CHAPTER 1

INTRODUCTION

1.1 PREFACE

The common need for accurate and efficient control of today’s industrial applications is driving the system identification field to face the constant challenges of providing better models of physical phenomena. Systems encountered in practice are often nonlinear or have time varying nature. So, it is difficult to identify accurate models of a nonlinear system. Approximate linear models are used in most of the industrial controllers, which may lead to lower the control performance. Hence, it is important to develop a simple and practical method for nonlinear process modeling and identification, and use that model for the control of nonlinear processes.

In nonlinear system identification, nonlinear AR(MA)X models, and neural-network models are often used. These models are complex in structure and difficult to compute numerically. Block-oriented nonlinear models such as the Hammerstein and Wiener models are simpler, but they can only model nonlinearity in static gains, which is often too limiting in process control applications. Thus, instead of a global nonlinear description of the plant, often an intermediate description is searched for, that preserves the advantageous properties of the LTI models, and is still able to represent a wide range of nonlinear systems.
In process systems, especially it can often be observed that the process dynamics are well approximated by a linear model, provided the operating conditions do not change considerably. In order to extend the validity of the linear models over a range of operating conditions, the concept of Linear Parameter-Varying (LPV) models appears very attractive.

This LPV framework is able to model nonlinear process dynamics in a dedicated modeling framework, where a scheduling variable represents the varying operating conditions of the process. The idea of LPV systems is to represent the physical reality as a set of LTI systems, from which one is selected at every time instance to describe the continuation of the signal trajectories. The resulting global LPV model gives a linear description of the dynamics over the entire operating regime of the plant. This LPV identification method is referred to as the local approach, and is observed to work well for processes with a relatively slow variation of the operating conditions. The LPV system class has a wide representation capability of physical processes and this framework is also supported by a well worked out and industrially reputed control theory.

1.2 CONTRIBUTORY FEATURES OF THE THESIS

This research work deals with the linear parameter varying modeling and control of various Industrial processes. Thus, the main contribution of the present investigation includes the following.

- Modeling of the Linear Parameter Varying model for the Boiler furnace.

- Modeling and control of the Boiler drum system, using the Linear Parameter Varying model.
• Development of a Linear Parameter Varying model and controller design for large scale Industrial processes like the coal fired Boiler, which includes the following subsystems, such as the Boiler furnace, Boiler drum, Furnace gas, primary super heater, attemperator, and secondary superheater.

• Modeling of a Linear Parameter Varying model for real time conical tank system and validating it with experimental data.

• Performance analysis of a multi-model PI and adaptive PI controller using LabVIEW for the real time conical tank system.

1.3 LITERATURE SURVEY

The previous works on Linear Parameter Varying modeling, modeling and control of the boiler system, and the modeling and control of the conical tank system are discussed in detail.

Jeff Shamma & Athans (1991) introduced the terminology of linear parameter varying in the study of gain scheduling. Shamma & Athans addressed the robust stability and robust performance of linear parameter varying systems in the context of gain scheduling and stated that the scheduling should vary slowly with respect to system dynamics.

1.3.1 Linear Parameter Varying Modeling

The implementation of feedback control for batch processes using linear models that describes the batch dynamics locally along its optimal trajectory was explained by Lakshmanan & Arkun (1999). A Linear Parameter Varying model obtained by interpolation between those multiple models was used to emulate the behaviour of the non-linear batch. The
interpolation functions and state estimates were computed using a recursive Bayesian technique. The control technique was based on model predictive control which was used for regulation and targeting the product specifications at the end of the batch.

Vincent Verdult & Michel Verhaegen (2000) described a subspace type of identification method for multivariable linear parameter-varying systems in a state space representation with affine parameter dependence. Applications of linear parameter varying control have been reported by Wilson Rugh & Shamma (2000) in the control of electro mechanical systems.

Bassam Bamieh & Giarre (2002) explained the LPV identification problem in terms of input output and parameter trajectory data is posed. This identification problem can be reduced to a linear regression, and provide compact formulae for the corresponding least mean square and recursive least-squares algorithms. Conditions on persistency of excitation in terms of the inputs and scheduling parameter trajectories are derived when the functional dependence is of polynomial type. These conditions have a natural polynomial interpolation interpretation, and do not require the scheduling parameter trajectories to vary slowly. This method is illustrated with a simulation example using two different parameter trajectories.

