DESIGN OF MULTI-MODEL CONTROL STRATEGIES FOR NON-LINEAR SYSTEMS: THEORETICAL AND EXPERIMENTAL INVESTIGATIONS

Submitted in partial fulfillment of the requirements for the award of the degree of

DOCTOR OF PHILOSOPHY

in

CHEMICAL ENGINEERING

by

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JULY 2021

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CERTIFICATE

This is to certify that the thesis entitled **"Design of Multi-Model Control Strategies for Non-Linear Systems: Theoretical and Experimental Investigations"** being submitted by **Mr. G. Maruthi Prasad** for the award of the degree of Doctor of Philosophy (Ph.D) in Chemical Engineering, National Institute of Technology, Warangal, India, is a record of the bonafide research work carried out by him under my supervision. The thesis has fulfilled the requirements according to the regulations of this Institute and in my opinion has reached the standards for submission. The results embodied in the thesis have not been submitted to any other University or Institute for the award of any degree or diploma.

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Date: July 29, 2021

DECLARATION

This is to certify that the work presented in the thesis entitled "Design of Multi-Model Control Schemes for Non-Linear Systems: Theoretical and Experimental Investigations" is a bonafide work done by me under the supervision of Dr. A. Seshagiri Rao and is not submitted elsewhere for award of any degree.

I declare that this written submission represents my ideas in my own words and where others' ideas or words have been included, I have adequately cited and referenced the original source. I also declare that I have adhered to all principles of academic honesty and integrity and have not misrepresented or fabricated or falsified any idea/data/fact/source in my submission.

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G. MARUTHI PRASAD

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ACKNOWLEDGMENTS

It gives me immense pleasure to express my heartiest and sincere gratitude, indebtedness to my supervisor and mentor **Dr. A. Seshagiri Rao**, Associate Professor, Department of Chemical Engineering for his patient guidance, timely appreciation, extraordinary support enormous enlightening discussion with constructive criticism, and sustain inputs during the research work and preparation of thesis. I am extremely fortunate to have **Dr. A. Seshagiri Rao** as my dynamic advisor. His guidance is a great learning experience to me throughout my stay at NITW by strengthening me all the time.

I owe a deep sense of gratitude to **Prof. M. Chidambaram,** Emeritus Professor, Department of Chemical Engineering, NIT Warangal, for his keen interest on me at every stage of my research.

I am very much thankful to **Dr. S Srinath**, Head of the Department of Chemical Engineering for their advice and encouragement.

I take this privilege to thank all my Doctoral Committee members, **Dr. P. V. Suresh**, Associate Professor, Department of Chemical Engineering, **Dr. G. Uday Bhaskar Babu**, Assistant Professor, Department of Chemical Engineering and **Dr. D. Jaya Krishna**, Associate Professor, Department of Mechanical Engineering for their detailed review, constructive suggestions and excellent advice during the progress of this research work.

I also appreciate the encouragement from teaching, non-teaching members, and fraternity of Department of Chemical Engineering of NIT Warangal. They have always been encouraging and supportive.

I wish to express my sincere thanks to **Prof. N. V. Ramana Rao**, Director, NIT Warangal for his official support and encouragement.

There is no way to express how much it meant to me to have been a member of Process control in NIT Warangal. These brilliant friends and colleagues inspired me over the many years: I convey my special thanks to Research Scholars Mr. E Chandramohan Goud, Mr. A Aditya, Mr. A Gaffar, Dr. D Purushottama Rao, Mr. Chiluka Suresh Kumar, Dr. B Anil and M.Tech students, Mr. Ravi Teja, Ms. Shivanky J, Ms. Soniya P, and Mr. Vatsal all the other current and former NIT Warangal students and visitors that I know.

I acknowledge my gratitude to all my teachers and colleagues at various places for supporting and co-operating me to complete the work.

My heartfelt gratitude and indebtedness are due to my parents Shri. Nagaraju & Smt. Gowri and my wife Jayanthi and elder & younger brother Raja shekar & Ashok for their sincere prayers, blessings, constant encouragement, shouldering the responsibilities and moral support rendered to me throughout my life. I heartily acknowledge all my relatives for their love and affection towards me.

I cannot forget my best friend Mr. Dmd Tausiff, Mr. N Hemanth, Mr. Noor and Mr. M Phanindra for their support.

Above all, I express my deepest regards and gratitude to "ALMIGHTY" whose divine light and warmth showered upon me the perseverance, inspiration, faith and enough strength to keep the momentum of work high even at tough moments of research work.

ABSTRACT

It is well known that control of nonlinear processes is difficult when compared to linear processes. All the methods developed in the literature for control of nonlinear processes are comparatively more complex when compared to Multi Model Approaches (MMA), and hence MMA is preferred due to its simplicity and easy implementation. In MMA, the nonlinear process is decomposed into multiple linear models based on partition strategies. These multiple linear models are further reduced into minimal number of models using reduction techniques. These reduction techniques are used to find out the optimized linear models to merge the sequential operating ranges. The linear controllers are designed for these reduced models and combination of these linear controllers forms the global controller.

Most of these methods in the literature are implemented in simulation. An experimental investigation provides more understanding and also practical difficulties of nonlinear process control. This work presents an experimental evaluation and comparison of gap metric based weighting methods for design of multi model control schemes for control of levels in a spherical tank and a conical tank process. Internal model control (IMC)-PI controllers are designed for the corresponding linear models. A simulation study is first carried out to examine the performance on these nonlinear systems, in which the weights for local controller's combinations are calculated by the weighting functions. The two weighting functions (1- δ and 1/δ, Where δ is gap metric function) based on the gap metric value of particular linear model are calculated and used for constructing the global multi model controller. Level control in spherical and conical tank systems is studied to show the experimental implementation of the considered multi model control schemes.

Further, Multi Model Predictive Controller (MMPC) is developed in this research. In MMPC, each MPC has weights determined from the gap metric and using these weights. Comparative performance analysis of those weighing functions is carried out by simulations and also by experiments.

Fractional controllers based MMA framework are developed for enhancing the control of nonlinear systems. For the purpose of comparison, MMA framework with integer order controllers are considered and it is observed that MMA framework with fractional controllers

provide improved closed loop performances. Experimental investigation is also carried out to verify the applicability of the proposed method and it is observed that the proposed method provide enhanced closed loop responses.

Cascade multi model control system using hard and soft switching for nonlinear process is addressed. Multi model approach (MMA) in cascade control strategy by using hard and soft switching for selection of the controller is developed. Simulation studies and experimental implementation is carried out on a conical tank process. The performance of the cascade multi model control strategy is superior when compared to the classical multi model control strategy.

Multi model smith predictor is designed and evaluated for long dead time nonlinear process. The long dead time in nonlinear process creates stability issues and to overcome this, smith predictor structure is integrated to multi model control structure. The multi model smith predictor structure is examined on nonlinear processes such as conical tank process and iCSTR and evaluated with Integral Absolute Error (IAE) and Total Variation (TV).

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ABBREVIATIONS

MMA	Multi Model Approach
MMCS	Multi Model Control Scheme
MMPC	Multi Model Predictive Controller
iCSTR	Isothermal Continuous Stirred Tank Reactor
IAE	Integral Absolute Error
ISE	Integral Square Error
IMC	Internal Model Control
PI	Proportional Integral
PID	Proportional Integral Derivative
SP	Smith Predictor
TV	Total Variation
LOLIMOT	Local Linear Model Trees
LMN	Local Model Network
$PI^{\lambda}D^{\mu}$	Fractional Proportional Integral Derivative
MMSP	Multi Model Smith Predictor
NP	Prediction horizon
NC	Control horizon
Δt	Control interval
MV	Manipulated variable
CV	Controlled variable

NOMENCLATURE

Symbol	Meanings
μ	Time delay
n	Time constant
k_c	Proportional gain
k_m	Model gain
k_p	Process gain
k_{p1}	Primary process gain
k_{p2}	Secondary process gain
Δ	Gap metric function
θ	Process time delay
θ_m	Model time delay
θ_{p1}	Primary time delay
θ_{p2}	Secondary time delay
H	Height of the process tanks
q_i	Inlet flow rate of spherical and conical tank process
q_o	Outlet flow rate of spherical and conical tank process
A	Spherical tank process valve coefficient
R	Spherical tank process outlet resistance
P_i	finite dimensional linear operator
$N_i M_i$	Right co-prime transfer functions
$\widetilde{M}_i \widetilde{N}_i$	Left co-prime transfer functions
δ_g	Gap metric
M_i	Multi linear models
C_A	Reactant concentration
C_{Ai}	Inlet feed concentration
Q	Inlet flow rate

K	Constant rate
y	Process output
y_1	Primary loop output
y_2	Secondary loop output
G_c	Conventional feedback controller
G_m	Model transfer function
G_p	Process transfer function
G_{p1}	Primary process
G_{p2}	Secondary process
$\varphi_i(\theta_t)$	Weighting function
$u(t)$	Output of global controller of MMCS
λ ($PI^{\lambda}D^{\mu}$)	Integral order
μ ($PI^{\lambda}D^{\mu}$)	Derivative order
J_v	Performance criteria

Chapter 1

Introduction

Chapter 1

Introduction

1.1General

In process industries, many times, the process outputs do not respond proportionally to change in the corresponding inputs and these type of processes are referred as nonlinear processes. Control of such processes is difficult and challenging when compared to the linear processes. Conventional PID controllers can be used to control the nonlinear processes but these controllers must be tuned in such a way that they provide stable performance over the entire range of operating conditions and hence the tuning of such controllers become conservative. Though these controllers are tuned conservatively, still there is degradation in control system performance. Researchers developed different nonlinear control strategies such as generic model control, adaptive control, gain scheduling control, nonlinear model predictive control and multi-model control to control nonlinear systems in which multi-model control approach (MMCA) is one of the simplest approach. The systematic steps involved in MMCA are

1. Decomposition of the nonlinear system into multiple linear models.
2. Reducing the number of linear models.
3. Design of multi-model control scheme based on the reduced number of models.

This approach primarily focuses on decomposing a non-linear system into multiple linear models based on the operating conditions. Based on the partition strategy, the multiple linear models are formed and combination of all these models represents the dynamics of the process. For each operating range, one linear model is used to represent the system behavior. Based on these local linear models, the controllers are tuned and the combination of all such local linear controllers forms the global controller. But too many models make the formation of global controller complicated. To overcome this, model reduction is carried out using gap metric techniques. The gap metric technique is useful to merge the ranges and select a single model, which is suitable for many ranges with a minute difference in the performance. For every local linear model, respective linear controller is designed and the corresponding conditional combination forms the global controller. Conditional combination is carried out in two ways i.e. hard switching method and soft switching method. In hard switching method, only one local controller acts as global controller which is selected based on operating conditions and error. However, in soft switching method, combination of all the controllers forms the global controller with determined weights for all local controllers.

The representation of multi model control scheme is shown in Figure 1.1 in which r(t) and y(t) are reference input and output at time t, e(t) is error at time t, u(t) is global controller output at time t, C_1, C_2 … C_n are local controller and W_1, W_2, … W_n are local weights.

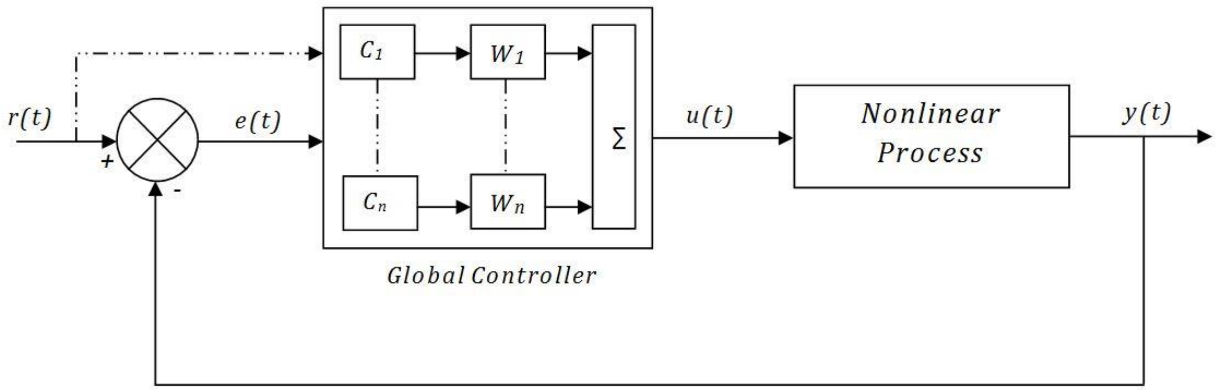

Figure 1.1 Multi model control block diagram

1.1.1 Theoretical developments of gap metric:

The gap metric is a suitable tool to measure the distance between two linear systems than a metric based on norms. The technique and its importance in control system is clearly explained by El-Sakkary et al. (1985).

The gap between two subspaces K_1 and K_2 is defined as

$$\delta(K_1, K_2) = \left\|\Pi_{K_1} - \Pi_{K_2}\right\| \qquad (3.3)$$

Where Π_{K_i} denotes the orthogonal projection onto subspace K_i.

A finite dimensional linear operator P_i defined in the H_2 space is considered which has a transfer function P_i that can have the normalized right co-prime factorization $\left(G_i = \begin{bmatrix} N_i \\ M_i \end{bmatrix}\right)$ and left co-prime factorization $\left(\tilde{G}_i = \left[-\tilde{M}_i \tilde{N}_i\right]\right)$given by $P_i = N_i M_i^{-1} = \tilde{M}_i^{-1} \tilde{N}_i$ ($N_i M_i$ and $\tilde{M}_i \tilde{N}_i$are stable, right and Left co-prime transfer functions (are the normalized co prime factorizations).

The gap metric is then computed as

$$\delta_g(P_1, P_2) = \max\,(\vec{\delta}_g(P_1, P_2), \vec{\delta}_g(P_2, P_1)) \quad (3.4)$$

where

$$\vec{\delta}_g(P_1, P_2) = \inf_{Q\epsilon H_\infty} \left\| \begin{bmatrix} N_1 \\ M_1 \end{bmatrix} - \begin{bmatrix} N_2 \\ M_2 \end{bmatrix} Q \right\|_\infty \quad (3.5)$$

The value of gap metric is between any two linear systems and can only take values in the range [0,1] and has several useful properties:

(1) $0 \leq \delta_g(P_1, P_2) \leq 1$.

(2) The gap metric defines the possible distance between two linear systems from a control perspective.

(3) If the metric value is close to 0, at least one controller can stabilize both systems; if the gap metric is close to 1, it is difficult to design a controller or a single controller cannot stabilize both the systems.

1.2 Model Predictive Control (MPC)

MPC is an advanced control strategy that is used in most of the process industries. It uses a dynamical model of the process to predict its likely future response and then choosing the best control action possible while satisfying set of constraints. Nowadays, it finds application in aerospace, automotive, smart electricity grids, etc. Because of the advantage associated with MPC over conventional control strategy, it has been employed. MPC inherently has feed forward nature as it takes measured disturbances as input and it negates the effect of the disturbance beforehand making it very popular in highly disturbed plants as well and is clearly explained by Dougherty(2003). The future control signal is computed in such a way that minimizes the quadratic objective cost function defined as, Minimize J

$$J = \sum_{l=1}^{N_P} \left\| \Gamma_y \big(y\,(K_i\ +\ l|K_i) -\ r\,(K_i\ +\ l) \big) \right\|^2 + \sum_{l=1}^{N_C} \| \Gamma_{\Delta u}\,(\Delta u\,(K_i\ +\ l\ -\ 1)) \|^2 \quad (5.7)$$

The 1st term denotes the objective of minimization of error between predicted outputs and set-point signal and the 2ndterm denotes the objective to find optimal Δu values such that error is reduced. Γy denotes the penalty on tracking error known as output weighting, ΓΔu denotes the penalty on the actuation known as input-rate weighting, y (Ki + l|Ki) represents the predicted value of output at Ki +l instant given information up to Ki instant. Tuning parameters of the

MPC are prediction horizon (NP), control horizon (NC), control interval (Δt), rate weight on MVs ($\Gamma\Delta u$), weight on CV(Γy). Few distinguishing features of MPC from conventional control strategy is, it has ability to forecast, optimize and good constraint handling capability. The disadvantages are it requires simple linear state-space model, too many degrees of freedom (horizons, weights, constraints, etc.), requires real time optimization, etc.

1.3 Fractional Order Controller

Implementation of Fractional calculus which is generalization of Integer order calculus is making a noteworthy advancement. Its significance lies in the fact that practical systems can be better identified as fractional order differential equations instead of integer order differential equations David et al. (2011). Fractional Order PID Controller which is usually described as $PI^{\lambda}D^{\mu}$ Controller was introduced by Podlubny (1999).

$$C(s) = K_p + \frac{K_i}{s^{\lambda}} + K_d s^{\mu}$$

where K_p is Proportional Gain, K_i is Integral Gain, K_d is Derivative Gain, λ and μ are integral and derivative orders and can be varied between 0 to 2.

1.4 Cascade multi-model control system

Generalized Cascade control system figure shown in 1.2, Cascade control using multi-model controller strategy uses two controllers for control of nonlinear primary process. The primary controller consists of a multi-model controller designed for a primary process. And in the secondary loop the secondary process is assumed to be linear and PI controller is designed as secondary controller using linear controller design strategies. Controller in inner loop will serve as slave controller which will act based on set point received form master controller. Primary controller will act as master controller here and the output of primary controller will act as set point for secondary controller.

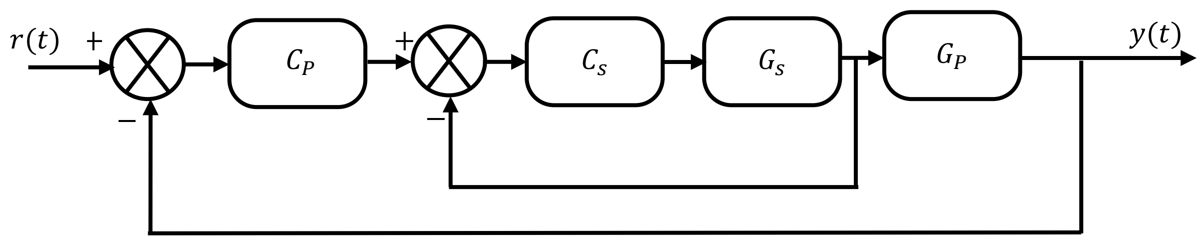

Figure 1.2 Generalized cascade control system.

1.5 Multi model Smith Predictor

To design a controller for nonlinear process is some difficult task and delay added to it and it makes even more difficult. Multi model control scheme will overcome these issue for lesser delay process and also some time system may move to unstable. If long dead process is present in nonlinear process then design a controller is cumbersome task.

To deal with larger delay system already smith predictor structure is proved to control from last few decades of researches. Otto smith as introduced the Smith Predictor control strategy in 1957. This strategy is modified the feedback strategy to compensate the delay. In this strategy, it consist of feedback loop with additionally inner loop where it's have the two terms. The first term of this inner loop represents process behavior without dead time. The second term represents is simply a time delay. To overcome this issue a simplified smith predictor structure is designed using multi model control scheme.

Chapter 2

Literature Review

Chapter 2

Literature Review

In this chapter, the literature is reviewed on application of multi model scheme to control the nonlinear system. The review is given on the existing control algorithm other than multi model scheme, formation of multi model structure, model reduction and multi model control scheme for nonlinear systems are presented.

2.1 Control of nonlinear processes

Numerous researchers have been focusing on controlling the nonlinear behaviorial systems and the major control algorithm in name of MMA, gain scheduling, adaptive control, optimal control, fuzzy and sliding mode.

Few literature are presented on the list of control algorithm, all this methods are having complicated calculations in designing the controller whereas MMA is simple as compared with other control algorithm.

Yooet al. (1998) introduced the adaptive fuzzy sliding mode control of nonlinear system. Fuzzy logic system is used to approximate the unknown function of the nonlinear system and adaptive law is proposed to in order to reduce the approximation errors between the nonlinear functions.

Chai et al. (1999) introduced fuzzy direct adaptive control for control of nonlinear systems and this method makes use of the fuzzy systems to provide an approximate optimal controller which is synthesized based on the assumption that the dynamics in the system are known. They developed fuzzy sliding controller to compensate for the plant uncertainties, smooth the control signals and increase robustness.

Camacho et al. (2000) have proposed the sliding mode control approach to control nonlinear processes. The approach is designed for first order plus dead time model of the process. This approach has fixed controller with tuning equations as a function of the parameters of the model.

Chen et al. (2003) have introduced the predictive control approach and is used to design the optimal controller for control of nonlinear system.

Iqbal et al. (2017) have presented an overview of nonlinear control systems and described the role of analytical concepts in design of nonlinear control systems and recent advancements are examined.

From above control algorithm it is observed that, there are complicated calculations in controller design and whereas multi model approach is simplest form with minor calculations in design. It can easily implement the all advance linear controller methods in MMA to control the nonlinear process. The approach is carried out in three steps that are

1. Decomposition of nonlinear process into multiple linear models.
2. Minimizing the multiple linear models.
3. Global controller formation

The researchers have suggested the simplest way of these approaches from last few decades and the upgraded process has reviewed and as follows

El-Sakkary et al. (1985) introduced the gap metric and presented the robustness of feedback systems. They concluded that any metric that preserves a relationship between open-loop processes and the corresponding stable feedback loops must have the topology of the gap metric.

Johansen et al. (1993) have proposed the method for decomposition of nonlinear processes based on state space model using operating regime and interpolation of local models are inherently empirical.

Johansen et al. (1997) multiple model approaches to modelling and control, book CNC Press.

Rodriguez et al. (1998) have proposed a supervisory multi-model control scheme, in which the supervisor layer identifies the appropriate local controller from a set of models. Multiple model observer is utilized for the selection of the mechanism. Switching among local controllers is carried out through a multi-model bump less transfer strategy.

Nystrom et al. (1999) have proposed a multi-model controller and evaluated on a strongly nonlinear chemical process. The controller design problem is then stated as a multi-model mixed H_2/H_1framework for achieving optimal quadratic (H_2) performance subject to (H_1-type) robustness bounds for the multi-model plant description. This method tested on a simulated pH neutralization process and compared with that of a linear controller.

Hannu et al. (2002) have proposed the velocity-based linearized models a modified internal model control structure which eliminates the steady state error. Velocity-based linearization are used to form linearized models set. The velocity-form linear parameter-varying system having offset term. Based on velocity-based linearized models a modified internal model control structure eliminates the offset and the structure is examined in simulation on pH neutralization process.

Galan et al. (2003) have examined the performance of the experimental implementation of multi model control strategies on a bench-scale pH neutralization reactor and compared with standard PI controllers.

Toivonen et al (2003) have introduced the multi model control scheme based on Velocity-based linearizations. Velocity-based linearizations are applied to construct a set of linearized models and this combination provides the nonlinear system dynamics. To achieve a zero off-set when using velocity-based linearized models a modified IMC structure is designed. This method is tested on pH neutralization process.

Srinivasan et al. (2003) have designed the T–S Fuzzy multi-model based non-linear PI controller for a Type 1 diabetic process, where the gap metric technique is used for finding the optimal number of local models to satisfy the closed-loop performance of the blood glucose process.

Arslan et al (2004) have introduced the novel gap metric approach for global controller formation. A global controller is formed from a weighted combination of all the local linear controllers in which the weights are functions of closed-loop gap metric. These local weights are updated at constant time intervals and this strategy is implemented on two simulated processes, one of which exhibits output multiplicity and the other exhibits input multiplicity.

Tan et al. (2004) have designed the multi-model controller based on gap metric and this gap metric is used for selecting operating points in multi-model control scheme. They identified a drawback in which the distance between the local models is dependent on the compensators, which is usually difficult to determine the operating points without having knowledge of the achievable closed-loop performance.

Arslan et al. (2004) have proposed the multi-model scheduling approach for controlling the nonlinear processes using gap metric. In global controller, the weights are defined using gap metric function. The strategy examined on two processes in simulation.

