# Chapter 8

# Conclusions and Recommendations

This chapter concludes this thesis and provides a summary of work done during the course of this research. Some recommendations for future work are also given at the end.

## 8.1 Summary

The use of multilayer feedforward networks for system identification, function approximation, and advanced control is investigated. The multilayer feedforward networks with one hidden layer are utilized. Sigmoid function is an activation function used in the hidden and the output layers of the networks. Error backpropagation and Levenberge-Marquardt algorithms are training techniques. An industrial acetylene hydrogenation system and a Continuous Stirred Tank Reactor (CSTR) are examples of nonlinear systems employed to explore such network capabilities. The application of the neural networks for system identification is studied on the former one and the application of the neural networks for function approximation and advanced control is studied on the latter one. Advanced control techniques: Generic Model Control (GMC) and Nonlinear Internal Model Control (NIMC) are used to control the CSTR temperature.

For system identification with neural networks, the industrial plant data are collected and used to train and test the neural network models. Since this system involves multiple inputs and multiple outputs, the error backpropagation is selected to train the networks. It can be seen that the trained networks can give good predictions of outputs, particularly the outlet temperature. However, more data are required in order to obtain the more accurate models. The reason why the Levenberge-Marquardt algorithm, the fastest training algorithm compared to other algorithms (see Appendix A), is not selected to train the networks for this system is that it is not suitable to train a multi-input multi-output (MIMO) system because it not only requires large memory but also spends long time to train the neural networks. Therefore, when this algorithm is applied to train such systems, it gives slow training results instead of fast training results.

For the use of neural network as an approximator, the network is implemented into the GMC configuration. The GMC is employed to control the temperature of a CSTR. Since the function $f$ is not available online due to the requirement of both state values: the effluent concentration of the reactant and the reactor temperature. The neural network approximator is used to predict the function $f$ based on the reactor and the coolant temperature. The control performance of the GMC with neural network (GMC-NN) approximator is compared to that of the GMC with a state estimator (GMC) derived from the component balance to predict the effluent concentration. It can be seen that the implementation of the neural network approximator in the GMC configuration is able to improve its control performance when the system is tested with disturbance rejection and set point tracking in a nominal case and the presence of plant-model mismatches. However, with the disturbance of feed temperature in the nominal case, the GMC with a state estimator can give the better control performance. This is because the feed temperature can be measured online, hence the state estimator can estimate the effluent concentration accurately. Therefore, the function $f$ is correctly calculated from the accurate estimated effluent concentration of the reactant and the measured reactor temperature. As the results, the GMC with a state estimator can give a better control performance than the GMC with the neural network approximator. With set point tracking test in nominal condition, both configurations provide the comparable performance.

The applicability of a neural network controller is explored in Nonlinear Internal Model Control (NIMC) which is an inverse-model-based technique. The control configuration is utilized to control the CSTR temperature. The assumption that only temperature is available online is also used in this research work. The neural network forward and inverse models are implemented in the control configuration. The performance of the configuration is evaluated as well as the performance of the GMC. From the results obtained, the neural network controller can control the system at its set point when the system is tested with set point tracking in nominal and plant-model mismatch conditions except the case that there is a mismatch of the heat of reaction value where some offsets are remarkably seen. For disturbance rejection studies, the neural network controller can maintain the system at a constant value with some offsets. This is because the forward and the inverse models are not an exact inversion of each other. Moreover, the concentration data may be needed to train the forward and the inverse models. However, with the assumption that only the temperature is available online, the concentration data are not available to train the networks. Consequently, the PI controller is placed after the neural network controller in order to remove the offsets. As the results, offset-free control performances are obtained.

For the PI control performance, it can be seen that the PI controller can control the reactor temperature by manipulating the coolant feed temperature even though the system is tested with disturbance rejection and set point tracking in nominal condition and the presence of plant-model mismatches. This may cause from the reason that the relationship between the reactor temperature and the coolant feed temperature is not highly nonlinear, the PI controller is then able to control the reactor temperature at the desired set point in all tests. However, the ability of the PI controller in regulating the nonlinear systems is limited in the narrow operating range. They performed poorly when the systems are operated out of the limited range and are highly nonlinear.

## 8.2 Conclusions

From this research work, it can be concluded as follows:

1. For the application of the neural networks for modeling, it can be seen that the multilayer feedforward networks with one hidden layer are capable to identify the MIMO system such as an industrial front-end acetylene hydrogenation system very well with maximum average model error of 8%.

2. For the application of the neural networks for function approximation, the neural network can be utilized as an approximator to estimate the function based on the measured reactor temperature and the measured coolant feed temperature. Furthermore, the neural network approximator can improve the control performance of the GMC in nominal case and the presence of plant-model mismatches.

3. For the application of the neural networks for advanced control, the neural network controller obtained from inverse modeling can be used as a nonlinear controller in the NIMC control configuration to control highly nonlinear systems. However, the performance of this controller depends on the inverse and the forward model obtained. If both are the exact inversion of each other, the offset-free control performances are generated. However both models are trained independently on each other, the exact inversion is then hard to obtain. Consequently, some offsets can be noticed from the results.

4. In summary, the use of the neural network technique are preferred when
    - The problem is difficult to pose mathematically.
    - The process is quite nonlinear.
    - It is not necessary to have a model that can be interpreted in term of physical principles.
    - Sufficient data are available for training.

## 8.3 Recommendations for Future Work

Some recommendations for future work are given below. Multilayer feedforward networks or backpropagation networks are the most widely used neural networks especially in chemical engineering. This research studied the applicability of such networks for system identification, function approximation and advanced control. The multilayer feedforward networks are very powerful in those applications. Nevertheless, the training algorithms, which is an optimization technique, for online training of the networks should be directed to, so that the neural network models and controllers can represent the system dynamics at all time although the operating condition or system parameters are changing. Since most of the neural network models used in many applications are trained and acquired offline, the generalization of the neural network models depends on the input and output data generated to train and test the networks. Then the offline-trained networks may not learn system dynamics well if the data employed to train the networks are not rich of information.

However, there are other types of neural networks that can be applied for process control. Recurrent neural networks are very powerful for multi-step prediction. Hence, future research should focus on this type of networks especially when multi-step prediction models are required. The control configuration such as predictive control technique needs to use the multi-step ahead prediction model, therefore the recurrent neural networks are more suitable than the multilayer feedforward networks.

To improve the neural network controller in the NIMC configuration besides using the PI control, the use of the recurrent neural networks to identify the forward and the inverse model of the CSTR is proposed for the future research. With the assumption that only temperature is available online, the recurrent neural network may be trained offline with the coolant temperature, the reactor temperature, and the effluent concentration of the reactant to predict the reactor temperature and the effluent concentration in the next sampling time. Then the obtained neural network forward and inverse models use the predicted concentration generated from itself as the input data in stead of the unmeasured effluent concentration.