Vincent Verdult et al (2002) described an identification method to determine a weighted combination of local linear state-space models from input and output data. Normalized radial basis functions were used for the weights, and the system matrices of the local linear models are fully parameterized. By iteratively solving a non-linear optimization problem, the centres and widths of the radial basis functions and the system matrices of the local models are determined.
Giarre et al (2006) approached the problem of identifying a nonlinear plant by parameterizing its dynamics as a linear parameter varying model. The system under consideration was the Moore–Greitzer model that captured surge and stall phenomena in compressors. The control task was formulated as a problem of output regulation at various set points (stable and unstable) of the system under inputs and states constraints. It was worth pointing out that the adopted technique allowed for identification of an LPV model’s coefficients without the requirements of slow variations amongst set points.

Heri Subagiyo & Bambang Riyanto (2007) addressed system identification of firing burner plant, based on LPV representation. Heri Subagiyo & Bambang Riyanto stated that, the models obtained by using the LPV identification and RLS algorithm with parameter trajectory sequence of sufficiently low frequency provided reasonable fit with the mean value of 95.52%.

Roland Toth et al (2007) presented a common approach for modeling LPV systems to interpolate between local LTI models, often obtained by system identification methods. The results of interpolating in different domains, the so called input/output domain and the state-space domain showed significant difference can occur between the interpolated models, due to differences in time propagation of the scheduling parameter. Canonical representations for LPV state-space realizations similar to the linear time varying framework was introduced and exact formulas for the connection between input/output and state-space based LPV models were derived.

The LPV model identification for waste heat recovery system as a sub-system in reforming process in an industrial ammonia plant was described by Riyanto Bambang et al (2008). Experimental input-output signals required
for identification process are taken from DCS historian data of the ammonia process plant during plant operations. The resulting LPV model was simulated and validated with respect to the measured data for ammonia process plant. The results obtained were promising to cover several operating conditions of waste heat recovery system, including start-up, normal-operation, and shut-down, which is difficult to handle using LTI identification.

Bei Lu et al (2008) evaluated experimentally a linear parameter-varying control design method for an active magnetic bearing system. A speed-dependent LPV model of the active magnetic bearing system was derived. Model uncertainties were identified using artificial neural networks, and an uncertainty weighting function was approximated for LPV control synthesis. Experiments were conducted to verify the robustness of LPV controllers for a wide range of rotational speed.


A method of nonlinear model identification for control is proposed by Yucai Zhu & Zuhua Xu (2008). The simulation example has shown high approximation power of the proposed LPV model. Zuhua Xu et al (2009) proposed a nonlinear MPC control algorithm that uses the identified LPV models and demonstrated it using simulation examples. The study was carried out using the CSTR Benchmark Process model and a model of a polymer
Zhu & Ji (2009) proposed a LPV model in the form of a blended linear models which adds weights at the input side. The stability of this kind of LPV models is guaranteed if the local linear models are all stable.

Jan De Caigny et al (2009) introduced a new method to estimate linear parameter-varying state-space models for single-input single-output systems whose dynamics depend on one or more time-varying parameters, called scheduling parameters. The method was based on the interpolation of linear time-invariant models that are identified for fixed operating conditions of the system. The underlying interpolation technique was formulated as a nonlinear least-squares optimization problem that can be solved efficiently by standard solvers. Vincent Laurain et al (2010) highlighted the lack of efficient methods in the literature to handle the estimation of LPV Box Jenkins models. It has been shown that the conventional formulation of a least squares estimation cannot lead to statistically optimal parameter estimates. As a solution, the LPV identification problem is reformulated and a method to estimate efficiently LPV Box Jenkins models with a p-independent noise process was proposed.

Two internal model control (IMC) controllers using gain-scheduling techniques were proposed and compared for open-channel systems with large operating conditions by Duviella et al (2010). In particular, in one side, a linear parameter varying model for an open-flow channel system based on a second-order delay Hayami model is proposed. This model was used to design a classic gain-scheduling strategy for the IMC controller. On the other side, the LPV model was discretized in a set of linear time invariant (LTI) models corresponding to different operating points. For each LTI model a IMC controller was designed off-line.

