/s^2, k_1=25, k_2=10, c_1=1, c_2=2.6. Also x_d= 0 meter and θ_d= 0 radian which are the desired position of the cart and angle of the pendulum respectively. A simulation model of the above control law was developed and is shown in Fig.3.

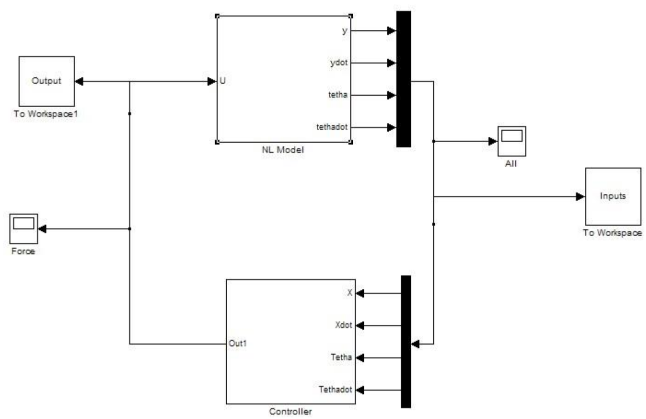


Fig.4.Simulink blocks of non-linear model of inverted pendulum and controller

C. Neural Network Controller for Inverted pendulum An artificial neural network model is a system with inputs and outputs based on biological nerves. The framework can be made out of numerous computational components that work in equal and are orchestrated in designs like natural neural nets. A neural network is typically characterized by its arthmatics operation, its network topology and the learning algorithm used. Proposed neural network controller architecture is shown in Fig.5. It consists three layers, which are input-layer, hidden-layer and output layer. The input-layer has four neurons for "cart displacement", "cart velocity", "deflection of pendulum", "velocity of pendulum". The choice of number of hidden layers and number of hidden neurons in each of the hidden layer plays a very important role for designing a neural network because in a number of situations, there is no specific way to determine the best number of hidden units without training several networks and estimating the generalization error of each. The aim of the control of nonlinear system , which can be solved by adjusting the network"s weights and modifying the input of plant.

Where e(t) is the objective function, r(t) is the desired plant output, and y(t) is the controller output, in our case best results i.e. e(t) is minimum for a single hidden layer with thirteen hidden neurons. The output- layer has only one neuron corresponding to the output force on the cart.