Tan et al. (2004) have proposed the gap metric based multi-model analysis and controller design for nonlinear processes in which H∞ loop-shaping approach integrates the procedure of selecting operating points and the corresponding local controller design.

Xue et al. (2006) have introduced the local model networks modeling method using satisfying fuzzy c-mean clustering algorithm. This satisfying fuzzy c-mean is used to define local models and different predictive controllers are designed for different local models with different local constraints. These modelling and controller procedure are examined on MIMO simulated pH neutralization process.

Lucas et al. (2006) have introduced modified brain emotional learning based intelligent controller (BELBIC) for controlling washing machine. The energy consumption of this controller is compared with fuzzy controller and observed that improvement in energy savings is achievable by using BELBIC.

Jamab et al. (2006) have proposed a predictive control based on modified locally linear model tree (LOLIMOT) to control an electromagnetic suspension system. This algorithm is improved the accuracy with fewer rules and reduced computational time.

Toscano et al. (2006) have developed the method for robustness analysis and synthesis of a multi-PID controller for non-linear systems based on uncertain multi-model approach. Simulation studies are demonstrated to examine the effectiveness of the method.

Hong et al(2007) have presented overview of model selection approaches and also described problems in nonlinear system identification for decomposition strategy to get suitable models from observational data. They outlined the developments on the convex optimization based model constructional approaches which includes support vector regression algorithms.

Toscano et al. (2007) have developed a method to design multi-PID controller for nonlinear systems where desirable robustness and performances can be maintained across a large range of operating conditions. Simulation studies are used to demonstrate the effectiveness of this method.

Bilbao et al. (2007) have designed a multi-model scheme for a triggering tunnel diode circuit. Here, it improves transient behavior and where switching from stable system equilibrium point to another one is known as a triggering process. Each model is calculated by considering a possible linearization near an equilibrium point so that the whole model is described by several transfer functions around many equilibrium operating points.

Nandola et al. (2007) have designed the multiple model approach for controlling the nonlinear hybrid systems using predictive controller. These multiple models are combined using Bayes theorem to describe the nonlinear hybrid system. Simulations on a benchmark three spherical tank system and a hydraulic process plant proved that their method is superior.

Jakubek et al. (2008) have introduced two concepts for the identification of neuro-fuzzy networks in which first one is the tallest squares method used for parameter estimation of local model parameters in the presence of input and output noise and second one is for the steady-state accuracy of dynamic models. They applied this idea by simulation on a gas engine and demonstrated the capabilities of the proposed concepts.

Nagy et al. (2009) have proposed a method where there is no loss in information from transformation of nonlinear system into multiple models using premise variables in order to design a multi-observer and reconstruct the state of this system. This method is examined on the three-tank system.

Orjuela et al. (2009) have suggested a structure based on a decoupled multiple model representation of a nonlinear system and the design of a multi integral unknown input observer. The dimension of each sub model can be different and some flexibility can be expected in black box modeling of complex system.

Sadati et al. (2010) have proposed the robust multiple model adaptive control strategy using fuzzy fusion. It is integrated with a fuzzy robust controller, the fuzzy multiple model adaptive estimation and a fuzzy switching to control the complex nonlinear systems. The proposed method is examined on the two cart system in Simulation and has given the effective results.

Cai et al. (2010) have proposed the velocity-based LPV modeling and control framework combined with nonlinear gain-scheduling controller for an air-breathing hypersonic vehicle. The effectiveness of the controller is examined on by simulation and implemented on anti-windup control schemes, can be used in application where the input is constrained owing to actuator saturation or rate limit.

Khezami et al. (2010) have proposed a multi-model optimal quadratic control for wind turbines in order to integrate high levels of wind power to provide a primary reserve for frequency control. Multi-model linear framework is determined for the wind turbine and is used for the development of an optimal control law consisting of state feedback, an integral action and an output reference model. This control scheme allows a rapid transition of the power of the wind turbine between different desired set points. This electrical power tracking is ensured with a high-performance behavior for all other state variables.

Zhang et al. (2010) have proposed an adaptive output feedback control scheme for a class of non-affine system in the non-strict feedback form with unknown nonlinearities. The work is examined on second order nonlinear process and also it can extend to n^{th} order non-affine functions on linear discrete-time systems. Simulations has shown that the algorithm is effective in controlling nonlinear dynamic systems.

ElFelly et al. (2010) have proposed the neural and fuzzy clustering algorithms for complex systems modeling and control. The approach is made in three steps are determination of the structure of the model base, parametric model identification and global control. The method is examined on second order nonlinear system to test the efficiency.

Janghorbani et al. (2010) have designed a local linear neuro-fuzzy model to predict the mean arterial blood pressure time. It can help the patients to prevent occurrence of hypertension or help doctors to select appropriate treatment for the physiological disorders.

Gugaliya et al. (2010) have proposed gap metric based fuzzy decomposition of nonlinear dynamics using multiple local linear models. The method showed the stable and parsimonious model set which can be deployed for online control and simulation case study on nonlinear polystyrene reactor is presented.

Novák et al. (2011) have designed a nonlinear model-based predictive control strategy based on a local model network. This is developed based on divide-and-conquer strategy process operations. This set of locally linearized models were effectively combined into a global description of a multivariable nonlinear plant. This strategy is examined experimentally to control the pH and level in a pH neutralization process

Novák et al. (2011) have introduced the optimization of local model network structure using Gustafson-Kessel and local least-squares method. The decomposed strategy done based on fuzzy clustering and simple local models are developed for each regime via least-squares method. The structure of the LMN is optimized using gap metric and prediction error. The method is examined in simulation and successfully to control such nonlinear processes.

Bedoui et al. (2011) have designed the multi-model approach for the representation of non-stationary time delay systems. This multi-model representation is validated by a generalized minimum variance multi-model control scheme. This method compared with adaptive generalized minimum variance control in simulation obtained the good response.

Skopec et al. (2011) have introduced an adaptive calibration technique with on-line growing complexity, in which adaptive method of the kinematical calibration merges with the classical calibration algorithm and LOLIMOT.

Du et al. (2012) have proposed the integrated multi-model control design procedure using gap metric based dividing algorithm, which integrates the multi-model decomposition and the local controller design through an improved gap metric algorithm and the $H\infty$ loop-shaping technique. The method is applied by simulation on two nonlinear chemical systems.

Martinez et al. (2012) have proposed local linear model tree algorithm and a recursive weighted least square algorithm for training the artificial neural network to find the appropriate parameters, number of model neurons and neural network learning factor and used them in multi-model frame work.

Rafimanzelat et al. (2012) have introduced the Adaptive network based fuzzy inference system and Locally Linear Neuro-Fuzzy models in automobile application for fuel consumption prediction. LOLIMOT algorithm is used to tune the parameters for identifying the most appropriate input variables to find the suitable model for predicting the miles per gallon of automobiles. The method is examined in simulation and defined the best performance.

Ioanas et al. (2012) have proposed the local linear Neuro-Fuzzy models for the identification of Common Rail diesel high pressure dynamics.

Bedoui et al. (2012) have proposed a multi-model approach for time varying delay systems. The method is based on the construction the number, the orders, the time delay and the parameters of the local models automatically without any knowledge about the full operating range of the system. Identification of the local models is carried out by a new recursive algorithm. The proposed algorithm allows simultaneous estimation of time delay and parameters of the process indiscrete-time.

Meskin et al. (2013) have proposed a real time fault detection and isolation scheme based on multiple model approach and applied on a dual spool jet engine. It is shown that the method is robust to the failure of pressure and temperature sensors and extensive levels of noise outliers. Simulation results demonstrate that the multiple model FDI algorithm for both structural faults and actuator faults performs well on the jet engine.

Hametner et al. (2013) have designed a PID controller for nonlinear systems based on the corresponding local model networks. Closed-loop stability by means of a Lyapunov stability criterion as well as closed-loop performance is studied. All the PID controller values are determined by a multi-objective genetic algorithm method, in which trade-off between stability and performance are handled.

Pourbabaee et al. (2013) have proposed an efficient sensor fault detection and isolation strategy approach based on multiple-models. The scheme consists of hybrid Kalman filter by integrating process model with a number of piecewise linear models to estimate sensor outputs. The simulation results demonstrated the effectiveness of the proposed method and robustness with respect to the process health parameters.

Du et al. (2013) have designed the multi linear model decomposition of MIMO nonlinear systems with multiple scheduling variables and gap metric division algorithm has proposed. The proposed method effectively decomposes a MIMO nonlinear system into a set of linear subsystems without linear model redundancy and designed multi linear MPC controllers and these combination forms the global controller for setpoint tracking control. Two bench mark nonlinear processes are studied to demonstrate the effectiveness of the proposed method.

Yubo et al. (2013) have proposed the stability robustness of the closed-loop system based on gap metric and robust stability radius. Where robust stability radius is used to generate the weights for multi model control scheme. This method is examined on simulation on typical nonlinear process and proved the tracking the set point.

Kolyubin et al. (2013) have proposed multiple model black box identification for control of nonlinear systems. Using a set of local NARX models combination representation the system dynamics. The method is designed for the combined feed forward/feedback controller.

Du et al. (2014) have proposed a two integrated multi-model control design frameworks based gap metric and stability margin criteria, where the multi-model decomposition and the multi-model combinations are integrated. One method uses the maximum stability margin and the other uses the actual stability margin.

Touzri et al. (2014) have introduced a internal multi-model controller design with a limited variable time delay. The method is designed based on the combination of Multi-Model concepts and Internal Model Control. The design method produced good results for a linear process with a limited variable time delay and showed the robust behavior.

Du et al (2014) have proposed gap metric based soft switching for formation of global controller to controller MIMO nonlinear system. A MIMO CSTR system is studied to demonstrate the effectiveness of the proposed weighting method.

Arasu et al (2016) have proposed the simple non-linear model based control scheme for the variable area tank process. The parameters of the nonlinear model have been determined using empirical approach. The proposed control algorithm has been experimentally implemented on conical tank and the performance is compared with gain scheduled PI controller.

Zribi et al (2017) have proposed a self-organization map method for decomposition of nonlinear process into multiple models and gap metric and the stability margin are used for reduction of multiple models without redundancy of the initial multi-model bank. Simulations confirm the method for selecting the appropriate number of local models which should be used in the controller design.

Li et al (2017) have introduced the Multi model control scheme for rehabilitation robotic exoskeletons. Three control modes are smoothly integrated into the global controller, where the robot-assisted mode allows the human to exert voluntary efforts within a desired region. The development of the proposed controller follows the singular perturbation approach, and the stability of the overall system is rigorously proved by using Tikhonov's theorem.

Adeniran et al. (2017) have reviewed modeling and identification of different nonlinear systems. A detailed survey has been presented about partitioning strategies.

Tan et al. (2017) have proposed the direct model reference adaptive control based on multiple-model switching control scheme. Itis capable of ensuring desired system performance, avoiding control singularity and possible persistent control switching. A control switching mechanism is designed with performance indexes formed from estimation errors.

Shaghaghi et al. (2017) have proposed designing of multiple linear model set based on nonlinearity measure and reduction of multiple models using H-gap metric. The designed model predictive controllers to achieve the high performance and experimentally tested on a pH neutralization process.

Sadati et al. (2018) have introduced the multi-model robust control scheme to control the depth of hypnosis during intravenous administration of propofol. This method is implemented to control the adequate drug administration regime for propofol to avoid overdosing and underdosing of patients.

Shun et al. (2018) have proposed an improved particle swarm optimization algorithm for identification of Takagi–Sugeno fuzzy model. Firstly, by using fuzzy c-means clustering algorithm found the rule number of the Takagi–Sugeno fuzzy model and utilizing the particle swarm optimization algorithm, the initial membership function and the consequent parameters of the fuzzy model are obtained. In addition, through an improved fuzzy c-regression model and orthogonal least-square method, the premise structure and consequent parameters can be obtained to establish the Takagi–Sugeno fuzzy model.

Zribi et al. (2019) have developed a method for decomposition and reduction of multiple models using with integrating of gap metric, margin stability and multi-objective particle swarm optimization algorithm (MOPSO). Where gap metric and margin stability are used for distance measuring tool and guidelines for selecting the model bank. MOPSO algorithm is used for tuning optimal PID controllers which provided less rise time with a lower overshoot percentage and good margin stability.

2.2 Design of Fractional Order Controller

From the literature it is found that fractional order controllers are not implemented in global controller design.

Chen et al. (2009) have introduced the concept of fractional order system and control and provided the review on numerical methods for simulating fractional order systems. Both digital and analog realization methods of fractional order operators are introduced.

Li et al. (2015) have given a review on different tools for the computation of fractional integration/differentiation and the simulation of different fractional order systems. They also introduced their usage and algorithms, evaluates the accuracy, compared the performance and provides informative comments for selection.

Ranganayakulu et al. (2016) have demonstrated the comparison of various tuning method of fractional $PI^{\lambda}D^{\mu}$ controller based on Integral of Absolute Error (IAE), Total Variation (TV) and Maximum Sensitivity (M_s).

Pritesh Shah et al. (2016) have given the review of the work done on the fractional PID controller which is proposed by Podlubny in 1999 and presented the latest contributions in the field of control systems. Highlighted the recent developments in the design and tuning of fractional PID controllers and software tools associated to the design of fractional PID controllers are also discussed.

The above authors have given a good contribution in developing the multi model approach for controlling the nonlinear process and their proposed models are examined on mostly Reactor by Arslan et al. (2004), Du et al [(2014), Tan et al. (2004), Tascano et al. (2007) Yubo et al.(2013), Zribi et al.(2017), pH control by Galan et al (2004), Novak et al(2011), Nystrom et al (1999), Shaghaghi et al. (2017), Xue et al. (2006), Distillation column by Rodriguez et al. (1998), Polystyrene by Gugaliya et al.(2010), Three tank system by Nagy et al.(2009), Inverted Conical tankby Du et al [(2013), Three tank spherical system & Hydraulic process by Nandola et al. (2008), Electrical nonlinear application by Bilbao et al.(2007), Jamab et al. (2006), Khezami et al. (2010), Lucas et al.(2006), Meskin et al.(2011), and Biomedical nonlinear application by Srinivas et al. (2011) and Sadati et al. (2018).

2.3 Pros and cons of different approaches, and research gaps

To control the nonlinear process, the different approaches are Adaptive PID Controller, Nonlinear Model Predictive Control (NMPC), Sliding Mode Control, Fuzzy controller and Multi Model Control Scheme.

Pros:

When the above methods are compared together, Multi Model Control Scheme approach is the simplest and can be implemented easily.

Basically, the tuning procedure for the Controllers depends on the type of Industrial applications. Pretty good number of Linear Controllers are already available to control the Industrial process. In the same way for controlling the different nonlinear applications, the Linear Controllers can be easily implemented in the Multi Model Scheme based on the Industrial Application.

Cons:

In case if the Nonlinearity of the system is very high, then identification of Linear Models will be a tough job.

Based on literature survey the following important research problems are noted:

- Lack of experimental investigation.
- Design a multi model fractional order controller.
- Design a multi model cascade control strategy to minimize the effect of disturbance.
- Design a multi model smith predictor to control long deadtime nonlinear process.

2.4 Motivation

To control nonlinear systems, there are different methods out of which model predictive control, gain scheduling, multi model techniques (MMT) are treated as more promising methodologies. MMT relies upon a problem decomposition strategy. In this approach, a global system model is formed by a set of local models which are integrated with different degrees of validity. Each local model represents the dynamics of the system in a specific region of the operating space. Although the multi-model approach has been criticized for creating suboptimal and input dependent models, the approach is simple, mathematically tractable, and like other techniques, it allows direct incorporation of qualitative plant knowledge. Most importantly, a well matured linear model and control analysis can be exploited when the local models are assumed to be linear.

Most of the researchers have introduced the development of multi-model control schemes and applied by simulation on different nonlinear processes, however, their application on practical experiments provide more understanding. Further, gap metric based evaluation of the multi-model control schemes and their experimental investigation is not carried out in the literature.

As model predictive control is a promising control methodology, it can be utilized for control of nonlinear systems but in a different form. Multi-model predictive control can be designed and experimentally implemented. Also, there are no works reported on multi-model fractional control strategies for control of nonlinear systems. Advanced regulatory control strategy such as cascade control is widely in industries. For nonlinear systems also, cascade control can be integrated with multi-model framework for improved control. Based on the gaps identified in the literature and above motivating factors, the following objectives are framed.

2.5 Objectives

1. To evaluate gap-metric based multi model control schemes for nonlinear systems.
2. To design multi model predictive controllers for nonlinear systems.
3. To design multi-model fractional order control strategies for nonlinear systems.
4. To design multi-model cascade control strategy for nonlinear systems.

5. To design multi-model Smith predictor based control strategy for nonlinear systems.

2.6 Organization of the thesis

The organization of the thesis is as follows:

Chapter 2 presents literature overview on different aspects of multi-model control schemes.

Chapter 3 presents multiple model identification for nonlinear systems.

Chapter 4 describes gap-metric based global controller of multi model control scheme for nonlinear systems.

Chapter 5 provides the evaluation of gap-metric based global controller using multi model predictive control for nonlinear systems with time delay.

Chapter 6 provides the design of multi-model fractional order controller for nonlinear systems.

Chapter 7 describes multi-model cascade control strategy design based on gap metric for nonlinear processes.

Chapter 8 provides multi-model smith predictor based control strategy for long dead time processes.

Chapter 9 provides summary and conclusions

Chapter 3

Multiple model Identification for Nonlinear Systems

Chapter 3

Multiple model identification for nonlinear systems

In the multi model approach, decomposition of nonlinear system is the first procedure as described in section 1.1. Using the partition strategy the decomposition of nonlinear system is carried out and developed multiple linear models. Here three systems are taken which exhibits nonlinear behavior and identified the multiple linear models based on sequential steady state partition strategy.

Spherical tank, conical tank and isothermal CSTR processes are the examples for describing nonlinear systems, the mathematical models of Spherical and conical tanks are developed by considering (i) level (height) as the control variable and (ii) input flow to the tank as the manipulated variable and the mathematical model of iCSTR is developed by considering (i) concentration as the control variable and (ii) inlet flow to the process as the manipulated variable. The detailed procedure is given below.

3.1 Case Study 1: Spherical Tank Process

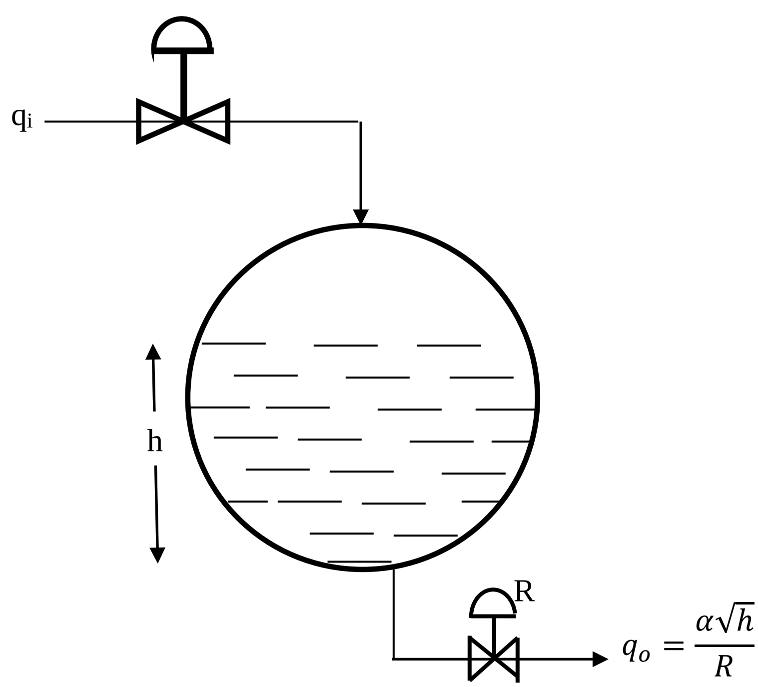

Figure 3.1 Spherical tank as a nonlinear process.

The spherical tank process is shown in Figure 3.1 in which level (h) is the controlled variable and input flow rate (q_i) is the manipulated variable. Applying mass balance, the mathematical model is described by the first-order differential equation as:

$$q_i - q_o = \pi[2rh - h^2]\frac{dh}{dt} \qquad (3.1)$$

$$\frac{dh}{dt} = \frac{q_i}{\pi(2rh-h^2)} - \frac{\alpha\sqrt{h}}{R\pi(2rh-h^2)} \qquad (3.2)$$

where 'r' is radius of the spherical tank, 'q_o' is the outlet flow rate and 'α' is a coefficient and is assumed as one. Here, 'R' is the resistance and is found experimentally by considering different steady state values for level.

After linearizing Eq. (3.1) by using Taylor series, state space representation of linearized model is obtained as

$$\dot{\mathrm{H}} = \left[\frac{1}{\pi\left(2rh_s - {h_s}^2\right)^2}\left[-2q_{is}(r-h_s) - \frac{\alpha\sqrt{h_s}}{R}(1.5h_s - r)\right]\right]\mathrm{H} + \left[\frac{1}{\pi\left(2rh_s - {h_s}^2\right)}\right]\mathrm{Q}$$

$$\mathrm{Y} = [1]\mathrm{H}$$

Where H and Q are the deviation variables and are H = h – h_s, Q = q_i – $q_{i,s}$ in which h_s and q_{is} are the steady state values of the level and inlet flow rate respectively. The corresponding transfer function model is derived and obtained as

$$\frac{H(s)}{Q(s)} = \frac{(-K_1/K_2)}{(-1/K_2)s + 1}$$

where as $K_1 = \frac{1}{\pi(2rh_s - {h_s}^2)}$ and $K_2 = \frac{1}{\pi(2rh_s - {h_s}^2)^2}\left[-2q_{is}(r-h_s) - \frac{\alpha\sqrt{h_s}}{R}(1.5h_s - r)\right]$

Figure 3.2 shows the photograph of the conical tank experimental setup. It consists of a spherical tank of 250mm inner radius and 500 mm height; rotameter of 1000 LPH; reservoir tank capacity of 100 liters, pump, air to open linear control valve, Electro-Pneumatic Positioner (4-20mA converter to open the valve between 0-100%); Differential Pressure Transmitter (DPT) for measurement of the level, and front panel display connection diagram. Data acquisition is carried out and MATLAB is used for implementation of the control algorithms.

Two different sample values are taken by slightly changing the outlet resistance 'R'. Based on sample one the different steady state values for level are considered and derived the corresponding multi-model transfer functions. Table 3.1 shows 9 different multi linear transfer function models at different steady states. Based on sample two the different steady state values for level are considered and derived the corresponding multi-model transfer functions. Table 3.3 shows 9 different multi linear transfer function models at different steady states.

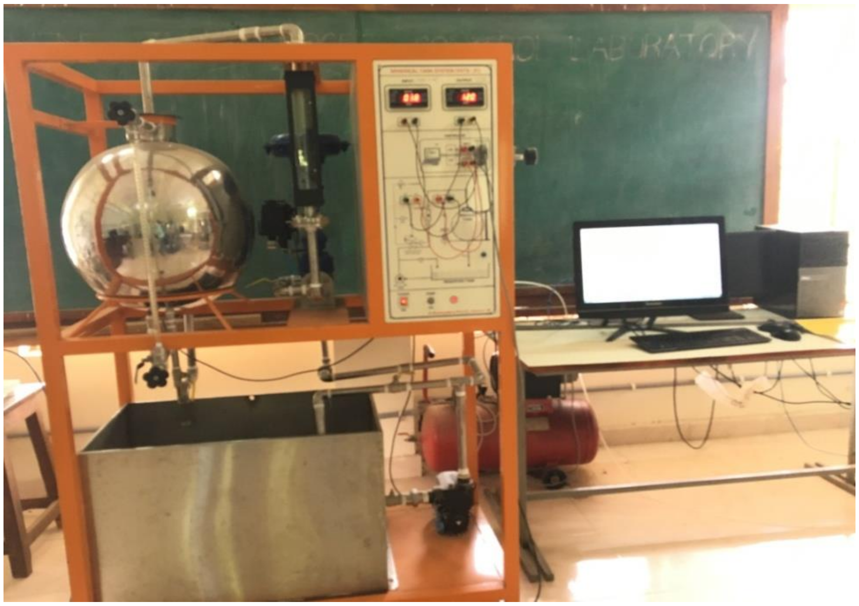

Figure 3.2 Spherical tank experimental test setup

According to multi-model control schemes, need to reduce the number of linear models for design of controllers. From the literature found that gap metric is simplest technique which is used for minimizing the multiple models to represent entire nonlinear system.