Cosku Kasnakoglu (2010) proposed a novel method for constructing linear parameter varying system models through adaptation. For a class of
nonlinear systems, an LPV model was built using its linear part, and its coefficients were considered as time-varying parameters. The variation in time was controlled by an adaptation scheme with the goal of keeping the trajectories of the LPV system close to those of the original nonlinear system. Using the LPV model as a surrogate, a dynamical controller was built by utilizing self-scheduling methods for LPV systems, and it was shown that this controller will indeed stabilize the original nonlinear system.

Toth et al (2010) demonstrated the strength of an orthonormal basis functions based LPV identification approach for modeling nonlinear process dynamics. LPV models served as an intermediate step between rigorous nonlinear process models and simple Linear Time-Invariant descriptions commonly used in process control. The performance of the proposed approach was demonstrated on a simulation example of a CSTR, showing that a LPV model that describes the process behavior for different inflow concentrations efficiently.

A systematic method for developing model-based controllers for solid-oxide fuel cell (SOFC) systems was described by Borhan Sanandaji et al (2011). The authors stated that to enhance the system efficiency and to avoid possible damages, the system must be controlled within specific operating conditions, while satisfying a load requirement. A linear parameter varying (LPV) model structure was developed and applied to obtain a control-oriented dynamic model of the SOFC stack.

Modeling of nonlinear process with multiple operating conditions was considered by Xing Jin et al (2011). An LPV model was identified for nonlinear process by incorporating process information such as scheduling variables, the number of operating point that the system is likely to be operated on, the model order of each local model identified around its corresponding operating point. The authors demonstrated through simulations
that within the specified working range, the identified model provided satisfactory approximation of the process dynamics. To further validate the effectiveness of the proposed identification method, an experiment was performed on a pilot-scale setup and it was demonstrated that the proposed LPV modeling method can be applied to the collected experimental data to effectively identify an LPV model for nonlinear process.

Yu Zhao et al (2012) derived the prediction error method (PEM) to identify the LPV model with input–output model structure. Colored noise was taken into account by using the Box–Jenkins LPV model. Yu Zhao et al demonstrated that under the PEM framework, both the parameter interpolation based LPV model identification and the model interpolation based LPV model identification problems can be effectively solved. The effectiveness of the proposed solution was validated by comparison with other existing LPV identification approaches through simulation examples and demonstrated it by experimental studies.

Jiangang Lu et al (2012) proposed a novel nonlinear model predictive controller (MPC) based on an identified nonlinear parameter varying (NPV) model. NPV model scheme was presented for process identification, which was featured by its nonlinear hybrid Hammerstein model structure and varying model parameters. The authors suggested that in the proposed scheme, only low cost tests are needed for system identification and the controller can achieve better output performance than MPC methods based on linear parameter varying (LPV) models.

1.3.2 Modeling and Control of Boiler System

Gordon Pellegrinetti & Joseph Bentsman (1996) developed a control oriented boiler model carried out on the basis of fundamental physical laws, previous efforts in boiler modeling, known physical constants, plant data, and
heuristic adjustments. The resulting fairly accurate model was nonlinear, fourth order, and included inverse response (shrink and swell effects), time delays, measurement noise models, and a load disturbance component. The author proposed that the obtained model can be directly used for the synthesis of model-based control algorithms as well as setting up a real-time simulator for testing of new boiler control systems and operator training.

Adam & Marchetti (1999) proposed two non-linear models, one for the evaporation in tubes and the other for the steam separation in a drum, and the same were combined to yield a dynamic model of large boilers. The development serves to simulate the waterside dynamic operation of steam generators. The dynamic behavior of every physical variable analyzed through the proposed model was satisfactory and consistent with the practical experience. Alberto Leva (1999) described the validation of a model library for the simulation of drum boilers on the basis of static and dynamic experimental data obtained from a small-scale plant. All the steps of the validation process were described in detail, with particular reference to the modeling principles, to the trade-off between model complexity and accuracy, to the solution strategy and to the data-reconciliation policy.

A nonlinear dynamic model for natural circulation drum-boilers was presented by Astrom & Bell (2000). The model describes the complicated dynamics of the drum, downcomer, and riser components. The model was derived from first principles, and is characterized by a few physical parameters. A strong effort has been made to strike a balance between fidelity and simplicity. Results from validation of the model against unique plant data were presented. The model describes the behavior of the system over a wide operating range. A simple two-by-two model for a boiler-turbine unit was demonstrated by Wen Tan et al (2004). The proposed model can capture the
essential dynamics of a unit and the design of a coordinated controller was discussed based on this model.

