Identification and Control of Nonlinear Systems using Soft Computing Techniques

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Abstract—**The inverted pendulum is a highly nonlinear and open-loop unstable system. This means that standard linear techniques cannot model the nonlinear dynamics of the system, Inverted pendulum system is often used as a benchmark for verifying the performance and effectiveness of a new control method because of the simplicities of the structure. In this paper an accurate model of the inverted pendulum system, a neural network controller and ANFIS (Adaptive Neuro-Fuzzy Inference System) controller to stabilize the system have been developed. A control law that removes some of the nonlinearities from the process and allows the process to exhibit its dynamics has been developed. This aids in stabilizing the nonlinear pendulum. The quality of the data input has also been improved, since only limited number of variables that can be measured accurately are included in the system identification Simulation results establishes that the proposed controller has good set point tracking and disturbance rejection properties.**

Index Terms—**Inverted Pendulum, Neural Network,ANFIS, Nonlinear system control.**

I. Introduction

Inverted Pendulum System consists of an inverted pole hinged on a cart which is free to move in the x direction. In this Section, the dynamical equations of the system model in Simulink and basic controllers are developed. The system dynamical equations are derived using 'Lagrange Equations'.

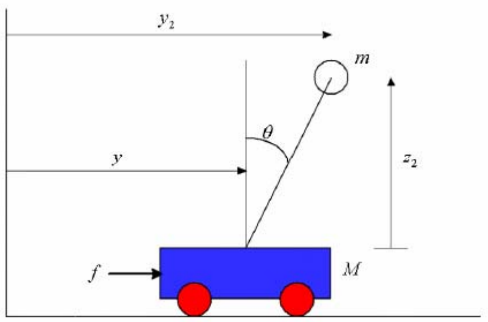

Fig.1 Free Body Diagram of Inverted Pendulum System

Fig.1is the free body diagram of inverted pendulum system.

The system state equations are

$$\begin{cases}(M+m)\ddot{x}+c\dot{x}-ml\cos\theta\ddot{\theta}+ml\sin\theta\dot{\theta}^2=f(t)\\ -ml\ddot{x}\cos\theta+(ml^2+I)\ddot{\theta}+b\dot{\theta}+mgl\sin\theta=0\end{cases} \quad (1)$$

Where M is the mass of the cart, m is the mass of the pendulum, l is the length of the pendulum, f is the control force.

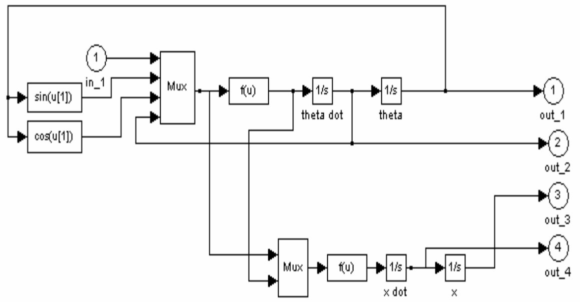

Fig .2 Simulink Model of Nonlinear Control Law

II. Simulink Model Of Control Law

Developing a controller for the non-linear pendulum is more difficult. Linear control techniques such as the PID, full-state feedback will have no success in controlling the non-linear pendulum. A feedback linearization controller has been proposed by[1]-[3] et.al., to control the non-linear pendulum system. Feedback linearization results in an improved linear closed loop system. Equations 2 to 6 have been developed to describe control law for the inverted pendulum controller. The Equation 6 for u, based on Equations 2 to 5, calculates the required force, u, to keep the pendulum stable. For accurate system identification the process has to be stable.

$$h_1=\frac{3}{4l}g\sin\theta \quad (2)$$

$$h_2=\frac{3}{4l}\cos\theta \quad (3)$$

$$f_1=\left(l\sin\theta\dot{\theta}^2-\frac{3}{8}g\sin 2\theta\right)-f\dot{x} \quad (4)$$

