

1.0 Introduction

1.1 Motivation

Control systems are being applied to a wide variety of nonlinear plants, and higher performance is expected from the controlled systems. The nonlinearities of the plant are often very difficult to model. Usually, an approximate linear model is created, and a control system is developed based on the linear model. However, the control system for this approximate model results in only limited performance for the closed-loop nonlinear system. The goal of this work was to improve upon the closed-loop nonlinear system performance once a controller has been put into place.

A neural network can be used in series with the control system to improve the closed-loop performance of the system. Neural networks have several unique characteristics that can be applied towards performance improvement, but they also have several characteristics that make them difficult to apply to control problems. Neural networks are adaptive, can approximate nonlinearities online, and can converge to useful solutions on a nonlinear environment. These three properties make neural networks a viable choice when trying to improve the control system of a nonlinear plant when the nonlinearities are unknown.

Three aspects of neural networks make them difficult to apply to control systems: the random initialization of the weights, the need to initialize the neural network several times before it converges to an acceptable solution, and the unknown performance that will exist until the neural network is converged. These negative aspects of neural networks have limited their use in the field of controls, allowing only for systems that can be run in the lab until an acceptable convergence of the weights has been reached; all of this must occur before they can be employed as the control for the realistic system. This work presents the challenges involved in overcoming the difficulties of using neural networks while maintaining their positive aspects.

1.2 Unique Work

As discussed in greater detail in Chapter 2, many researchers have combined traditional control methods with neural networks in parallel. This work places the neural network inside the closed loop, in series with the existing controller. With the neural network inside the closed-loop, randomly initialized weights, unknown performance levels, and multiple reinitializations are more difficult. A problem not so readily seen is that the weight update rules for neural networks were not designed to work in a feedback setting but in a feed-forward setting. The derivation of the update rules, particularly for back propagation, were based on the independence of the weights and the input to the neural network. For a neural network in the closed-loop, the assumption is not valid; therefore, a new update rule had to be derived. In the initial research into the new algorithm for nonlinear systems, linear systems were investigated. No analogous research had yet been done into a new update algorithm for a linear filter in the closed-loop control system. Each of these problems needed to be addressed before the performance of the closed-loop system could be improved with a neural network.

The unknown initial gain across the neural network was a serious problem if the neural network were to be used in conjunction with the existing controller because the system could be driven unstable. By not randomly initializing the neural network, the weights can be initialized in a manner that leaves the gain across the neural network equal to one. Using a linear node on the hidden layer, and setting all of the weights on the hidden layer equal to zero except one weight set equal to one, gives a gain of one across the neural network. The initialization scheme was given the name “feed-through neural network” because the initial input values to the neural network become the output value until the neural network starts to converge. The closed-loop system will initially have the exact same performance with the neural network as without the neural network. The system can then be put on-line, and the neural network can be

converged in the field without any initial loss of performance due to randomly initialized weights. The feed-through neural network is an excellent choice when using neural networks in situations where the nonlinear plant cannot be tested in the lab and the neural network can only be converged once.

A weight updating algorithm had to be derived for the neural network, because the back propagation algorithm was developed under the assumption that the weights were independent of the input to the neural network. However, this is not true when the neural network is in the closed-loop. To give a better understanding of the challenges faced in deriving an algorithm for the nonlinear case, an algorithm was first derived for the linear systems. The linear filter in the closed-loop for a linear plant was first examined because there was no algorithm to update the weights of a linear filter in the closed-loop. The algorithm derived for the linear system looks very much like the Least Means Squared (LMS) algorithm with a correction term for the closed-loop.

Similarly, the update algorithm for the neural network is similar to the back propagation algorithm with an additional term that results from the weights and the input to the neural network not being independent of each other. The algorithm was derived in similar fashion as the back propagation algorithm by trying to minimize the square of the error. The error for the closed-loop system is difficult to establish because there are two possible errors. Ideally, the error should be the difference between the output of the neural network and an ideal output of the neural network, which is based on the reference model. The second possible error is simply the difference between the output of the plant and a reference model. An algorithm for each of the two errors was developed and the results were compared.

1.3 Results and Examples

The derivations of the algorithms for the linear and nonlinear plants, as well as the development of the feed-through neural network, are unique to the work that

is presented in this dissertation. The feed-through neural network with the new update algorithms are developed and then used on several different examples. Several nonlinear plants were controlled with the feed-through neural network. Two examples had a saturation in the middle of the dynamics, making the plants nonlinear. The difference between the two plants was that one was open-loop stable and the other one was open-loop unstable, thus requiring feedback. Generally for unstable plants with neural network control, the plant is first stabilized with feedback and the neural network is added outside of the closed-loop. In this research, the plant is stabilized by feedback with the neural network inside the closed-loop. A third nonlinear plant controlled by the feed-through neural network was a boiler plant that had sensor saturation; the feed-through neural network succeeded in improving the performance of the existing, closed-loop control system.

In the next chapter, the literature review shows the work that preceded this dissertation and reveals the absence of work for neural networks in series with the closed-loop. The feed-through neural network stands out because no one else has worked on non-randomly initialized neural networks. The derivation of the update algorithm for the neural network in the closed-loop is completely unique to this work. The literature review gives an overall view of the previous research that was the basis for this work.