CHAPTER 1

INTRODUCTION

1.1 GENERAL

The control of liquid level in tanks and the flow between tanks is a basic problem in process industries. The process industries require the liquids to be pumped and stored in tanks, thereafter pumped to another tank. Many times the liquid will be processed by chemical or mixing treatment in the tanks, but always the level of fluid in the tanks must be controlled. A common control problem in process industries is the control of fluid levels in storage tanks, chemical blending and reaction vessels (Falkus et al 1993 and Zahrani et al 1995). The rate of change of flow from one vessel to another as well as the level of fluid are two important operational factors. Vital industries where liquid level and flow control are essential include petrochemical industries, paper making industries, water treatment industries, etc.

Serious difficulties arise in a system when the liquid level in a chosen process varies. In many processes such as distillation columns, evaporators, reboilers and mixing tanks, the particular level of liquid in the vessel can be of great importance in process operation. In process industries like hydrometallurgical industries, food process industries and wastewater treatment industries, conical tanks are widely used. Their shape contributes to better disposal of solids while mixing provides complete drainage, especially for viscous liquids. A level that is too high may upset reaction equilibria, cause damage to equipment, or result in spillage of valuable or hazardous material. If the level is too low, may have bad consequences for the sequential operations. The level control of liquid in a conical tank presents a challenging problem due to its constantly changing cross section and non-linearity of the tank. Hence, control of liquid level is an important and common task in process industries.

Also, level control plays an essential part of thermal power generating plants. Steel producing companies have repeatedly confirmed the benefits gained from accurate mould level control in continuous bloom casting (Graebe et al 1994 and Ziolko et al 1993). In this case, mould level oscillations tend to stir foreign particles and flux powder into molten metal, resulting in surface defects in the final product. Hence, level is the critical parameter to be controlled here and some form of accurate and optimal control is essential for this purpose.

1.2 LITERATURE REVIEW

1.2.1 Summary of reported work on PID control

Most of the control theory deals with the design of linear controllers with linear systems. PID controllers are proved to be a perfect controller for simple and linear processes. These controllers have been installed at most process plants, since they are simple, robust and familiar to the field operator. Nikolaou et al (2001) presented the recent developments and future directions on linear control of non-linear processes and summarized that virtually all chemical processes are non-linear, but for many of them, linear controllers are adequate. Lee et al (1996) have brought out the limitations of PI controllers.

The problem is the control of non-linear (Bequette 1991; Chidambaram 1995) and multivariable processes are that the controller parameters have to be continuously adjusted (Ziegler and Nichols 1942). In order to cope with time varying dynamics of the process, PID controllers have been evolved to include adaptive features such as gain scheduling and self-tuning. Bamieh and Giarre (1999) considered least square type identification problems with polynomial dependence on the parameters. Once the model has been developed, the design of a robust gain scheduling predictive controller can be implemented.

Adaptive control schemes (Astrom et al 1984) automatically adjust their control characteristics under various operating conditions in order to maintain effective control of a process. Dhinakaran et al (2004) deals with the adaptation of the gains of a PID controller according to process parameters such as control valve resistance and area of the conical tank. Astrom and Wittenmark (2001); Mayuresh V Kothare et al (2000) proposed a scheme for self adaptation of the gains using predictive control. Jorgen Malmbarg et al (1997) proposed a two mode controller for eliminating the level oscillations that are commonly observed in level process when PID controllers are used. As these unwanted oscillations tend to cause defects in final products, particular attention is paid to their suppression. This objective has guided the development of different control strategies which have been implemented with variable success.

Practical systems (Chidambaram 1998) are not precisely linear but may be represented as linearised models around a nominal operating point, the controller parameters tuned at that point may not reflect the real time system characteristics due to variations in the process parameters. An attempt has been made to apply variable transformation method to improve the performance of level process (Anandanatarajan et al 2003). Liu et al (2001) proposed a novel method that allows the identification of the process parameters using Recursive Least Square (RLS) technique and then designing the level controller. Huang et al (2002) employed online adaptive tuning based on online parameter estimator. Alternative state feedback linearization techniques and estimators are then derived to achieve an improved level control. Christos et al (1987) have proposed a deterministic adaptive control based on Laguerre series representation. Due to lack of proper modeling technique, the controller performance of such adaptive schemes is found to be unsatisfactory.

