7.0 Conclusions and Future work

The body of work done so far in this research is merely a starting point for the research that can be done in this area. The conclusions drawn from the completed work are that neural networks can be used to augment closed-loop control of nonlinear systems, both stable and unstable, without any initial loss of performance, that neural networks are not as risky of a control methodology with the feed-through neural network, and that the new update algorithms can be used to improve closed-loop control systems that are linear or nonlinear, as well as stable or unstable. Future work will include the laboratory demonstration of the algorithms and the development of update algorithms for IIR filters and Recursive Neural Networks inside the closed loop.

7.1 Conclusions

The performance of a closed-loop control system can be degraded by nonlinearities and an unexpected dynamics in the plant. The techniques developed in this research can increase the performance of ill-modeled plants when a fixed-gain, closed-loop control system already exists. The feed-through neural network was devised to initially maintain the performance of the closed-loop control system. As the neural network converges, the performance of the closed-loop system will be improved. Back propagation was used to update the weights of the neural network. This technique worked well but converged very slowly. Back propagation was originally derived to work on an open-loop system, and it does not use any a-priori knowledge of the system.

The feed-through neural network is a neural network with its weights initialized to have a unity gain. The linear version of the feed-forward neural network is an FIR filter; back propagation is analogous to the LMS update algorithm for the

FIR filter, which is also derived for the open loop. There did not exist an update algorithm for the FIR filter inside the closed-loop.

In Chapter 4, two new update algorithms for the FIR filter were derived and applied to linear systems. The first update algorithm minimizes the difference between the output of the FIR filter and the ideal output of the FIR filter. The ideal output of the FIR filter is obtained by using the desired output of the plant through the inverse model of the plant. This technique reduces the effect of the magnitude and phase of the plant's dynamics on the convergence process. This technique has two distinct problems: (1) the plant is ill-modeled, potentially resulting in a mis-adjustment of the magnitude and phase; (2) the inverse plant could be unstable. The first update algorithm for FIR filter worked very well on the linear system except for the possibility that the error would not converge to zero in some of the cases. The second update algorithm minimizes the difference between the plant's output and the desired plant output. This algorithm does not make adjustment for the magnitude and phase of the plant's dynamics, but it does not require the inverse plant model. The second update algorithm minimizes the primary variable of interest. The goal of the adaptive filter is to minimize the difference between the plant's output and the desired plant output. Both update algorithms improved the performance on the linear, ill-modeled closed-loop systems.

The linear, closed-loop system can improve its performance through the FIR filter inside the closed loop. The two new update algorithms for the FIR filter converge the weights to match the system to the reference model. The algorithms were shown to converge to the analytical solution when it exists for both the stable and unstable plants. When the plant is ill-modeled, the update algorithms will increase the performance of the system and, in most cases, will match the reference model. There is a definite advantage to using either algorithm on an ill-modeled, closed-loop control system. The final conclusion for linear, closed-loop control systems is that the second update algorithm for the

FIR filter is the better, more conservative choice of the two algorithms for ill-modeled control system.

Once a linear solution was created, it was used as a road map to develop a nonlinear solution. In Chapter 5, with the starting points of the feed-through neural network and the linear solution, two new update algorithms were derived for the neural network. The first update for the neural network minimizes the difference between the neural network's output and the ideal neural network output. The ideal neural network output requires an inverse model of the plant. For the nonlinear plant, the model of the plant will not be accurate, thus opening up the possibility of inaccurate correction of the plant's dynamics. Despite the inaccurate model, the first update algorithm was shown to improve the performance of the closed-loop control system for nonlinear plants. The first update algorithm converged the neural network much more quickly, but with slightly less performance, than the back propagation algorithm. The second update algorithm for the neural network minimizes the difference between the plant's output and the desired plant output. Like back propagation, the second update algorithm minimizes the difference between the variables of interest. The second update algorithm converged the neural network to the performance level of the back propagation algorithm and with the convergence rate of the first update algorithm. All three update algorithms were converged a single time to obtain the results shown in the previous chapters. Both of the new update algorithms improve the performance of the nonlinear, closed-loop system.

Using the feed-through neural network first developed in Chapter 3, back propagation and the two new update algorithms improved the performance of nonlinear systems inside the closed-loop with the existence of a fixed-gain controller. In all of the examples of both stable and unstable plants, the fixed-gain controller was designed using a linear model, and the nonlinearities of the plant were unknown. The two new update algorithms require a priori knowledge of the system and the back propagation algorithm does not require a model. All three update algorithms improve the performance of the closed-loop control system. If no model of the plant exists, back propagation can be used to improve system performance. If a reasonable model of the plant exists, the second update algorithm for the neural network is the better, more conservative choice to implement.

Direct and indirect adaptive control methods have similar configuration to this research when a feedback loop is established. The direct adaptive control method utilizes the existence of a priori knowledge, but the indirect adaptive control method does not use a priori knowledge. The indirect adaptive control method uses a second neural network to model the plant off-line then uses the model to form the derivatives needed to converge the neural network controller. The direct and indirect methods do not have a known initial performance because they do not use the feed-through neural network. The direct and indirect methods have not developed in a series configuration with a fixed-gain controller.

The direct and indirect methods could be develop to work in conjunction with the feed-through neural network. However, the two update algorithms developed in this research are unique. There are similarities with the dynamic and static back propagation algorithms. Narendra and Parthasarathy were trying to solve a similar problem. They crossed the similar problem of the input to the neural network not being independent of the weights of the neural network because the output of the plant was being used as an input into the neural network. This is similar to the problem seen in this research because the output of the plant passes through the fixed-gain controller and into the neural network. Narendra's work uses the back propagation algorithm with the derivative added to the error signal used to adjust the weights. In contrast, this research derived the two update algorithms based on closed-loop system with an existing fixed-gain controller assumption. In the direct and indirect adaptive control method, Narendra takes into account the linear dependence of the inputs and weights of the neural network but does not account for nonlinear effects of the dependence relationship due to the nonlinear squashing function. In order to take that nonlinear effect into account, it required the derivation of a new update algorithm; which we have done.

The developed control methodology gives the capability to improve the performance of the closed-loop system. Neural networks are used to adaptively improve the performance of the system. With the initial performance of the system guaranteed to be equal to that of the system when the neural network is not included, the system's performance is improved upon with a single convergence of the neural network's weights. The control methodology addresses the major concerns of no performance guarantees and the need to converge the weights several times which has inhabited the use of neural networks in controls. With this methodology, neural networks can be more widely used in the area of controls.

7.2 Future Work

There are two main future thrusts to this research. The first is the laboratory demonstration of both the linear and nonlinear update algorithms. The next is the development of the IIR filter and Recursive Neural Network update algorithms.

The laboratory demonstration of the update algorithms will help to show the viability of neural networks. Neural networks have been thought of as a high-risk control methodology because of the lack of analytical understanding of their convergence and the lack of initial performance. The feed-through neural network gives the system a reasonable initial performance and a single convergence to an improved solution. The laboratory demonstration gets this methodology one step closer to being applied in an industrial setting.

The development of IIR filter and Recursive Neural Network update algorithms for the closed loop would be another powerful set of tools that can be used to improve the performance of ill-modeled systems. The FIR filter can shift the poles of the closed-loop control system but cannot shift the poles of the FIR filter. The IIR filter's poles can be moved, which adds another dimension to the adaptation process. The Recursive Neural Network also has another dimension that the feed-forward neural network does not have, which is the option to move the poles of the neural network. These two sets of update algorithms could be developed to improve an even wider array of ill-modeled, closed-loop control systems.

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