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

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

Manuscript received March 21, 2011.
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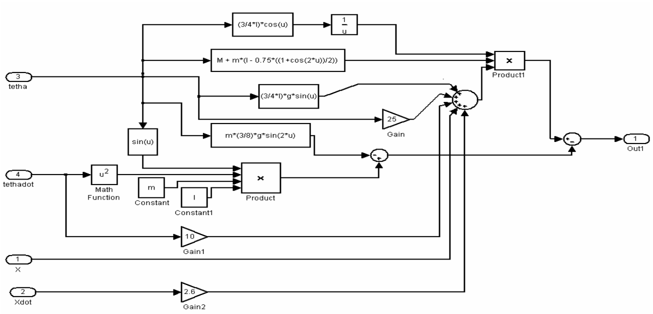

Fig.3 Simulink Model of Nonlinear Control Law

For the simulations M, m, l, g are set to numeric values namely: M = 1.2 Kg, m = 0.1 Kg, l = 0.4 m, g = 9.81 m/s, $k1$ = 25, $k2$ = 10, $C1$ = 1, $C2$ = 2.6. xd and qd are set to zero which are the initial position of the cart and angle of the pendulum respectively. The Simulink model of the control law is shown in Fig.3.The set-up of the non-linear pendulum with control law is as in Fig.4.

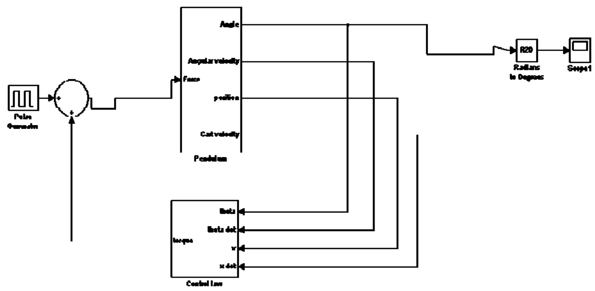

Fig.4 Nonlinear system with Control Law

Closed loop pendulum angle obtained through MATLAB simulation is plotted in Fig.5. The closed loop response has been observed to be stable with the introduction of the control law.

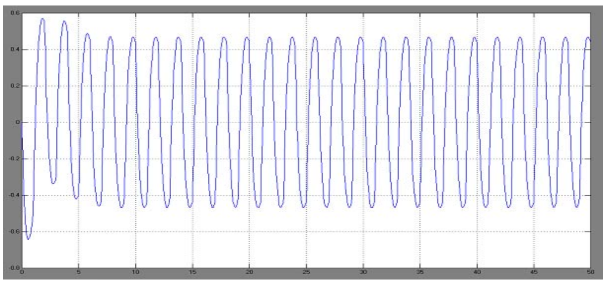

Fig.5 Closed Loop Response of Nonlinear System with Control Law

III. Modeling Of Inverted Pendulum Using Artificial Neural Network

A. *Introduction To Artificial Neural Network (Ann)*

In order to understand the structure of artificial networks, the basic elements of the neuron should be understood. Neurons are the fundamental elements in the central nervous system. A neuron is made up of 3 main parts -dendrites, cell body and axon. The dendrites receive signals

from the neighboring neurons and send their signals to the body of the cell. The cell body contains the nucleus of the neuron. If the sum of the received signals is greater than a threshold value, the neuron fires by sending an electrical pulse along the axon to the next neuron.

B. *Types Of Learning & Structures*

Neural networks have 3 main modes of learning operations, namely, supervised, reinforced and unsupervised learning. In supervised learning the output from the neural network is compared with a set of targets, The error signal is used to update the weights in the neural network. Reinforced learning is similar to supervised learning but no targets are specified. Unsupervised learning updates the weights based on the input data only. There are 3 main types of structures namely, single layer feed forward, multi-layer feed forward and recurrent networks.

