Adaptive Control of a Non-isothermal Fixed Bed Reactor

Submitted in
fulfillment of the requirements for the degree of
Doctor of Philosophy
by

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CERTIFICATE

This is to certify that the thesis entitled **"Adaptive Control of a Non-isothermal Fixed Bed Reactor"** being submitted by **Avdesh Singh Pundir (2013RCH9513)** is a bonafide research work carried out under my supervision and guidance in fulfillment of the requirement for award of the degree of **Doctor of Philosophy** in the Department of Chemical Engineering, Malaviya National Institute of Technology, Jaipur, India. The matter embodied in this thesis is original and has not been submitted to any other University or Institute for the award of any other degree.

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ABSTRACT

Fixed bed reactors are extensively used in chemical and process industries. Tight temperature control can play a crucial role in determining the performance of such devices and has therefore been a subject of many investigations over the past few decades. These studies addressed fluid-packed particle heat transfer, the transient response of fixed bed reactor, and various useful parameters under the unsteady state including effective axial and radial thermal conductivities, wall to fluid heat transfer coefficient and overall heat transfer coefficient.

Process control systems inevitably include adjustable controller settings that facilitate process operation over a wide range of conditions. Typically, controller settings are tuned after the control system has been installed using time-consuming, trial-and-error procedures. If process conditions change significantly, then the controller must be retuned to obtain satisfactory control. Recently, there has been broad interest in adaptive control systems that automatically adjust the controller settings to compensate for unanticipated changes in the process or the environment. Adaptive control schemes provide systematic, flexible approaches for dealing with uncertainties, nonlinearities, and time-varying process parameters.

A semi-analytical approximate solution has been obtained for a fixed bed reactor model having strong nonlinearity. A hydrolysis endothermic reaction of ethyl acetate in presence of porous catalyst, Amberlyst-15, has been considered for the study. Classical Adomian Decomposition Method (ADM) is not found to be very successful to acquire an approximate solution for longer period of time. Therefore, a Multistage Adomian Decomposition Method (MADM) has been applied for solving the nonlinear distributed parameter model of the fixed bed reactor and the reliable solution has been obtained. To demonstrate the reliability, a comparison between MADM and Method of Lines (MOL) has been shown. Further, it has been demonstrated that accuracy of the solution can be increased by reducing time discretization step and increasing the number of series components.

A Chattering Free Sliding Mode Control (CFSMC) with observer based adaptive Radial Basis Function Neural Network (RBFNN) has been designed for first-

order transfer function model of temperature trajectory in a fixed bed reactor. The steady-state behavior and effect of different operating parameters such as feed velocity and temperature influenced on the operation of the fixed bed reactor have been discussed. Due to RBFNN's capability to map the nonlinear dynamics online through self-learning ability, it is combined with CFSMC to reduce the chattering behavior. The adaptive RBFNN has been used to approximate the nonlinear dynamic behavior of the packed bed. To predict the states of the system, high gain observer based on adaptive RBFNN has been used. Design parameter of the observer has been estimated using Hurwitz polynomial. The effect of neuron number on the mapping error and the effect of space discretization step on modeling error have also been discussed. To decrease the chattering generated by the Sliding Mode Control (SMC) in the temperature trajectory tracking, an equivalent control term is neglected from the final controller. It has two main advantages: one is the reduction in chattering behavior which is the main drawback of SMC and the second is the reduction of the high gain requirement. The SMC is used to overcome against external disturbance, load variation, variation in key parameters and model mismatch. To make the simulation realistic, constraints have been applied to control input and input rate in the experimental setup. For guaranteeing the system stability, Lyapunov theorem has been applied. To show the suitability of the hybrid controller, a comparison has been carried out between the hybrid and PID controller. To quantify the performance, Integral Time Weight Absolute Error (ITAE) has been estimated. Under the condition of existing model errors and external disturbances, simulation study of the control of the fixed bed reactor shows that the hybrid control algorithm consisting of sliding mode control and observer-based adaptive RBFNN performs good both for tracking the temperature trajectory and reducing the chattering**.**

Several control methodologies have been proposed in academia but only a few of them have been implemented in industries due to their difficult implementation. This study is motivated by not only using low cost data acquisition system such as Arduino in Matlab with little programming but also easy implementation of complex chemical process systems such as fixed bed reactor. An online identification and parameter estimation of a fixed bed reactor with MATLAB package was developed. Designing a controller by using a nonlinear complicated model is a difficult task. A first order

discrete transfer function with unit delay has been identified for a fixed bed reactor for which a Recursive Least Squares (RLS) method with forgetting factor has been chosen. The MATLAB program has been developed including Adaptive Sliding Mode Control (ASMC), determination of model order and model verification. This work describes a Simulink based model using Arduino, a data acquisition card used for interfacing with fixed bed reactor. A temperature trajectory tracking study has been used in order to analyze the performance of the proposed strategy for control of the reactor. The controller implemented has been developed using ASMC to control temperature of the fixed bed reactor. For safety concern, a constraint has been applied to the control signal which is bounded between 0 to 130 °C. Temperature trajectory tracking using this algorithm is found to be good. The value of Integral Absolute Error (IAE) is found to be 387.6 for the experimental run up to 300 s.

Publications from the thesis

The following papers on the research work presented in this thesis have been published

Papers in Journal (SCI):

[1] A. S.Pundir,. K.Singh, Temperature control of real - time identified fixed bed reactor by adaptive sliding mode control equipped with Arduino in Matlab, Asia-Pacific J. Chem. Eng. (2019) 1–15.

[2] A.S. Pundir, K. Singh, Chattering Free Sliding Mode Control with Observer based Adaptive Radial Basis Function Neural Network for Temperature Tracking in a Fixed Bed Reactor, Int. J. Chem. React. Eng (2019) 1-24.

[3] A.S. Pundir, K. Singh, Semi-analytical Approximate Solution for a Fixed Bed Reactor Model using Multistage Adomian Decomposition Method, Lat. Am. Appl. Res. (2019).(Communicated since April 2018-under review).

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[2] A.S. Pundir, K. Singh, Design of Adaptive Control for Oxidation of O-xylene in Packed Bed Reactor : A highly Sensitive System, in: CHEMCON, 2015, Dec 27-30: p. 189.

[3] A.S. Pundir, K. Singh, Study of Transient Behaviour of One Dimensional Packed Bed Reactor for High temperature Reaction System, in: CHEMCON, 2015, Dec 27-30: p. 184.

[4] A.S. Pundir, K. Singh, PID Controller Design for Cascade CSTRs : A Model Reduction Approach, in: CHEMCON, 2014, Dec 27-30: p. 2.

[5] A.S. Pundir, K. Singh, R.K. Dohare, Simulation of Fixed Bed Catalytic Reactor through Analytical Approach, in: Process Autom. Control, 2016,May 28-29.

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List of Abbreviations

ADC	Analog to Digital Converter
ADM	Adomian Decomposition Method
AISMC	Adaptive Integral SMC
ANN	Artificial Neural network
ATD	Approximation-then-design
BVP	Boundary Value Problem
CFSHE	Counter Flow Shell and Tube Heat Exchanger
CFSMC	Chattering Free SMC
CSTR	Continuous Stirred Tank Reactor
DAC	Digital to Analog Converter
DC	Direct Current
dc	Duty Cycle
DME	Di-methyl Ether
DO	Dissolved Oxygen
DSM	Discrete Sliding Mode
DSP	Digital Signal Processing
DTA	Design-then-approximation
EA	Ethyl Acetate
EMG	Electromyography
FFT	Fast Fourier Transformation
FOPTD	First Order Plus Time Delay
FTSMC	Fast Terminal SMC
GA	Gain Scheduling
GCS	Geographical Coordinate System
GG	Good Gain
GLC	Globally Linearized Control
GUI	Graphical User Interface
IC	Initial Condition