Based on the gap metric value of 0.04 for sample one, the multiple models of spherical tank are minimized into only 3 models and as shown in Table 3.2. These models can be used to understand the dynamic behavior in the ranges of 0 - 20 cm (M2), 20 – 35 cm (M6) and 35 – 50 cm (M9). Based on the gap metric value of 0.05 for sample two, the multiple models of spherical tank are minimized into only 3 models and as shown in Table 3.4. These models can be used to understand the dynamic behavior in the ranges of 0 - 20 cm (M2), 20 – 35 cm (M6) and 35 – 50 cm (M9). Based on reduced models the controllers are designed.

Table 3.1 Multi linear transfer function models for spherical tank process at different steady states for sample 1

Multiple Multi Linear Models			
h_s in cm	Transfer function model	h_s in cm	Transfer function model
5	$M_1 = \frac{0.0382}{26.805s + 1}$	30	$M_6 = \frac{0.1773}{334.22s + 1}$
10	$M_2 = \frac{0.0735}{92.40s + 1}$	35	$M_7 = \frac{0.1906}{314.42s + 1}$
15	$M_3 = \frac{0.1068}{176.28s + 1}$	40	$M_8 = \frac{0.2058}{258.57s + 1}$
20	$M_4 = \frac{0.1355}{255.42s + 1}$	45	$M_9 = \frac{0.2232}{157.78s + 1}$
25	$M_5 = \frac{0.1553}{304.89s + 1}$		

Table 3.2 Reduced number of models for gap metric of 0.04 for sample 1

Operating Range	Transfer Function
0 - 15 cm	$\frac{0.0735}{92.40s + 1}$
15 - 40 cm	$\frac{0.1773}{334.22s + 1}$
40 - 50 cm	$\frac{0.2232}{157.78s + 1}$

Table 3.3 Multi linear transfer function models for spherical tank process at different steady states for sample 2

Multiple Multi Linear Models			
h_s in cm	Transfer function model	h_s in cm	Transfer function model
5	$M_1 = \frac{0.06816}{48.48s + 1}$	30	$M_6 = \frac{0.3166}{596.8s + 1}$
10	$M_2 = \frac{0.1313}{165s + 1}$	35	$M_7 = \frac{0.3404}{561.5s + 1}$
15	$M_3 = \frac{0.1908}{314.7s + 1}$	40	$M_8 = \frac{0.3674}{461.7s + 1}$
20	$M_4 = \frac{0.242}{456.1s + 1}$	45	$M_9 = \frac{0.3986}{281.8s + 1}$
25	$M_5 = \frac{0.2773}{544.4s + 1}$		

Table 3.4 Reduced number of models for gap metric of 0.05 for sample 2

Operating Range	Transfer Function
0 - 15 cm	$\frac{0.1313}{165s + 1}$
15 - 40 cm	$\frac{0.3166}{596.8s + 1}$
40 - 50 cm	$\frac{0.3986}{281.8s + 1}$

3.2 Case Study 2: Conical Tank Process

The Conical tank process is shown in Figure 3.3 in which the level (h) is controlled by using the input flow rate (q_i). It is a nonlinear process whose mathematical model is obtained by writing unsteady state mass balance and is given in Eq.3.6.

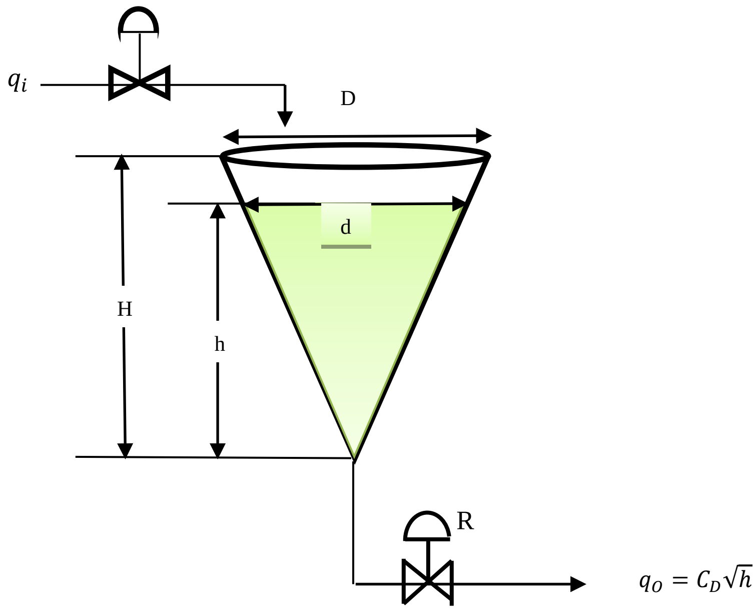

Figure 3.3 Conical Tank process

$$\rho q_i - \rho q_O = \rho \frac{dv}{dt} \tag{3.6}$$

In which the volume is

$v = \frac{h\pi d^2}{12} = \frac{\pi h}{12}\left(\frac{Dh}{H}\right)^2 = K''h^3$Substituting in Eq. 3.6,

$$q_I - C_D\sqrt{h} = K''\frac{d(h^3)}{dt} \tag{3.7}$$

Where $C_D = \frac{\alpha}{R}$ valve coefficient. Here C_D is used find out from experimental steady state samples.

Linearizing the above equation using Taylor's expansion, the state space representation of linearized model is obtained as

$$\dot{H} = \left[\frac{2q_{is}}{3K''{h_s}^3} - \frac{C_D}{2{h_s}^{5/2}}\right]H + \left[\frac{1}{3K''{h_s}^2}\right]Q$$

$Y` = [1]H$

The corresponding transfer function model is obtained as

$$\frac{H(s)}{Q_I(s)} = \frac{\frac{1}{3K''{h_s}^2}}{s+\frac{2q_{is}}{3K''{h_s}^3}-\frac{C_D}{2{h_s}^{5/2}}} \qquad (3.8)$$

Figure 3.4 shows the photograph of the conical tank experimental setup. It consists of two conical tanks of 700 mm height and 300 mm radius at the top; however, only one tank is used as a single input single output (SISO) process. The setup consists of rotameter with capacity 440 LPH; reservoir tank of 150 Liters, pump, air to open linear control valve, Electro-Pneumatic Positioner (4-20mA converter to open the control valve between 0 - 100%), Differential Pressure Transmitter (DPT) for measurement of level, and front panel for the user. Data acquisition is carried out and MATLAB is used for implementation of the control algorithms.

Figure 3.4 Conical tank experimental test setup

Two different sample values are taken by slightly changing the outlet valve coefficient 'C_D'. Based on sample one, the different steady state values for level are considered and derived the corresponding multi-model transfer functions. Table 3.5 shows 12 different multi linear transfer function models at different steady states. Based on sample two the different steady state values for level are considered and derived the corresponding multi-model transfer functions. Table 3.7 shows 12 different multi linear transfer function models at different steady states.

According to multi-model control schemes, need to reduce the number of linear models for design of controllers. To do this, Gap metric value of 0.04 for sample one is considered and only 3 models are retained as shown in Table 3.6. These models can be used to understand the dynamic behavior in the ranges of 0 - 25 cm (M3), 25 – 50 cm (M8) and 50 – 65 cm (M12). Gap metric value of 0.05for sample two is considered and only 3 models are retained as shown in Table 3.8. These models can be used to understand the dynamic behavior in the ranges of 0 - 25 cm (M3), 25 – 50 cm (M8) and 50 – 65 cm (M12). Based on reduced models the local controllers are designed.

Table 3.5 Multi linear transfer function models for spherical tank process at different steady states for sample 1

Multiple Linear Transfer Models			
h_s in cm	Transfer function model	h_s in cm	Transfer function model
5	$M_1 = \frac{0.02917}{0.1388s + 1}$	35	$M_7 = \frac{0.1089}{25.4s + 1}$
10	$M_2 = \frac{0.04861}{0.9253s + 1}$	40	$M_8 = \frac{0.1147}{34.95s + 1}$
15	$M_3 = \frac{0.06441}{2.759s + 1}$	45	$M_9 = \frac{0.1326}{51.13s + 1}$
20	$M_4 = \frac{0.07864}{5.988s + 1}$	50	$M_{10} = \frac{0.1442}{68.63s + 1}$
25	$M_5 = \frac{0.08558}{10.18s + 1}$	55	$M_{11} = \frac{0.1523}{87.67s + 1}$
30	$M_6 = \frac{0.09948}{17.04s + 1}$	60	$M_{12} = \frac{0.1587}{108.8s + 1}$

Table 3.6 Reduced number of models for gapmetric0f of 0.04 for sample 1

Operating Range	Transfer Models
0 - 20cm	$M_3 = \frac{0.06441}{2.759s+1}$
20 - 50 cm	$M_8 = \frac{0.1147}{34.95s+1}$
50 - 62 cm	$M_{12} = \frac{0.1587}{108.8s+1}$

Table 3.7 Multi linear transfer function models for spherical tank process at different steady states for sample 2

Multiple Linear Transfer Models			
h_s in cm	Transfer function model	h_s in cm	Transfer function model
5	$M_1 = \frac{0.4}{1.8379s + 1}$	35	$M_7 = \frac{1.4942}{336.41s + 1}$
10	$M_2 = \frac{0.667}{12.253s + 1}$	40	$M_8 = \frac{1.5737}{462.785s + 1}$
15	$M_3 = \frac{0.8833}{36.5288s + 1}$	45	$M_9 = \frac{1.82}{677.02s + 1}$
20	$M_4 = \frac{1.0785}{79.2896s + 1}$	50	$M_{10} = \frac{1.978}{908.856s + 1}$
25	$M_5 = \frac{1.1737}{134.822s + 1}$	55	$M_{11} = \frac{2.088}{1160.91s + 1}$
30	$M_6 = \frac{1.3643}{225.683s + 1}$	60	$M_{12} = \frac{2.177}{1440.43s + 1}$

Table 3.8 Reduced number of models for gap metric of 0.05 for sample 2

Operating Range	Transfer Models
0 - 20cm	$\frac{0.667}{12.253s+1}$
20 - 50 cm	$\frac{1.3643}{225.683s+1}$
50 - 62 cm	$\frac{2.088}{1160.91s+1}$

3.3 Case Study 3: Isothermal CSTR

An isothermal CSTR, consider a first-order irreversible reaction takes place and figure as shown in . The mass balance is

$$\frac{dC_A}{dt} = -KC_A + (C_{Ai} - C_A)u \quad (3.9)$$

Where reactant concentration (C_A(mol/L)) is controlled variable, input(u = q = V(min^{-1})) is the manipulated variable, q (l min^{-1}) is the inlet flow rate and C_{Ai} is the inlet feed concentration(1.0 mol/L) and constant rate k is 0.028 (min^{-1}). Linearizing the above equation using Taylor's expansion, the transfer function model is

$$\frac{C_A(s)}{u(u)} = \frac{1-C_{As}}{s+(0.028+u_s)} \quad (3.10)$$

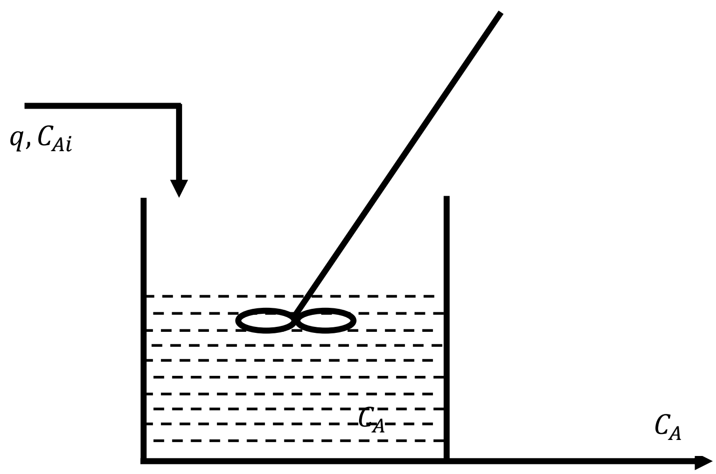

Figure 3.5 Isothermal continuous stirred tank reactor

The iCSTR model is divided into multi linear model based sequential steady states (u_s;C_{As}) of different operating ranges. Eighteen linear models are found and shown in Table 3.9, these are minimized into three model by using gap metric value of approx. 0.1 and minimized models are shown in Table 3.10, based on these controller parameters are tuned.

Table 3.9 Multi linear models for isothermal CSTR at different steady states

Multiple Linear Transfer Models			
C_{Ai} in mole/unit	Transfer function model	C_{Ai} in mole/unit	Transfer function model
0.2522	$\frac{0.7478}{25.14s+1}$	0.83583	$\frac{0.164}{5.9s+1}$
0.37166	$\frac{0.62834}{21.84s+1}$	0.850833	$\frac{0.15}{5.32s+1}$
0.4975	$\frac{0.5}{18.62s+1}$	0.8675	$\frac{0.132}{4.77s+1}$
0.616666	$\frac{0.38}{13.614s+1}$	0.881666	$\frac{0.12}{7.17s+1}$
0.68	$\frac{0.32}{11.46s+1}$	0.895833	$\frac{0.1042}{3.66s+1}$
0.7408	$\frac{0.26}{9.34s+1}$	0.912333	$\frac{0.088}{3.22s+1}$
0.7725	$\frac{0.223}{8.27s+1}$	0.929166	$\frac{0.071}{2.57s+1}$
0.805833	$\frac{0.194}{7.11s+1}$	0.95833	$\frac{0.042}{1.474s+1}$
0.82	$\frac{0.18}{6.47s+1}$	0.990833	$\frac{0.009}{0.356s+1}$

Table 3.10 Reduced number of models by using gap metric

Operating Range	Transfer Models
0-0.5 mole/L	$M_2=\frac{0.62834}{21.84s+1}$
0.5-0.77 mole/L	$M_5=\frac{0.32}{11.46s+1}$
0.77 - 1 mole/L	$M_{14}=\frac{0.10417}{3.662s+1}$

Chapter 4

Evaluation of Gap-metric based Multi-model Control Schemes for Nonlinear Systems: An Experimental Study

Chapter 4

Evaluation of gap-metric based multi-model control schemes for nonlinear systems

There are number of methods proposed in the literature based on multi model approaches to control the nonlinear systems. Many of these methods are by simulation. An experimental investigation provides more understanding and also practical difficulties of nonlinear process control. This chapter presents an experimental evaluation and comparison of gap metric based weighting methods for design of multi-model control schemes for control of levels in a spherical tank process and a conical tank process.

4.1 Introduction

Controlling the nonlinear processes is typical when compared to linear process. Conventional PID controllers are used to control nonlinear process such that the controllers must be tuned to provide a very stable behaviour over the entire range of operating conditions. As tuning of the controllers is conservative, it results in degradation of the control system performance. In order to stabilize nonlinear behaviour, multi model control approaches are found suitable for a system as stated by Johansen et al. (1997).

Adeniran et al. (2017) provided a detailed review on Multi-model approaches. The approach relies on a problem decomposition strategy where a nonlinear system is segregated into set of many linear models based on their operating points. The local linear model represents the dynamics of the process in a particular operating point. However, there can be many linear models for a given nonlinear system but it might not be a wise practice to use all the linear models to control. Hence proved in the literature that few models represents the whole non linearity of the process which is required to control the process. In such context, Gap metric is suggested by El-Sakkary et al. (1985) to reduce the number of models from highest to lowest number. This approach based on Gap metric is simple and mathematically tractable as it can be used to process behaviour incorporation. Multi-model controllers use linear control methods due to their hassle free implementation; availability of more linear control methodologies. To start with, a nonlinear process is divided into a group of local linear models by using the corresponding partition techniques. Then, the corresponding local controller C_i is designed with any good linear controller design method. Combination of these local controllers in a systematic way forms the global controller. Formation of global controller can be carried out using two different approaches, fusion methods and weighting methods.

In fusion method, only one local controller is fused at the sampling period based on the different performance indices such as operating conditions developed by Banerjee(1998), output error developed by Chen(2009), estimate error developed by Rodriguez(2003). This method might cause output oscillations for processes having high nonlinearities, even though if the local linear controller is designed well and kept in the closed loop. However, in weighting methods it varies, the global controller is determined by a weighted sum of the local controllers' outputs. There existing number of weighting functions, such as gap metric weighting function developed by Arslan(2004), Galan(2003) and Du(2014), Gaussian functions and trapezoidal functions developed by Tan(2003), Bayesian weighting functions developed by Aufderheide(2004).

Gap metric weighting function method is more feasible, as it uses average weights of local controllers which makes the system outputs smooth also reduces output oscillation. Gap metric weighting function has an advantage of only one tuning parameter when compared to other weighting methods (Gaussian and trapezoidal), reducing the complex tuning procedure. Based on gap metric, two methods namely 1-δ and 1/δ weighting functions are defined by Arslan(2004) and Du (2014) respectively. They applied these methods for temperature and concentration control in reactors. Du et al. (2014) developed multi linear model predictive control (MLMPC) algorithms for nonlinear chemical processes using gap-metric-based weighting method. They applied the developed methodology on a continuous stirred tank reactor (CSTR) in both SISO and MIMO mode. Du and Johansen (2014) also developed a multi-model control scheme with 1/δ gap-based weighting method to combine the local controllers and applied by simulation on a CSTR process. Galan et al. (2003) explained the implications of gap metric concept for multi-model control schemes with applications of CSTR and a pH process.

As it is well known that many people studied the development of multi-model control schemes and applied by simulation on different nonlinear processes, their application on practical experiments provide more understanding. Also, it may be appropriate for the control community if these methods are evaluated experimentally. In the present chapter, the implementation of these methods is carried out on different nonlinear systems both by simulation and experiment.

The main contribution of the present chapter is to experimentally implement the gap metric based weighting function multi-model control schemes with the combination of local controllers to control the nonlinear systems. Level control in spherical and conical tanks is considered for experimental investigation. The two weighting functions (1-δ and 1/δ) based on gap metric are applied first by simulation for level control in both these tanks. The corresponding multi model controllers are evaluated by simulation. For this, a mathematical model of the process is developed using the corresponding mass balance equations. Further, these two methods are applied experimentally to control the level in spherical tank and conical tank for different regions.

For clear illustration, the chapter is organized as follows. Section 4.2 briefly describes the theoretical developments and construction of global controller using weighting methods based on gap metric. In Section 4.3, weights of each region are explained for spherical and conical tank systems. In Section 4, results are discussed followed by summary in Section 5.

4.2 Development of gap metric based weighting function:

Consider the following nonlinear system representation in state space format.

$$\begin{cases} \dot{x} = f(x,u) \\ y = g(x,u) \end{cases} \tag{4.1}$$

where $x \in R^n$ is the state vector, $u \in R^n$ is the control input vector, and $y \in R^n$ is the output vector. $f(\cdot)$ and $g(\cdot)$ are nonlinear functions.

For Eq. (4.1), chosen a proper scheduling vector θ which contains one or more control inputs, or one or more outputs. In general, the scheduling variables may include a subset of inputs, states and disturbances. The scheduling space of system (4.1) is Φ, then $\theta \epsilon \Phi$. Where Φ is the variation range of θ and also the operating range of system given in Eq. (4). The value of θ is denoted as θ_t at time (t). The steady state corresponding to θ_t is (x_{st}, u_{st}, y_s). After linearizing the system around (x_{st}, u_{st}, y_s), the linear model is obtained as P(θ_t)[12].

$$\begin{cases} \delta\dot{x} = A_t\delta x + B_t\delta u \\ \delta y = C_t\delta x + D_t\delta u \end{cases} \tag{4.2}$$

Where $\delta x = \delta x - x_{st}$, $\delta u = \delta u - u_{st}$, $\delta y = \delta y - y_{st}$, $A_t = \frac{\partial f\ (x_{st}, u_{st})}{\partial x}$, $B_t = \frac{\partial f\ (x_{st}, u_{st})}{\partial u}$, $C_t = \frac{\partial g(x_{st}, u_{st})}{\partial x}$, and $D_t = \frac{\partial g(x_{st}, u_{st})}{\partial u}$.

Let us consider that the nonlinear process can be approximated and represented with N_m local linear processes. The operating point of the i^th local linear process is denoted as (x_{si}, u_{si}, y_{si}), which is one possible steady state point of the nonlinear process i.e., f(xs, us)=0, y=g(x_s,us). linearized Eq. (4.1) around (x_{si},u_{si}, y_{si}) to obtain the i^th local linear system P_i. The Nm local linear models are reduced to minimum possible number of linear models using gap metric. Based on the reduced local models the PI controllers are designed using IMC method. Once the local controllers are designed, the global controller is determined using gap metric based weighting function in two possible ways as explained below.

4.2.1 1-δ weighting method

The nonlinear process at time t is nP_t. Then $P(\theta_t)$ is the linearized model of nP_t. The gap metric between local linear model P_i and $P(\theta_t)$ is $\gamma_i(\theta_t)$ where

$$\gamma_i(\theta_t) = \delta\big(P_i, P(\theta_t)\big), \text{ i=1,...., } N_m \qquad (4.3)$$

The i^{th} local linear controller at time t of 1-δ weighting function is:

$$\varphi_i(\theta_t) = \frac{(1-\gamma_i(\theta_t))^{K_w}}{\sum_{j=1}^{N_m}(1-\gamma_j(\theta_t))^{K_w}} \qquad (4.4)$$

4.2.2 1/δ weighting method

Then the i^{th} local linear controller at time t of 1/δ weighting function is defined as:

$$\varphi_i(\theta_t) = \frac{(\frac{1}{\gamma_i(\theta_t)})^{K_w}}{\sum_{j=1}^{N_m}(\frac{1}{\gamma_j(\theta_t)})^{K_w}} \qquad (4.4)$$

where $k_w$is the tuning parameter which is usually selected as ≥ 1. Also, $\varphi_i$satisfies$\sum_{i=1}^{N_m} \varphi_i(\theta_t) = 1$. In this work, k_w= 1is considered. Therefore, the output of the multi-model controller is:

$$u(t) = \sum_{i=1}^{N_m} \varphi_i(\theta_t) u_i(t) \qquad (4.5)$$

where$u_i(t)$is the i^{th} local linear controller. According to (4.8), when the weighting function φ_i is small, the corresponding gap metric value will be close to one and when the weighting function φ_i is high, the corresponding gap metric value will be close to zero. The weighting functions given in Eq.(4.7) and (4.8) are used in the corresponding 1/δ and 1-δ weighting methods.

4.3 Case studies:

In this chapter, proposed method is examined on spherical and conical tank processes

4.3.1 Spherical Tank Process:

Weights for each controller are selected and their values are given in Table 4.1 for (1-δ) Weighting method. The corresponding representation is also shown in Figure. 4.1 and it can be seen that the total weights in any region is close to 1. Similarly, weights for each controller are selected and their values are given in Table 4.2 for (1/δ) Weighting method. The corresponding representation is also shown in Figure4.2 and it can be seen that the total weights in any region is close to1.