Many systems and manufacturing processes encountered in the real world are highly non-linear (Wright 1981 and Kravaris 1992) and multivariable. The authors have focused on synthesizing non-linear decoupling controllers for multivariable non-linear systems represented by a state space model, in presence of dead time. The dead time appears in both the inputs and the outputs but not in the states and are physically associated with sensors and actuators. In such cases establishing accurate analytical models is often very difficult. Despite such difficulties, needs often arise to control such complex systems and processes. Advances in artificial intelligence, soft computing and related scientific fields have brought new opportunities and challenges for researchers to deal with complex uncertain problems and systems, that could not be solved by traditional methods. Many approaches that have been developed for mathematically well-defined problems with accurate models may lack in autonomy and decision making ability and hence cannot provide adequate solutions under uncertain or dynamic environments. Hence the need is felt for designing “classical” techniques, alternative methods based on the use of expert knowledge have been proposed (Miller et al 2000).

1.2.2 Summary of reported work on intelligent control

The principal objective is to take advantage of the expert ability for the design of the controller. In particular, the applications involving fuzzy logic and neural network in the control loop are more and more numerous. After the introduction of fuzzy logic by Zadeh (Bart Kosko and Timothy J. Rose 1997), many researchers have applied fuzzy logic for several real-time control applications. Fuzzy logic uses linguistic rules (Chidambaram 2002) to describe complex systems. These rule-based techniques are more useful for complex systems where it is difficult to describe them mathematically. Chidambaram et al (2003) and Anandanatarajan et al (2006) have developed two different controllers at two different operating points, globalized local controller and fuzzy logic controller for the control of conical tank process. Hence two controllers are required to control the level in the conical tank Madhubala et al (2004) designed a fuzzy controller for conical tank process by tuning the membership functions of the input variables and optimizing the peak of the fuzzy sets using genetic algorithm. The above method is a time consuming, trial and error method. Daniel Wu et al (2005) used Fuzzy logic and Neural control for water level control.

Noureddine Golea et al (2002) proposed a fuzzy model reference adaptive control for non-linear systems where adaptive law is obtained using PI control law. Mayuresh V. Kothare et al (2000) proposed predictive control for controlling level in the steam generator of a nuclear power plant. Man Gyun Na (1998) designed a genetic fuzzy controller for the water level control of steam generator. Young-Moon Park et al (1995) have proposed a self-organizing fuzzy controller for dynamic systems using Auto-Regressive Moving Average (ARMA) model. Jaganathan et al (2000) have dealt with unknown non-linear dynamical system using a discrete time fuzzy controller.

Pauli Viljamaa et al (1995) and Zhao et al (1993) have developed a fuzzy logic system using PID gain scheduling.

In the above research papers, the design with fuzzy logic requires best knowledge about the process. Due to lack of proper knowledge about the process, the controller performance of these Fuzzy Logic Control (FLC) adaptive schemes is not satisfactory. Also when the process parameter changes, the entire knowledge base and rule base have to be modified. So the method based on ANN is proposed.

Guoping et al (1999) proposed a variable neural network for deriving the adaptive algorithm for a non-linear process and tuned the radial basis function center and width for adaptive control. Daniel Wu et al (2003) presented water level control by Fuzzy logic and Neural networks and adaptive control was not discussed. Cartes Wu et al (2005) presented experimental evaluation of adaptive three tank level control by Model Reference Adaptive Control (MRAS) technique with RLS estimator. Only cylindrical tank was considered for study.