IMC	Internal Mode Control
IP	Invariance Principal
ISM	Induction Servo Motor
ITAE	Integral Time Weight Absolute Error
LDR	Light Dependent Resistor
MADM	Multistage ADM
MAN	Maleic Anhydride
MEP	Minimum Algorithm Profile
MIMO	Multi Input Multi Output
MOL	Method of Lines
MOSFET	Metal-oxide-semiconductor-field-effect
MPAS	Model Preference Adaptive System
MPC	Model Predictive Control
MRAC	Model Reference Adaptive Control
MRASMC	Model Reference Adaptive SMC
MSEM	Modified Simple Equation Method
NNSMC	Neural Network SMC
ODE	Ordinary Differential Equation
OS	Overshoot
PCA	Principal Component Monitor Analysis
PDE	Partial Differential Equation
PFC	Predictive Functional Control
PID	Proportional Integral Control
PWM	Pulse Width Modulation
RBFNN	Radial Basis Function NN
RELS	Recursive Extended Least Squares
RLS	Recursive Least Squares
RMS	Root Mean Squares
SEOM	Statically Equivalent Output
SISO	Single Input Single Output

SMC	Sliding Mode Control
SR	Swarm Robotic
SSE	Steady State Error
STC	Self Tuning Control
TSM	Terminal Sliding Mode
TT	Thresholding Techniques
VIM	Variational Iteration Method
ZN	Ziegler Nichols

Nomenclature

A_s	heat transfer surface area,m^2
A_s	heat transfer surface area,m^2
a_1, b_0	discrete plant parameters
A, B,L,M	continuous plant parameters
B	width vector
C_i	concentration of ethyl acetate mol/m^3
C_0	initial concentration, mol/m^3
c	parameter of sliding surface
$C_A / \hat{C}_A$	concentration of plant ethyl acetate/observer, mol/m^3
c_{ij}	centre vector
C_P	specific heat of reaction , J/(mol. K)
d	disturbance
D_{AB}	diffusivity of ethyl acetate, m^2/s
dc	duty cycle
DC	direct current
$e, \hat{e}$	error of plant model and observer
E	activation energy, J/(mol. K)
E^l	error function for neural network
E	activation energy, J/(mol. K)
Δf	model uncertainty in f
fx	nonlinear term due to Arrhenius law

$G(s)$	transfer function of PID
Δg	model uncertainty in g
g	x_d - c e
h_j	Gaussian function
ΔH	heat of reaction ,J/mol
h	space discretization step
k	reaction rate constant, s^{-1}
k_{mix}	thermal conductivity of solution, W/ (m. K)
k_0	frequency factor, s^{-1}
k	feedback gain and sampling number
K	gain matrix
l	Hurwitz polynomial matrix
L	length of reactor, m
L	Lyapunov function
P	covariance vector
R	ideal gas constant, J/(mol. K)
$S, \hat{S}$	sliding surface of plant model and observer
s	sliding surface
sat	saturation function
T_s	sampling time
T	time, s
$T/\hat{T}$	temperature of plant/observer ,K

t	time, sec
T_d	setpoint temperature trajectory, K
T_i	temperature, K
T_0	initial temperature, K
$u_{eq}, \hat{u}_{eq}$	equivalent sliding mode control of plant model and observer
$\hat{u}_1, \hat{u}_2$	feedback and robust control term
U	overall heat transfer coefficient, W/(m^2.K)
$u(k)$	kth value of control input variable
u_{s1}	feedback control
u_{s2}	switching control
u_a	adaptive control
v_e	velocity of reactant, m/s
V	volume of reactor,m^3
v	velocity of reactant, m/s
v_o	void fraction
V	volume of reactor,m^3
w	weight vector
W	semi representation of temperature equation
x	state vector
X	data vector in compactness matrix form
y/y_m	plant/RBF model output
y	state variable

$y(k)$	k^{th} value of output variable
z	distance along the length of reactor, m

Greek Symbols

$\propto$	$\frac{k_{mix}}{\rho C_P}$
β	$\frac{\Delta H}{\rho C_P}$
γ	$\frac{A_s U}{V \rho C_P}$
λ	grouping parameter
A_n	Adomian polynomial
α	momentum rate
β	robustness parameter
ϵ	high gain parameter
ε	Chattering parameter
η	learning rate
λ	Hurwitz polynomial parameter
λ_1, λ_2	tuning parameter
ρ	density of solution
τ	$= V\rho C_P / UA_s$
γ	a parameter of Lyapunov function
θ	parameter vector of the reactor & adaptive parameter
λ	forgetting factor

Φ	data vector
φ	a parameter used for stability of sliding surface
η	Robust term
ε	boundary layer thickness

Chapter 1: Introduction and Literature Review

Chapter 1 : Introduction and Literature Review

1.1 Introduction

Fixed bed catalytic reactors have extensive utilization in chemical and allied industries. They are the heart of the Chemical Industries. The fixed bed reactors are used to carry out many heterogeneous reactions, in which reaction occurs on the surface and inside of the catalyst. Generally, in a chemical plant, the reactors are connected with other unit operations such as separation processes, distillation column, etc. Thus, the output of the downstream processes strictly depends on the products quality from the reactors; hence, proper operation of reactors in the plant plays a key role. The process simulation of the reactor constitutes itself the centerpiece of the computer-aided design. The primary rationales for this are: (a) the reactor design calculation is necessary for further simulation work; (b) to meet the economic and operation restrictions, it is necessary to adjust and update the process parameters continuously; (c) a large quantity of data is generated from the process, which is taken into consideration to update the process identification model.

A large number of processes in chemical engineering involves distributed parameter systems. Most often these processes are non-linear; tubular reactor carrying out homogeneous reaction is an example of a distributed parameter model. The nonlinearity is mostly attributed to the dependency of reaction kinetics on temperature and concentration. If the reaction kinetics is different from a simple first-order, the process becomes a non-linear system. The mathematical description of such a process consists of a set of non-linear partial differential equations. If the operating region of reactor is in the laminar flow regime, the radial distribution of velocities and concentrations must be considered. The analytical solution of distributed parameter problems is difficult to obtain without simplifying assumptions are made. However, with the rapid development in digital computation, numerical solutions are possible. Unfortunately, to get these solutions, a large amount of computational time is required.

Therefore, it is appealing to investigate for acquiring approximate solutions which, although too complicated for an analytical solution, can be solved numerically within a reasonable cost of computational time. Certainly, merely solving the theoretical equations has simply academicals use unless one can compare the solutions to real experimental data (Isaacson, 1968). The increasing use of advanced process control methods has demanded for better control of such processes. Thus, the acquisition of data from actual plant processes is of utmost importance. From a technical point of view, investigation of the transient behavior of such processes is necessary. An understanding of the transient response is necessary for designing good control algorithms. The study of transient behavior may, in general, give extra insight into the steady state behavior of such processes.

One important problem that encounter in a catalytic fixed-bed reactor is deactivation of catalyst. The active sites on the surface of the catalyst take part in reactions. The availability of active sites may be lost for a number of reasons like coking, poisoning or sintering. The reduction of available active sites results in a decreased catalyst activity, as the catalytic process is proportional to the number of existing active sites. Deactivation of catalyst can have a multiplicity of consequences. It can have harmful effects on the conversion and selectivity of the reaction. This will indirectly affect the productivity and energy efficiency of the used reactor. To balance the effect of catalyst deactivation, the process operating state of the reactor is gradually changed to maintain the selectivity and conversion, which is equivalent to maintain the quality and production rate. This is, in general, performed by estimation of optimal pathways for operating conditions with a dynamic optimization problem. The selected pathways are used as the set-point variables for the controllers. It, therefore, needs to design efficient controllers that are capable of tracking the pre-defined paths of the operating conditions.

Temperature is one of the main parameters which play a critical role to affect the reaction rate and selectivity. In controlling the temperature of a fixed-bed reactor, the critical issue is to make sure that the predefined temperature trajectory does not go beyond the maximum allowable temperature limit for the catalyst to handle. In addition to this, thermal instability of the reactor may be caused by catalyst deactivation. This problem may get more severe in an exothermic reaction system. Catalyst activity depends on the concentration and temperature of a reaction system which results in uneven catalyst activity in fixed-bed reactors. If odd temperature disturbances occur on the upstream side of the reactor, it leads to variation in catalyst activity and therefore, can result in a temperature that is much higher than those in beds of uniform operation (Jaree et al. 2001, Jaree et al. 2008). In general, a reasonable strategy for temperature control of the fixed-bed reactors is to control the temperature profile at different points along the length of the reactor which requires the accessibility of many thermocouples along the length of the reactor and an efficient controller.