Wen Tan et al (2008) analysed the boiler turbine unit as nonlinear unit and selected the appropriate operating points and designed the linear controller to achieve wide-range performance. Simulation and experimental results at the No. 4 Unit at the Dalate Power Plant shows that the linear controller can achieve the desired performance under a specific range of load variations.

A complete system identification procedure of steam pressure variation process inside fire-tube boilers has been developed by Rodriguez Vasquez et al (2008). The results of parameter estimation and model validation proved that the best dynamic performance of steam pressure variation process inside the fire-tube boilers was obtained with a second order linear ARMAX model structure and time delay. Un-Chul Moon & Lee (2009) proposed two possible step-response models in designing the dynamic matrix control. One was developed by linearizing the mathematical model and the other was developed with the process test data.

Batool Labibia et al (2009) designed a decentralized robust PI controller for a real industrial utility boiler and a control oriented nonlinear model for the boiler was identified. The nonlinearity of the system was modeled as uncertainty for a nominal LTI multivariable system. Using the proposed method, a decentralized PI controller for the uncertain LTI model was designed. The designed controller was applied to the real system and the simulation result shows the effectiveness of the proposed methodology.

Agees Kumar & Kesavan Nair (2010) presented a new design method in the study of multi-objective particle swarm optimization used for tuning of non-linear PID controller parameters for steam temperature control
of boiler unit in thermal power plant. Dejan Ivezic & Petrovic (2010) demonstrated the design of the multivariable robust controllers for an industrial boiler subsystem. Steam water part (i.e. a steam drum, downcomers and risers) of an industrial boiler system has been modeled and the input model uncertainty was defined. The controllers were designed using $\mu$ analysis control theory and they achieve robustness against uncertainties and disturbance. The procedure for deriving the parameters of drum type boilers dynamic model for long-term transient stability studies by use of heat balance data was presented by Ramezan Ali Naghizadeh et al (2011).

Orosun Rapheal & Adamu Sunusi Sani (2012) modeled a physical boiler system as a multivariable plant with two inputs (feed water rate and oil-fired flow rate) and two outputs (steam temperature and pressure). The plant parameters are modeled by identification based on experimental data collected directly from the plant. The routines of System Identification Toolbox with structure selection for Autoregressive Moving Average together with Recursive Least Square were used to identify the model. Furthermore, Proportional Integral Derivative controller was developed to control the identified model. The Simulation results obtained indicate the effectiveness of the technique. The controller was able to track the temperature and pressure set points steadily and rapidly.

Yunjing Liu & Deying Gu (2012) proposed the fuzzy-PID control strategy applied in steam temperature control. Simulation results for different cases of boiler combustion system shows that the control strategy has better ability. Osama et al (2012) described the two artificial intelligence techniques, fuzzy control and genetic fuzzy control applied to control both of the water/steam temperature and water level control loops of boiler and it was proved that the fire tube boiler that fitted with GFLC controller has a reliable
dynamic performance as compared with the system fitted with traditional FLC controller.

Hendookolaei & Bahrami Ahmadi (2012) explained the two methods of Adaptive Control for pressure control of a drum type boiler. The aim of the control was to keep the pressure at its per unit value in the presence of the load changes as the disturbance. The first method was based on the linear identification of the process and the second one was based on the neural identification. The simulations showed that the neural identification was more efficient in pressure control of a boiler because of the nonlinearity aspects of the boiler.

Hamed Moradi et al. (2012) implemented two control strategies for desired performance of drum water level. Robust sliding mode and $H_\infty$ controllers are designed for time varying dynamic system and the results are compared for regulation and various desired commands of drum water level. Sliding mode control leads to more smooth, rapid and robust time responses, less oscillatory behavior of control efforts and less energy consumption.