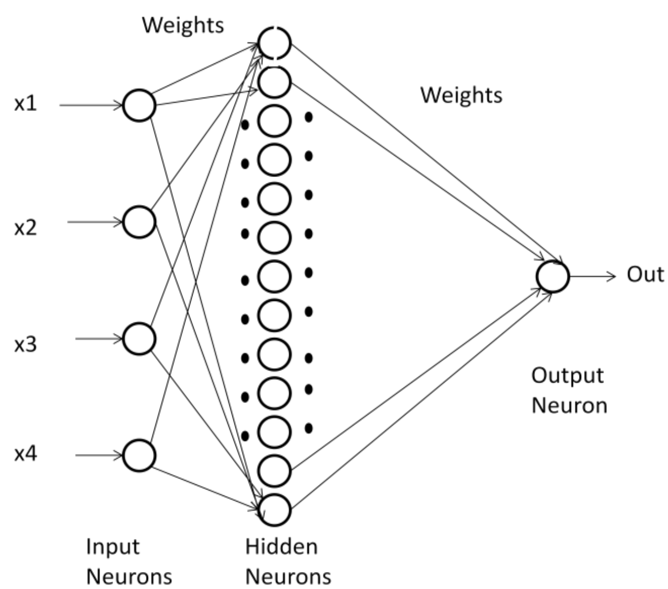


Fig.5. Architecture of neural network controller

It is conceivable to show a neural organization the right activities by utilizing a current regulator or human input. This type of control is called supervised learning. Most traditional controllers (feedback linearization, rule based control) are based around a operating points. This implies that the regulator can work accurately if the plant/measure works around a specific point. These controllers will fail if there is any sort of uncertainty in the unknown system. The advantages of neural-control is if an uncertainty in the plant occurs the ANN will be capable to modifyit"s parameters and maintain controlling the plant when other robust controllers would fail. In AI control, a assistant provides correct actions for the neural network to learn. In offline training the targets are provided by an existing controller, the neural network adjusts its weights until the output from the ANN is similar to the control law.To train the neural network the training data is exported to the Matlab workspace as shown in Fig.4 from there we can use the neural network toolbox or appropriate m-code to generate neural network controller in this paper training has been done by m-code with the following settings. Network type is feed-forward, network training function is Levenberg-Marquardt algorithm (trainlm), input activation function sigmoid (tansig), output activation function is linear(purelin), no. of iterations (epochs) is 1800, learning rate is 0.2, momentum control factor to avoid the problem of local minima is 0.1, no. of neurons in input hidden and output layers are 4,13,1 respectively. After training the neural net with the above settings the simulation block has been generated using the command gensim(network_name,desired_sample_time) in the Matlab command prompt. The simulation model of the trained neural network controller is shown in Fig.6.

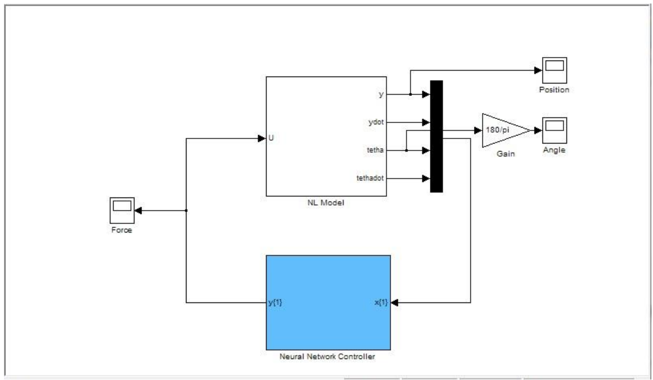


Fig.6. Simulation model of IP & ANN controller system

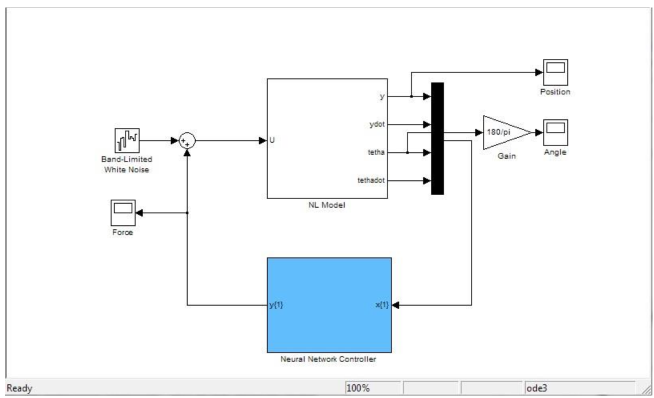


Fig.7. Simulation model of IP & ANN controller system

III. SIMULATIONRESULTS AND ANALYSIS

The simulation results show the closed loop response of inverted pendulum and neural network controller system. The simulation time is 10 seconds for all simulations with fixed step size solver of sample time 0.01 second. Three experiments are performed to demonstrate the controlling ability of the proposed neural network controller for the inverted pendulum system under the application of initial condition, band-limited noise and for some parameter variations of the inverted pendulum system. In the first experiment the initial parameters of the inverted pendulum system are listed as

follows: x(0)=0.0m, $\dot{x}(0) = 0.0m/s$, θ(0)=0.1rad, $\dot{\theta}(0) = 0.0rad/s$.

These values are putted in the initial condition column of the integrator blocks of nonlinear inverted-pendulum model corresponding to cart position, cart velocity, pendulum angle and pendulum angler velocity respectively. The simulation setup for the first experiment is shown in Fig.6 and corresponding results are shown in Fig.8.The experiment result shows that the ANN controller is able to control the cart position and pendulum angle within 2sec with a little force of 1.7N.