In general, most of the industries almost exclusively employ simple control strategy which is based on linear control theory. One of the reasons for this is that there is a good experience together with mathematically concepts and methods to design a linear controller. In this current scenario the important fact is that stability margins are based on linear system theory while for nonlinear, it is governed by the Lyapunov theorem. For these approaches, the real plant's nonlinear dynamics to be controlled is linearized nearby steady state condition based on a model of the real plant. Then after, the control design is derived based on the linearized model. The so designed controller is capable of performing its job also for the nonlinear system if few conditions are fulfilled. From them, the two most dominant are that i.) the nonlinear plant has to be controlled around the steady condition where the linearization was done and that ii.) the identification and model order must be near enough to the real nonlinear plant. However, the classical linear control only guarantees that the designed controller fulfills its jobs for the linear and the nonlinear system when controlled nearby linearization operating point. Controllability of the plant for any deviation of the model from reality and the operating point may be regarded as robustness of the system. These reasonable restrictions are slightly relaxed by the theories of robust control, where perturbation between assumed and real dynamics could actively be specified in term of uncertainty.

It is a controller's job to keep the plant within prescribed constraints; the controller must satisfy the desired properties of both the mathematical model and the physical plant (e.g., adapting to the existing discrepancies between the proposed model and real model). There are in general two common techniques for designing controllers to deal with uncertainty, and variable parameters are robust control and adaptive control. The goal of robust control is to design a fixed (time-invariant) controller which takes care of both stability and acceptable performance, even in the presence of uncertainty. Adaptive control is another design method for controlling uncertain in plants. An adaptive controller consists of a tuning mechanism, which adjusts the compensator gains to match the plant. Because of the modification law, an adaptive controller is often nonlinear. Thus, even with presence of the first order adaptive control, linear plant leads to a nonlinear plant which is no longer enclosed by linear theories.

In light of the recent development of advanced process control technologies at the industrial level, implementation of model-based controllers has become much easy. The identification of robust model of the process under study plays a critical role for the successful implementation of model-based controllers.

In the broad field of adaptive control, Model Reference Adaptive Control (MRAC) and Gain Scheduling (GA) schemes gained significant attention, and the discussion on them can be found in many standard textbooks on control. However, these schemes compromise with robustness issue. With the progress of time that was made through during the last three decades, these approaches gained enormous attention from the control community. Literature has shown that in some cases adaptive control can be superior to robust control with large uncertainties or failures (Bierling, 2014) . In the light of reactor control, the approach of an adaptive control scheme has been used for the temperature control with uncertainties and nonlinearities and in unfavorable conditions (runaway, failure). In these cases, the considered system is under the influence of uncertainties, however, in the first case, uncertainties are frequently more significant, and adaptation might be slower. There is a requirement of fast adaptation rate with reconfiguration to deal with the uncertainties which otherwise may lead the system un-control.

Hence, extensive studies need to be performed to design controllers using fine models of the processes. The study of modeling and control of fixed-bed reactors has been challenging for numerous researchers since the early ’70s. The most initial fixed-bed reactor models were developed by approximation of a fixed-bed reactor by a sequential arrangement of a continuous flow stirred tank reactor. In this sequential approach to model the fixed bed reactor, a suitable number of well-mixed reactors in a series arrangement are considered. With the increase in the number of the reactors, the performance of the proposed model can be increased, but a very large number of interacting stirred tank reactors could be capable of duplicating the response of an accurate model of a real fixed-bed reactor. Theoretical models of a fixed-bed reactor can be acquired by solving simultaneously mass and energy balance equations of the reactor. To capture all of the real behavior (i.e., reactions, diffusion, and convection mainly), the developed model of a fixed-bed reactor consists of a set of parabolic partial differential equations. As per the nature of the governing transport mechanism in a chemical process, i.e., diffusion/ convection, the partial differential equations modeling the process may be a set of parabolic/hyperbolic equations (Bierling, 2014).The model in which the observed property is a function of time and space, .i.e. along the length of the reactor, similar to a fixed-bed reactor, is called as a distributed parameter model; as contrasting to lumped parameter model where the observed property variables are only dependent on time (e.g., a well-mixed reactor).

In general, the majority of control schemes have been proposed for lumped parameter model due to its ease. Therefore, the distributed parameter models are generally approximated as a lumped parameter model, and they are controlled using algorithms designed for lumped systems. In reality, there is major existence of a distribution parameter system in the chemical process and allied industries; it is better to implement control on these systems along with economic feasibility. The designed controllers that use the robust and good model of the system can have not only economic benefit but also a safety concern. This study is motivated to design a fine and robust controller for a distributed parameter model and its real-time implementation through low-cost data acquisition system.

The method of lines (MOL) is semi-analytical. It is a very well-known technique in computational. The applications of this method have increased more multifold in the past years. However, there is no introductory article which shows how to utilize it simply. Sadiku and Obiozor (2000) discussed the application of the MOL to solve Laplace's equation in rectangular and cylindrical coordinates system. Two easy numerical examples were solved to demonstrate the methodology. The obtained results were compared well with analytical solutions. In (Pamuk & Atac, 2013), the MOL was used to obtain the numerical solution of the developed model for tumor angiogenesis. The motive of the study was to know the roles of endothelial, pericyte and macrophage cells in the tumor angiogenesis. The proposed method is a way to get the numerical solution of partial differential equations that consist of time and space variables.

Shakeri and Dehghan (2008) investigated MOL scheme for dealing the one-dimensional hyperbolic equation with an integral condition. The proposed algorithms were tested with many problems. The simulation results confirmed the effectiveness reliability, and accurateness of the algorithms, MOL 1 and MOL 2 (second- and fourth-order finite differences, respectively). It demonstrated the improved accuracy of the higher-order (MOL 2) method along with very little computational effort. Adu et al. (2012) presented MOL approach to solve the Schrödinger's equation. This study described the effect of computational effort concerning accuracy and identified the relationship level between discretization size and the convergence property to get the numerical solution of 1-dimensional Schrödinger's equation. It was shown that by increasing the number of grids and maintaining the step size lead to the high accuracy of the result while decreasing the number of grid points and maintaining or reducing the step size only leads to less computing effort with less accuracy of the result. The study also revealed the fact that, even though there exists a closeness between numerical and analytical solution, the more the number of grids, the lesser the error difference between them and vice-versa. A. Campo and Lacoa (2014) presented a hybrid of an analytical and MOL for solving the traditional 1-D Stefan problem. The subsequent execution of MOL in a MATLAB platform with event location characteristic had confirmed to be efficient, accurate and economical. The results produced an oscillation-free hybrid solution, because the phase boundary was treated as a line rather than a control volume. Knapp (2008) showed the flexibility of the symbolic approach taken for discretization using Mathematica software for solving evolutionary PDEs within NDSolve. The developed solver for a specific equation does better job on that equation but NDSolve does a good enough job in general for those who are not comfortable to handle in the details of solving differential equations to get a solution. In (Neild, Yang, & Wagg, 2008), MRAC is applied to nominally first-order systems. This study identified two main problems. The first one was noise-induced gain wind-up and the second was instability due to higher-order un-modelled dynamics. It showed analytically that gain wind-up occurred due to the integral term in the adaptive scheme. In contrast, instability occurred due to higher-order un-modelled dynamics. To overcome against these demerits, a modified MRAC strategy proposed and tested. Mechee et al.(2014)

proposed a method to solve numerically third-order PDEs. They classified three types of third-order PDEs as Type I, II, and III. They developed a new numerical scheme for solving third-order PDEs of type I. The PDE of type I transformed into a system of third-order ODEs by using traditional method of lines (MOL). The system of ODEs was then solved by using Runge–Kutta method for special third-order ODEs, which derived to solve particular third-order ODEs. The suggested direct method required less computational work with reasonable accuracy. Various examples of third-order PDEs demonstrated the usefulness of the proposed method. Also, the new method provided good results in comparison to the very well-known finite difference method.

