CHAPTER 7

CONCLUSIONS

In this thesis, AI techniques have been employed for the fault detection and diagnosis in a simulated deaerator system and in a real time three-tank system. The first part of the work is about the deaerator system, its mathematical modeling and fault detection (presented in chapter 3) and fault diagnosis based on AI techniques (presented in chapters 4 and 5). The second part of the work is about the real time three-tank system to test the proposed technique on-line (presented in chapter 6) as the implementation of fault diagnosis scheme in real time deaerator system is not feasible. In this chapter, a summary of the work done is presented, highlighting main results and conclusions. Also possible research directions are suggested for future work based on the unsolved problems.

7.1 SUMMARY OF WORK DONE

This thesis aims at designing an integrated FDD system for the deaerator that can effectively detect eight possible faults in the deaerator. The performances of the fault detection and diagnosis techniques have been demonstrated by simulation in deaerator system and experimentally in three-tank system. Specific results and conclusions for the deaerator and the three-tank system are summarized separately in the following subsections.
7.1.1 Fault detection in the deaerator

The fault detection in our work consists of two steps, namely, fault simulation and symptom generation. Fault simulation is done using the mathematical model. Initially the real time plant data were used to obtain the system parameters (A, B, C) of the deaerator under normal operating conditions using RLS algorithm. It was found that the obtained parameters of the state matrix for the deaerator model indicated open loop instability. Hence, a state feedback control system based on the pole placement technique was employed to make the system open loop-stable. Based on the plant controller settings and state feedback gain matrix, the parameter model estimated by RLS algorithm was simulated for the normal operating condition. The problem with the model obtained through RLS algorithm is that the system parameters for any fault condition cannot be obtained until the specified fault is introduced in the system.

This problem was solved using the linearised mathematical model. The nonlinear deaerator model by Abdennour et al (1993) is referred in this work. The model is a nonlinear one and it was linearised around the operating point based upon plant data used for the RLS algorithm. In order to validate the mathematical model, the system outputs of both the models are compared for positive and negative step changes in the setpoint. It was found that the system outputs of both models are matching approximately.

Based on discussions with industrial experts, eight different faults in the deaerator are simulated using the linearised mathematical model, namely, leakage in tank, sedimentation deposit, positive bias in the inlet water valve, negative bias in the inlet water valve, positive bias in the inlet steam valve, negative bias in the inlet steam valve, decrease in inlet water temperature and steam mixing with water in preheater. Some important
double faults were also identified and simulated by changing the system parameters.

The second part was to obtain the fault symptoms from the mathematical model. In our work, a single layer neural network was used to obtain the system parameters of the deaerator system under normal and fault conditions. The parameters are nothing but the weights of the neural network. The network was trained by both RLS algorithm and backpropagation algorithm. It was found that the error obtained between the network output and the target was very less when the network was trained by RLS algorithm. It was thus decided to train the network based on RLS algorithm. The parameters are evaluated for fault diagnosis only after the system reached the stable state.

7.1.2 Fault diagnosis in the deaerator

The fault diagnosis was carried out using the Kohonen network, BPN, RBFN and fuzzy expert system and the performance of these techniques were compared. The parameters obtained from the single layer neural network were given as the input to the diagnosis system. When the Kohonen network was used for fault diagnosis, it was found to be well suited for the detection of single faults. It was possible to classify the eight different faults in 10×10 output. The network does not indicate the severity of the fault and if the severity information is required then the size of the output matrix should be increased. Moreover, the Kohonen network can also be used for the detection of double faults and in that case the output size of the network increases thereby increasing the training time. The network trained with a single fault data, did not give accurate results when presented with double faults.
The fault diagnosis was also done using BPN. It was found that the network with 10 neurons in the hidden layer is more suitable for fault diagnosis from the viewpoint of least sum squared error. It was necessary to train BPN with single fault and double fault data for fault identification. The BPN identified the single faults along with severity accurately. However, about 90% success was achieved for double fault classification with severity. The other limitation of the BPN is that the training time is more compared to that of RBFN. The training time for Kohonen network is 1 minute, that of BPN is 3 minutes and that of the RBFN is 1 minute approximately.

When RBFN was used for fault diagnosis, it was found that the network was able to identify the double fault with severity accurately even though it was trained with single fault data. The choice of the spread constant is important in RBFN for accurate fault diagnosis. The success percentage for double faults tested on BPN trained with single fault is about 70% whereas this percentage is about 90% in the case of RBFN. Further, Kohonen network cannot be used for diagnosis of double faults. Hence it may be concluded that RBFN is better than the BPN and Kohonen networks for fault diagnosis in the deaerator application.

The fuzzy based expert system used for fault diagnosis belongs to a special type where in the fuzzy rule specifies a singleton output (instead of fuzzy output). The fuzzy rules are framed for single faults and double faults. The fuzzy expert system was able to identify the single and double fault with severity accurately. It was also noticed that when the fuzzy system was presented with fault symptoms corresponding to unwritten rules it was able to diagnose the fault accurately. The success percentage for the diagnosis of double faults using fuzzy expert system in 100%. Thus, the results of fuzzy expert system are found to be better than that with neural network based techniques in terms of accuracy.
7.2 FAULT DETECTION AND DIAGNOSIS IN THREE-TANK SYSTEM

The fault detection and diagnosis is implemented in the three-tank system. A multivariable PI controller was designed using Davison method. The performance of the closed loop three-tank system with multivariable PI controller was tested for the servo operation and found to be satisfactory. The clogging faults were introduced in two different locations (with different severities) of the three-tank system. The single layer neural network was used to obtain the parameters of the system after steady state conditions were reached. The obtained parameters were used for fault diagnosis using Kohonen network, BPN, RBFN and fuzzy expert system. The Kohonen network was able to detect the two faults along with severity. The BPN, RBFN and the fuzzy expert system were also able to identify the fault with its severity accurately. It may be concluded that there is not much difference in the performances of the four fault diagnosis method as far as the three-tank system is concerned. This is probably because only two single faults were introduced.

The findings of the research work may be found useful in the detection of faults in a real time deaerator and to set the alarm for taking appropriate corrective action. As computer control is employed in most of the process industries it is necessary to add only the required software in order to implement the online fault diagnosis.

It may be noted that there is no overlap in the range of system parameters due to occurrence of different faults. If such an overlap occurs, the fault diagnosis becomes complex, as more parameters have to be considered. In some processes the system parameters may change even without the occurrence of the faults. In such cases the fault diagnosis becomes somewhat
complicated. This problem is not addressed in our work. Further study on the performance of the fault diagnosis techniques has not been made when some other single fault or double fault combination (other than the specified ones) occurs.

7.3 FUTURE WORK

The application of AI techniques for fault diagnosis can be implemented in a real time deaerator. The work can be extended to detect all kind of faults (single fault, double fault and triple fault) even with overlapping of system parameters. Fault diagnosis using the AI techniques can also be attempted in some other critical plant apparatus such as, nuclear reactor, catalytic crackers, etc.

In this work a single layer neural network is used for identification of system parameters. However, a multilayer neural network in which the weights from hidden to output layer indicating the system parameters can also be tried. Also some other neural network architectures such as Probabilistic network, Hopfield network and ART network can be tried for fault diagnosis. In this work, change in system parameters has been used for the detection of faults along with its severity. If the trend analyses of the important variables of the deaerator are used in addition to the system parameters more accurate fault diagnosis may be possible.