ISSN: 2277-3754
International Journal of Engineering and Innovative Technology (IJEIT)
Volume 1, Issue 3, March 2012

Role of Adaptive Neural Network in the Stabilization of Non-Linear System

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Abstract— Neural networks have unique characteristics, which enable them to control the non-linear systems. An adaptive neural network controller can be designed so that it estimates some uncertainty within the system, and then automatically designs a controller for the estimated system uncertainty. In this way the controller uses information gathered on-line to reduce the system uncertainty, that is, to figure out exactly what the system is at the current time so that good control can be achieved. For comparison purposes it is useful to point out that we can broadly think of many conventional adaptive estimations and control approaches for linear systems as techniques that use linear approximation structures for systems with known system order (of course, this is for the state feedback case and ignores the results for models where the order is not assumed known). Most often, in these cases, the problems are set up so that the linear approximator (e.g., a linear model with tunable parameters) can perfectly represent the underlying unknown function that it is trying to approximate. In this paper the adaptive neural network simulation of non-linear system is presented for stabilization purpose. Inverted pendulum is taken as the non-linear system. The purpose of this paper is to keep the inverted pendulum stable. Inverted pendulum is a highly non-linear system and it is difficult to make it stable.

***Keywords*— Adaptive Neural Network (ANN), RBF (Radial Basis Function), MLP (Multi Layer Perceptron).**

I. INTRODUCTION

Neural networks are parameterized as non-linear functions. There parameters are weights and biases of the network.The following model is based on the components of the biological neuron (Fig. 1). The inputs X0-X3 represent the dendrites. Each input is multiplied by weights W0- W3. The output of the neuron model, Y is a function, F of the summation of the input signals [5].

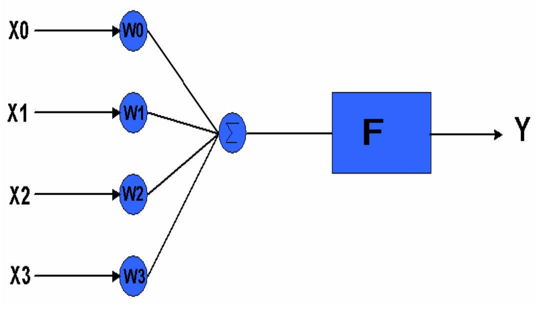

Fig.1: Diagram of neuron model

The advantages of using ANNs are listed below:

1. The main advantage of neural networks is that it is possible to train a neural network to perform a particular function by adjusting the values of connections (weights) between elements. For example, if we wanted to train a neuron model to approximate a specific function, the weights that multiply each input signal will be updated until the output from the neuron is similar to the function.
2. Neural networks are composed of elements operating in parallel. Parallel processing allows increased speed of calculation compared to slower sequential processing.

II. ADAPTIVE CONTROL SCHEME

In the area of adaptive control, to reduce the effects of parameter variations, robustness is achieved by adjusting (i.e., adapting) the controller on-line. For instance, an adaptive controller for the cruise control problem would seek to achieve good speed tracking performance even if we do not have a good model of the vehicle and engine dynamics, or if the vehicle dynamics change over time (e.g., via a weight change that results from the addition of cargo, or due to engine degradation over time). At the same time it would try to achieve good disturbance rejection.

Adaptive mechanisms are used within the control laws when certain parameters within the plant dynamics are unknown. An adaptive controller will thus be used to improve the closed-loop system robustness while meeting a set of performance objectives [1]. If the plant uncertainty cannot be expressed in terms of unknown parameters, one may be able to reformulate the problem by expressing the uncertainty in terms of a fuzzy system, neural network, or some other parameterized nonlinearity.

An adaptive controller can be designed so that it estimates some uncertainty within the system, and then automatically designs a controller for the estimated plant uncertainty. In this way the control system uses information gathered on-line to reduce the model uncertainty, that is, to figure out exactly what the plant is at the current time so that good control can be achieved.

A. Direct Adaptive Control Method

Yet another approach to adaptive control is shown in Fig. 2. Here the adjustable approximator acts as a controller. The adaptation mechanism is then designed to adjust the approximator causing it to match some unknown nonlinear controller that will stabilize the plant and make the closed-loop system achieve its performance objectives. Note that we call this scheme “direct” since there is a direct adjustment of the parameters of the controller without identifying a model of the plant [2].