Heydweller et al. (1976) proposed the biased differencing scheme that could be used with an ordinary differential equation integrator to get a solution of hyperbolic partial differential equations by the Method of Lines (MOL). Numerical results showed that it could be applied on both linear and nonlinear equations which had good solutions. However, this scheme failed to deal with a set of equations which develops a shock discontinuity type solution without the adding up of dissipative terms.

DC motor speed control system was designed and implemented through Arduino Uno data acquisition board (Ghni, 2014). For this, Artificial Neural Network (ANN) controller and PID controller were designed and tested. The desired reference trajectory was set by using Model Reference. ANN was trained by Levenberg-Marquardt back propagation scheme. The speed of the DC motor was controlled by changing the duty cycle of the Pulse Width Modulation (PWM) signal through the gate of the mosfet irf 640. The results showed the effectiveness of the DC control system with ANNs in comparison with the conventional PID control scheme in MATLAB (Rai & Rai, 2013).

1.2 Sliding Mode Control

Controllers based on Lyapunov theory have received much attention recently due to their robustness and ability to control linear/nonlinear systems directly with tracking stability guaranteed. In general, the Sliding Mode Control (SMC) scheme uses Lyapunov's direct method to ensure asymptote tracking stability of state trajectories within the phase plane in the presence of modeling uncertainties and can be applied to nonlinear system models directly. However, to apply on the system, a mathematical model must be developed first that can be either linear or nonlinear, and from that model, it is to derive the form of the sliding mode controller. If an SMC law can be developed that does not rely on a system model but is solely based on measurements the application of the control law which can be generalized encompassing all system types (Pierri, 2006). In (Rezoug, Tondu, Hamerlain, & Tadjine, 2016), a robust scheme called Radial Based Function Neural Network Nonsingular Terminal Sliding Super Twisting Controller (NNSTW) was proposed for controlling n-DOF RM. The authors used NTSMC with time delay estimation method to design the equivalent control without the model knowledge. They proposed RBFNNs based on STW algorithm to eliminate the chattering phenomenon and to get better control performance. The feasibility and effectiveness of the suggested scheme were proven through simulation experiments. The proposed NNSTW scheme showed better performance compared with the STW. The control can be acquired without the robot model knowledge with improved performances and robustness. Ji and Dabin (2010) presented a Fast Terminal Sliding Mode Control Method (FTSM) for a submarine course control system having hard nonlinearity, time variation, and strong coupling characteristics. In general, traditional linear control schemes cannot achieve the preferred performance; therefore, many nonlinear ways were used to control it. In comparison to the conventional sliding mode control scheme, the FTSM has many characteristics such as finite time convergence, smaller error, faster convergence rate, and good robustness. The finite time convergence of the FTSM submarine course control method was assured using the Lyapunov theory. In order to obtain the differential signals, the tracking differentiator was used. The authors numerically studied the proposed control method and verified its effectiveness. Yu et al. (2013) presented the adaptive integral sliding mode control scheme with an average dwell-time technique for a class of uncertain switched non-linear systems. It is known that the closed-loop system is asymptotically stable using Lyapunov theory and the sliding surface of the control system was obtained. Simulation investigation showed that the proposed control method had excellent performance and had demonstrated the robustness with respect to model uncertainties and external disturbance. The authors suggested that it can be easily implemented to a real system. In (Y. B. Shtessel & Lee, 1996) , a chattering phenomenon as a low-frequency fluctuation in systems with sliding modes was analyzed and described via functions technique. The authors proposed a sliding surface to offer the passivity condition to the open loop dynamics of a modeled system. They showed that first-order stable lag un-modeled dynamics did not imply chattering in a real sliding mode. Sliding Mode Controllers' design algorithm was proposed to avoid chattering of high order stable lag un-modeled dynamics. They recommended that chattering analysis in nonlinear systems with various assumptions in mathematical modeling and control realization can be addressed in future research. Young et al.(1999) presented the systematical examination of SMC designs for the continuous-time domain. Design of the SMC is paying attention on guaranteeing the robustness of sliding mode in the presence of real constraints such as limited bandwidth of actuators, finite switching frequency. However, in the practical situation, the application of the Discrete Sliding Mode (DSM) is more appropriate, and reconfiguration of the SMC design in a framework of sampled data system are a good approximation, and constructive steps in sliding mode control research. This directly takes care of the microprocessor implementation problem. The research in this way is more responsive to the concerns of practicing control engineers who are dealt with advanced control methods and having a fear of the reported implementation difficulties. However, as compared with the ideal continuous-time sliding mode, the authors suggested the realistic restrictions of DSM control designs in rejecting disturbances, and in its capability to withstand parameter variations. The job of the researchers in the coming years will be to experiment with these SMC design approaches in their professional practice. In (Feng, Ma, Wen, & Wang, 2008) , the model uncertainties and external disturbance were assumed at the same time and to deal with such practical aspect; a robust sliding mode controller was presented using the Lyapunov direct method along with dissipative theory by which it was certain that the L_2 gain from disturbance to tracking error was below than the given index γ. To eliminate the significant demerit that is chattering phenomenon of the traditional Sliding Mode Control (SMC), an RBF neural network with online adaptation laws was used to enhance the controller output for real application. Simulation results verified that the control method was valid. Chen and Peng (2006) presented a new, SMC scheme for the robust control of nonlinear uncertain chemical plant. The simultaneous presence of the non-minimum phase and input-delay make the system the most challenging. The main idea of the proposed approach was to get the advantages of the Statically Equivalent Output (SEOM), non-linear state predictor and a SMC strategy. To get rid of the unwanted effect of inverse response behavior and to eliminate the steady-state offset, a new algorithm was proposed such that the planned output can be statically the same to the actual output along with the minimum phase of the system despite the influence of the process uncertainties. Incorporation of the constructed statically equivalent output map as well as a time-advanced nonlinear predictor, a predictor-based SMC scheme was established to deal the difficult control problem consist of uncertain non-minimum phase and input-delay chemical processes. Assurance of the convergence characteristics of the proposed SMC control technique was guaranteed by the Lyapunov theorem. To test the effectiveness of the proposed control scheme, the authors applied it to the regulation control of a Van de Vusse reactor in the presence of input-delay, non-minimum phase behavior, and multidirectional uncertainties such as un-modeled side reaction, error in measurement e, variations of parameter, dynamic uncertainties, and extra unmeasured disturbances. They investigated the potential use of a sliding observer along with the proposed scheme. Simulation results revealed that the proposed sliding mode control scheme was a not just robust but powerful approach too. It was used in regulation control of chemical processes in the presence of simultaneously the input-delay, inverse response, and, process uncertainties. They claimed that the SMC control system design methodology presented gave rise to a non-linear model-based controller, but the design specifications were local, around a given steady state operating condition. However, they reported that the stability issue concerning the whole sliding mode control system with a non-linear sliding observer is beyond the scope of the present study. In (Amini, Shahbakhti, & Pan, 2018) , along with an adaptation mechanism , a novel formulation of an adaptive second-order DSMC for MIMO nonlinear uncertain systems, and a new switching control input, was proposed. The first step for managing the uncertainties within the model, the adaptation law, was driven based on a discrete Lyapunov stability theorem. The second step was to study the behavior of the second-order DSMC for both reaching and sliding phases. To make certain the controller robustness with respect to external ADC limitation, a new switching control input was considered, which contains the information of ADC indistinctness via an online sampling and propagation mechanism and quantization uncertainties prediction. The third step was to ensure the asymptotic stability of the proposed controller by implication of the new Invariance Principal (IP) for nonlinear discontinuous systems. The designed controller was tested for a strongly nonlinear combustion engine tracking control problem. The proposed second-order adaptive MIMO/SISO DSMC was real checked on an actual ECU inside a PIL setup. In (Eom &

