Chapter - 5

CONCLUSIONS

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This chapter attempts to bring out salient accomplishments of this work, to critically evaluate the same and to outline the related areas of future research. The underlying theme of the work has been to establish the effectiveness of artificial neural network for the betterment of the control in highly nonlinear processes such as CSTR-pH and Inline-pH process. An artificial neural network has been considered for the implementation of an IMC framework. Unlike existing IMC design techniques; this approach needs no mathematical models. The efficiency of the approach has been verified with simulation studies and real time process experiments, where it exhibited good and robust control characteristics.

The review of the different approaches to advanced pH control schemes shows that, the model-based control is useful for this problem. The multilayer perceptron neural network is chosen for modeling and control of the pH process. As ANNs are inherently nonlinear, they are better able to represent the highly non-linear pH processes. The results are seen to be substantially verifying this fact.

The mathematical models of the CSTR-pH process and Inline-pH process have been successfully obtained. The main purpose of this is to provide input-output data, which is representative of these processes. The series-parallel model of the CSTR-pH process has been obtained with second order NARX model. A multilayer perceptron network has been used with only one hidden layer with sigmoid activation function and a single linear output node. Once trained and validated over the test sets, series-parallel model is restructured to provide a parallel model of CSTR-pH process. The importance of choosing the right magnitude and range of input excitation signals which suits for its intended application when training the neural models, has been clearly seen.

The other important consideration when choosing the right sort of training data is to incorporate steady state as well as transient data in the training data set for neural networks. This means that the input excitation signal has to be of sufficient duration and frequency to be able to produce both transient as well as steady state conditions. Due to the significant nonlinearity of the pH processes, the use of transient data only may not give any unique one-to-one relationship between inputs and outputs, which may result in an unstable system when applied in the IMC control strategy. It is also observed that, composite amplitude random signal provides good results as compared with single amplitude random signal in the open loop identification. Prediction accuracy in the high gain area is also quite satisfactory.

The model order has been decided by comparing the loss function for various model orders. The results show that 2nd order NARX model is the most reasonable structure to model both the processes. The similar results are also obtained using other model parsimony indices such as AIC and BIC weighted functions. A reasonable sampling time of 1 second is found out by trial and error method. The inverse model of CSTR-pH process has been obtained from an approach known as specialized training. The results obtained with the specialized training show that the inverse models so obtained are having minimal offset.

The forward and inverse models of the Inline-pH process use two disturbances along with process inputs during the training. The inclusion of the disturbance in the model development helps in improving the disturbance rejection performance. The design methodology used resulted in the model with 2nd order NARX structure with TLVA method for the variable time delay compensation.

The ANN-IMC strategy has been implemented by means of identified forward and inverse neural network models for the simulated CSTR-pH and Inline-pH processes. Successful implementation of the IMC approach relies heavily on the simultaneous accuracy of the forward and inverse models. For this, the forward model output, instead of the plant output is fed back to the inverse model. In the present work, IMC structures have been tested with and without these adaptations. A filter is added prior to the controller to compensate for inaccuracies and sustain robustness in the control implementation.

The ANN-IMC controller is evaluated with regulatory and servo performance. The two benchmark controllers have been developed for the comparison of performance viz. PID controller and feed forward-feedback controller. To obtain the best performance in case of these benchmark controllers, tuning is necessary each time when the set point is changed, which is a time consuming job. In case of CSTR-pH process, the ANN-IMC design performs much better than the benchmark controllers in set point tracking and disturbance rejection.

The robustness of the controller has been verified in case of Inline-pH process by testing the regulatory performance of ANN-IMC controller. The performance is tested even for the base flow disturbances, which were not used during training of the inverse model. The same is found to be fairly good. The superiority of the IMC becomes evident in the disturbance rejection case. In the ANN-IMC controller, IMC model uses measurements of disturbances for the computation of control action, but they also depend on the effects of the disturbances on error, which is fed back to the controller.

The proposed ANN-AIMC scheme seeks to use ANN-IMC controller in the form of additive feed forward control along with conventional PID controller to improve the overall performance. The important advantage of this scheme is that there is no need to open the existing control loop; either for training data collection or for control action.

The disturbance rejection performance is better than both conventional benchmark controllers. The control actions taken by the controller are much quicker. This was expected as the controller reacted immediately to the measured disturbances. Various disturbances were applied to the both pH processes at different set points. These disturbances were rejected in a very effective manner by the AIMC controller.

The overall contribution of the PID controller in the net correction flow is found to be very small. Secondly, the PID controller flow tends to zero as the AIMC controller alone handles the disturbance successfully. This situation is as if the existing controller is removed out from the loop. Thus, the control signal from the IMC controller is totally dominating, while the component of the control signal from the existing PID controller is very small. This performance of the AIMC controller has been verified at different set points in the operating region.

The studies on the performance of the AIMC controller for the non-constant disturbances reveal that controller response to corrective action is very quick and with very small oscillations at the output. Even, the correction flow decided by the AIMC controller is also very smoothly varying. The proposed AIMC control scheme guarantees that even after the removal of the existing controller, it is capable of a sustained performance.

Further, ANN-AIMC scheme is applied to the laboratory pH control processes. The training dataset is generated by the system under closed loop control with a PID controller. The forward and inverse ANN models are developed. ANN-AIMC control scheme incorporates these models; give better results as compared with conventional feed forward-feedback controller in both set point tracking and disturbance rejection performance. Experimental results using a laboratory setup test plant show the effectiveness of the proposed control scheme. Improvement in the performance after the removal of the existing controller has been verified at the test plant. In comparison with the simulated experiment, results of laboratory pH process control are showing marginal improvement.

Future Scope of Work

The effectiveness of the internal model control approach with predictive control strategy has been established. In order to study the realistic wastewater neutralization problem, more input streams should be considered. However, the modeling for such a system is likely to be more complex.

The real life pH process has the time variant behavior. The neural network needs to be retrained offline, to get the good model characteristics. However, online training of the process could be a good exercise to solve this problem. Also, the use of different neural network modeling techniques such as radial basis function, recurrent networks can be explored as alternatives in the online training.

An integration of the neural networks and the unstructured mathematical model of the process can be used to improve the performance of the neural networks prediction accuracy. Self-learning systems are concerned with the control of systems with unknown or time varying structure or parameters. The self-organizing fuzzy logic controller has the ability to realize adaptation by building its fuzzy rules on-line as it controls the process, altering and adding as many rules as it judges necessary from off-line criteria.

Anti-logging technique is variable transformation approach. The technique removes nonlinearity at source and yields a hydrogen ion concentration, which is easier to handle. Such an anti-logging technique can be used in conjunction with various alternative classical and modern control techniques viz. smith predictor, Fuzzy Logic and Model Based Predictive Control (MBPC).