Table 4.1 Weightings for each controller according to (1-δ) weighting method

Operating Range	PI-1	PI-2	PI-3
0-20 cm	0.3623	0.3264	0.3104
20-35 cm	0.3204	0.3567	0.3229
35-50cm	0.3096	0.3280	0.3623

Table 4.2 Weightings for each controller according to (1/δ) Weighting method

Operating Range	PI -1	PI - 2	PI – 3
0-20 cm	0.9841	0.0093	0.0066
20-35 cm	0.0094	0.9807	0.0100
35-50cm	0.0066	0.0100	0.9834

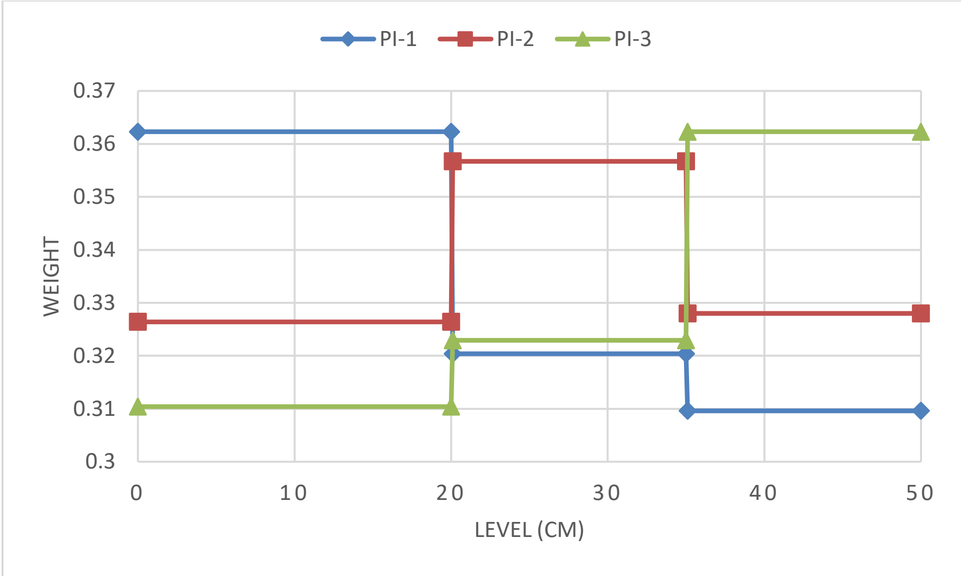

Figure 4.1 Weight values of particular operating point according to 1-δ method, solid: PI-1, dot: PI-2, dash: PI-3.

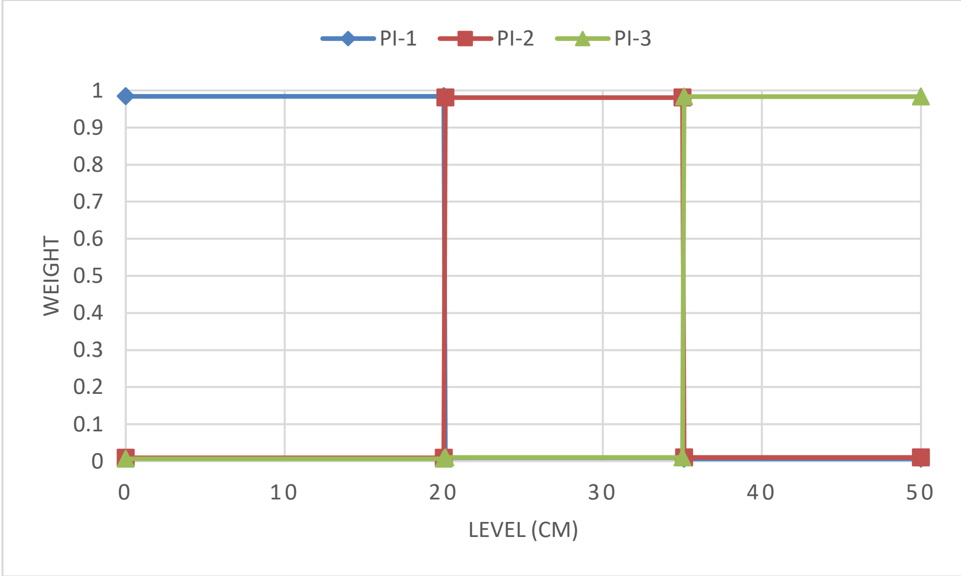

Figure 4.2 Weight values of particular operating point according to 1/δ method, solid: PI-1, dot: PI-2, dash: PI-3.

4.3.2 Conical Tank Process:

Weights for each controller are selected and their values are given in Table 4.3 for (1-δ) Weighting method. The corresponding representation is also shown in Figure4.3 and it can be seen that the total weights in any region is close to 1. Similarly, weights for each controller are selected and their values are given in Table 4.4 for (1/δ) Weighting method. The corresponding representation is also shown in Figure 4.4 and it can be seen that the total weights in any region is close to 1.

Table 4.3 Weightings for each controller according to (1-δ) Weighting method

Operating Range	PI 1	PI 2	PI 3
0-25 cm	0.3503	0.3319	0.3178
25-50 cm	0.3272	0.3454	0.3275
50-60cm	0.3177	0.3321	0.3502

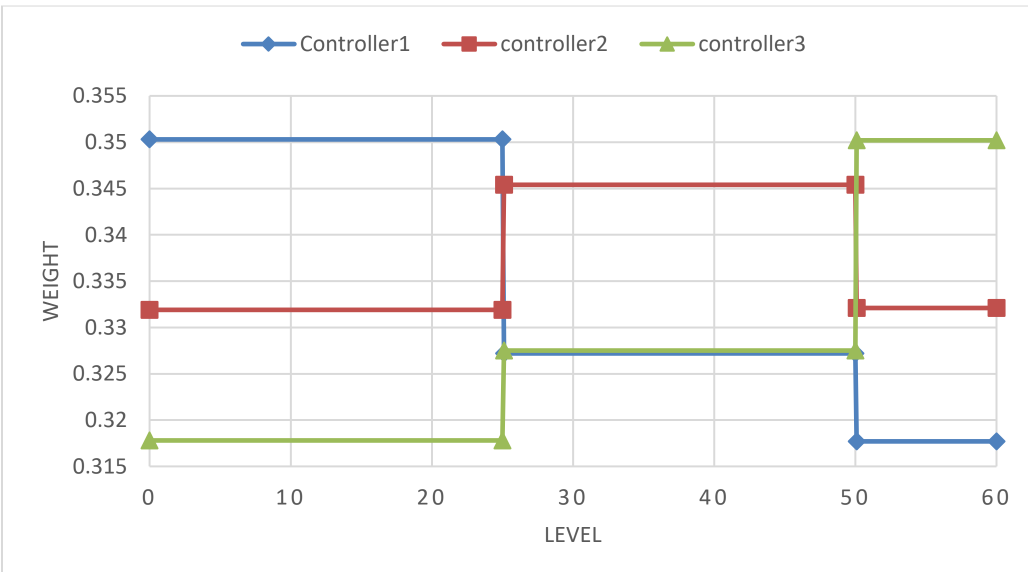

Figure 4.3 Weight values of particular operating point by using 1-δ.

Table 4.4 Weightings for each controller according to (1/δ) Weighting method

Operating Range	PI 1	PI 2	PI 3
0-25 cm	0.9722	0.0177	0.0101
25-50 cm	0.0175	0.9646	0.0179
50-60cm	0.0101	0.018	0.9719

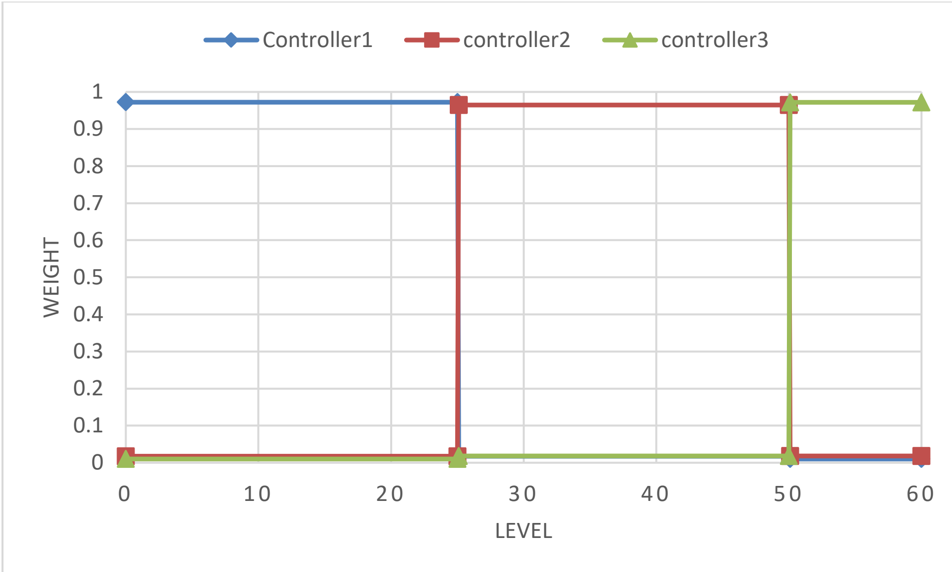

Figure 4.4 Weight values of particular operating point by using 1/δ.

4.4 Simulation and Experimental Results:

Simulation results for spherical tank and conical tank processes are carried out using sample one of both and are given below. Experimental implementation is also carried out and the corresponding results are also presented here.

4.4.1 Spherical Tank Process:

Both 1-δ and 1/δ weighting methods are implemented in simulation for tracking of different set points of level and the corresponding responses are shown in Figure 4.5. It is observed that, if compared 1-δweighing method, this method yields high values of level and 1/δ weighting method provides good performance in lower values of level. Experimental implementation is carried out to track the same set points for both the methods and the corresponding results for 1-δ weighing method are shown in Figure 4.6 and for 1/δ weighting method in Figure4.7. To evaluate the closed loop performance quantitatively, IAE and ISE values are calculated and are given in Table 4.5. From these values, it can be observed that 1-δ weighting method is comparatively better.

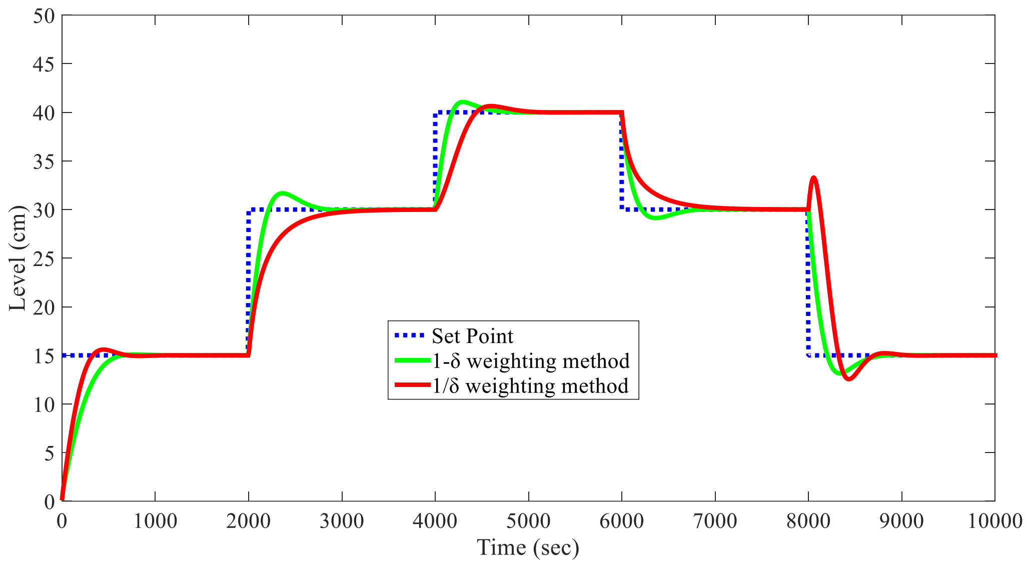

Figure 4.5 Comparison of simulation responses for spherical tank process.

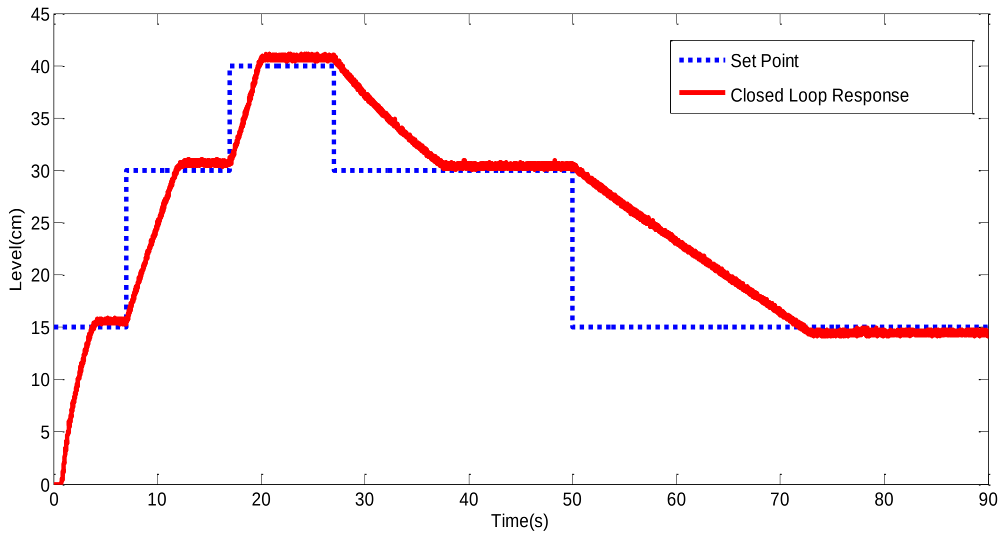

Figure 4.6 Experimentally obtained closed loop responses for 1-δ weighting method for spherical tank process.

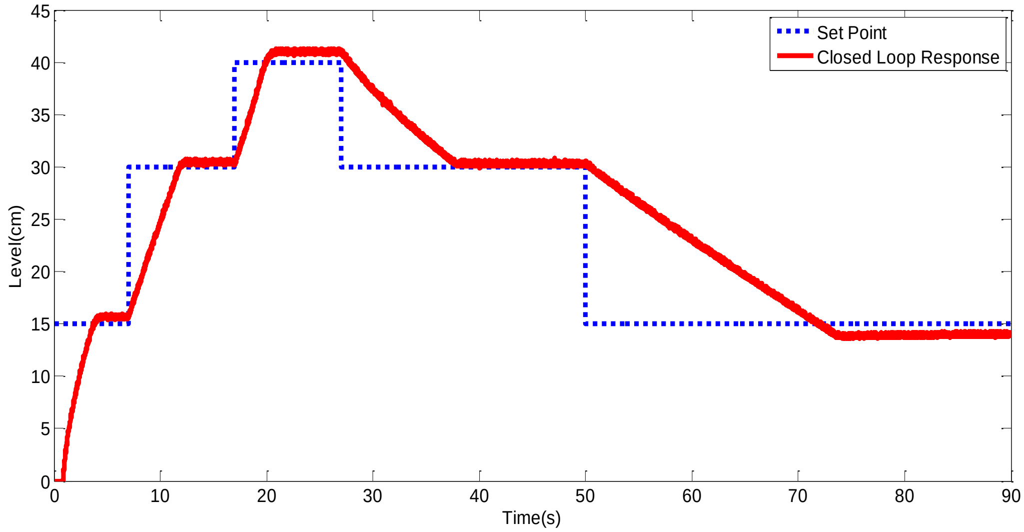

Figure 4.7 Experimentally obtained closed loop responses for 1/δ weighting method for spherical tank process.

Table 4.5 Experimental quantitative comparison of weighting methods for spherical tank process.

Time (1unit=40sec)	Height (cm)	1-δ weighting method		1/δ weighting method	
0	0	IAE Value	ISE Value	IAE Value	ISE Value
-↓	↓	34.84	345.12	32.09	344.25
7	15				
↓	↓	35.82	334.53	36.22	326.85
17	30				
↓	↓	18.74	91.94	20.87	102.86
27	40				
↓	↓	58.63	371.51	58.47	387.86
50	30				
↓	↓	176.51	1687.90	182.11	1649.40
90	15				

4.4.2 Conical Tank Process:

Here also, both 1-δ and 1/δ weighting methods are implemented in simulation for tracking of different set points of level and the corresponding responses are shown in Figure 4.8. Hence noticed that 1-δ weighing method is comparatively better at all values of level. Experimental implementation is carried out to track the same set points for both the methods and the corresponding results for 1-δ weighing method are shown in Figure 4.9 and for 1/δ weighting method in Figure 4.10. To evaluate the closed loop performance quantitatively, IAE and ISE values are calculated and are given in Table 4.6. From these values, it can be observed that 1-δ weighting method is comparatively better.

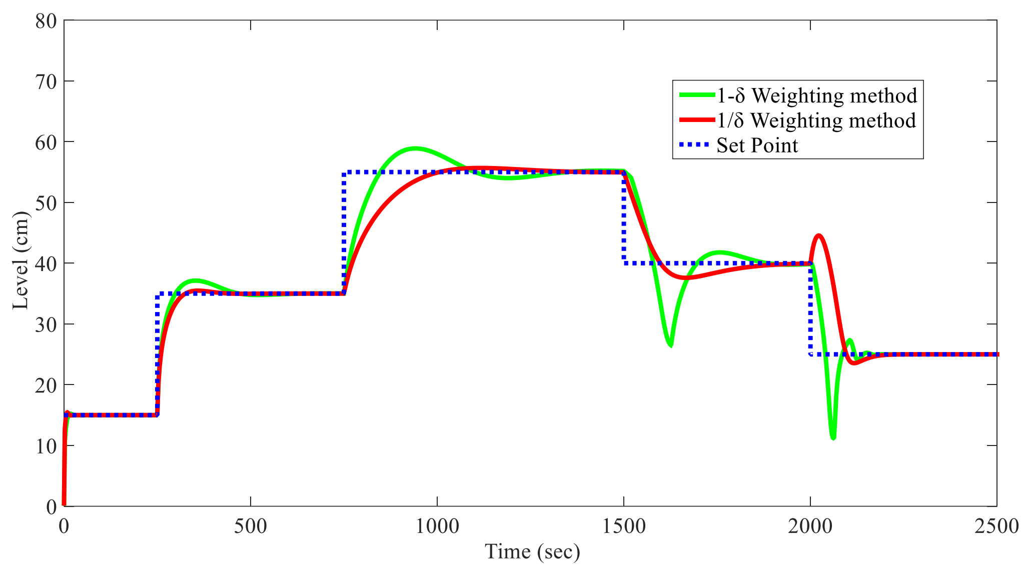

Figure 4.8 Comparison of simulation responses of 1-δ and 1/δ weighting methods for conical tank process.

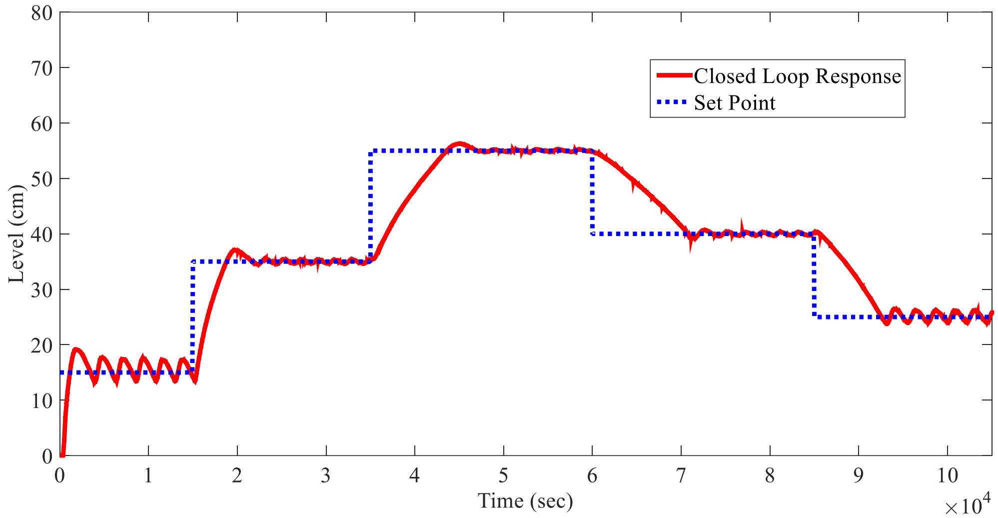

Figure 4.9 Experimentally obtained closed loop responses for 1-δ weighting method for conical tank process.

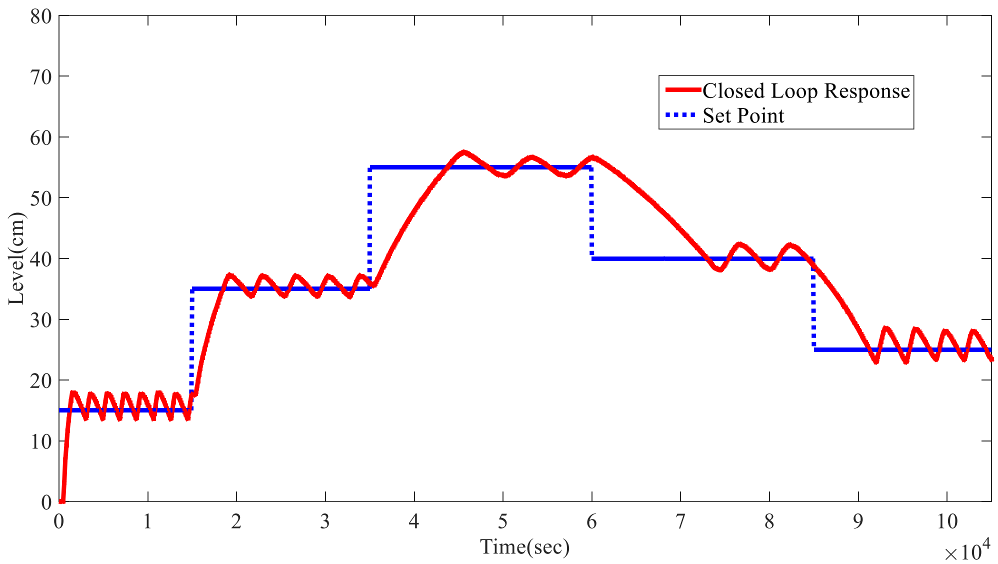

Figure 4.10 Experimentally obtained closed loop responses for 1/δ weighting method for conical tank process.

Table 4.6 Experimental quantitative comparison of weighting methods for conical tank process.

Time (100 unit=1sec)	Height (cm)	1-δ Weighting Method		1/δ Weighting Method	
0	0	IAE Value (10^4)	ISE Value (10^5)	IAE Value (10^4)	ISE Value (10^5)
↓	↓				
15000	15	3.2048	1.8007	3.1635	1.912
↓	↓				
35000	35	4.3358	5.2864	4.7601	3.8752
↓	↓				
60000	55	8.2875	10.216	9.7564	10.821
↓	↓				
85000	40	9.2532	9.4199	13.454	14.46
↓	↓				
105000	25	7.5034	7.4836	6.8508	4.9437

4.5 Summary:

Controlling the level of spherical tank and conical tank using the inlet flow rate is a typical nonlinear process and a simple linear controller might fail in providing required closed loop performances. Two different non-linear process control methods are evaluated in this work to control the nonlinear processes. Multi model control scheme based on Gap metric is used to control the nonlinear processes. In order to reduce the number of linear models Gap metric is selected and then to design the corresponding controllers weights. These two weighting functions (1-δ and 1/δ) based on gap metric are applied first by simulation for level control in both these tanks to observe that the level is controlled effectively. Experimental implementation is carried out for controlling the level and Comparative analysis has also been done using IAE and ISE. On comparing the 1- δ weighting method with 1/δ weighing method, it is noticed that 1- δ has shown ≈ 10% improvement on performance.

Chapter 5

Multi-model Predictive Control (MMPC) for Non-linear Systems with Time Delay

Chapter 5

Multi-model Predictive Control (MMPC) for Non-linear Systems with Time Delay

Controlling nonlinear processes is a difficult task and the difficulty increases when there is time delay in the process. Multi model technique is the simplest approach and is used to control the nonlinear process from decades. In this chapter, model predictive control is developed in a multi model framework (MMPC).

5.1 Introduction:

Control of nonlinear processes is challenging and this problem has been addressed by many researchers by using different types of controllers such as linear controllers, nonlinear control strategies, etc. When compared to single model control approach, multi-model control approaches are found to be more effective for control of nonlinear systems.

