CHAPTER 7

RESULTS AND DISCUSSION

A non-linear system, the conical tank level process whose time constant and gain are functions of process variable is considered for testing the performance of various non-linear intelligent controllers. The laboratory conical tank level process for real time implementation is presented. A PC is used to log data and perform the functions of various controllers. The reaction curves for different magnitudes of inflow rate of the conical tank level process at various operating points are obtained. The first order plus dead time model parameters are computed from these reaction curves. There is nearly a two fold increase in the gain and 20 times increase in the time constant of the conical tank level process as the level changes from 5 to 70 centimeters. A controller designed at one operating point does not give satisfactory response for other operating points. Hence different non-linear intelligent control methods are carried out. In the following sections, the performance of the ZN-PID, non-linear intelligent control such as FLC, Neural network based control, ANFIS based control, Neurobased DP control and Adaptive control are summarized.

7.1 LIMITATIONS OF PID CONTROL SCHEME

The experimental reaction curves are obtained at various operating points for different input magnitudes. The ZN settings are then evaluated using the reaction curves. Using these settings in PID controller algorithm, the servo and regulatory responses for various magnitudes of set point changes and load changes are obtained. The responses for process parameter variation are also obtained. The limitations of the conventional PID controller tuned using Ziegler Nichols (ZN) settings for the chosen process are brought out.

The response obtained at the bottom of the tank is fast and the response near the top of the tank is very sluggish because of increase in time constant. It is also found that, for positive step change in the set point, settling time is more than the negative step change in the set point for the same magnitude.

It is inferred that the load disturbance gives rise to large errors for a short period. The response is reaching the set point after a small time due to the controller action.

The servo and regulatory operations exhibit oscillations, when the process parameter is varying and it is varied by keeping the outlet valve position at various positions. It takes very long time to settle particularly when the process variable is at the top of the tank.

7.2 LIMITATIONS OF NON-LINEAR INTELLIGENT CONTROL SCHEMES

The performances of the first order non-linear level process are obtained with various non-linear intelligent controllers such as FLC scheme, Neural network based control scheme and ANFIS based control scheme.

The servo and regulatory responses are obtained with these schemes in real time for various step changes in set point and load disturbances. The settling time is less than the conventional scheme for positive and negative step change. So the responses are found to be superior than that of the conventional scheme.

When the process parameters vary, these control schemes generate steady state error, because in FLC scheme, the control rules and membership functions are formed with original process and in neuro control scheme, the data for training are taken from the original process and the trained network with fixed architecture along with fixed optimum weights is used as a controller. Similarly the ANFIS networks with fixed weights are used after the training with respect to original process. If process parameters vary, in FLC scheme the rules and membership functions are to be changed and in the neuro scheme, the architecture with different weights should be used depending on the process parameter variations. Similarly in the ANFIS network, different architecture with different optimum weights will be used for the new process parameters. Otherwise steady state error created. Hence, some form of adaptive network is required.

7.3 PERFORMANCE OF NEURAL NETWORK BASED DYNAMIC PROGRAMMING METHOD

To achieve fast response, the time optimal control method is suggested. This intelligent controller is designed for controlling conical tank level using neural network with dynamic programming approach. A mathematical step-by-step procedure known as dynamic programming method is used to obtain the optimal valve position path in the level control problem and is trained by neural network, based on the Back-propagation algorithm. The dynamic programming procedure allows the set point to be reached as fast as possible without overshoot. Simulation studies are carried out using MATLAB to find the optimum path for set point changes and trained using neural network. This optimal path is used in real time. The servo responses show that the response is very much fast and superior than other types of control schemes discussed. The performance criteria ISE, ITAE are also reduced by 40% than the conventional scheme.

7.4 PERFORMANCE OF ADAPTIVE CONTROL USING NEURAL NETWORK

Simulation studies are carried out using MATLAB for finding the controller parameter changes for process parameter variations. Then these controller parameter changes for the process parameter variations are used in real time. Because the controller parameters are updated, the steady state errors created in the previous methods are completely eliminated here and the response becomes optimal.