Om Prakash Verma & Gaurav Manik (2013) compared the control performance of advanced approaches namely cascaded control, internal model control, feedback-feed forward and fuzzy logic control. The results of proposed control systems demonstrated the optimized performances in terms of overshoot, rise time, settling time and tracking of set point. A comparison of results for such variables indicated that internal model control based feedback-feed forward cascade controller and fuzzy logic control have reasonably better performance versus others in terms of steam water flow pressure disturbance rejection capability. The designed model of drum level has been simulated in MATLAB environment.
1.3.3 **Modeling and Control of Conical Tank System**

Bhaba et al (2007) implemented weiner model based PI controller in conical tank liquid level system. Comparison of Ziegler Nichols tuning rule and Padmasree and chidambaram tuning rule was carried out. Padmasree and chidambaram tuning rule proves better in terms of integral square error. Bhuvaneswari et al (2008) dealt with the adaptive control of a continuous time nonlinear system of conical tank level process using neural networks. Experimental studies were carried out for conventional control, fuzzy control, neuro control, and adaptive neuro control. The performances of all the above schemes were investigated. The advantages of the proposed scheme, over other methods, were also highlighted.

Nithya et al (2008) designed an intelligent madhami and Takagi Sugeno model based fuzzy logic controller for conical tank system. Experimental results proved that the response was smooth for both set point and regulatory changes for Takagi Sugeno based fuzzy logic controller compared to mamdhanii fuzzy and PI controller.

Girirajkumar et al (2010) implemented ants colony optimisation in order to obtain optimal values for control parameters, $K_p$ and $K_i$ of a PI controller for a conical tank process, which is highly non-linear. The problem of non-linearity was overcome by linearizing over four suitable ranges. The various results presented based on time domain specification and performance index proved that the betterness of the ants colony optimisation tuned PI settings than the IMC tuned ones.

Nithya et al (2010) implemented controllers based on soft computing techniques in real time for a non-linear process. The soft computing based controllers like fuzzy logic controller and genetic algorithm based controller has been implemented and compared with conventional PI
tuning method. The soft computing based controller tracked the set point faster with fewer oscillations. Suddenly 10% of load disturbance was introduced in the level tank setup for different controllers. The soft computing based controllers tracked the load disturbances and settled in faster time.

Anand et al (2011) proposed an idea for designing a continuously tuned adaptive PI controller for a non-linear process such as conical tank. The performance of the adaptive PI controller was compared with the conventional PI controller and validated. A servo response for the entire span of level and regulatory response was also simulated. The response of adaptive PI control was less oscillatory and has lesser over-shoot than conventional PI controller. Bhaba & Somasundaram (2011) designed the Coefficient Diagram Method - PI control schemes for a conical tank liquid level maintaining system. Real time implementation of this control scheme was carried out in a conical tank liquid level maintaining system and the performance of the control schemes in set point tracking cases was analyzed. The results clearly favor Coefficient Diagram Method - PI control scheme.

Marshiana & Thirusakthimurugan (2012) described the controller design of a nonlinear system. The nonlinear system taken up for the study was the conical tank which was approximated to a first order system. In this method design of controllers based on ZN tuning method was determined and a comparison was made between the values of P, PI and PID. For the analysis it was determined that PID controller gave the better performance when compared with the P and PI controller. The servo and regulatory response provided a better result for the different set points.

Conical tank level process was studied experimentally to obtain the process model by Sukanya & Sivanandam Venkatesh (2012). The linear portion of this non linear model was considered and different control schemes such as discrete time Proportional Integral Derivative control and discrete
time Model Predictive Control were implemented. The rising time, settling time and the overshoot of PID and MPC was calculated from the graphs obtained and it clearly understood that Model Predictive Control was giving better performance than conventional discrete time Proportional Integral Derivative controller.

Ganesh Ram & Abraham Lincoln (2012) proposed fuzzy adaptive PI control algorithm for non-linear level process to improve the control performance better than the conventional PI controller. The various results have been presented to prove the improved performance of the Fuzzy Adaptive PI over the conventional PI.

The process model for conical tank system was determined by using system identification technique at a particular operating point by Anna Joseph & Samson Isaac (2013). The conventional controller tuning was accomplished using Zeigler Nichols based PI controller settings and the performances were compared with model reference adaptive controller based on settling time and Integral Squared Error. The result show that better controller performance and error was minimized in model reference adaptive controller.

Aravind et al (2013) described a nonlinear model of conical tank level control system. For each stable operating point, a first order process model was identified using process reaction curve method and they were controlled by synthesis method and skogestad method. By direct synthesis method minimum rise time and quick settling time was achieved.

Dhanalakshmi & Vinodha (2013) attempted to adapt the PI controller suitable to control the conical tank by two methods namely an adaptive PI controller and neural network based PI controller. The proposed controllers use the same control law and differ only in the adaptation of controller parameters. The real time results revealed that proposed controllers
have good set point tracking and disturbance rejection at different operating points.