Controlling nonlinear processes is a difficult task and the difficulty increases when there is time delay in the process. The conventional PID multi model controller can control a low level nonlinear system effectively, if the degree of nonlinearity is increased these controllers are observed to give some degradation in performance. To address such problems an advanced control strategy is required. Model predictive control (MPC) has been employed for better performance over conventional control strategy is proved in Chi(2015). By using the each local linear model, corresponding MPC has to be modeled known as a local controller. To form a global controller weighting methods are used. In the weighting methods, finding proper weighting functions is essential. There are many weighting methods available in the literature but gap metric based weighting method of $1 - \delta$ (δ is gap metric function) and $1/\delta$ is more popular. These weighting functions are define the weights of each controller and combination forms the global controller developed by Du(2014). Now the gap metric weighting method was employed to find the weights of each local controller and the weighted sum of local controllers (MPC) result to global controller. Hence the approach becomes multi-model predictive control (MMPC). Gap metric based MMPC are very effecting in controlling complicated nonlinear system is proved by Du(2014), in order to test the effectiveness of this method, a case-study on conical tank (level control) process is considered. The method was employed on MATLAB simulation platform and was also validated experimentally. Comparison of both the weighting methods on both the scenarios was done to justify the need of advanced control strategy. The chapter is arranged as: In section 5.2 detailed explanation on theoretical development of weighting function based on gap metric and global controller formation using respective weights. In Section 5.3, simulation and experimental results are presented and followed by summary.

5.2 Theoretical development of Multi-Model Predictive Control (MMPC)

MPC is an advanced control strategy that is used in most of the process industries. It uses a dynamical model of the process to predict its likely future response and then choosing the best control action possible while satisfying set of constraints. Nowadays, it finds application in aerospace, automotive, smart electricity grids, etc. Because of the advantage associated with MPC over conventional control strategy, it has been employed. MPC inherently has feed forward nature as it takes measured disturbances as input and it negates the effect of the disturbance beforehand making it very popular in highly disturbed plants as well and is clearly explained by Dougherty(2003). The future control signal is computed in such a way that minimizes the quadratic objective cost function defined as, Minmize J

$$J = \sum_{l=1}^{N_P} \left\| \Gamma_y \left(y\,(K_i + l|K_i) - r\,(K_i + l) \right) \right\|^2 + \sum_{l=1}^{N_C} \| \Gamma_{\Delta u}\,(\Delta u\,(K_i + l - 1)) \|^2 \quad (5.7)$$

The 1st term denotes the objective of minimization of error between predicted outputs and set-point signal and the 2ndterm denotes the objective to find optimal Δu values such that error is reduced. Γy denotes the penalty on tracking error known as output weighting, ΓΔu denotes the penalty on the actuation known as input-rate weighting, y (K_i + l|K_i) represents the predicted value of output at K_i +l instant given information up to K_i instant. Tuning parameters of the MPC are prediction horizon (NP), control horizon (NC), control interval (Δt), rate weight on MVs (ΓΔu), weight on CV(Γy). Few distinguishing features of MPC from conventional control strategy is, it has ability to forecast, optimize and good constraint handling capability. The disadvantages are it requires simple linear state-space model, too many degrees of freedom (horizons, weights, constraints, etc.), requires real time optimization, etc. If Nm number of local linear models then need to design Nm numbers of local MPC controllers and the response of all local controllers are merged together to form an exhaustive controller according to Du(2014).

5.2.2 Controller design

Identified models are specified in chapter 3 additional delay 5 sec added to the process, MPC controller has to be designed corresponding to each model. Three MPC Controller has been designed and their parameters are shown in the Table 5.1. The prediction horizon is considered based on the linear model obtained around the operating point. For three linear operating regions, three different prediction horizons are considered. However, control horizon is not changed. After designing the individual controllers, based on gap metric weighting approach weights for each controller is selected for $1-\delta$ and $1/\delta$ weighting method respectively as explained in chapter 4 and the weights are shown in the Figure 4.3 and Figure 4.4 respectively.

Table 5.1 Multi-model MPC controller tuning parameters for different set-point ranges.

Operating Range (cm)	Regional Controller	Control interval (secs)	Prediction horizon (interval)	Control horizon (interval)
0-15	MPC-1	5	40	2
15-40	MPC-2	10	150	2
40-60	MPC-3	10	600	2

5.3 Simulation and Experimental Studies

In order to test the effectiveness of these methods on nonlinear system plus delay, a simulation and experimental analysis was carried out on conical tank process and with sample one. The two weighting function, $1/\delta$ and $1-\delta$ was implemented for multi set-point change to the level of the process and the responses are presented below. For testing the controller performance, two performance metrics were used namely Total Variation (TV) and Integral Absolute Error (IAE).

From the simulation response i.e. Figure 5.1 and from Table 5.2, it can be deduced that in overall sense $1-\delta$ weighting function shows better performance as compared to $1/\delta$ weighting function. From the experimental response i.e. Figure 5.2 and from Table 5.3, it can be deduced that $1-\delta$ weighting function shows better performance as compared to $1/\delta$ weighting function at higher level while $1-\delta$ weighting function shows better performance as compared to $1/\delta$ weighting function at lower level.

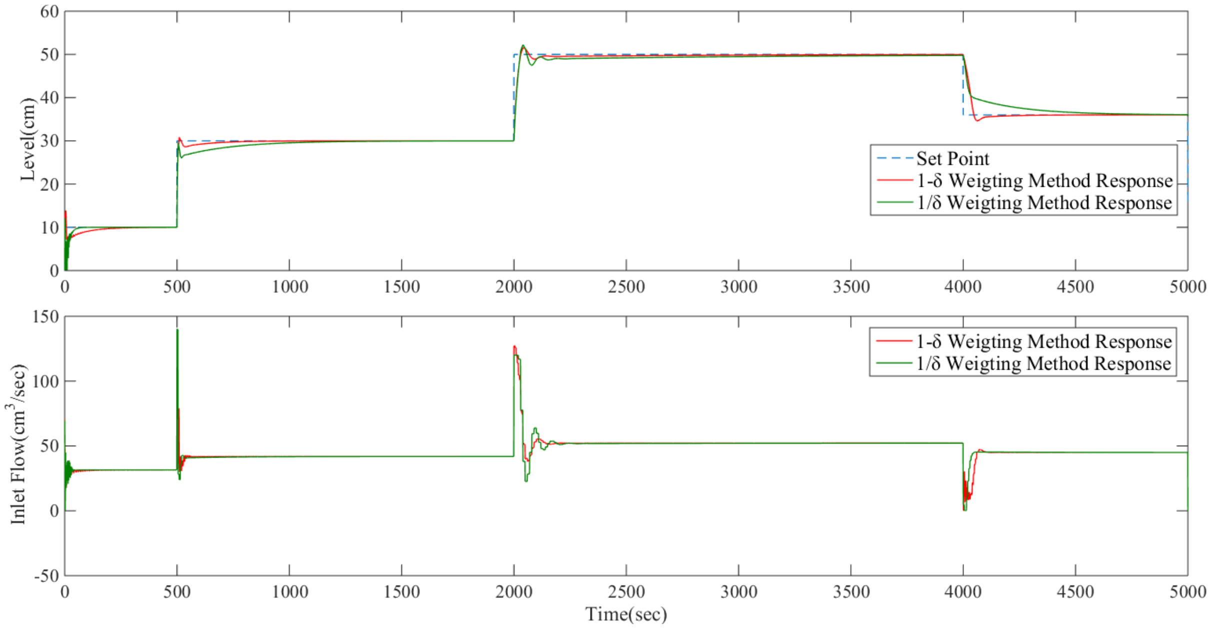

Figure 5.1 Closed loop response for different weighting methods to multi set point change (Simulation result).

Table 5.2 Comparative analysis of controller performance for simulation case.

	1-δ weighting method	1/δ weighting method
IAE Value (10^3)	1.0850	2.0991
TV Value (10^3)	1.0618	1.1879

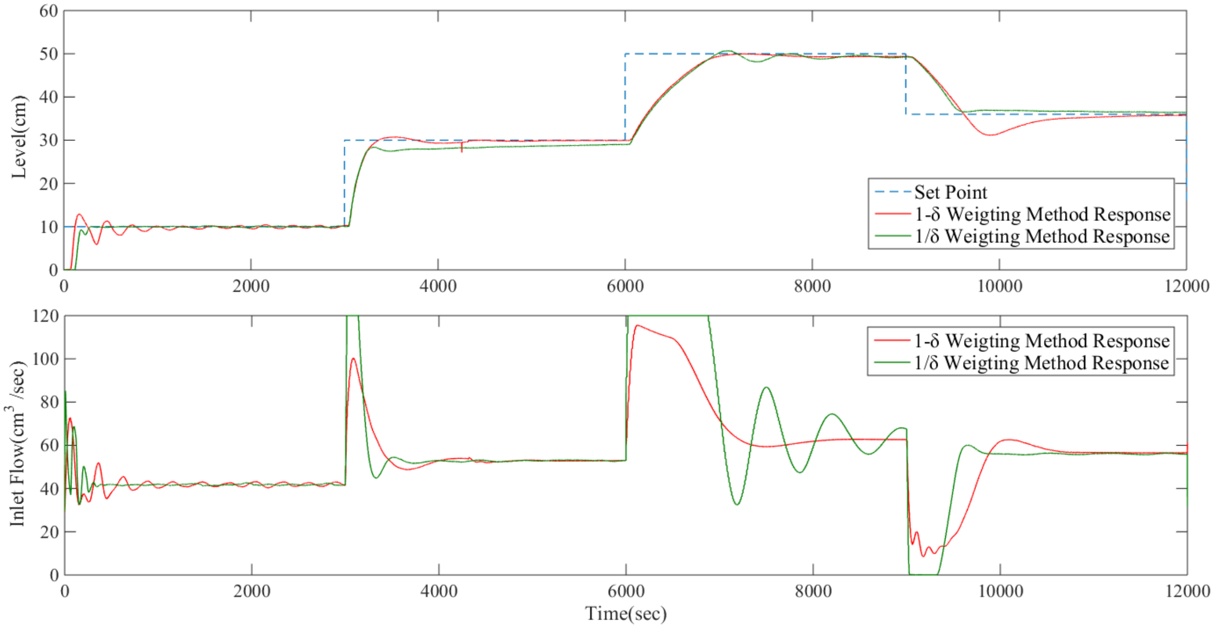

Figure 5.2 Closed loop response for different weighting methods to multi set point change (Experimental result).

Table 5.3 Comparative analysis of controller performance for experimental case.

	1-δ weighting method	1/δ weighting method
IAE Value (10^3)	23.999	25.602
TV Value	606.8786	863.0312

5.4 Summary:

The gap metric based weighting methods were evaluated for control of conical tank process with delay using MMPC. The effectiveness of the method was justified using simulation and experimental studies. On comparing the 1- δ weighting method with 1/δ weighing method of MMPC, it is noticed that 1- δ has shown ≈ 9% improvement on performance.

Chapter 6

Design of Multi Model Fractional Controllers for Nonlinear Systems

Chapter 6

Design of multi-model fractional controllers for nonlinear systems

In the literature, all the methods are proposed to design the local controllers in MMA framework are integer order controllers. In this chapter, fractional controllers based MMA framework is developed for enhanced control of nonlinear systems. Gap metric based weighting methods are used with proper weighting functions to obtain the global controller.

6.1 Introduction

In process industries, behavior of most of the systems will be nonlinear and this type of systems mostly have performance degradation by using conventional PID controller. In order to overcome this degradation there are different types of techniques available and one of the most popular techniques which has been consider by several researches is the multi model approach (MMA) Adeniran and El Ferik (2017). This approach divides nonlinear systems into multi linear models sequentially based on the operating points. Controllers are designed by using this linear model and over decades most of the researchers considered integer order controllers only. When integer order controllers are implemented practically overshoot and resonance are observed and in order to deal such effects fractional order controllers can be used which shows more promising results Podlubny (1999). In this chapter an attempt has been made to apply fractional order controllers in order to design a new system called Multi model fractional order controller. This paper presents effectiveness of Multi model fractional order controller and Extensive numerical studies on nonlinear system demonstrate its performance.

6.2 Multi Model Fractional controller

The MMA deals with decomposition of nonlinear system into multi linear models based on sequentially steady states and mathematical model is developed for each of the operating range. These models now as a set, can be used as a valid representation of the nonlinear process. These models are further reduced into minimal set using gap metric.

6.2.1 Fractional Order Controller

Implementation of Fractional calculus which is generalization of Integer order calculus is making a noteworthy advancement. Its significance lies in the fact that practical systems can be better identified as fractional order differential equations instead of integer order differential equations David et al. (2011). Fractional Order PID Controller which is usually described as $PI^{\lambda}D^{\mu}$ Controller was introduced by Podlubny (1999).

$$C(s) = K_p + \frac{K_i}{s^{\lambda}} + K_d s^{\mu} \tag{6.1}$$

where K_p is Proportional Gain, K_i is Integral Gain, K_d is Derivative Gain, λ and μ are integral and derivative orders and can be varied between 0 to 2. Non Integer Order Controllers offer more degrees of freedom and by using these controllers for Integer Order plants, there is more flexibility in adjusting the gain and phase characteristics than using Integer Order controllers. Methods for design of fractional order controllers are discussed in Podlubny (1999); Monje et al. (2008). One such tuning method for Fractional Order PI controllers was proposed by Gude and Kahoraho (2009) in which a performance criteria (J_v) is minimized which is a measure of system ability to handle low frequency load disturbances. Finally the normalized controller parameters are designed based on normalized dead time τ.

6.3 Simulation and Experimental Results

Simulation results for spherical tank process, conical tank processes and CSTR are carried out and are given below. Based on sample two for spherical and conical tank process the proposed method is examined. Experimental implementation is also carried out for conical tank, the corresponding results are presented here. Multi model local controller parameter values of level control of spherical tank process are shown in Table 6.1, respectively for level control in conical tank process are shown Table 6.3 and concentration control in CSTR are shown in Table 6.5.

6.3.1 Spherical Tank Process

Comparative results of Multi model integer and fractional order control are implemented in simulation for tracking of different set points of level and the corresponding responses are shown in Figure 6.1. Quantitative analysis of the spherical tank process has been done with integral absolute error (IAE) values for different set points is shown in Table 6.2. It is observed that multi model fractional order control approach is efficiently reducing the overshoot and the response is enhanced.

Table 6.1 Multi model local controller parameter values of level control of spherical tank process

	Integer Order Controller	Fractional Order Controller
Controller 1	$0.2626 + \frac{0.000795}{s}$	$7.633 + \frac{0.00218}{s^{1.01}}$
Controller 2	$3.1584 + \frac{0.0026}{s}$	$3.164 + \frac{0.0025}{s^{1.01}}$
Controller 3	$2.5088 + \frac{0.0045}{s}$	$2.51 + \frac{0.0042}{s^{1.01}}$

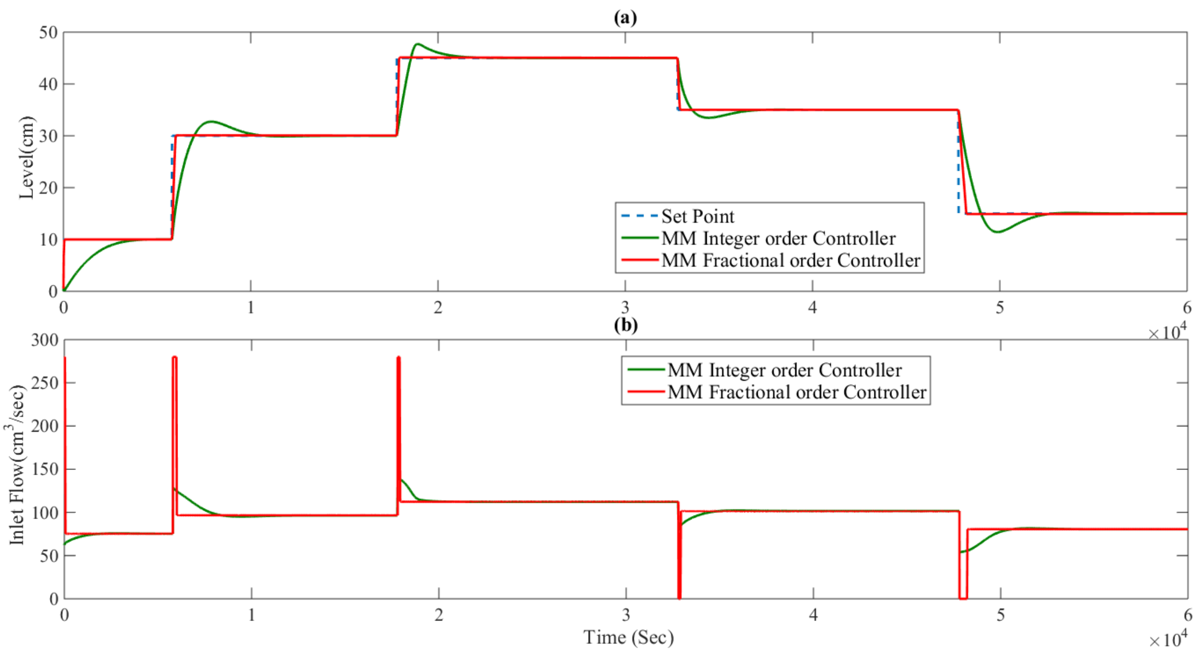

Figure 6.1 Compared closed loop response of spherical tank process(a) Plant Output (b) Manipulated Signal.

Table 6.2 Quantitative analysis of the spherical tank process.

Different set points	Multi model integer order control IAE Value (10^3)	Multi model fractional order control IAE Value (10^3)
10	32.695	0.12355
30	14.143	2.5699
45	8.940.5	2.1274
35	5.475.3	0.57944
15	16.853	5.5127

6.3.2 Conical Tank Process

In the same way, for conical tank also the comparative results of Multi model integer and fractional order control is implemented in the simulation for tracking of different set points of level and the corresponding responses are shown in Figure 6.2. Simulation quantitative analysis of the conical tank process has been done with IAE values for different set points is shown in Table 6.4. Experimental implementation is carried out for this process and response curves are plotted. The Figure 6.3 shows closed loop response of multi-model integer order controller and Figure 6.4 shows closed loop response of multi-model fractional order controller. The oscillations observed in Figure 6.3 (Integer order response) are very low in amplitude and in the case of fractional order controller, these oscillations become miniscule. Experimental quantitative analysis of the conical tank process has been done with IAE values for different set points is shown in Table 6.5.

Table 6.3 Multi model local controller parameter values of level control of conical tank process

	Integer Order Controller	Fractional Order Controller
Controller 1	$3.183 + \frac{0.0458}{s}$	$0.2731 + \frac{0.1262}{s^{1.12}}$
Controller 2	$6.25 + \frac{0.0873}{s}$	$12.3482 + \frac{0.1665}{s^{1.12}}$
Controller 3	$19.1994 + \frac{0.2731}{s}$	$10.9762 + \frac{0.2996}{s^{1.12}}$

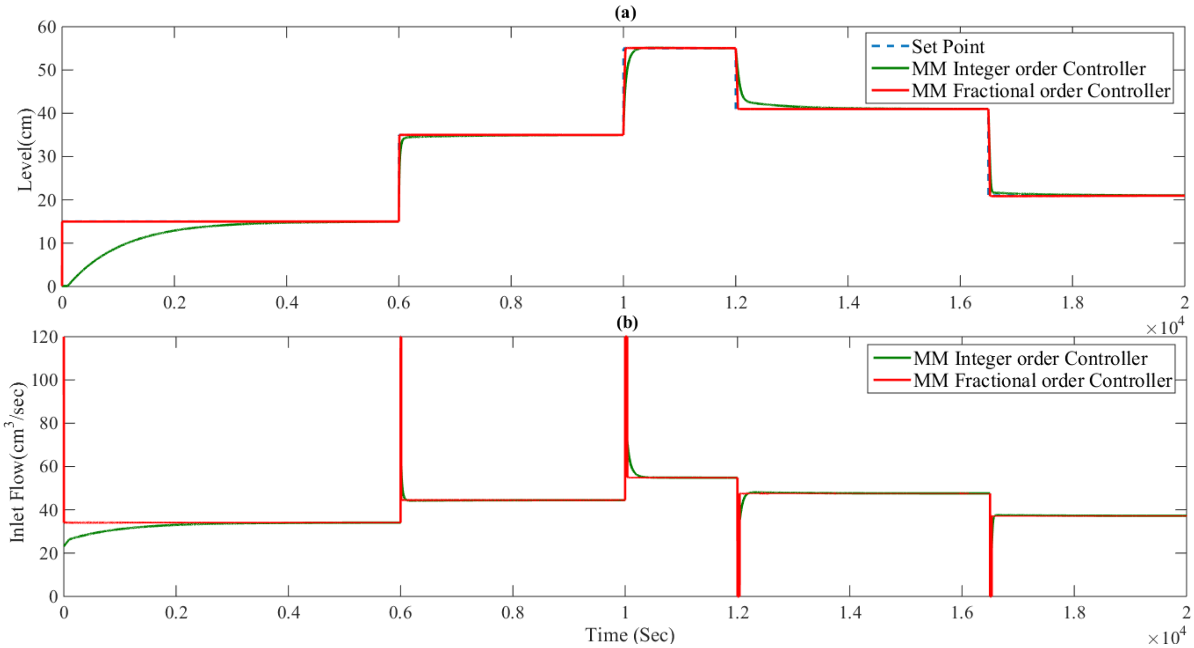

Figure 6.2 Compared closed loop response of conical tank process(a) Plant Output (b) Manipulated Signal.

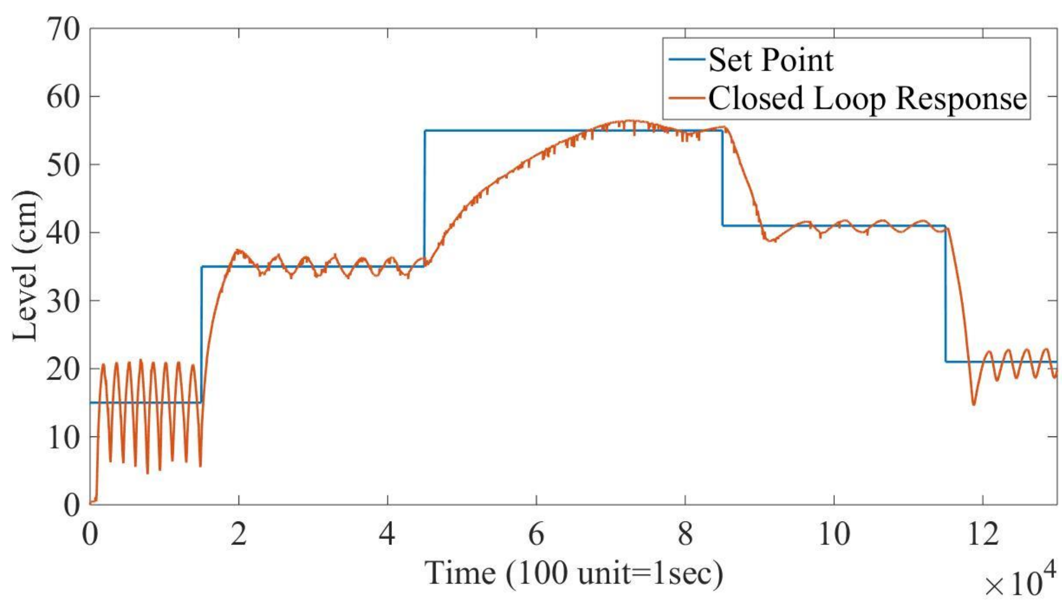

Figure 6.3 Experimental closed loop response of conical tank process using multi model integer order controller.