C. *Identification And Modelling Of Inverted Pendulum*

The most common method of neural network identification is called forward modeling. During training both the process and ANN receive the same input and outputs from the ANN and process are compared. This error signal is used to update the weights in the ANN. The pendulum system provides target values for the neural network. Feed-forward type of network will be used for identification. In order to provide a set of targets for the network to learn, the Simulink model with feedback control is used.Fig.6 shows the supervised learning from inverted pendulum system with control law

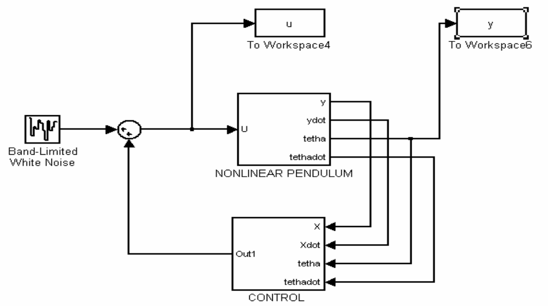

Fig.6 Simulink diagram for generation of neural targets

D. *Single-Output Identification*

Initially single-input single-output networks were developed, the input being the control force and the output pole angle. The first type of neural network to be developed is feed-forward. Using matlab it is possible to develop multi-layer perceptions (MLP).The matlab code creates a feed-forward network. The 'newff' function allows a user to specify the number of layers, the number of neurons in the hidden layers and the activation functions used. These networks use the back-propagation learning rule to update the weights. The number of epochs for this example is set to 100. The learning rate of the network is also set. The 'train' function adjusts the weights of the network, Fig.8 shows the training, testing and validation of the MLP.When the training is finished, the neural network is exported to Simulink using the 'gensim' command.Fig.7shows the neural network in simulink environment. Notice that the neural model and the process receive the same input signal. The quality of the neural model is tested by calculating the MSE(Mean Squared Error) The MSE gives a good indication of the accuracy of the model. The output from the model and process is plotted to compare the dynamics.