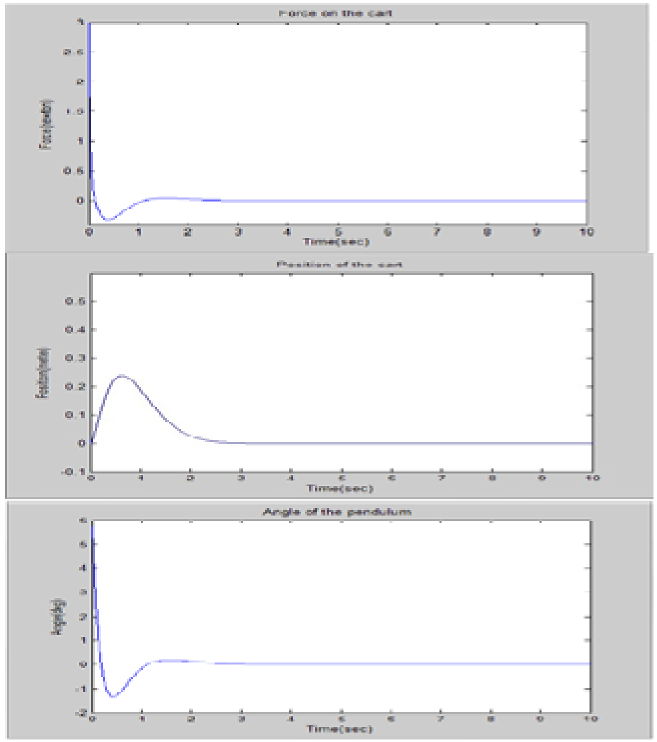
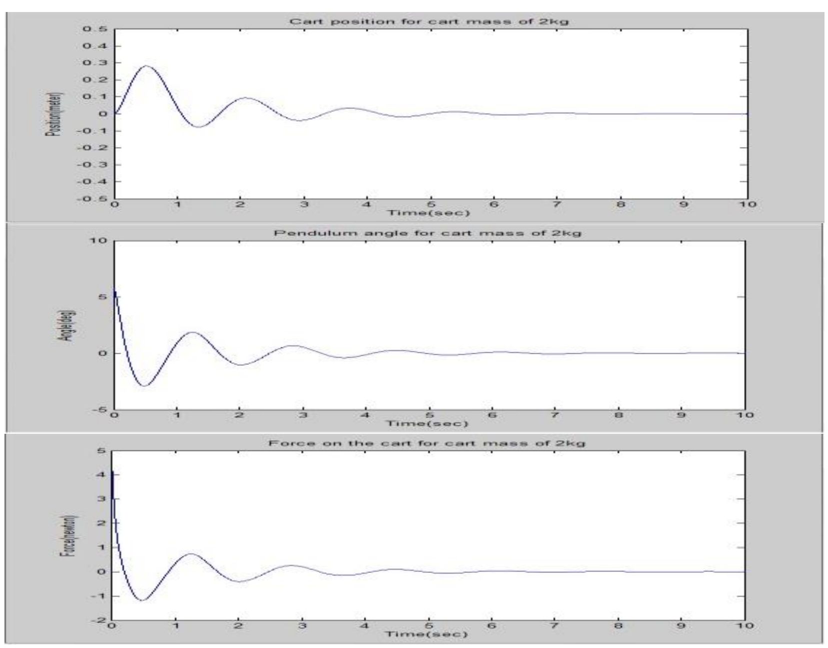


Fig.8. Simulation results for initial value of 0.1rad in pendulum angle(a)force on the cart(b)position control of cart(c)angle control of pendulum

Now in second experiment the parameters are set to zero initial values as x(0)=0.0m, $\dot{x}(0) = 0.0m/s$, θ(0)=0.0rad, $\dot{\theta}(0) = 0.0rad/s$, and the disturbance is introduced externally in the form of band limited white noise with noise power 0.1 sample time 0.01 and seed value of 16. The simulation setup for the second experiment is shown in Fig.7 and results are shown in Fig.9 from the results it is clear that maximum of 4N force in either directions is required to control the cart pendulum system in which pendulum angle ling between (-5 to 5)deg and cart position within (-0.4 to 0.4)m.