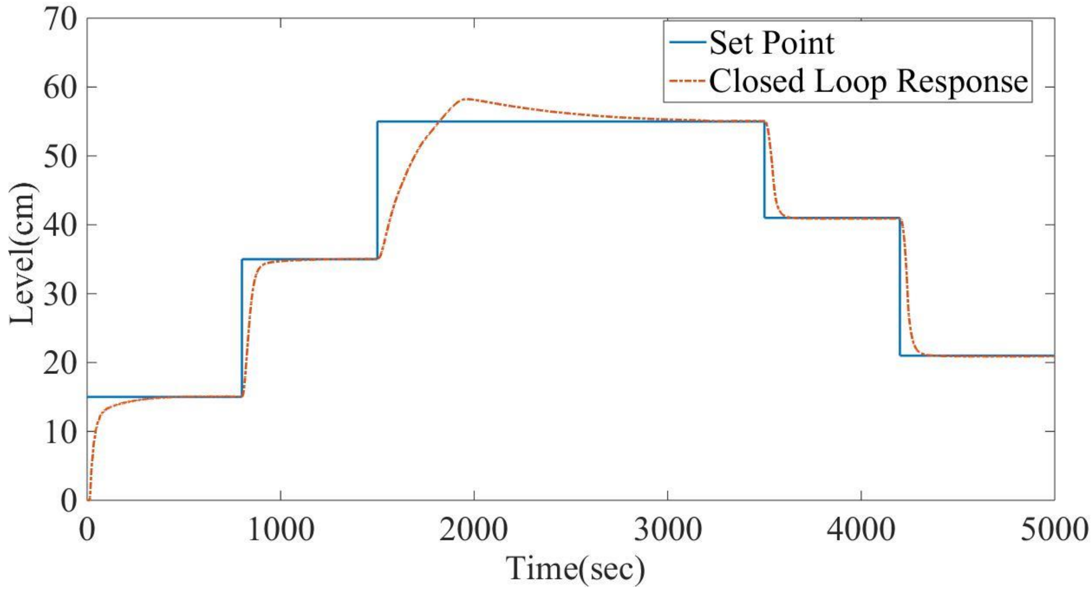

Figure 6.4 Experimental closed loop response of conical tank process using multi model fractional order controller.

Table 6.4 Simulation quantitative analysis of the conical tank process.

Different set points	Multi model integer order control IAE Value	Multi model fractional order control IAE Value
15	1590.4	4.31
35	91.70	13.29
55	109.9	50.14
41	231.64	37.61
21	123.42	68.46

Table 6.5 Experimental quantitative analysis of the conical tank process.

Different set points	Multi model integer order control IAE Value (10^3)	Multi model fractional order control IAE Value (10^3)
15	70.995	0.86205
35	53.654	0.91157
55	178.050	4.4285
41	60.935	0.68081
21	91.032	0.89764

6.3.3 Isothermal CSTR

Similarly, for CSTR also the comparative results of Multi model integer and fractional order control is implemented in the simulation for tracking of different set points of concentration and the corresponding responses are shown in Figure 6.5. Quantitative analysis of the CSTR process has been done with IAE values for different set points is shown in Table 6.7.

Table 6.6 Multi model local controller parameter values of concentration control of iCSTR

	Integer Order Controller	Fractional Order Controller
Controller 1	$3.183 + \frac{0.146}{s}$	$186.8 + \frac{0.571}{s^{1.12}}$
Controller 2	$6.25 + \frac{0.545}{s}$	$173.16 + \frac{0.697}{s^{1.12}}$
Controller 3	$19.199 + \frac{5.24}{s}$	$142.31 + \frac{1.032}{s^{1.12}}$

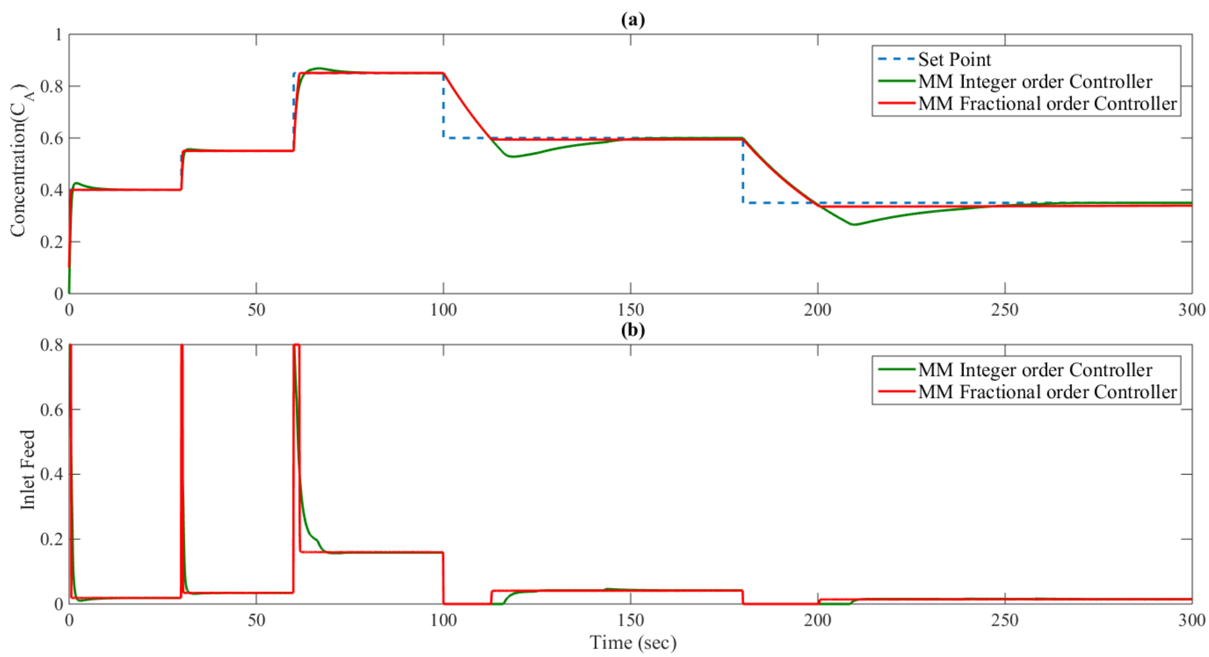

Figure 6.5 Closed loop response of CSTR(a) Plant Output (b) Manipulated Signal.

Table 6.7 Experimental quantitative analysis of the conical tank process.

Different set points	Multi model integer order control IAE Value	Multi model fractional order control IAE Value
0.4	2.71	0.096
0.55	0.0872	0.0464
0.85	0.408	0.2337
0.6	2.865	2.865
0.35	4.3766	4.3766

6.4 Summary:

Multi-model fractional order controller is evaluated for control of nonlinear processes and is compared with multi-model integer order controller. Both the methods are evaluated first by the simulation and then by performing experiments on conical tank process. On comparing the multi-model fractional order controller with multi-model integer order controller, it is noticed that multi-model fractional order controller has shown improvement on performance.

Chapter 7

Multi-model Cascade Control Strategy Design based on Gap Metric for Nonlinear Processes

Chapter 7

Multi-model cascade control strategy design based on gap metric for nonlinear processes

The major disadvantage of multi-model feedback control approach is that the compensation for disturbances does not start until the output of process vary from the set point. To overcome this issue a multi model cascade control strategy is designed in this chapter.

7.1 Introduction:

The major disadvantage of multi-model feedback control approach is that the compensation for disturbances does not start until the output of process vary from the set point. Cascade control strategy overcomes this drawback Ribi (2014) and takes the corrective action even before the disturbance effects controlled variable. This leads to better and faster control. Here implemented this control strategy on nonlinear system for effective control of the output and improved disturbance rejection. The implementation of the cascade control strategy is widely increasing in industries due to its effectiveness in controlling the slower primary nonlinear loops with the help of the faster nested secondary linear loops Lee (1998). In this cascade multi model strategy, the primary controller consists of a multi-model controller designed for a primary process. The global controller formation is done using soft switching.

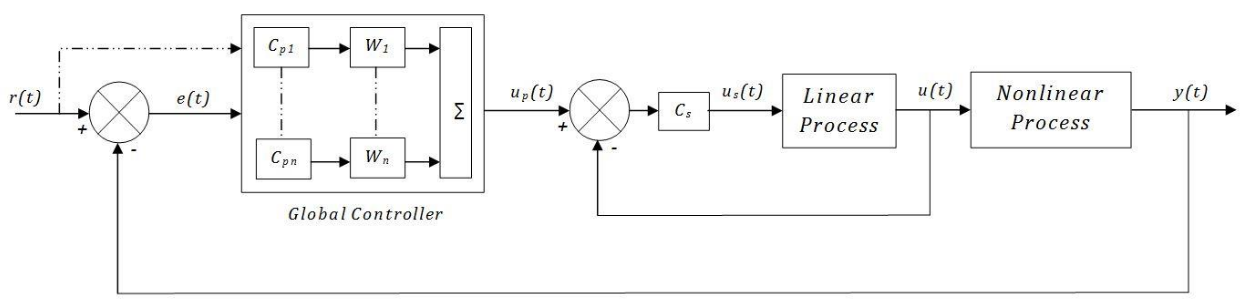

Figure 7.1 Multi model cascade control schematic diagram.

7.2 Development of Cascade multi-model control system

Cascade control using multi-model controller strategy uses two controllers for control of nonlinear primary process. The primary controller consists of a multi-model controller designed for a primary process. And in the secondary loop the secondary process is assumed to be linear and PI controller is designed as secondary controller using linear controller design strategies. Controller in inner loop will serve as slave controller which will act based on set point received form master controller. Primary controller will act as master controller here and the output of primary controller will act as set point for secondary controller.

7.2.1 Global controller

After reducing multiple linear models using gap metric, the PID values are calculated for primary and secondary controllers using IMC technique. The global controller is formed by combination of local controllers and these formation are done by using hard switching (only one of multiple controllers are selected as per operating conditions) and soft switching using gap metric weighting function ($1-\delta$ and $1/\delta$) weighting function are illustrated by Du (2014).

7.3 Simulation and Experimental Results

The primary multiple linear models are defined in chapter 3 with sample two of spherical and conical tank process and secondary linear for respective cases are presented in Table 7.1. Simulation results for spherical, conical tank processes and CSTR are carried out and are given below. Multi model primary local controller parameter values of level control of spherical tank process are shown in Table 7.2, respectively for level control in conical tank process are shown Table 7.4 and concentration control in CSTR are shown in Table 7.7.

Table 7.1 Secondary linear models for respective example cases.

S.No	Case Study	Secondary Process model	Secondary loop Controller
1	Spherical Tank Process	$\frac{2.7}{1.7s+1}$	$0.7404\left(1+\frac{1}{1.7s}\right)$
2	Conical Tank Process	$\frac{1.2}{1.7s+1}$	$1.6667\left(1+\frac{1}{1.7s}\right)$
3	iCSTR	$\frac{0.028}{0.033s+1}$	$71.4286\left(1+\frac{1}{0.033s}\right)$

7.3.1 Spherical Tank Process

Simulation studies are carried out for both normal feedback multi-model and cascade multi model control system. The performances are observed for various operating points of level responses as shown in Figure 7.2 for hard switching, Figure 7.3 for 1-δ method and Figure 7.4 1/δ method and its quantitative analysis such as IAE and TV has been carried out as shown in Table 7.3. Based on this, the cascade multi model control system effectively control the output and improved the disturbance rejection for level control in spherical tank.

Table 7.2 Multi model primary local controller of level control of spherical tank process

	Multi-model Normal Feedback control	Multi-model Cascade control
Controller 1	$5.556+\frac{1}{166.7s}+1.6827s$	$15.31+\frac{1}{168.85s}+0.8456s$
Controller 2	$2.287+\frac{1}{598.5s}+1.6952s$	$6.33+\frac{1}{597.65s}+0.8488s$
Controller 3	$1.822+\frac{1}{283.5s}+1.6898s$	$5.033+\frac{1}{282.65s}+0.8474s$

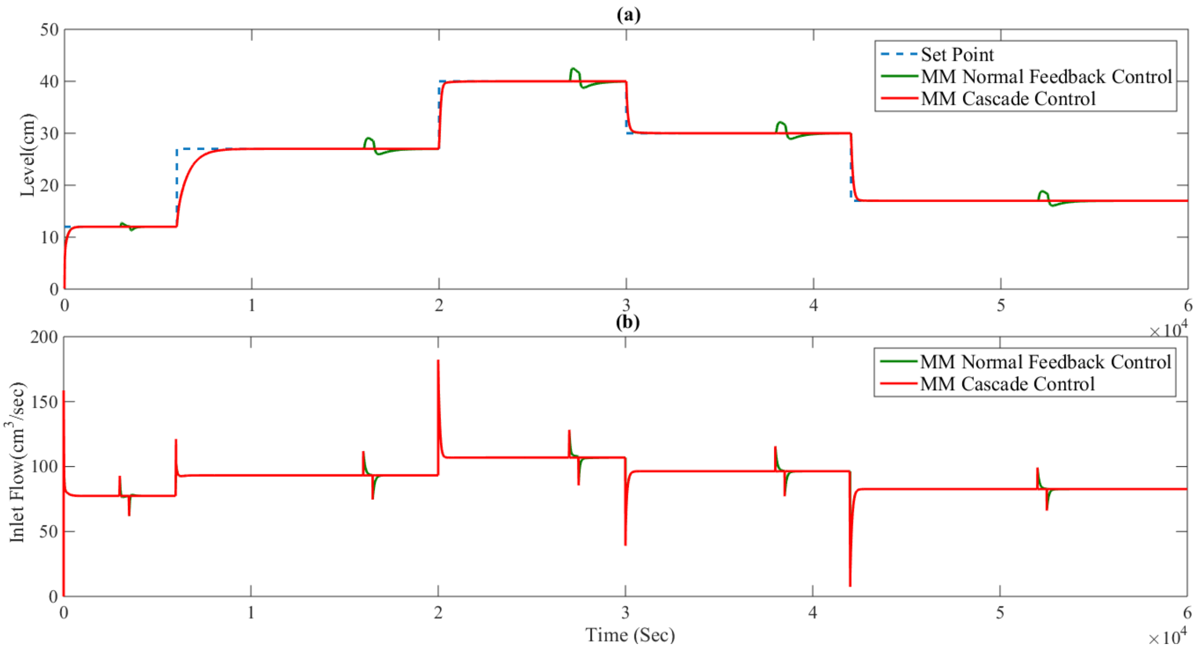

Figure 7.2 Closed loop response for spherical tank using hard switching (a) Plant Output (b) Manipulated Signal.

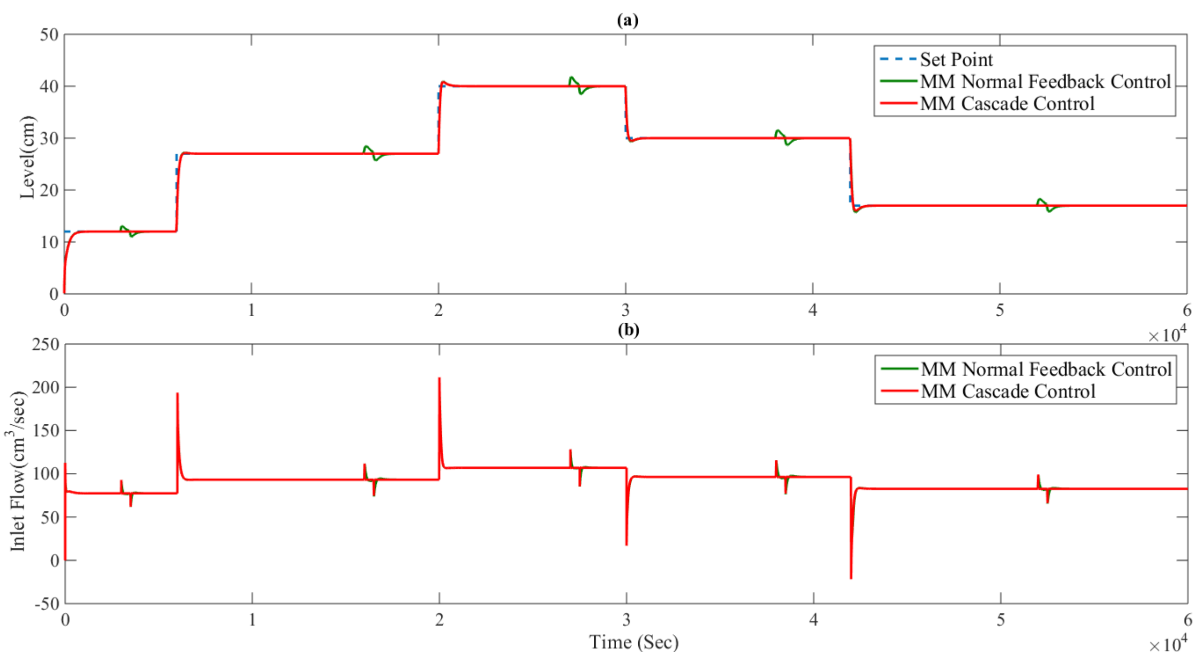

Figure 7.3 Closed loop response of spherical tank using 1-δ method (a) Plant Output (b) Manipulated Signal.

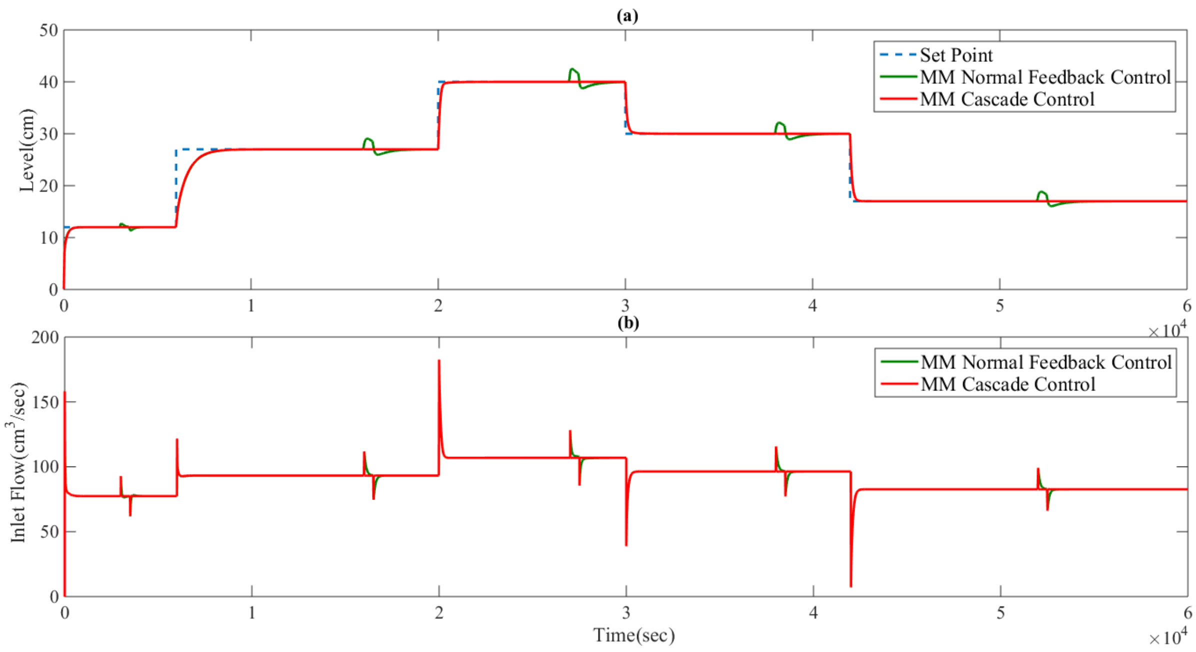

Figure 7.4 Closed loop response of spherical tank using 1/δ method (a) Plant Output (b) Manipulated Signal.

Table 7.3 Quantitative analysis of normal multi-model and cascade multi-model control system for spherical tank process.

	Hard Switching		1-δ Soft Switching		1/δ Soft Switching	
	Normal	Cascade	Normal	Cascade	Normal	Cascade
IAE Value (10^3)	1.9982e+04	1.2442e+04	1.0212e+04	5.5867e+03	1.9873e+04	1.2169e+04
TV Value	995.8716	1.1361e+03	1.1661e+03	1.3540e+03	1.0022e+03	1.1377e+03

7.3.2 Conical Tank Process

Similarly, studies on conical tank are also carried out in simulation for both normal and cascade multi model control system. The performance is observed for various operating points of level responses as shown in Figure 7.5 for hard switching, Figure 7.6 for 1-δ method and Figure 7.7 1/δ method and its quantitative analysis such as IAE and TV are carried out as shown in Table 7.5. From the simulation response gap metric based cascade multi model system shows better performance. These gap metric based weighing functions are experimentally investigated for comparative analysis and shown in Figure 7.8 and quantitative analysis such are also carried out as shown in Table 7.6. Based on this, the cascade multi-model control system effectively controls the output and improved the disturbance rejection of level control in conical tank process.

Table 7.4 Multi model primary local controller parameter values of level control of conical tank process

	Multi-model Normal Feedback control	Multi-model Cascade control
Controller 1	$2.8468 + \frac{1}{13.95s} + 1.4928s$	$3.208 + \frac{1}{13.1s} + 0.7948s$
Controller 2	$1.145 + \frac{1}{227.38s} + 1.6873s$	$1.369 + \frac{1}{226.53s} + 0.8468s$
Controller 3	$1.74 + \frac{1}{1162.6s} + 1.6975s$	$2.089 + \frac{1}{1161.8s} + 0.8494s$

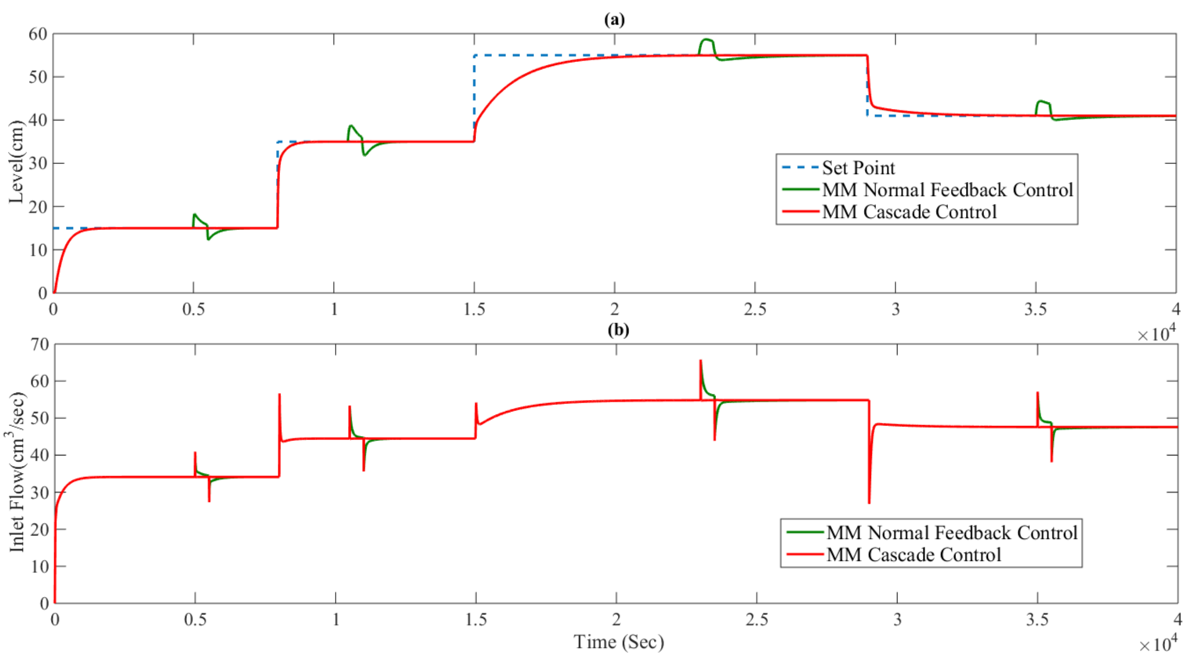

Figure 7.5 Closed loop response for conical tank using hard switching (a) Plant Output (b) Manipulated Signal.