B. Indirect Adaptive Control Method

An indirect approach to adaptive control is made up of an approximator (often referred to as an “identifier” in the adaptive control literature) that is used to estimate unknown plant parameters and a “certainty equivalence” control scheme in which the plant controller is defined (“designed”) assuming that the parameter estimates their true values. The indirect approach is shown in Figure 3. Here the adjustable approximator is used to model some component of the system. Since the approximation is used in the control law, it is possible to determine if we have a good estimate of the plant dynamics.

III. Learning Of Adaptive Neural Network

Neural networks have three main modes of operation- supervised, reinforced and unsupervised learning [6]. 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 [7]. Reinforced learning is similar to supervised learning however there are no target given. Unsupervised learning updates the weights based on the input data only.

In this paper the Adaptive neural network is used for supervised learning of Inverted Pendulum system. The RBF neural networks as a controller for invrted pendulum system are used. The supervised learning method is used for the same.

A. Supervised Control

It is possible to teach a neural network the correct actions by using an existing controller or human feedback. This type of control is called supervised learning. Most traditional controllers (feedback linearization, rule based control) are based around operating points. This means that the controller can operate correctly if the plant/process operates around a certain point. These controllers will fail if there is any sort of uncertainty or change in the unknown plant. The advantages of neuro-control are if an uncertainty in the plant occurs the ANN will be able to adapt its parameters and maintain controlling the plant when other robust controllers would fail. In supervised control, a teacher 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 controller [9] .The supervised learning using an existing controller is shown in fig.4. When the neural network is trained, it is placed in the feedback loop. Because the ANN is trained using the existing controller targets, it should be able to control the process. At this stage, there is an ANN which controls the process similar to the existing controller. The real advantage of neuro-control is the ability to be adaptive online.

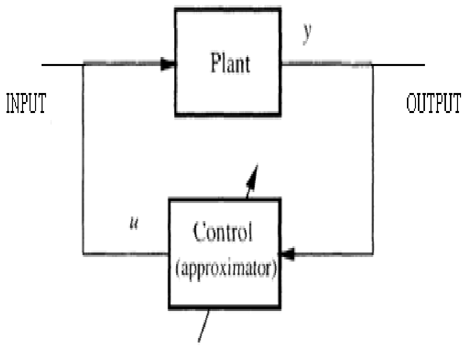

Fig. 2: Direct Adaptive Control

An error signal (desired signal- real output signal) is calculated and used to adjust the weights online. If a large disturbance/uncertainty occurs in the process- the large error signal is feedback into the ANN and this adjusts the weights so the system remains stable.