Kao-Shing Kwang et al (2003) proposed reinforcement learning based adaptive control for non-linear systems. Sudath R. Munasinghe et al (2005) proposed a neuro-fuzzy controller for water level control in nuclear power plants. For this work, the data was taken from the closed loop system using PI controller and used in neuro-fuzzy controller design. Aidan O'Dwyer et al (1999) have proposed a classification techniques for the compensation of time delayed processes with parameter-optimized controllers. Dong Kwa Kim (2004) proposed a neural network based tuning PID controller for the level control of steam generator. In the literatures cited, the performances were found to be better than the FLC schemes. In some of the research papers, the data for the neural network were taken from the real time process and used in the feedback system. When the process parameters vary, this method requires the new set of data to be taken and to be retrained. Hence, there is a need for the development of adaptive neuro control schemes.

1.2.3 Summary of reported work on adaptive and optimal control

Feng et al (2000) have proposed an adaptive algorithm for PID controllers based on a theory of adaptive interaction. Byung Kook Yoo et al (2000) have proposed two types of adaptive control laws for Robot manipulator taking into account the uncertainties also. Wencheng Luo et al (2005) have dealt with the attitude tracking control of a rigid spacecraft with external disturbances and uncertainties. Kumpati S. Narendra et al (2000) developed adaptive control schemes for deterministic and stochastics discrete time systems subjected to random disturbances.

In steel industries, to maintain the quality of the final product, accurate and optimal control in level is required (Graebe et al 1994 and Ziolko et al 1993). Some researchers have done work on the optimal control needed for this type of application. Manson (1982) presented time optimal solution of an overhead crane model and optimal solutions are obtained only for the idealized model. Kin et al (1985) presented optimal proportional plus integral control for regulator and tracking problems. Only linear systems with perfect models have been considered. Jiaquing Wang et al (1987) have presented an optimal output feedback control method applied to a Motor-Generator system. Here Synthesis method with output feedback was discussed. Rugh (1987) presented a non-linear PI controller design based on linearization techniques. The design does not work for step input functions. Douglas et al (1991) presented optimal temperature control of Jacket-cooled fermentation reactors, The designed optimal controller requires two extra measurements and needs correct operating point for removing offset.

Kanagasabapathy et al (2000) proposed a time optimal control using dynamic programming method for two tank system. They proved that, this method was the best, for the servo problem in the level process. Jorgen Malmbarg et al (1997) proposed time optimal control for a hybrid control of a double tank system. They dealt with non-linear switching curves that are linearised and then implemented. Francesco Borrelli et al (2003) proposed dynamic programming time optimal control method for discrete time hybrid systems where computations are more.

Bhattacharya et al (2002) presented control of water levels of regional water systems using reinforcement learning. Modeling an optimal controller with reinforcement learning is discussed. Taek Lyul Song et al (1999) used time optimal control algorithm for Impact angle control of vertical plane engagements in which switching instants with random weighting factors are used. Norimitsu Sakagami et al (2004) proposed time optimal control for underwater robot manipulators. The position error described is not negligible and hence during fast motion the dynamics get changed and it needs a redesign of the controller.

Jayant E. Kulkarni (2003) proposed time optimal control for a swing. The linearised assumptions are made during the formation of state and co-state vectors. In the work by (Taek Lyul Song et al 1999), the authors used time optimal controller algorithm which is analytically solved by numerical methods for vertical plane engagement. Using phase plane approach, the time optimal control algorithm is derived and used in disk drive systems (Chanat La-orpacharapan 2004). Many papers seek to solve the time optimal control problem using the Pontryagin’s principle (Fang and Dissanayake 1998), the calculus of variations, the linear-quadratic Gaussian regulator, etc. Tomass Hirmajer et al (2006) presented dynamic optimization of a hybrid coupled tanks system was discussed. Only simulation studies have been done and adaptive control was not discussed.

Difficulties in solving the differential equations in the above methods, lead to new approaches. The use neural networks for control, have increased significantly in recent years. The learning ability of neural networks helps in the development of flexible controller design, especially when plant dynamics are complex and highly non-linear. Nguyen and Widrow (1989) showed the possibility of using neural networks in controlling a plant with high non-linearity. Chen (1990) proposed a self-tuning adaptive controller with neural network and constructed a neural network controller combined with linear optimal controller to compensate for the uncertainties in model parameters. The use of neural networks in control has been focused mostly on the Model Reference Adaptive Control (MRAS) problem (Yamada et al 1992).