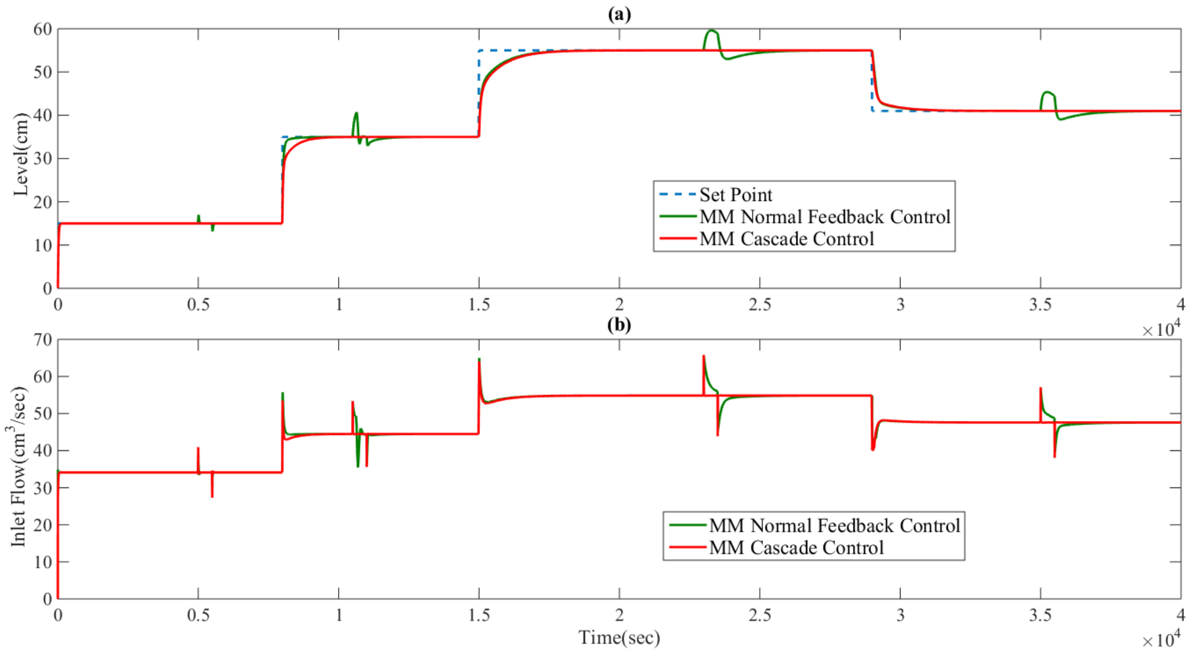

Figure 7.6 Closed loop response for conical tank using 1-δ method (a) Plant Output (b) Manipulated Signal.

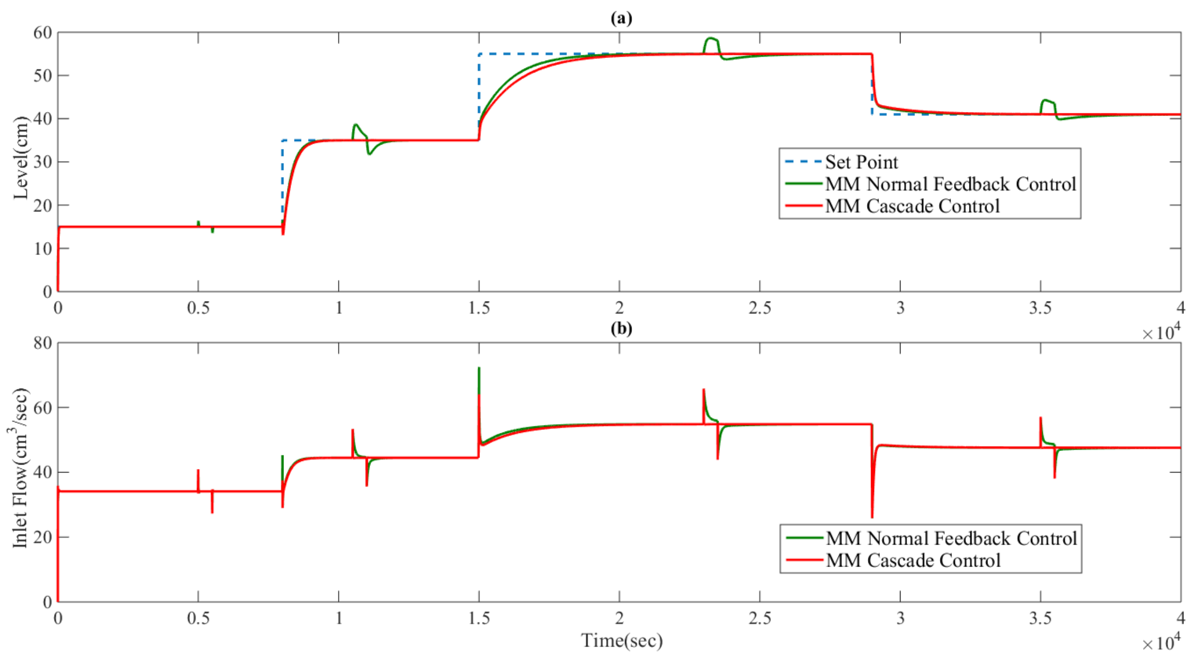

Figure 7.7 Closed loop response for conical tank using 1/δ method (a) Plant Output (b) Manipulated Signal.

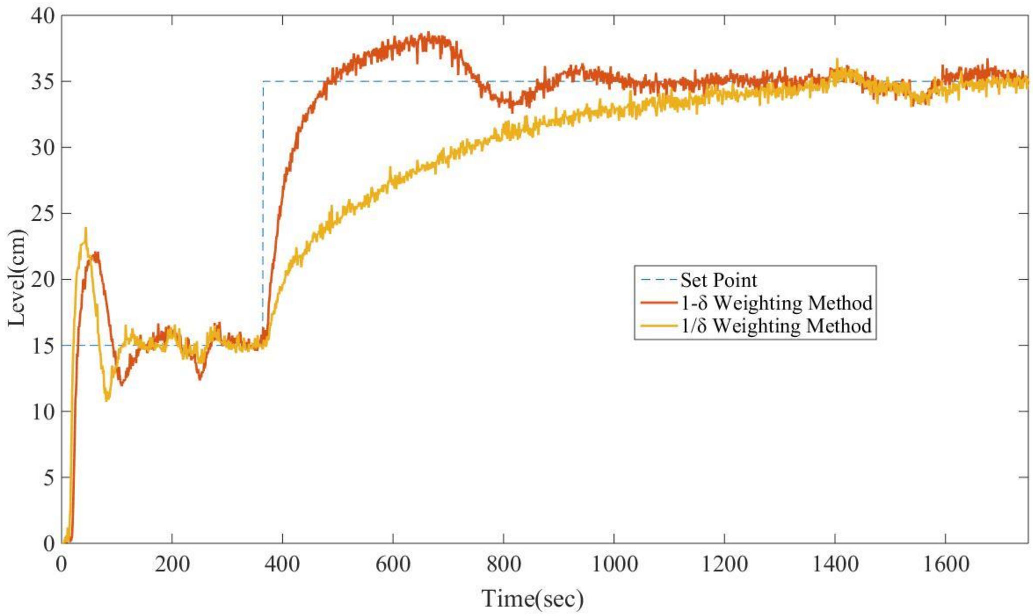

Figure 7.8 Experimental closed loop response of gap metric based cascade multi-model control for conical tank for 1-δ and 1/δ method.

Table 7.5 Quantitative analysis of normal multi-model and cascade multi-model control system for conical tank process.

	Hard Switching		1-δ Soft Switching		1/δ Soft Switching	
	Normal	Cascade	Normal	Cascade	Normal	Cascade
IAE Value (10^3)	45.064	34.585	21.584	14.55	36.299	34.397
TV Value	275.34	290.498	300.74	274.37	329.64	313.19

Table 7.6 Experimental quantitative analysis of gap metric soft switching based cascade multi-model control system for conical tank process.

	1-δ	1/δ
IAE Value (10^3)	2.7027	5.849
TV Value (10^3)	1.0121	1.0284

7.3.3 Isothermal CSTR

Similarly, for iCSTR the comparative results are carried out of normal and cascade multi model control system. The performance is observed for various operating points of level responses as shown in Figure 7.9 for hard switching, Figure 7.10 for 1-δ method and Figure 7.11 1/δ method and its quantitative analysis such as IAE and TV has been carried out as shown in Table 7.8. Based on this, the cascade multi model control system effectively control the output and improved the disturbance rejection for concentration control in CSTR.

Table 7.7 Multi model primary local controller parameter values of level control of spherical tank process

	Multi-model Normal Feedback control	Multi-model Cascade control
Controller 1	$113.85 + \frac{1}{21.87s} + 0.033s$	$3.1854 + \frac{1}{21.87s} + 0.0165s$
Controller 2	$223.86 + \frac{1}{11.49s} + 0.0329s$	$6.259 + \frac{1}{11.48s} + 0.0165s$
Controller 3	$688.37 + \frac{1}{3.693s} + 0.0327s$	$19.188 + \frac{1}{3.676s} + 0.0164s$

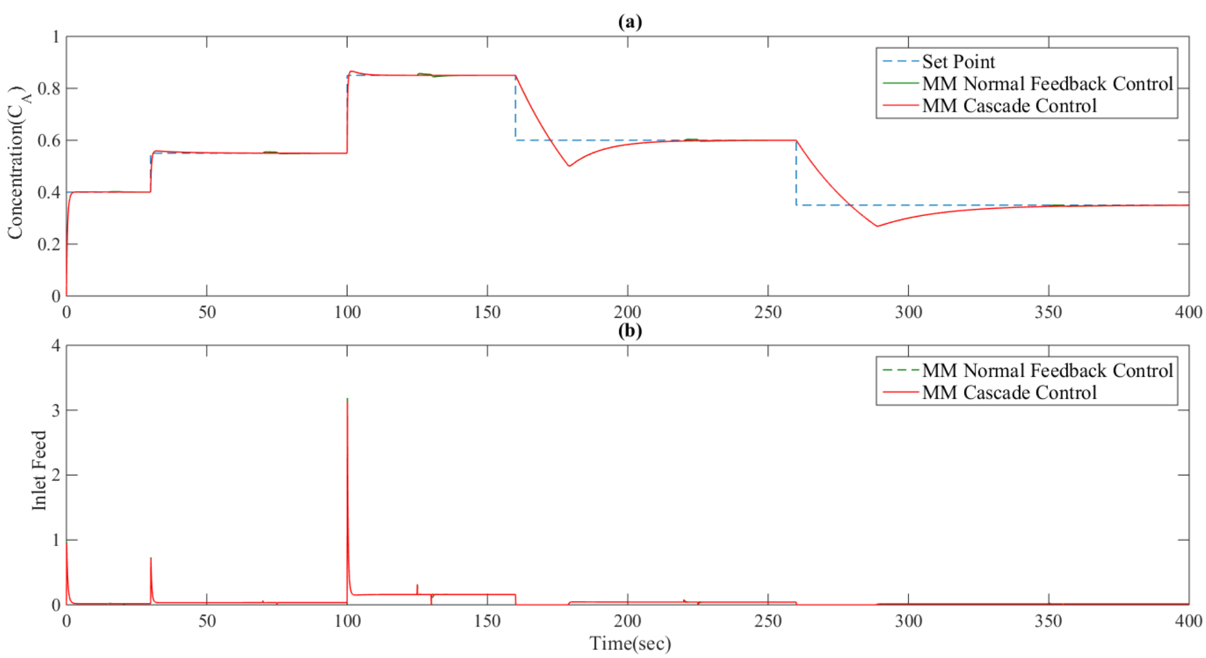

Figure 7.9 Closed loop response for CSTR using hard switching (a) Plant Output (b) Manipulated Signal.

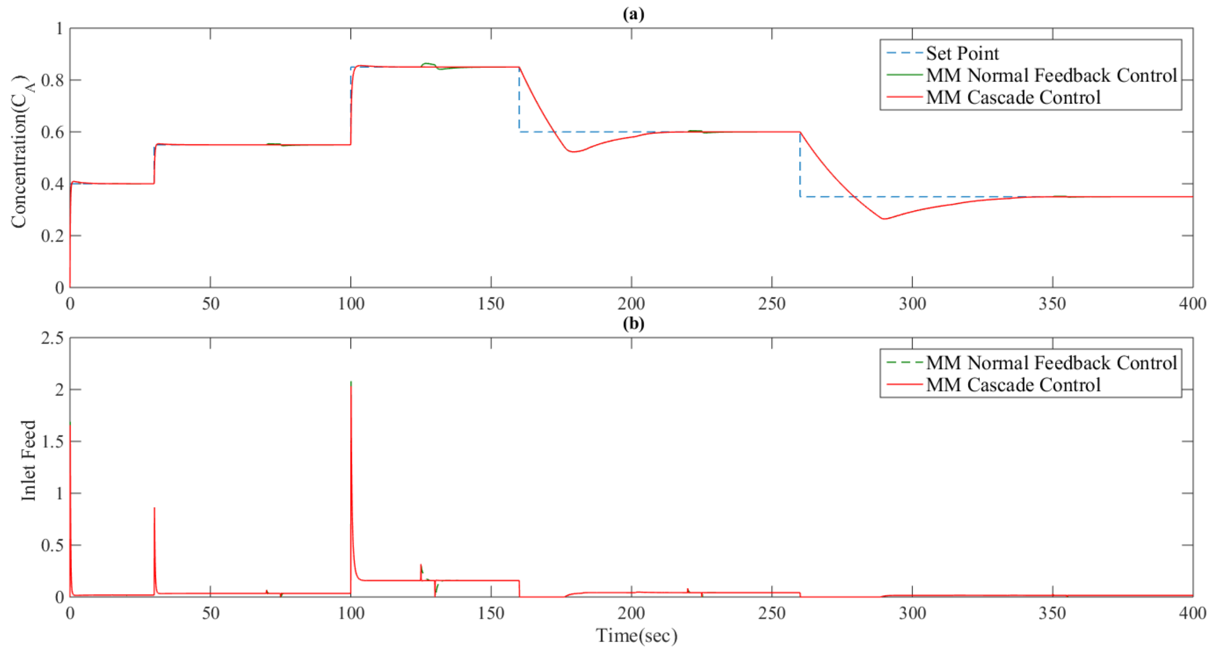

Figure 7.10 Closed loop response for CSTR using 1-δ method (a) Plant Output (b) Manipulated Signal.

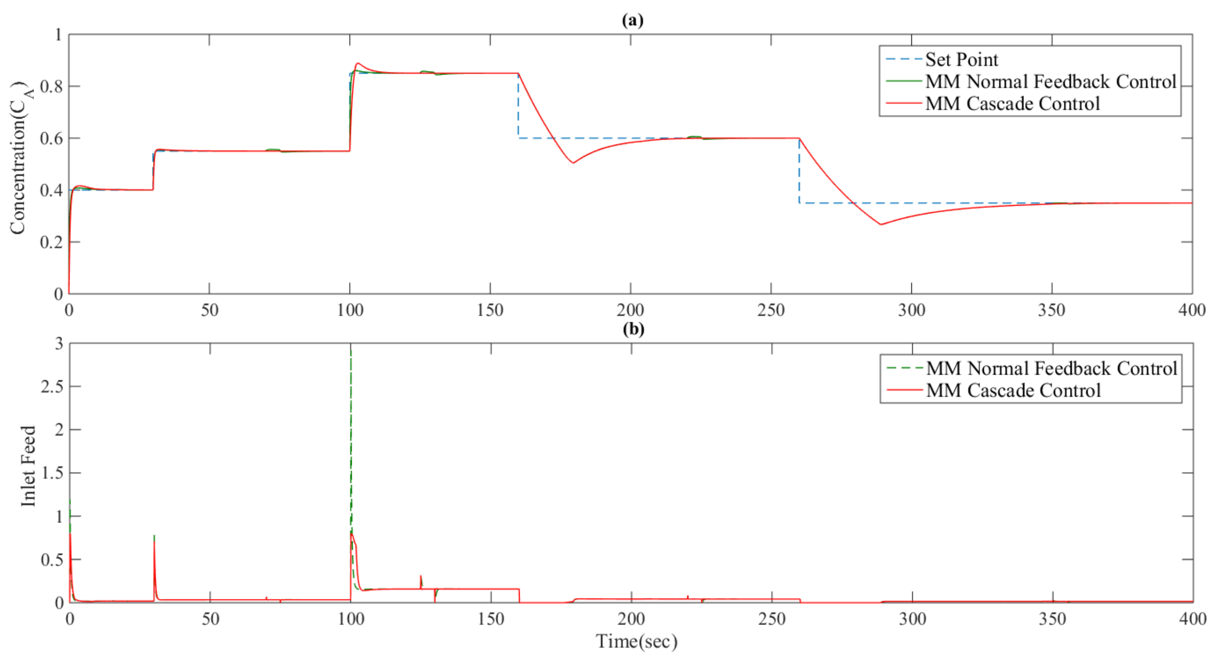

Figure 7.11 Closed loop response for CSTR using 1/δ method (a) Plant Output (b) Manipulated Signal.

Table 7.8 Quantitative analysis of normal multi-model and cascade multi-model control system for CSTR.

	Hard Switching		1-δ Soft Switching		1/δ Soft Switching	
	Normal	Cascade	Normal	Cascade	Normal	Cascade
IAE Value	80.2928	79.0444	78.1884	76.0404	79.3043	81.4813
TV Value	10.8158	10.6549	10.3512	10.1723	10.8460	10.23

7.4 Summary:

Different switching based cascade multi-model control system is evaluated for control of nonlinear processes and is compared with normal feedback multi model system. Both the methods are evaluated by the simulation for three nonlinear processes. Gap metric based weighing function cascade control system are evaluated in experimentally for conical tank process. On comparing the cascade multi model control system of soft and hard switching method, it is noticed that soft switching based cascade multi model control system has shown improvement on performance.

Chapter 8

Design and Evaluation of Multi Model Smith Predictor for Nonlinear Processes with Long Dead Time

Chapter 8

Design and evaluation of multi-model Smith predictor for nonlinear processes with long dead time

Multi model smith predictor is designed and evaluated for long dead time nonlinear process. Multi model approach is simplest and finest control system to control the nonlinear process from last decade of researches. The long dead time in nonlinear process creates unstable in controlling, to overcome this smith predictor structure is modified according to multi model control structure.

8.1 Introduction:

In chemical process industries works on lot many number of processes combination and more number of these processes behaves like nonlinear. The researchers are designing the controller to satisfy the industrial requirement for the nonlinear process. From the decades of researches, the researchers proved that Multi Model Approach (MMA) is one of the simplest and finest approach to design a controller for nonlinear process and also using this approach easily can implement latest linear controllers.

MMA works on by making piece of nonlinear process into multiple based on operating strategy and the pieces becomes linear process for that operating constraints. Using these linear process, a linear controller is designed and combination of all these forms global controller. The combination can be formed by using hard and soft switching. Most of researches are suggested to use soft switching for smooth response while set points move from one region to another.

To design a controller for nonlinear process is some difficult task and delay added to it and it makes even more difficult. Multi model control scheme will overcome these issue for lesser delay process and also some time system may move to unstable. If long dead process is present in nonlinear process then design a controller is cumbersome task.

To deal with larger delay system already smith predictor structure is proved to control from last few decades of researches. Otto smith as introduced the Smith Predictor control strategy in 1957. This strategy is modified the feedback strategy to compensate the delay. In this strategy, it consist of feedback loop with additionally inner loop where it's have the two terms. The first term of this inner loop represents process behaviour without dead time. The second term represents is simply a time delay. Most of researchers modified the smith predictor strategy to control long dead time process and are complicated procedure. To overcome this issue a simplified smith predictor structure is designed using multi model control scheme.

In this chapter, smith predictor strategy is modified according multi model control scheme to control the nonlinear process. Here multi model smith predictor strategy inner loop generalized model plays major role.

8.2 Development of Multi Model Smith Predictor (MMSP):

Generally smith predictor structure is used to compensate delay in control process and its schematic diagram is shown in Figure 1. Multi model control scheme is used in controlling the nonlinear process. Smith predictor structure is modified according MMA to compensate delay in nonlinear process. In this development two parts are modified in smith predictor. One is controller section, here multi model control scheme is implemented and another is generalized model with multiple model. In generalized multiple model section switching is carried using hard method based on operating condition. In multi-model control scheme, gap metric based soft switching is used to form global control.

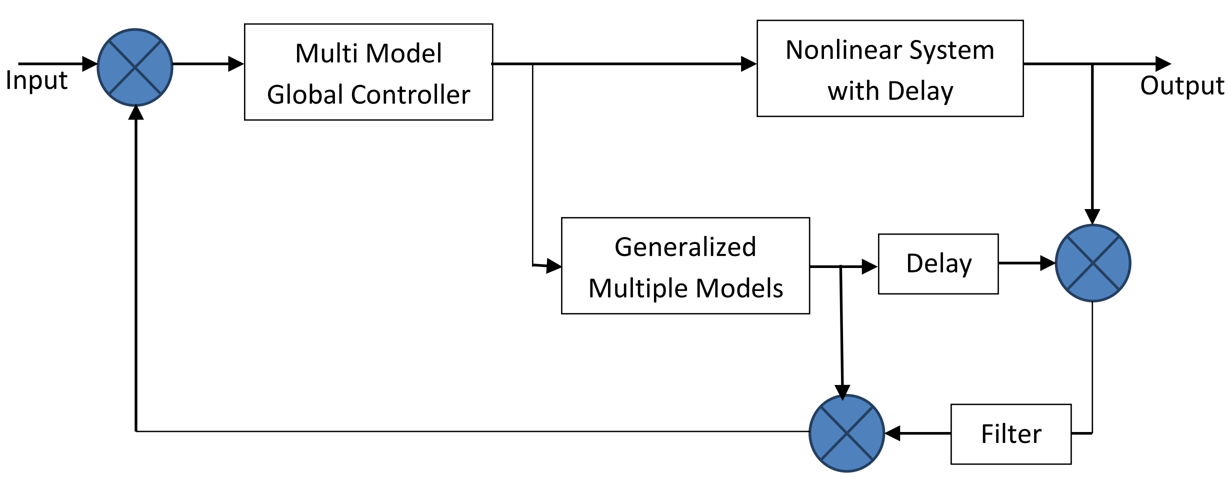

Figure 8.1 Schematic structure of multi model smith predictor.

Smith predictor is designed for long dead time nonlinear process and model block shown in figure 8.2.

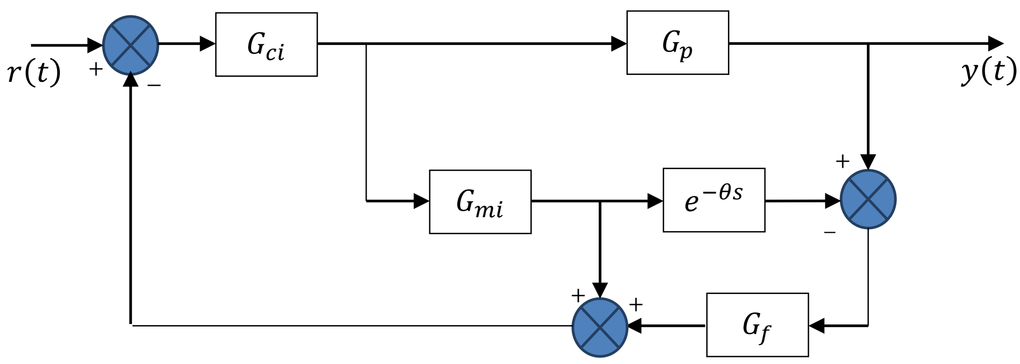

Figure 8.2 Block diagram of multi model smith predictor.

The nonlinear process $G_p$is

$$G_p = G_{mi}e^{-\theta s}$$

The transfer function is

$$G(s) = \frac{Y(s)}{R(s)} = \frac{G_{ci}G_p}{1+G_mG_{ci}+G_{ci}G_pG_f-G_{ci}G_{mi}e^{-\theta s}G_f} \quad (8.4)$$

whereG_{mi} is a ith number of generalized linearized models, θ is dead time, G_f is filter(used for noise elimination) and G_{ci} is global controller. The structure compensates the delay and becomes

$$G(s) = \frac{G_{ci}G_p}{1+G_{mi}G_{ci}} \quad (8.5)$$

In two ways, it is designed and analyzed. In this two method, the global controller is designed by using minimized models for both but combination has done using hard and 1-δ (soft) switching methods. Whereas in generalized model, in first method used all the multiple models and second one used only minimized models.