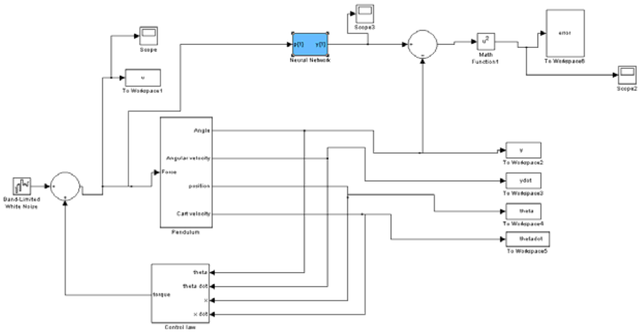

Fig.7 Comparison of actual model with neural model

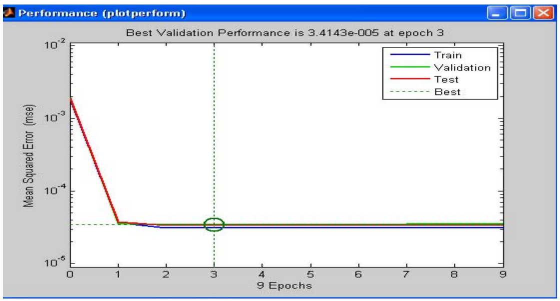

Fig.8 Validation Performance of neuron model

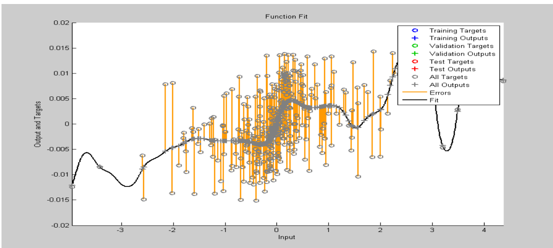

Fig.9 Data's taken from the neural network

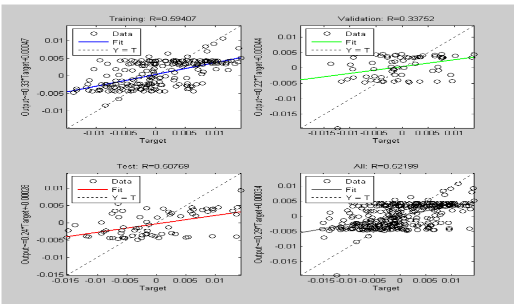

Fig.10 Training and testing data's for validation

Fig.9 shows the training data's taken by the neural network for validation, increasing the number of hidden layer neurons allows for more complex functions to be modeled. It was expected that as the number of hidden neurons increased the more accurate the model would become. The MSE error is low and the neural model predicts the pendulum angle. The results in Table.1 indicate that increasing the number of hidden neurons improve the MSE between the model and the process.

E. Multioutput Identification

In Section 3.4 neural models have been for single-input single output systems with just the pendulum angle output. A neural network which models one input and 4 output states has been developed. Fig.11 shows the nonlinear pendulum. Multi-output system has been modeled using feed-forward networks.

TABLE.1 SINGLE OUTPUT IDENTIFICATION RESULT

Type of ANN.	No. of Neurons in Hidden layer	Epochs	Mean Square Error
FF	5	100	5.627e-005
FF	10	100	5.7256e-005
FF	20	100	5.6207e-005
FF	30	100	6.0269 e-009

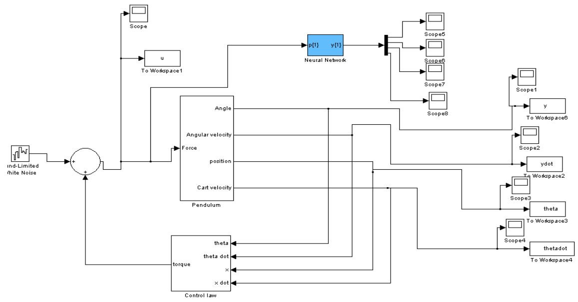

Fig.11 Comparison of actual model with neural model

The process and the neural model will receive the same input. The neural network is trained by presenting the 4 targets together at each time interval. The results obtained from MATLAB Simulink simulations are tabulated in Table.2.

TABLE.2 RESULTS OF FEED FORWARD NETWORKS

Type of ANN.	No. of Neurons in Hidden layer	Epochs	Mean Square Error
FF	4	100	5.617e-005
FF	5	100	5.4256e-005
FF	20	100	5.1207e-005
FF	30	100	6.069 e-009

IV. NEURAL NETWORK CONTROL

A feed-forward neural network trained to imitate the controller with the control law developed in Section II. The four input and output data's were taken from the control law. The FF network has 50 neurons in the hidden layer. The activation functions in the hidden layer are tan-sigmoid and the output layer is a linear function. The neural network is trained to imitate the controller.

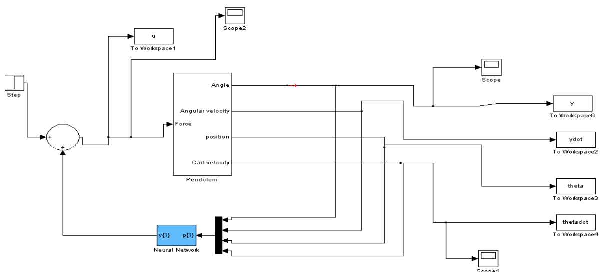

Fig.12 Control law replaced by ANN control

V. ANFIS CONTROL OF INVERTED PENDULUM

ANFIS are a class of adaptive networks that are functionally equivalent to fuzzy inference systems.. ANFIS uses a hybrid learning algorithm [4]. The ANFIS-control is developed using supervised learning. The input and the targets were collected from the inverted pendulum with control law and stored in notepad in DAT format.