Gu Fang et al (2002) proposed time optimal feedback control of a non-holonomic vehicle using neural networks. For this work, the data has been taken as many optimal trajectories from the process and trained using neural networks. If the process parameters vary, the network has to be retrained, other wise steady state error will be created. Yue Chen et al (2003) proposed optimal control for non-linear reactor problem. Reza Dehghan Nayeri et al (2004) proposed neural optimal control for spacecraft where optimal data are generated from the cost function evaluation through plant Jacobians. Mahboubi et al (2006) presented hybrid modeling and optimal control of a two-tank system It involves highly analytical design procedure and adaptive control was also not discussed and simulation studies only have been discussed

There are many existing time optimal trajectory planning methods for industrial robots (Fang et al 1998). In addition, the applications of neural networks and fuzzy logic in optimal control have also been suggested in the literature (Park et al 2001).

Hence for any non-linear process, a gain scheduled controller (Bamieh and Giarre 1999) can be used, but when the time constant is varying, the control procedure is lengthy such as linearization, model finding and then tuning which makes the controller design more complex and time consuming one. Hence non-linear controllers (Kravaris and Wright 2001) such as FLC, ANN based controllers are proposed. If FLC is used, with the available human knowledge, membership functions and rules are framed initially. However, the fuzzy control method has some limitations from the fact that its performance largely depends on initial membership function parameters and initial rule base setting. Hence, the performance purely depends on the human knowledge available for the process.

In the ANN based control scheme, the open loop data is taken from the real time process and trained for giving inverse response and used as a controller which leads to accurate results. Along with this real time data, if the optimal selection of rules and membership functions in FLC are done, the response would be still better. Hence, these two methods are integrated in the neurofuzzy approach. It uses both the learning ability of ANN and knowledge base of fuzzy.

Though the intelligent control methods are suitable for the process considered, the methods are optimal, but not adaptive that is, when the process parameters vary, finally these methods produce steady state error. Hence, adaptive control is required. It takes care of parameter variation also.

To minimize the settling time further, a time optimal controller is also designed based on the dynamic programming concept.

Most of the literature cited is only on simulation studies of transfer function models. Analysis, control strategies, Adaptive control, optimal control and real-time implementation on a first order non-linear process are totally missing in the survey done so far. Practical systems are not precisely linear but may be represented as linearized models around a nominal operating point, the controller parameters tuned at that point may not reflect the real time system characteristics due to variations in the process parameters. Therefore testing the performance of the non-linear controllers on a time varying process model by Anandanatarajan et al (2004). is essential to evaluate the robustness and usefulness Hence a non-linear process, the conical tank level process whose parameters vary with respect to process variable is considered for study. The time constant and gain of the chosen process vary as a function of level. The state variables of the system considered for study can be measured easily and the system is a pure single input single output system. Even though the process is first order and simple, it has non-linear characteristics. Hence control of conical tank presents a challenging problem due to its non-linearity and constantly changing cross section. The selected process is considered for testing various linear, non-linear controllers, adaptive and optimal control laws.

There are many existing control methods for conical tank level process discussed in many literatures. They have discussed the limitations of conventional controller and suggested the use of intelligent controllers in level process. But adaptive control for the described process was not discussed. The applications of neural networks and fuzzy logic in adaptive control have been suggested in the literature. They have discussed about the adaptive control for non-linear systems. But the optimal control was not discussed. In many research papers, the optimal control methods have been suggested based on the variational approach, which are mathematically difficult to solve.

In the proposed method, the method introduced in Kanagasabapathy et al (2000) and Heckenthaler et al (1994) are used to generate the time optimal trajectories for servo problems. In order to perform on-line time optimal feedback control, a neural network is used. In particular, the neural network is trained to produce the time optimal control signal to the process. The main contribution of this thesis is the development of a time optimal control law using dynamic programming with neural network for controlling the level in the conical tank and the development of adaptive control law using neural network.