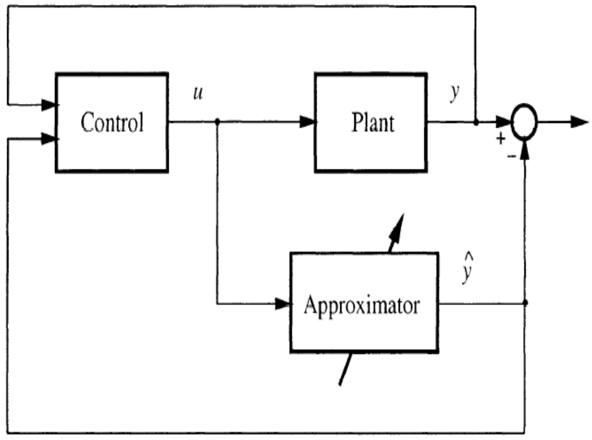

Fig. 3: Indirect adaptive control

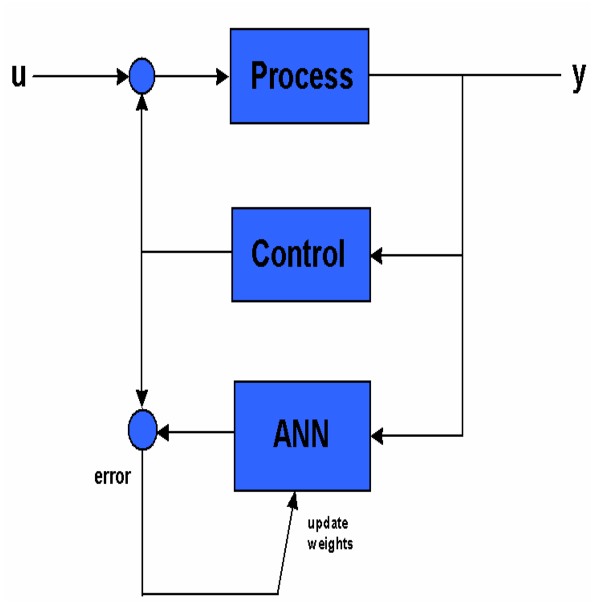

Fig. 4: Supervised learning using an existing controller

IV. Adaptive Neural Control Of Non-Linear System

In this section a direct adaptive neural-network control strategy for unknown nonlinear system is presented. The system considered by an unknown nonlinear inverted Pendulum and a GRBF is used to learn the system. The free body diagram of inverted pendulum is shown below in figure. The control force f will be calculated from the control law which will be fed back to the inverted pendulum. These parameters are taken as: M=0.5Kg, m=0.2Kg, l=0.3m. The main task of this paper is to present a controller which keeps the pendulum system inverted. As the disturbance occurs the pendulum goes unstable. This is not a problem if the parameters of the pendulum system are fixed and there is no disturbance to the system. This is because the ANN cannot

ISSN: 2277-3754
International Journal of Engineering and Innovative Technology (IJEIT)
Volume 1, Issue 3, March 2012

adapt its weights using an error signal to counteract the disturbance. This problem was solved by using an adaptive neural toolbox which is an add-on for simulink [10]. The Adaptive neural networks can adapt the learning process to remove the uncertainties. Adaptive mechanisms are used within the control laws when certain parameters within the plant dynamics are unknown. An adaptive controller will thus be used to improve the closed-loop system robustness while meeting a set of performance objectives [1].

There are a few important points to remember when designing a controller for the inverted pendulum. The inverted pendulum is open-loop unstable, non-linear and a multi-output system. This toolbox basically allows for online neural learning to occur. The block diagram of the toolbox is shown below. This toolbox contains RBF (Radial Basis Function) ANN. All of the blocks have the same interface so its possible to try out many different networks quickly and easily. The toolbox of ANN is shown in fig.6.

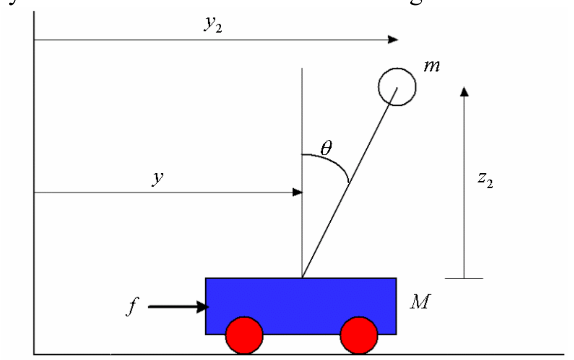

Fig. 5: Free body diagram of inverted pendulum

M – Mass of the cart
m – Mass of the pole
l – Length of the pole
f – Control force

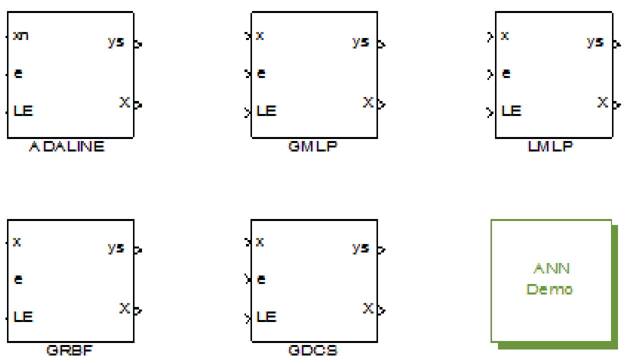

Fig. 6: Adaptive Neural Network Toolbox

The inputs to each blocks are:

x: The input vector to the neural network.

e: The error between the real output and the network approximation.

LE: A logic signal that enables or disables the learning.

The outputs of each block are:

Ys: The value of the approximate function.

X: All the "states" of the network, namely the weights and all the parameters that change during the learning process.

There is an interface for each block so that the user can set the network parameters such as learning rate, number of the neurons in each layer, etc.