Chwa, 2016), a chattering free Adaptive Integral Sliding Mode Control (AISMC) was proposed for a nuclear research reactor system to tackle the system uncertainties and input changes. The proposed control method was ensured finite time stability and also reduced the chattering phenomenon. Based upon a dead zone technique, uncertainty in the upper bound unknown system can be estimated. The authors claimed that the proposed AISMC could compensate for a feedback term considerably upsetting the reactor system in the form of input deviation, which was not possible in the case of Integral Sliding Mode Control (ISMC). Simulation investigation revealed the effectiveness of the proposed controller as compared to the ISMC method for a nuclear research reactor system. In (Y. Wang, Feng, Yu, & Zhangl, 2003) , a Terminal Sliding Mode (TSM) control method for the MIMO linear systems with unmatched uncertainties was presented. There are two types of parameters uncertainties existing in systems: matched and unmatched uncertainties. Numerous control methods have been proposed to reduce the effect of the uncertainties. But in general, the real-time uncertainties is challenging to satisfy the matched condition, in that case, the system control is a challenging task to the researchers. The authors designed a special TSM manifold and control method not only to assure the system states to arrive at the TSM manifold within a finite time but also converge to the vicinity of the equilibrium point in a finite time. Simulations were done to evaluate the effectiveness of the proposed method. Camacho et al. (2007) proposed a way to design an SMC of an inverse response system. To separate the inverse response systems into two components, an internal model structure was used and then from the invertible part of the model; the controller equation was derived. A PI-type sliding surface was considered for designing SMC. This study showed the effectiveness of the mixing of the two different approaches, an internal model approach and sliding mode control concept, for processes with the inverse response. The proposed control scheme was simulated and its performance was compared against the published literature. Simulation results showed that the proposed approach performed better against the old approach. Kumar et al.(2009) presented a control scheme for Induction Servo Motor (ISM) to control the position for a given reference input signal in a very efficient way. The authors compared the two control schemes, total SMC and Adaptive SMC, using MATLAB/Simulink. Total SMC system is not sensitive to uncertainties, parameter variations and external disturbances in the control process. Adaptive SMC system adjusts the bound of uncertainties in real time and also reduces the chattering phenomena in the control effort using a simple adaptive algorithm. The simulation results showed the effectiveness of the control schemes for ISM. In (Palazoglu, 1995) , SMC scheme was applied to distributed parameter chemical processes which are modeled by a set of nonlinear partial differential equations. The method of characteristics is used to transform the distributed parameter model system into a finite set of ordinary differential equations. Geometric methods were then used to extend sliding mode concepts for application to a class of partial differential equations. The combination of the method of characteristics along with SMC was shown to be an efficient tactic to design controllers for a type of nonlinear systems described by first-order partial differential equations. Simulations investigation revealed that the SMC technique was effective in controlling typical chemical process units. Davies and Spurgeon (2007) presented the selection of smoothing parameter required for real-time implementation of Sliding Mode Control (SMC) strategies. Earlier work published in this domain which considers the consequence of the smoothing parameter upon the simple system used for the control design was presented. The authors extended to study the potential effects of the smoothing parameter upon the sliding mode behavior of an uncertain system. It had shown that for the matched uncertainty, the smaller value of the smoothing parameter was good against the system perturbations which can be tolerated. It was to be predictable as ideal sliding mode control systems which are inherently insensitive to matched uncertainty. But as the smoothing parameter moves to zero, the system performance leads towards ideal sliding. However, it was shown that for unmatched uncertainty, it might not be the situation. By merely selecting a small positive value of smoothing constant, robust stability of the sliding motion cannot be attained as has previously been described. It confirmed that a structured singular value analysis could be used to examine and lay down the smoothing strategy required for a robust implementation of a sliding mode control scheme. Morales et al. (2017) presented a Sliding-Mode Control (SMC) to a compact system model using a PID-type sliding surface. The controller was implemented to a Ball and Plate system which was highly non-linear characteristics and therefore did not have a unique solution regarding ball stabilization control. The results were obtained by numerical simulations and with real-time experiments. Comparative performance analysis was made between the proposed scheme and a PID controller for stabilization of the ball at fixed point's position of the plate. The results obtained from simulation were matched to those obtained experimentally, which demonstrated that the performance of the SMC method was better than PID because it allows to stabilize the ball in a small time with reduction in overshot. The methodology proposed in this work allowed to design controller based on Sliding-Mode with a PID-type sliding surface and the controller presented good results. However, to develop this controller, it was crucial to know the true mathematical model of the plant. A novel Terminal Sliding Mode control (TSMC) of MIMO linear systems was proposed in (Zhihong & Yu, 1997) . The authors were shown that, by incorporating a nonlinear part of the system state in the MIMO linear sliding mode, a new terminal sliding mode was design for MIMO linear systems. A TSMC was designed to enforce the system state variables to reach and remained in the terminal sliding mode. With the help of suitably developed parameter matrices of the TMS, the system state variables acquire the system origin in finite time. Finally, the closed-loop system is infinite stable in the TMS. A simulation example was investigated in support of the proposed control scheme. Rojas et al. (2004) presented a SMC for controlling open-loop unstable systems which was based on a first-order-plus-dead-time model of the process. The design of the proposed fixed structure controller was simple. To obtain the desired performance, a set of tuning equations was obtained. Linear and nonlinear mathematical models were used to investigate the controller performance through numerical simulations. Sree et al. (2004) proposed a simple scheme for PI/PID controller tuning for stable FOPTD and unstable FOPTD systems. The proposed method was a simple set of equations for the controller settings and was robust with respect to uncertainty in the model parameters. It was shown that the proposed method for stable systems gave the good performance when compared to the literature.

Sivaramakrishnan et al.(2008) extended the delay-time constant ratio (e) up to 1.8 in comparison to proposed by Rojas et al.(2004) for the design of sliding mode controllers (SMC) to deal with unstable first order plus time delay systems. The SMC tunings were obtained for various e in terms of fitted equations. It was found that up to e = 1.2, the method was additional robust than that of most recent PID Controller proposed by Sree et al.(2004).There was no method mentioned in the literature to deal with unstable systems using PID controller for e > 1.2. Simulation results were also specified for a nonlinear bioreactor control problem. Rojas et al.(2004) presented the synthesis of a sliding mode controller SMC for a second-order linear model with an integral-differential surface. Unlike from similar strategies, the tuning parameters were kept in a near relationship with the dynamics of system regarding conventional specifications of transient response. The proposed controller needed merely the output feedback of system. It could be used satisfactorily in controlling of single input-single output nonlinear electric systems such as electronic power converters with pulse width modulation. The designed SMC controller performed well, based on an integral-differential surface of the tracking-error, when the reference and load step changes were introduced. It showed zero steady-state error and had no chattering.