8.3 Results and Summary

In this section, simulation analysis are presented. Multi model smith predictor is examined on conical tank process to control level and iCSTR to control concentration on simulation using MATLAB. Filter is used for noise elimination and it differs for process to process and here for conical tank chosen as $\frac{1}{100s+1}$and iCSTR chosen as$\frac{1}{2s+1}$. Simulation results are presented here and Figure8.3 shows of response MMSP on conical tank process using all multiple linear models in generalized section based hard switching method and Figure 8.4 shows of response MMSP on conical tank process using minimized linear models in generalized section based hard switching method and Figure 8.5 shows of comparison response MMSP on conical tank process using all and minimized linear models in generalized section based hard switching method and Table 8.1 presents the quantitative analysis MMSP response using hard switching on conical tank process.. Figure 8.6 shows of response MMSP on conical tank process using all multiple linear models in generalized section based 1-δ switching method and Figure 8.7 shows of response MMSP on conical tank process using minimized linear models in generalized section based 1-δ switching method and Table 8.2 presents the quantitative analysis MMSP response using hard switching on conical tank process.

Figure 8.8 shows of comparison response MMSP on iCSTR process using all and minimized linear models in generalized section based hard switching method and Table 8.3 presents the quantitative analysis MMSP response using hard switching on iCSTR. Figure 8.9 shows of comparison response MMSP on iCSTR process using all and minimized linear models in generalized section based 1-δ switching method and Table 8.4 presents the quantitative analysis MMSP response using 1-δ switching on iCSTR.

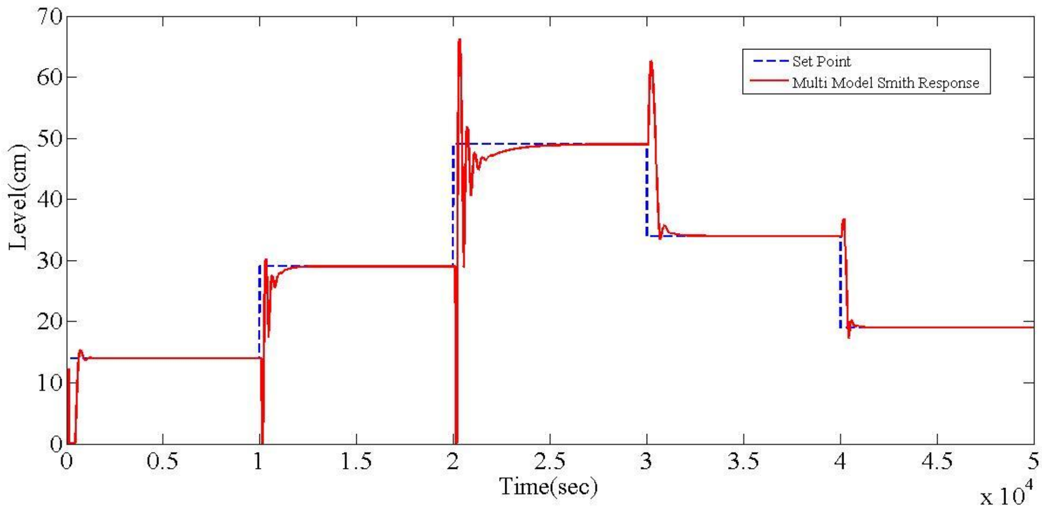

Figure 8.3 Multi Model Smith Predictor Response using all Generalized Models

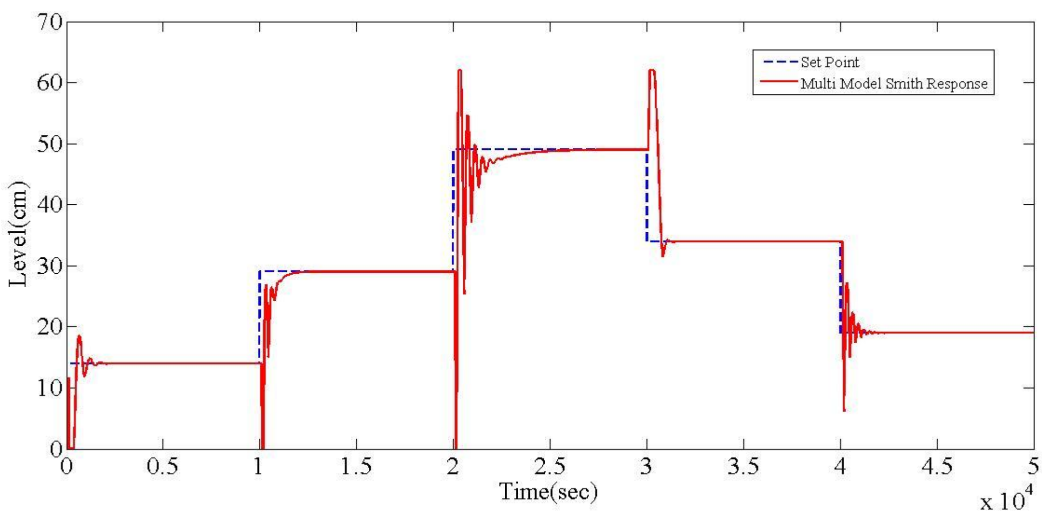

Figure 8.4 Multi Model Smith Predictor Response using Minimized Models

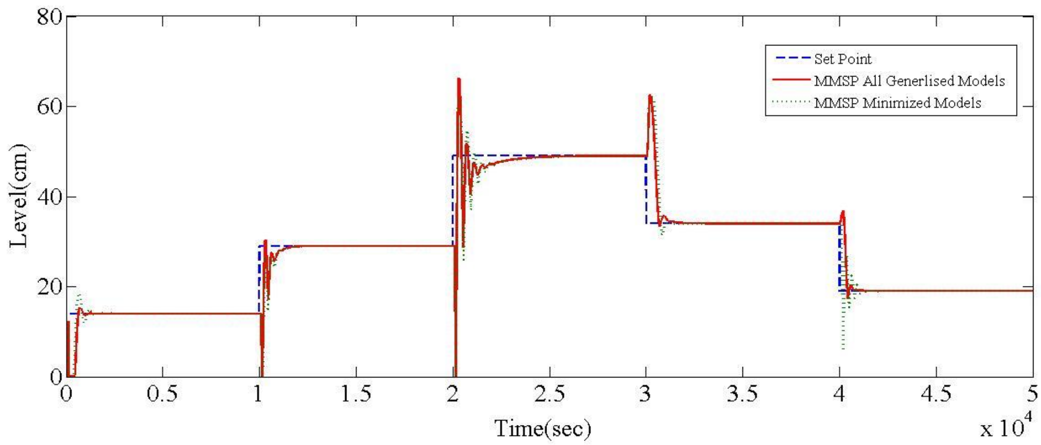

Figure 8.5 MMSP Response using Hard Switching

Table 8.1 Quantitative analysis MMSP response using hard switching on conical tank process.

	All Multiple Models	Minimized Models
IAE Value	5.1597e+04	5.7484e+04
TV Value	1.5597e+03	977.4883

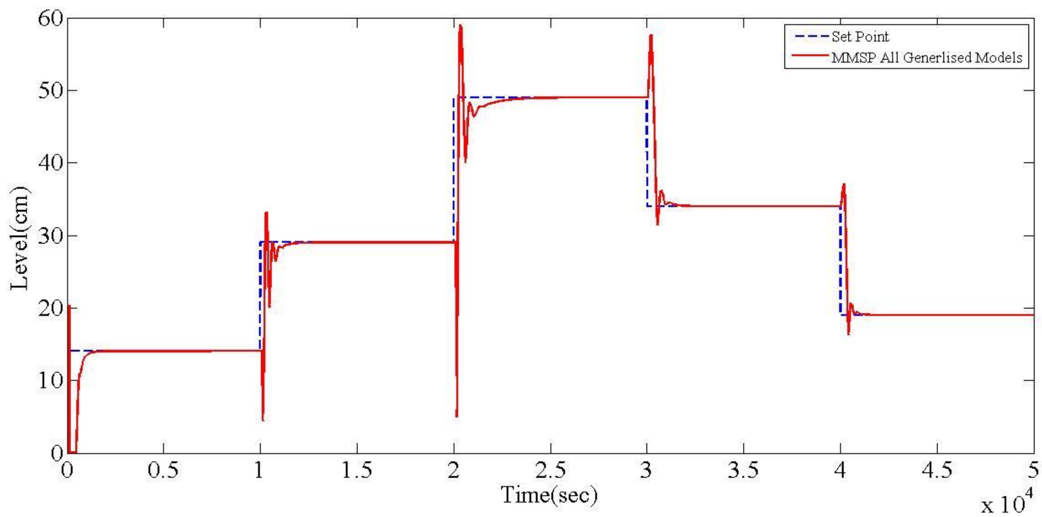

Figure 8.6 MMSP Response using 1-δ (All Generalized Modes)

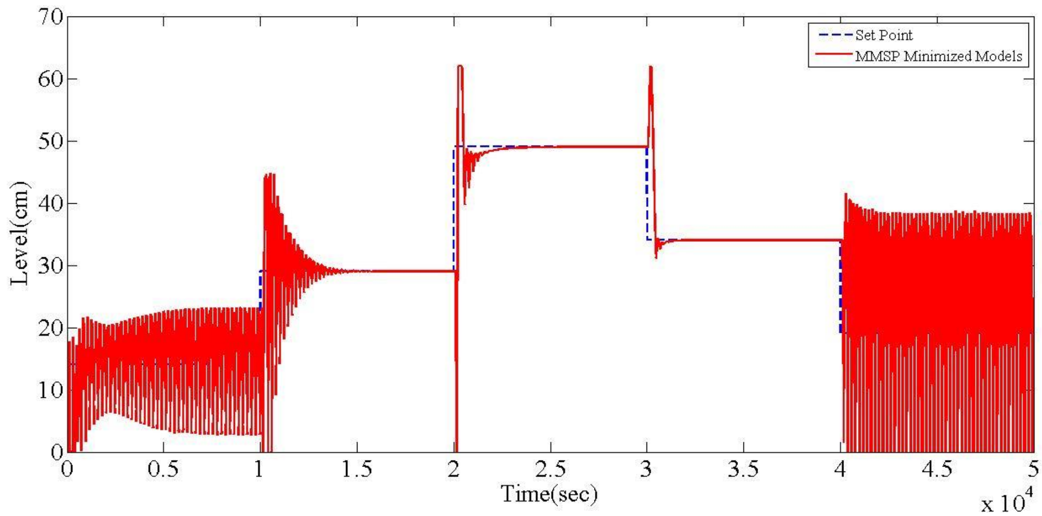

Figure 8.7 MMSP Response using 1-δ (Minimized Modes)

Table 8.2 Quantitative analysis MMSP response using 1-δ switching on conical tank process.

	All Multiple Models	Minimized Models
IAE Value	4.0777e+04	2.5280e+05
TV Value	1.3366e+03	3.4028e+04

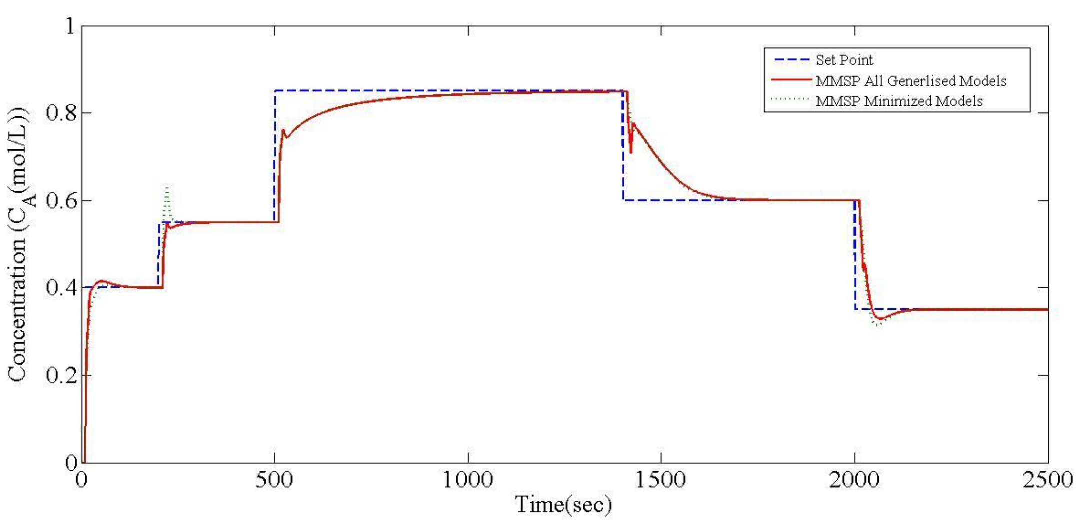

Figure 8.8 MMSP Response using Hard Switching on iCSTR

Table 8.3 Quantitative analysis MMSP response using hard switching on iCSTR.

	Multiple Models	Minimized Models
IAE Value	58.6853	59.4595
TV Value	2.0003	2.1298

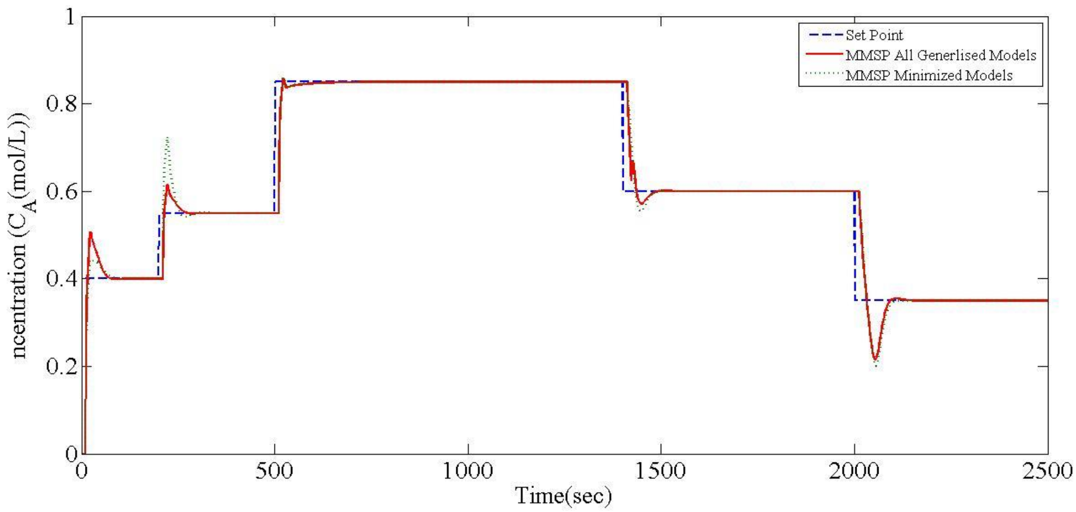

Figure 8.9 MMSP Response using 1-δ Switching on iCSTR

Table 8.4 Quantitative analysis MMSP response using 1-δ switching on iCSTR.

	Multiple Models	Minimized Models
IAE Value	31.1026	33.9027
TV Value	2.8164	3.1161

8.4 Summary:

Multi model smith predictor is designed for long dead time nonlinear process and examined on conical tank and iCSTR process. Comparison has done with minimized models and all multiple models. From the evaluation and results, it is concluded that multi model smith predictor compensates the long delay on nonlinear process. While in comparison effective response has got for using all multiple models. 1-δ Soft switching base global controller and generalized model with all multiple models gives minimal values of IAE and TV. It is concluded that multi model smith predictor compensates the long delay on nonlinear process.

Chapter 9

Summary and Conclusions

Chapter 9

Summary and Conclusions

9.1 Summary

In this research, Evaluation of Gap-metric based Multi-model Control Schemes for Nonlinear Systems is analysed experimentally,a Multi-model Predictive Control (MMPC) has designed for time delay non-linear process, An enhanced designing of Multi Model Fractional Controllers and Multi-model Cascade Control Strategy for Nonlinear Systems is studied and performed experimentally, finally noticed the effects of Scan Time on the Controller Performance in Computer based Process Control during ourexperimental investigation and modified PID controller is designed based on scan time.The results obtained in each section are summarized below.

9.1.1 Evaluation of Gap-metric based Multi-model Control Schemes for Nonlinear Systems

Controlling the level of spherical tank and conical tank using the inlet flow rate is a typical nonlinear process and a simple linear controller might fail in providing required closed loop performances. Two different non-linear process control methods are evaluated in this work to control the nonlinear processes. Multi model control scheme based on Gap metric is used to control the nonlinear processes. In order to reduce the number of linear models Gap metric is selected and then to design the corresponding controllers weights. These two weighting functions ($1-\delta$ and $1/\delta$) based on gap metric are applied first by simulation for level control in both these tanks to observe that the level is controlled effectively. Experimental implementation is carried out for controlling the level and Comparative analysis has also been done using IAE and ISE.

9.1.2 Multi-model Predictive Control (MMPC) for Non-linear Systems with Time Delay

The gap metric based weighting methods are evaluated in controlling of conical tank process with delay using MMPC. The effectiveness of the method is justified using simulation and experimental studies.

9.1.3 Design of Multi Model Fractional Controllers for Nonlinear Systems

Multi-model fractional order controller is evaluated for control of nonlinear processes and is compared with multi-model integer order controller. Both the methods are evaluated first by the simulation and then by performing experiments on conical tank process.

9.1.4 Design a Multi-model Cascade Control Strategy for Nonlinear Systems

Different switching based cascade multi-model control system is evaluated for control of nonlinear processes and is compared with normal feedback multi model system. Both the methods are evaluated by the simulation for three nonlinear processes. Gap metric based weighing function cascade control system are evaluated in experimentally for conical tank process.

9.1.5 Design and Evaluation of Multi Model Smith Predictor for Long Dead Time Nonlinear Process

Multi model smith predictor is designed and evaluated for long dead time nonlinear process. Comparison has done with minimized models and all multiple models. The multi model smith predictor structure is examined on nonlinear processes such as conical tank process and iCSTR and evaluated with IAE and TV.

9.2 Conclusions

9.2.1 Evaluation of Gap-metric based Multi-model Control Schemes for Nonlinear Systems

Multi model control scheme based on Gap metric is used for controlling the nonlinear processes. Gap metric is selected to reduce the number of linear models and then to design the corresponding controllers weights. The two weighting functions (1-δ and 1/δ) based on gap metric are applied first by simulation experimental implementation is carried out and the following conclusions are drawn.

(i) Whenever a positive step change is given around steady state operating point, 1/δ weighting method showed better performance when compared with 1-δ weighting method.

(ii) Whenever a positive step change is given in a region other than the steady state, 1-δ weighting method showed better performance.

(iii) Irrespective of positive and negative step changes, it is observed that 1-δ weighting method always shows better performance for higher values of level and 1/δ weighting method showed better performance for lower levels.

(iv) Based on all the evaluations made and on comparative analysis, 1- δ weighting method is recommended for control of level in a nonlinear process by using gap metric based multi-model approach.

9.2.2 Multi-model Predictive Control (MMPC) for Non-linear Systems with Time Delay

Multi-model predictive control is designed and the effectiveness of the method was justified using simulation and experimental case scenarios. It is concluded that 1-δ weighting function provides better performance as compared to 1/δ weighting function. In most of the practical cases, 1-δ weighting function is recommended because it gives lower IAE value that leads to good controller performance.

9.2.3 Design of Multi Model Fractional Controllers for Nonlinear Systems

Multi-model fractional order controller is evaluated for control of nonlinear processes and is compared with multi-model integer order controller. Both the methods are evaluated first by the simulation and then by performing experiments on conical tank process. It is observed that multi-model fractional order controller provides better performance when compared to multi-model integer order controller.

9.2.4 Design a Multi-model Cascade Control Strategy for Nonlinear Systems

An integrated framework of cascade control and multi-model control system is evaluated for controlling the nonlinear process in the presence of disturbances and is compared with normal multi-model control system. Both the methods are evaluated by the simulation on three nonlinear process. Gap metric based weighing function cascade control system is evaluated experimentally for conical tank process. The evaluation from the simulation and experimental response and quantitative analysis indicated that 1-δ gap metric based weighing method of cascade multi model control system effectively controls the output and improves the disturbance rejection of nonlinear system. It is concluded that 1-δ gap metric based weighing method of cascade multi model control system provides better performance when compared to hard and 1/δ gap metric based weighing method of cascade multi model control system.

9.2.5 Design and Evaluation of Multi Model Smith Predictor for Long Dead Time Nonlinear Process

Multi model smith predictor is designed for long dead time nonlinear processes and examined on conical tank and iCSTR process. Comparison is carried out with minimized models and all multiple models. From the results, it is concluded that multi model smith predictor compensates the long delay on nonlinear process and provided less values of IAE and TV.

9.3 Suggestions for Future Work

Based on the research carried out in this thesis, one can extend the ideas to solve different other problems related to control nonlinear systems. The suggestions for future work include the following.

i. One can carry the experimental implementation of multi model control scheme on MIMO nonlinear systems and verify the applicability of the scheme. Also, any issues due to the multivariable nature can be studied when the number of inputs and outputs are more (>3). Different multi-model control schemes including PID controllers, fractional order PID controllers, MPC controllers can be tested experimentally.

ii. One more extension can be the design of multi-model fractional order controls MIMO square and non-square systems. Typically, design of controllers for square systems is straight forward whereas for MIMO non-square systems, it is not. Hence, the present multi-model fractional controllers design may be extended to control of MIMO non-square systems when there are more inputs than outputs.

iii. One more extension is to study the effect of different types of disturbances such as ramp, periodic and sine wave type while implementing multi-model control schemes. Analyzing the effect of such disturbances both by simulation and experiment may be carried out.

iv. In this research, different multi-models are considered for the given process whose dynamics are stable. However, some times, the linearized model nature may be unstable in nature based on the operating point. Controlling processes involving unstable dynamics may be studied with proper integration of controllers meant for unstable systems.

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List of Publications

International Journals

1. G. Maruthi Prasad and A. Seshagiri Rao. "Evaluation of gap-metric based multi-model control schemes for nonlinear systems: An experimental study" ISA Transactions, 2019, 94, 246-254.
2. G. Maruthi Prasad, A. Seshagiri Rao. "Multi-model cascade control strategy design based on gap metric for nonlinear processes." Indian Chemical Engineer, 2020, 1-14.
3. G. Maruthi Prasad, E. Chandra mohan Goud, A. Seshagiri Rao. "Design of multi-model Smith predictor for nonlinear process with time delay" to submit to ISA Transactions.

Book Chapter

1. G. Maruthi Prasad, A. Adithya, and A. Seshagiri Rao. "Design of Multi Model Fractional Controllers for Nonlinear Systems: An Experimental Investigation. "Computer Aided Chemical Engineering. Vol. 46. Elsevier, 2019, 1423-1428.

Conference Proceedings

1. G. Maruthi Prasad, Vatsal Kedia, and A. Seshagiri Rao. "Multi-Model Predictive Control (MMPC) for Non-linear Systems with Time Delay: An Experimental Investigation." IEEE International Conference on Measurement, Instrumentation, Control and Automation (ICMICA), NIT Kurukshetra, Haryana India. (IEEE Xplore, 2020, 1 – 5).
2. G. Maruthi Prasad, A. Adithya, and A. Seshagiri Rao. "Multi-model Control of Nonlinear Processes - A Fractional Order Filter based Approach. "International Conference on Instrumentation and Control Engineering (ICECON), December 19 to 21, 2019, NIT Tiruchirappalli, India.
3. G Maruthi Prasad and A. Seshagiri Rao, Design of a Cascade Multi-model Control Strategy using Hard Switching for Nonlinear Systems, International Conference on new Frontiers in Chemical, Energy, and Environmental Engineering (INCEEE), February15-16, 2019, NIT Warangal, India.

4. G Maruthi Prasad, L Rajesh, Uday Bhaskar and A. Seshagiri Rao, “Design of Novel Multi Model Switching Controller for Non-linear System” 70th Annual session of Indian Institute of chemical Engineers, CHEMCON 2017, December 27-30, 2017, HIT, Haldia, India.

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