In this paper, the adaptive neural network used for the stabilization is RBF neural network.

V. RESULTS AND DISCUSSION

The main objective of this paper is to present RBF based neural network for highly non-linear inverted pendulum to keep it stable.

A. Radial Basis Function

Radial basis function network can be used to control the inverted pendulum system using supervised control strategy [13]. RBF uses Gaussian Potential functions. The Gaussian potential functions are also used in networks called regularization networks [14].

Fig.7 shows the supervised control of adaptive network with RBF as a controller [5]. RBF is connected in the feedback of inverted pendulum and control law. The closed loop response with sine input is shown in Fig.8 which shows that the response of the inverted pendulum is stable. RBF can also be tested by introducing external disturbances on changing the mass of the pendulum like as from .4kg to .8kg or by including any other type of disturbance in the system [5]. The dynamical system will still give a stable response because RBF is an adaptive neural network which can adapt the learning process according to the parameter variation and stabilize the dynamical system by removing the uncertainties from the system.

VI. CONCLUSION

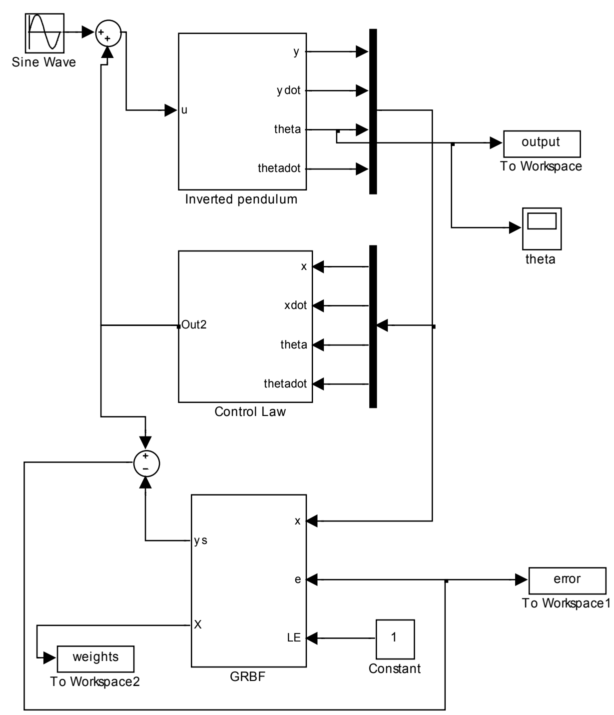

Fig. 7: RBF based controller with sine input

The supervised control technique is the most efficient to implement as seen from the results. In the case of RBF neural

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network it is seen that the pendulum angle goes stable. RBF gives better result and also approximate the control law very accurately. This is about the supervised learning, the next possible research area may include unsupervised learning.

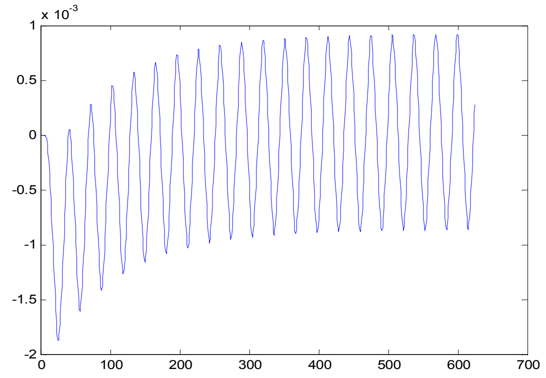

Fig.8. Close loop response using RBF controller with sine input

ACKNOWLEDGMENT

Words are often too less to reveal one's deep regards. An understanding of the work like this is never the outcome of the efforts of a single person. I take this opportunity to express my profound sense of gratitude and respect to all those who helped me through the duration of this thesis. In the first place I would like to record my gratitude to Mr. Mohd. Sabir, A.P. in SECS, Sikar (Rajasthan) for his supervision, advice, continuous and patience guidance throughout the work. Above all and the most needed, he provided me unflinching encouragement and support in various ways which has made him as a constant oasis of ideas and passions in science, which exceptionally inspire and enrich my growth as a student. Above all I thank Almighty GOD for his manifold mercies to carry out the study successfully.

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