1.3 Identification

Zhou et al. (2006) proposed a novel method developed using the Recursive Extended Least Squares (RELS) technique regarding the computation and operated in such a manner that the system model's parameters were updated under the condition when numerous proper new groups of data were obtained. The numerical simulation and online direct closed-loop system identification of the system indicated that, by selecting the updated step, this method was able to successfully reduce the identifying cost time while getting satisfactory estimation accuracy. The identification method for the estimation of the electrical and mechanical parameters of the DC motor using online least square was presented in (Gaiceanu, Solea, Codres, & Eni, 2014) . The parameters of the DC machine are time-dependent; therefore, for the DC drive control, the online parameters identification procedure is mandatory. By knowing the DC motor parameters accurately, the parameters of the DC speed and a current cascade controller was obtained. Sivaram et al.(2013) discussed the identification of the process parameter using Recursive Least Square algorithm (RLS) and control of a Counter Flow Shell and Tube Heat Exchanger (CFSHE) with Self Turning Controller (STC). The authors had modeled the process with the help of experimental data using RLS Algorithm. After that, an STC scheme which comes under adaptive controller was used to control the process. The outlet temperature of the tube was regulated with the flow of cold fluid through the shell side. The conventional scheme was used to tune a PID controller, and the performance was compared with STC in MATLAB. To overcome the difficulties of implementation for a controller to the practical process, the training of a user-friendly simulator language is the most. Zulkeflee et al. (2013) proposed the Simulink model based Graphical User Interface (GUI) for signal visualization and parameter tuning for real-time implementations. The integration between MATLAB Simulink external mode and Real-Time Windows target software (MATLAB-Simulink-Real-Time-Windows Target) can be acquired. The utilization of developed GUI was confirmed through the real-time execution of the PID controller to control the reaction temperature in a batch process. From the achieved results, the authors concluded that the proposed embedded design architecture could deliver the desired outcome. In (Muga, Tzoneva, Krishnamurthy, & Campus, 2016), dynamic decoupling control design scheme was discussed for the MIMO Continuous Stirred Tank Reactor (CSTR). This system consists of unstable dynamics, nonlinearities and loop interaction. Simulations study of the behavior of the closed loop decoupled system was performed in MATLAB/Simulink. Software transformation technique was design to build a real-time module in MATLAB/Simulink environment software and to transfer data from it to the real-time environment of TwinCAT 3.1 software of the Beckhoff PLC was used. The simulation results in Simulink and TwinCAT 3.1 software platforms showed the suitability and the potentials of the method for design of the decoupling controller and of merging the MATLAB/Simulink control function blocks into the TwinCAT 3.1 function blocks in real-time. The merits derived from such integration implied that the existing software and its components could be re-used. System identification consists of parameter and non-parameter identification. Identification is used to find a mathematical model based on the input and output observation of the system. Zhang et al. (2012) discussed the system identification theory and developed a second-order vibration system model. With the help of identified discrete transfer function, the system difference equation was obtained to identify the system with two different schemes, RLS and RELS. To test the performance, a comparative analysis was carried out for the vehicle model. The results showed that the RELS method was more accurate and had a fast convergence rate than the RLS method. It provides the basis to find the algorithm for control system, its ‘simulation and making control scheme. Good control of biodiesel reactors consists of some challenges. These problems are generated from the occurrence of multiple chemical reactions, the difficult heat and mass transfer individuality, and the highly nonlinear dynamics. Kuen et al. (2010) proposed a new adaptive control scheme with its implementation to tune the controller automatically using the recently efficient process dynamics. The suggested scheme demonstrated the powerful addition of an online process modeling tool (RLS) into a well-known but simple model-based controller design scheme (Internal Model Control, IMC). Two different adaptive control schemes were developed, in which genetic algorithm was used to implement under constrained optimization environment for the sampling time of the RLS algorithm and for the time constant of IMC closed-loop. In comparison to conventional PID controllers, the proposed adaptive control scheme revealed the superiority in case of set-point tracking. Fine disturbance rejection characteristics were also confirmed with the help of new adaptive control scheme. The results obtained in this work demonstrated that a good adaptive control scheme can be utilized for the biodiesel trans-esterification reaction having minimal information regarding the process model.

In the above section, various latest identification schemes have been discussed but during selection of the identification techniques, its real-time implementation and computational load aspect have been kept in mind. In general, the simpler the better approach has been utilized.

1.4 Arduino as a Data Acquisition Board

To learn control theory by doing practical simulation becomes quite interesting for students as well as for professional. Uyanik and Catalbas (2018) presented inexpensive experiments setup for laboratory sessions of a feedback control systems course. It consists of introduction of modeling based negative feedback control systems, Proportional-integral-derivative (PID) controller design, root locus, and Bode plots. Many sets of experiments were planned using the Arduino-based identification and control of a DC motor via MATLAB/ Simulink. The authors explained laboratory session to teach feedback control systems with the help of experimental investigations on a low-priced laboratory kit. They designed in-house setups support for Arduino–Simulink interface by which students can implement their control algorithm in Simulink to the Arduino board directly. Such type of interface not only help to understand but also teach them how to utilize high-level control design tools, like MATLAB/Simulink while working on a low-priced hardware laboratory setup. The students' performance was reported in the written exams before and after the laboratory setup so that the effectiveness of the instructional could be judged. Other than that, student feedback of four semesters was also presented to evaluate the usefulness of the laboratory experiments.

Roell et al.(2015) used the Electromyography (EMG) technique to record the electrical activity of skeletal muscles. With the help of EMG, many signals can be obtained from the body, evaluated by signal processing, and then utilized in various applications. Noninvasive EMG methods have been used to control some of the world's most advanced prosthetic devices, besides, to help in the field of robotic rehabilitation. The authors proposed a low-cost method for controlling an individual finger movement of a robotic hand through the use of surface EMG (sEMG) signal acquisition from the human forearm. EMG signals were extracted from five muscles of the forearm via surface electrodes. These signals were then amplified up to 4V DC, filtered using a second-order bandpass filter of 20-1000 Hz, and rectified through a designed analog integrated circuit. Then the signals were converted to the digital form with the use of 10-bit Analog-to-digital converter (ADC) within the Arduino microcontroller board. The obtained signals in Simulink model were used Fast Fourier Transform (FFT), Root Mean Square (RMS), and Thresholding Techniques (TT) to determine changes in the signal to generate Pulse Width Modulation (PWM) for the five Futaba®S3114 micro servos of the Mecha TE™ Hand. They concluded that a method of using sEMG signal acquisition for robotic hand control in real time was attained. Krivić et al.(2012) discussed one of the often encountered practices in the chemical process industry - water level control. Proportional Integral Derivative (PID) control scheme is commonly used for the said purpose. It is known that control parameters of PID controller have a fixed structure and real tank system has naturally nonlinear property, near boundary level range, PID controller should not be used. Therefore, the authors analyzed the usefulness of water level control using a fuzzy controller. The fuzzy controller was implemented using a mathematical model of the tank in MATLAB. The controller was implemented on ARM. Arduino board was used as a data acquisition board for collecting sensor data from the tank system. Experimental results verified that the fuzzy control system was good adaptability in comparison with PID. Often, chemical processes need liquids to be pumped to the desired level. Kumara and Narayana (2015) developed a Proportional-Integral-Derivative (PID) controller to control the desired liquid level of a tank. Three conventional techniques of PID tuning that is the Ziegler-Nichols (ZN) method, and Good Gain (GG) method, and Trial & Error method were tested to obtain the PID controller parameters. A model was built in the Simulink, and the liquid level of a tank was controlled by using TI Delfino F28355 Experimental kit consisted a Digital Signal Processing (DSP) control board. Arduino UNO board was used for real-time data acquisition and was used to plot required graphs in LabVIEW. The performance of the system was evaluated regarding Rising Time (Tr), Settling Time (Ts), Steady State Error (SSE) and Overshoot (OS).