Kesavan & Rakesh Kumar (2013) suggested an idea to design an adaptive PID controller for Non-linear liquid tank System and the same was implemented with PLC. Online estimation of linear parameters (Time constant and Gain) brought an exact model of the process to take perfect control action. The adaptive PID has been implemented on PLC and was used to control the level of conical tank. Abhishek Sharma & Nithya Venkatesan (2013) demonstrated the efficient method of tuning PI controller parameters by comparing different tuning rules for conical tank system. It was observed that controller tuning method projected by Astrom & Hagglund is appropriate for non linear process because it had least settling time than other controller tuning methods.

Ganesh Ram & Abraham Lincoln (2013) proposed a model reference tracking based fuzzy adaptive PI controller for non-linear process plant. The performance of the proposed control strategy was found to be quite satisfactory for set point as well as load variations under different operating levels. Pushpaveni et al (2013) made comparison between adaptive PID control and model predictive control in the conical tank process. The simulation result proved that the model predictive control method was an easy-tuning and more effective way to enhance stability of time domain performance of the conical tank system. Angeline et al (2014) proposed to obtain the mathematical modeling of a conical tank system and to design model based controller (Internal Model Control) for controlling the level in it. The peak overshoot was reduced in Internal Model Control when compared to the PID controller. The settling time is also reduced in Internal Model Control.
A time-optimal control for set point changes and an adaptive control for process parameter variations using neural network for a non-linear conical tank level process were proposed by Bhuvaneswari et al. (2009). Time-optimal level control was formulated using dynamic programming algorithm and basic properties of the solutions were analysed. A prototype of conical tank level system has been built and implementation of dynamic programming based neural network control algorithm for set point changes and implementation of adaptive control for process parameter variations are performed. Finally, the performance was compared with conventional control. The results prove the effectiveness of the proposed optimal and adaptive control schemes.

1.4 OBJECTIVES AND METHODOLOGY

The main objectives of the thesis are as follows:

- First principle modeling of boiler subsections, such as the Boiler furnace, Boiler drum, furnace gas, primary super heater, attemperator, and secondary superheater have been developed, using the mass and energy balance equations.

- Each subsection of the Boiler is combined to form the Integrated Boiler model.

- Input and output data sets are generated by doing an Identification test for the Boiler furnace, Boiler drum and Integrated Boiler process.

    The following procedure has been done separately for the Boiler furnace, Boiler drum and Integrated Boiler process to obtain the Linear Parameter Varying model.
- Development of a linear model with data sets obtained at various operating regions.

- Development of a Linear Parameter Varying Model by interpolating linear models using the scheduling variable.

- The Developed Linear Parameter Varying model is validated, using the first principle model of the process.
  
  - Design and analysis of a multi-model PI and adaptive PI controller for the first principle and LPV model of the Boiler drum.
  
  - Design and analysis of a multi-model PI controller for the LPV modeled Integrated Boiler model.

  - Formulation of the LPV model for a real time conical tank system, and its validation using experimental data.

  - Design and real time implementation of a multi-model PI controller and adaptive PI controller for the conical tank system.

  - Design and implementation of a multi-model PI controller and adaptive PI controller for the Linear Parameter Varying modeled conical tank system.

The flow chart of the methodology is shown in Figure 1.1 in a comprehensive manner.
1.5 ORGANIZATION OF THE THESIS

This thesis is organized into seven chapters.

Chapter 1 deals with the need and scope of the present work, and organization of the thesis along with the related literature survey. An introduction to the Linear Parameter Varying model identification method for Industrial processes is discussed in Chapter 2. Chapter 3 discusses the first principle modeling of the Industrial Boiler furnace, Boiler drum and Integrated boiler process. In chapter 4, the Linear Parameter Varying modeling of the Industrial Boiler furnace, Boiler drum and Integrated boiler process is carried out, and they are validated using the first principle modeling. The control of the first principle and linear parameter varying
model of the Boiler drum and Integrated Boiler model is dealt with, along with servo performance and time domain specification in Chapter 5. The Real time implementation of the linear parameter varying model and control of conical tank system, using the multimodel based PI controller and adaptive PI controller is discussed in Chapter 6. The summary, conclusion and future scope are given in Chapter 7.