The servo and regulatory responses are similar to the neurocontrol scheme where the response was fast. The response for the process parameter variation is superior to that of all the methods discussed previously. By predicting the steady state error and hence updating controller parameter leads to a better transient and steady state response. Process parameters are varied by varying the outlet valve position from nearly fully closed condition to fully opened condition. For both the direction of the valve movement, the controller parameters are updated in the correct direction and optimal results are obtained.

7.5 CONCLUSION

Comparing the servo response of all control schemes obtained through real time, the neural network based DP method outperforms all. For a 25cm increase and 50cm increase in the set change at any operating point, the proposed DP method gives minimum ISE and ITAE than all other control schemes. Comparing the performance of the regulatory response obtained through real time, the non-linear intelligent control schemes give minimum ISE and ITAE than all other control schemes. Comparing the performance of responses for process parameter variations, the adaptive control using NN performs very well as it eliminates the steady state error. The performance indices ISE and ITAE are also minimum in this case.

Considering the experimental results, it is found that no controller works at all situations. The following are the conclusion for selecting the appropriate controller. For servo operation, neurobased DP method can be employed. For regulatory operations and process parameter variations operations, the adaptive method using neural network can be employed. The Tables 7.1 and 7.2 show the comparison of performance measures for all the schemes and % improvement in performance indices over conventional control scheme discussed respectively.

The responses for PID, Fuzzy, Neural, Neurofuzzy control schemes for various combinations of positive step changes of set point, load and process parameter variations with respect to steady state values are compared from the response figures given in the respective sections. From Table.7.1, it is observed that the proposed control schemes for positive step changes in the set point, disturbance variations and process parameter variations with respect to steady state values has less rise time and settling time when compared with conventional controllers. It is also observed that the proposed schemes for level control has minimum integral square error (ISE) and integral time absolute error (ITAE) when compared with conventional controllers

Table 7.1 Comparison of performance measures for various control schemes

Control scheme	SP change	ITAE	ISE	Settling time
PID	0 to 50	398.95	2960.456	100
	30 to 50	348.177	2765.767	92
	0 to 25	156.84	1046.964	36
Fuzzy	0 to 50	218.177	1765.767	88
	30 to 50	193.663	951.609	85
	0 to 25	138.56	994.55	30
Neural	0 to 50	179.663	1551.609	75
	30 to 50	156.56	856.55	80
	0 to 25	128.177	825.767	28
Neurofuzzy	0 to 50	156.56	976.55	72
	30 to 50	146.177	756.167	70
	0 to 25	119.663	721.609	25
Adaptive control	0 to 40	350.75	1986.987	80
	0 to 60	450.98	2376.55	90
Time optimal controller	0 to 50	125.678	564.7324	58
	30 to 50	134.358	625.359	62
	0 to 25	92.3846	523.374	20

Table 7.2 Percentage improvement in performance indices for all control schemes over conventional control

Control scheme	% improvement in ISE			% improvement in ITAE			% improvement in settling time		
	0 -50	**30-50**	**0-25**	**0-50**	**30-50**	**0-25**	**0-50**	**30-50**	**0-25**
Fuzzy logic	40	65	05	45	60	12	12	08	16
Neural network	47	69	21	55	55	18	25	13	22
Neuro-fuzzy	67	72	31	60	58	23	28	23	30
Time optimal	80	77	50	68	61	41	42	32	44

7.6 SUGGESTIONS FOR FURTHER WORK

This method can be applied to the control of level in the two interacting conical tank system also and the hardware implementation can also be done to verify the results. The algorithm suggested is a general one and can be employed for the adaptive and optimal control of other dynamic systems as well. In the present work the time optimal control and adaptive control are done separately. By combining these two, robust response can be obtained. The method suggested can be applied to any non-linear, higher order system.