Nowadays, computer control has indulged in many fields of study. Binary system has a simple and clear understanding, and due to that, it can very quickly control the signals from devices. In (Hiticas, Marin, & Mihon, 2013) , the authors focused on the analysis of PWM technologies. Today, many engines are equipped with an electronic injection system. They made a connection between a few parameters which contributed to the increase of the engine performance. PWM was used as a standard technique deployed for controlling power to inertial electrical devices to get the benefits of the injection time control; the results regarding the engine management were excellent. They had taken into account a few process parameters such as pressure, battery voltage, lambda signals, fuel and air amount, etc., as well as their time evolution, with the help of the ECU control. MATLAB/Simulink software was used to control the reference speed, the throttle position, as well as other parameters with the help of the PWM, and data, was collected from the tests carried out on Dacia Logan 1.4 MPI (powered by Renault), and the evolution of the injection time. Recently, the use of a Swarm Robotic (SR) system has been increasing. It has many applications such as in defense system, material handling, agriculture and many more. Swarm robots consist of many analog and digital sensors. Sensors can be humidity, temperature, ultrasonic, IR sensors, Light Dependent Resistors (LDR), etc. SR transmits information to its neighbor SR as well as to the control room. For obtaining real-time data from SR, it is a primary requirement to know the condition of the environment in which SR work. In (Parikh, Shah, & Sheth, 2014) , the authors dealt with only real-time wireless multichannel data acquisition. Each SR was linked with Arduino UNO microcontroller and WIRDIN 1186 wireless module for transmitting the information to the control room. The technique of finding the root locus of the acquired signal was also described. Solar energy is used in a wide range of modern power plant because it is a vast source of clean energy. The maximum efficiency can be obtained by control the angle of the solar panel to be in 90 degrees with the sunlight. Ozerdem and Shahin (2014) got different results from the traditional method. The results discussed with consideration for the stability, response time, performance, costs, and error probability. They recommended that the Geographical Coordinate System (GCS) is the best system from the technical approach. Wind tunnels are an essential experimental tool for the investigation of airflow parameters in numerous areas. Agricultural research has been much effected by it, but still there is need of few more contributions for the development of automatic control systems for wind tunnels. Espinoza et al. (2015) proposed an electronic control system that provided precision and speed measurement. They did the experiment and collect efficient data processing methodology for low-speed wind in tunnel specially to deal with greenhouse gases. The optimum PI controller parameters was estimated using identification model based on the proposed algorithm. The validation of the system was carried out on a cellulose evaporative cooling pad and on insect-proof screens to review its response to perturbations. Berahim et al. (2015) presented the simulation and hardware investigation to control voltage for DC motor with the help of PID Controller. This analysis was performed for open loop and closed loop systems. With the simulation for both open loop and closed loops, it was found that the actual voltage was nearby to a reference voltage and had a minimum error. To test the controller performance, the comparison was carried out between measured voltage (output voltage) and the reference voltage (target voltage). Results investigation suggested that the error in the closed loop was lower than the open loop. In the hardware implementation, the output voltage was closed to the target or reference value. This output DC voltage was lower than the target value, but the controller tried to follow the reference signal. The error was due to the different switching speed in Arduino and power Metal-oxide-semi-conductor-filed-effect (MOSFET). The waveform pattern of this DC output was not pure but had slightly rippled. The authors implemented the PID controller successfully to control the output voltage of the DC motor and performance results were good in term of reducing the error. They concluded that the PID control system was quite robust and practical in implementation.

The above section shows that the low-cost data acquisition board such as Arduino can be used to capture the real control data in MATLAB. The ADC and DAC are sufficient to deal practical aspect at industry level.

1.5 Adaptive Control of Distributed Parameter System

In general, mostly the physical systems existing in chemical industries are represented by distributed parameter models. A lumped parameter model is generally considered for a complex system, and the performance may be satisfactory. However, it sacrifices sometimes the actual behavior and is not adequate while designing a feedback controller for broad operating range conditions. In these conditions, one has to take the spatial distribution into consideration and analyze the dynamics of system with Partial Differential Equations (PDEs).

Farsi et al.(2011) showed a comparison study between simulation and industrial data for the dehydration of methanol under steady and unsteady state conditions. The one-dimensional heterogeneous mathematical model was considered. The suggested model was able to predict the reactor outlet temperature and concentrations within the permissible limit of error. Wen and Ding (2006) discussed the heat transfer behavior of a gas flowing through a packed bed under transient and steady-state. The experimental results revealed a high-temperature drop near the wall region, and it was also found that the temperature drop depended on the entrance distance. The 2DADPF model was successfully able to describe well the axial temperature distribution, but the prediction of radial temperature distribution was not satisfactory. In (Dente, Pierucci, Tronconi, Cecchini, & Ghelfi, 2003), the total kinetics for conversion of n-butane to maleic anhydride over the surface of a V-P-O catalyst studied for more than hundred test runs. The mathematical model of the fluidized-bed reactor was validated with experimental data. Boubaker and Babary (2003) studied SISO and MIMO control variable structure of non-linear and time-varying distributed parameter systems. A fixed bed biological reactor was used to purify drinkable water. The control of biofilter was done at the reactor outlet by adding suitable dose of carbon-containing material. There were many parameters which imparted the non-linearity and the varying time behavior which were responsible for making the complex problem. The contribution of this study was in the development of a theoretical proof for distributed parameter systems convergence. Ayachi et al. (2012) discussed adaptive and robust-adaptive control schemes for a fixed bed bioprocess system. The proposed control technique had a few un-measurable process states which were calculated based on the known measurements with suitable state estimators. The new robust-adaptive control scheme developed with the practical assumptions that the bacterial growth rate was time-varying and unknown along with the unknown influent substrate concentration. The results agreed with the adaptive controller.

Chen et al. (2002) presented a Model Predictive Control (MPC) for a fixed-bed reactor with an exothermic reaction. The scheme had used nonlinear inferential control to predict the concentration of product with linear-multivariable control of bed. The performance of the proposed technique evaluated under various operating conditions. In (Yasari et al., 2010) , a catalytic shell and tube fixed-bed reactor was used for the production of Di-methyl Ether (DME) which is highly exothermic in nature for the production of DME. This type of reactor may be able to provide strictly temperature control and heat removal from the reactor. They proposed two control loops for level and pressure system along with an optimizer that took into account the feed variations. The numerical simulation results indicated that the control system including the optimizer kept the production rate at the maximum value within prescribed the temperature limit. W.Arnold III and Sundaresan (1989) proposed that under a non-isothermal condition, the oxide catalyst was a source of oxygen storage and its liberation during oxidation reaction. They experimentally investigated the dynamics of packed bed reactor in light of storage of oxygen for the oxidation of 2-butene over the vanadium oxide. They found that the overshoot in reaction rate was responsible for overshoot in temperature. In (Uraz & ATALAY, 2012), the performance comparison of fluidized-bed and fixed-bed reactors was carried out for oxidation of benzene to Maleic Anhydride (MAN) with silica gel supported vanadium pent-oxide catalyst. The effect of various operating parameters such as temperature, space-time, and air-to-benzene molar ratio on the reaction selectivity was studied under similar operating conditions. They found that the conversion of benzene to MAN increased with increasing temperature in both reactors. Aksikas et al.(2013) developed an LQ-optimal controller of hyperbolic equations with two time scale. It was shown that an equivalent matrix Riccati partial differential equation could be used to deal with the optimal control problem. Numerical simulations were performed to evaluate the performance of the proposed controller under closed loop condition on a hydro-treating fixed-bed reactor. To evaluate the performance of the designed controller, a comparison was carried out with an infinite dimensional controller formulated.

In general, the first approach is to find the analytical solution of the problem. If the obtained solution is complex or closed form of the solution doesn't exist then we try to use numerical methods. In the last few decades, many efforts have been made to get the approximate analytical solution of nonlinear PDEs, which requires less computational load as compared to numerical method. Various methods to acquire the analytical solution of a system of PDEs have been proposed such as tanh-coth method (Wazwaz, 2007b, 2007a), Hirota bilinear method (Tam, Ma, Hu, & Wang, 2000; Wazwaz, 2008), Darboux transformation (Fan, 2000; Zhaqilao, Chen, & Li, 2009), Variational Iteration Method (VIM) (Abassy, 2012; Abassy, El-Tawil, & El-Zoheiry, 2007; Abassy, El-Tawil, & El Zoheiry, 2007; Berkani, Manseur, & Maidi, 2012; Geng, 2010), exp-function method (Abdelrahman & Khater, 2015; Applications, Misirli, & Usak, 2011; Fazliaghdaei & Manafianheris, 2012; He & Wu, 2006; Mahdavi, 2014; Manafianheris & Aghdaei, 2012; Noor, Mohyud-Din, Waheed, & Al-Said, 2010; Parand & Rad, 2012; Yomba, 2009; Zahra & Hussain, 2011), homogeneous balance method (Lei, Fajiang, & Yinghai, 2002) and the differential transform method (Finkel, 2010; Khan, Svoboda, & Šmarda, 2012; Moon, Bhosale, Gajbhiye, & Lonare, 2007). Adomian decomposition method (ADM) was used to deal effectively with a large number of problems such as linear/nonlinear, deterministic/stochastic, etc. (Achouri & Omrani, 2009; George Adomian, 1994; Kaya & El-Sayed, 2003). The main advantages of ADM include rapid convergence rate, straightforward method for both linear/nonlinear problems, avoidance of linearization and perturbation, efficiency to handle moving boundary condition, etc. Zayed (2014) applied the Modified Simple Equation Method (MSEM) to find the analytical closed form solutions of nonlinear equations. They studied two dissimilar models of nonlinear diffusion-reaction equations generally encountered in many practical situations. The applicability of the method for constructing the exact solutions was demonstrated. The obtained accurate solutions for these two nonlinear models were complex. The MSEM was able to find the accurate solutions of nonlinear evolution reaction-diffusion equations.