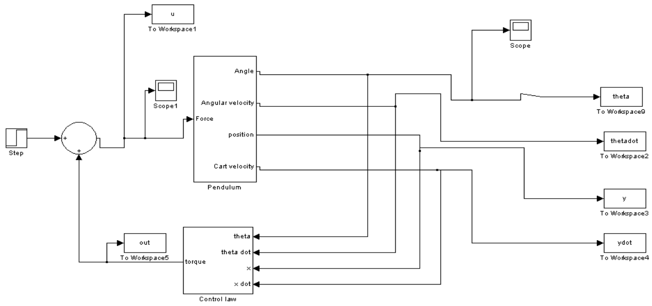

Fig.13 Nonlinear pendulum model and the control law.

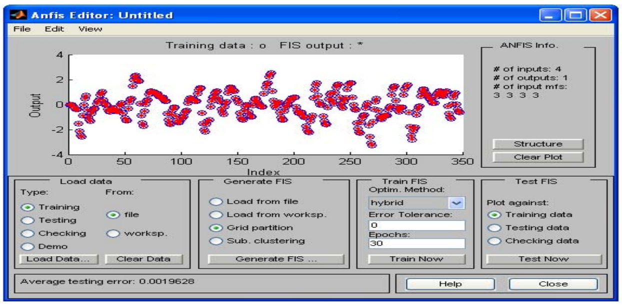

Fig.14 Training and testing using ANFIS

Fig.14 shows the training and testing of the inverted pendulum data set. Finally, the ANFIS structure is exported as FIS.The four inputs (y, y dot, theta, theta dot) signals are stored in matlab. The target for the ANFIS control is the output from the controller, The training data set is uploaded in the ANFIS editor, grid partition type FIS is selected with number of epochs given as 30, the ANFIS complete the training in two epochs, the obtained ANFIS is converted in to Fuzzy Inference System (FIS) and saved in workspace.

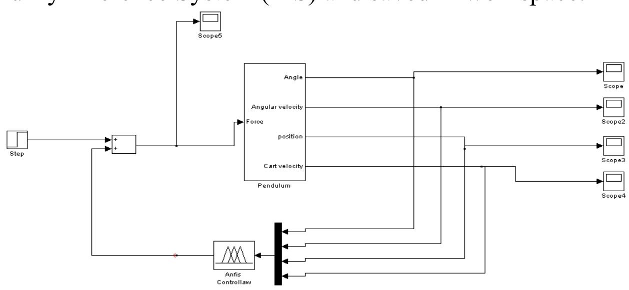

Fig.15 Control law replaced by ANFIS control

ANFIS controller replaces the control law and makes the system to stabilize with in 7 seconds, Fig.15 shows the inverted pendulum control using ANFIS in Simulink environment

VI. RESULTS AND DISCUSSIONS

The quality of the neural model is tested by calculating the MSE (mean squared error).

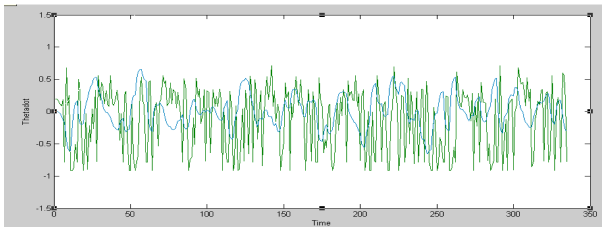

Fig.16 Angular velocity response (30 hidden neurons)

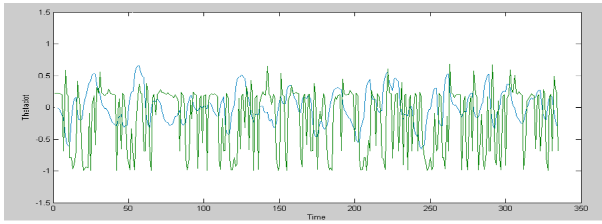

Fig.17 Angular velocity response (20 hidden neurons)

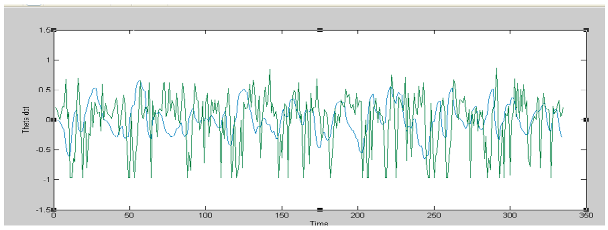

Fig.18 Angular velocity response (5hidden neurons)

The output from the model and process is plotted to compare the dynamics. As the number of hidden neurons increases the model provides higher accuracy. (Fig. 15-17) shows the process and model output with different number of hidden neurons.