1.3 OBJECTIVES OF THE PRESENT WORK

A non-linear process, the conical tank level process whose parameters vary with respect to process variable, is considered for study. The time constant and gain of the chosen process vary as a function of level. Even though the process is a first order single input, single output system, it has non-linearity. Therefore it is difficult to design a controller for the chosen process.

Considering the above points, the limitations of conventional controller on the chosen non-linear process are to be obtained. Since the process has high non-linearity, a gain scheduled approach has to be implemented to handle the non-linearity. Also, an attempt is made here to design intelligent non-linear controllers for the selected process. Apart from this, adaptive and optimal control using intelligent controllers also have to be implemented for achieving adaptive ness and optimal response. Finally, a lab scale experimental setup for conical tank level process can be used for real-time implementation.

Hence the main objectives of the present work are:

i) To find the limitation of the gain scheduled controller for the conical tank level process by conducting experiment on fabricated experimental setup.

ii) To design non-linear controllers such as Fuzzy logic controller, neural controller and Neurofuzzy controllers and to verify them practically in the experimental setup.

iii) To design adaptive and optimal control using neural networks and to conduct experiment, on the fabricated setup.

iv) To compare the performances of all the above control schemes

1.4 ORGANIZATION OF THE THESIS

Chapter 2 provides the description of the lab scale experimental setup of conical tank level process and the mathematical model of the conical tank level process derived from the fundamental concepts. The input-output characteristics and piecewise linearization of the non-linear characteristics, the process reaction curves in different regions and the mathematical model obtained from the process reaction curves are also given. The input-output characteristics when the process parameters changed are also given.

Chapter 3 explains the tuning of controllers in various operating regions and the use of PID conventional control for this control problem. The limitations of PID controller in providing exact adaptive control for complete range of heights and errors and the need for intelligent control such as Fuzzy logic control and neural network based control are brought out. The results obtained for various servo and regulator problems are presented.

Chapter 4 presents the various non-linear intelligent control schemes such as Fuzzy logic control, Neural network based control and Neurofuzzy based control.

At first, Fuzzy controller is tried out. The fuzzy controller is designed with two input variables, error in level and change in error and one output variable voltage to motor. The membership functions and rule base are formed, from which the FLC is designed. The results are obtained with this scheme for servo, regulator and process parameter variations operations.

In FLC scheme, the performance purely depends on the initial membership functions and rules. Hence, without the proper human knowledge, the optimal performance cannot be obtained. So an inverse model based neuro controller is suggested. For this, the input-output patterns are created from the experimental setup and the training is carried out employing back-propagation algorithm.

In the previous scheme, if the input-output patterns are more non-linear, the training time is more in case of ANN based control and in FLC, the initial membership functions and rule base are approximately assumed which lead to inaccurate results. By combining these two methods, the ANFIS is used, where the problems with these methods are eliminated and the response obtained would be still better and it is presented in this chapter.

Chapter 5 explains the neural network based dynamic programming for obtaining exact time optimal control of conical tank level. The methodology adopted for generating optimal control input for various set point changes are illustrated. The generated data are trained using a neural network based on back-propagation algorithm. This trained network is used as a controller and the results are obtained in real time setup.

Chapter 6 explains the adaptive control using conventional model reference adaptive system (MRAS) and neural networks. The conventional MRAS is designed first, by finding the mathematical model and designing the adaptive mechanism for updating the controller parameters for process parameter variations. The drawback with this method is given and the need of neural network based adaptive control is explained. Here four neural networks are being used for process modeling, for control, for finding steady state value from the transient data and for adapting the weights. Based on the process parameter change, the steady state error generated is predicted and the weights in the inverse model based neurocontroller is adjusted to nullify this steady state error. The weight adaptive laws are developed using the neural network approach. The tracking errors converge to the required accuracy through the adaptive control algorithm. The best results are obtained with process parameter variations.

Chapter 7 presents the results and discussion. The results obtained based on various methods discussed above are compared and the suggestions for further research work are also laid down in this chapter.