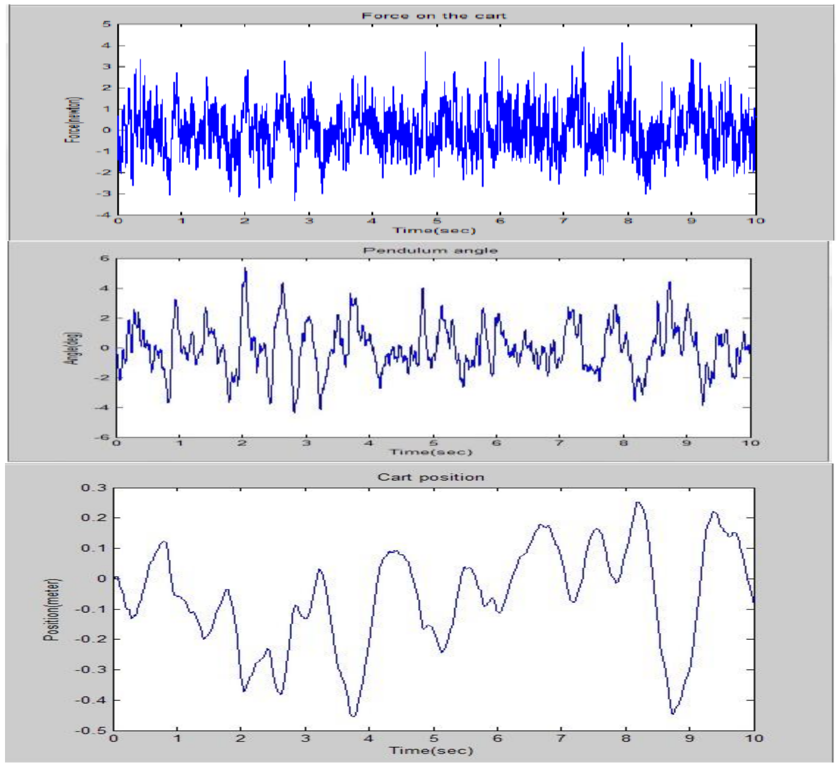


Fig.9. Simulation results after addition of noise (a) applied force to control IP system

(b) Pendulum angle control(c) cart"s position control

Finally in third experiment the parameters are set to Initial values given as x(0)=0.0m, $\dot{x}(0) = 0.0m/s$, θ(0)=0.1rad, $\dot{\theta}(0) = 0.0rad/s$.In this experiment the value of cart mass M is increased nearly 100% and it is changed to 2kg the simulation setup is same as that of first experiment except that now the cart mass is 2kg. Simulation result for the changed mass of cart is shown in fig.10. Results shows that control action is satisfactory although it takes a little more time to settle down with oscillations, but with that much change in cart mass the response is quite good.

A neural network is nonlinear nature to predict the nonlinearity in the system. To generate supervised data to train the ANN controller the IP system is stabilized by the control law. The data generated is used train the neural network so that it can mimic the output of control law by optimizing the linking weights and bias values using LM back-propagation algorithm. This trained neural network is tested in MATLAB Simulink with nonlinear inverted pendulum model. Simulation results shows that the ANN controller not only stabilize the IP system under uncertain parameters and it is also able to handle external disturbances. Based on the simulation results proposed ANN controller can be used to control the real time IP system.

IV. CONCLUSION

The paper introduced artificial neural networks to control the inverted pendulum system. The advantage of neural network is its nonlinear nature to predict the nonlinearity in the system. To generate supervised data to train the ANN controller, the IP system is stabilized by the control law. The data generated is used to train both type of neural network controllers so that they can mimic the output of control law by optimizing the linking weights and bias values. These trained neural network controllers are tested in MATLAB Simulink with nonlinear inverted pendulum model. ANN proves to be very fast and accurate in online prediction and control. Based on the simulation results proposed the ANN controllers can be used to control the real time IP system. By comparing both results we can say artificial neural network intelligent controller more stable,fast and accurate in comparison to the conventional controller.

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