A. Inverted Pendulum Control

Fig.18 illustrates the angle response of the inverted pendulum with control law which stabilizes the system with in 10 seconds. Fig. 19 shows the angle response of inverted pendulum using ANFIS control which stabilizes the system with in 7second. Fig.20 shows the angle response of the inverted pendulum with ANN control. This has failed to stabilize the system. Whereas ANFIS control produces better control strategy.

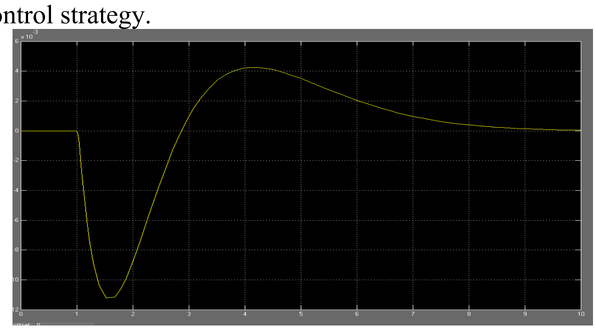

Fig.18 Angle response using control law

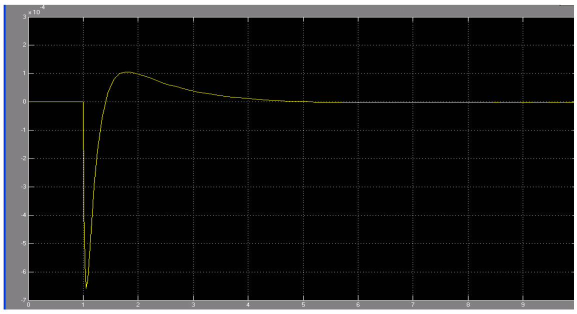

Fig.19 Angle response using ANFIS control

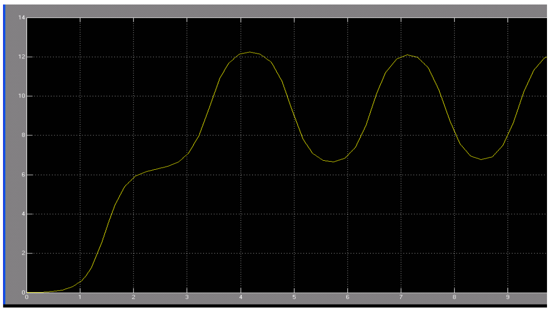

Fig.20 Angle response using ANN control

VII. Conclusions

Methods for applying ANN and ANFIS techniques for the identification and control of the inverted pendulum system has been presented in this paper. Before identification techniques could be tested, a model representing the inverted pendulum has been developed. One of the requirements for accurate identification is experimental input-output data that describes the dynamics of the system. For closed-loop identification system stabilizing feedback controllers have been developed for the nonlinear inverted pendulum [3]. A control law has been evolved to stabilize the nonlinear pendulum. The control law removes some of the nonlinearities from the process. Feed forward networks with a range of hidden layer neurons were tested. The Angular velocity for actual system and ANN model were compared. MSE obtained through the simulation is 6.0269 e-009. Further refining of the model is in progress for improving the MSE to a lower value. In controlling the inverted pendulum system actual control law stabilizes the system in 10 seconds whereas ANFIS control stabilizes the inverted pendulum system with in 7 seconds. Thus it is concluded that ANFIS control will be a positive choice for the stabilization rather than the neural networks.

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