Hosseini and Jafari (2008) discussed nonsingular and singular third-order ordinary differential equation with standard ADM and modified ADM using Maple 8. The main advantage of the proposed technique is that it is more efficient than the standard ADM for higher-order system. Duan (2015) suggested a new algorithm for calculating Adomian polynomial and a new modified ADM for Boundary Value Problem (BVP), particularly the second-order nonlinear Ordinary Differential Equation (ODE). Modified Adomian polynomial technique doesn't require the differentiation operator to deal with nonlinear term as involved in estimation of standard Adomian polynomial. Pue-on.P and Viriyapong (2012) presented a modified ADM for the third order ODE which can be applied to both singular and nonsingular problem. Qin and Sun (2014) used ADM to get approximate analytical solution for a shrinking core model for the release of a lithium-iron-phosphate electrode having moving boundary condition. This investigation showed that ADM is a well-organized method for solving moving boundary problems.

All the literature discussed in the adaptive control section describes the need of the adaptive control strategy in different areas of process control. This is a challenging method to implement on varying dynamics system.

1.6 Scope

Numerous problems in chemical engineering entail distributed parameter systems; i.e., the dependent variables of the system vary with time and spatial coordinates. Further such processes are often non-linear. The heterogeneous tubular chemical reactor is an example of a distributed parameter system. If the kinetic of reaction is not a first-order, it will be non-linear in nature. The mathematical model of such a process consists of non-linear partial differential equations. For the complex reaction of multiple species, each species of the reaction has to be described by a separate equation. In real practice, obtaining an analytical solution of a non-linear distributed parameter system is difficult and for simplification, many assumptions are needed to be considered. But, numerical solutions with the help of a digital computer are more common. However, unfortunately, such type of solutions requires a good amount of computational time. Therefore, it is significant to investigate semi-approximate solutions which can be solved numerically within a realistic amount of computational time and accuracy.

Due to the robustness, Sliding Mode Control (SMC) method is introduced with Artificial Neural Network (ANN). To illustrate the performance of the fixed bed reactor, a known nonlinear model is presented. The primary concern is how to reduce the inherent chattering characteristic of the SMC with ANN. The SMC method is based on Lyapunov Direct Method, which provides stability for nonlinear systems. To evaluate the performance of the proposed controller, a comparative analysis with conventional controller is considered.

The other objectives of this study are how to identify the real-time model with the simplest approach and to develop an adaptive control system which looks after the system under changing environment in real-time.

1.7 Research Objectives

This thesis deals with the problems of modeling, real-time identification and adaptive control for fixed bed reactors. The objectives of the thesis are:

i) To obtain a mathematical model of a fixed bed reactor in which a hydrolysis reaction takes place.
ii) To obtain Semi-analytical and numerical solution of the developed model.
iii) To use Radial Basis Function Neural Network (RBFNN) to develop Adaptive Sliding Mode Control (ASMC) for the fixed bed reactor.
iv) To compare ASMC with conventional control system
v) To implement a method to get real-time identification of the fixed bed reactor and implement Adaptive Sliding Mode Control (ASMC) in MATLAB.

1.8 Thesis Outlines

A controller design technique should be simple in development and it requires a less computational load for implementation purpose. The first part of this thesis presents a semi-analytic technique to solve nonlinear parabolic type partial differential equations and its validation by a well-established numerical method that is called a method of lines (MOL). The semi-analytical used in the study is adomian decomposition method (ADM). This shows that how the traditional analytical method can be replaced by ADM. There are in general two approaches to deal with nonlinear systems. The first one is Approximation-then-design (ATD) and the second one is

Design-then-approximation (DTA). The work in this thesis consists of both the approaches to design control system for temperature control of the fixed bed reactor.

In real control practices, the exact values of the system parameters are hardly known. These parameters define the characteristic property of the systems. Few examples of the parameters are such as Diffusion coefficient, a coefficient of viscosity in fluid flow applications, and mass transfer coefficient in convective flow problems. The values of the unavailable states have been predicted by radial basis function in a neural network system. Implementation of any controller, as designed using the inaccurate value of the parameters, may lead to the system's instability. A high gain-based observer control scheme has been developed, and its comparison has been carried out with the most commonly used PID controller in the second part of the dissertation that addresses the issue of parameter uncertainty.

The third part of the thesis explains the real-time implementation of an adaptive control scheme based on approximate-then-design philosophy for a fixed bed reactor. A reduced first order discrete transfer function model is identified by following its transformation in the continuous domain to design the proposed controller. An adaptive controller has been designed based on the reduced order model. A simple adaptive architecture has been used for the controller synthesis.

In the last part, the dissertation summarizes conclusions on the work carried out and recommendations for future work.

1.9 Thesis Organization

This dissertation consists of five chapters. Chapter 1 introduces the facts and role of distributed parameter systems and their applications in the chemical industries. Literature survey presents a glimpse of design techniques in various problem domains.

Chapter 2 presents a semi-analytical technique to solve the system of partial differential equation and demonstrate its performance in comparison to numerical method of lines (MOL). The primary emphasis of this chapter is to utilize some new analytical scheme in computational simulation.

Chapter 3 discusses the control design technique for nonlinear distributed parameter systems with parameter uncertainty based on neural network architecture is described for nonlinear systems. A stepwise procedure of controller formulation has been described. The applicability of advanced control is demonstrated for a fixed bed reactor system.

Chapter 4 introduces the Approximation-then-Design (ATD) approach to deal with the real-time system. The section consists of a separate simple adaptive control scheme to control the temperature of the fixed bed reactor as described in chapter 3. The adaptive controller development is discussed along with its real-time implementation. The developed controller is demonstrated for real-time temperature control of the fixed bed reactor. The section of chapter 4 describes the development of reduced order models identification of the control system. The Recursive Least Square (RLS) with forgetting factor has been employed for online identification of the reactor. A step-wise procedure has been discussed to obtain reduced order First Order Plus Delay Transfer (FOPDT) function model and adaptive control formulation has been implemented.

Chapter 5 consists of conclusion of the whole study and recommendation for future scope.

Chapter 2: Semi-analytical Approximate Solution for a Fixed Bed Reactor Model using Multistage Adomian Decomposition Method (MADM)

Chapter 2 : Semi-analytical Approximate Solution for a Fixed Bed Reactor Model using Multistage Adomian Decomposition Method (MADM)

2.1 Introduction

Mathematical models of many chemical processes are nonlinear transient distributed parameter systems, which involve variables as a function of time and space. One of these processes used in chemical synthesis is a fixed bed reactor. Partial differential equations (PDEs) are generally used for describing the behavior of this kind of models. Many numerical techniques such as finite difference, finite element, and orthogonal collocation are applied to solve such mathematical models. For the design of a controller, linearization of the nonlinear term is generally carried out so that a linear state space form can be obtained. The application of finite difference scheme to analyze transient behavior of the fixed bed reactor is simple, reliable and easy in implementation although it requires heavy computational load to get the solution with desirable accuracy.

In the last few decades, many efforts have been made to get the approximate analytical solution of nonlinear PDEs, which requires less computational load as compared to numerical method. Various methods to acquire the analytical solution of a system of PDEs have been proposed such as tanh-coth method (Wazwaz, 2007b, 2007a), Hirota bilinear method (Tam et al., 2000; Wazwaz, 2008), Darboux transformation (Fan, 2000; Zhaqilao et al., 2009), variational iteration method (VIM) (Abassy, 2012; Abassy, El-Tawil, & El-Zoheiry, 2007; Abassy, El-Tawil, & El Zoheiry, 2007; Berkani et al., 2012; Geng, 2010), exp-function method (Abdelrahman & Khater, 2015; Applications et al., 2011; Fazliaghdaei & Manafianheris, 2012; He & Wu, 2006; Mahdavi, 2014; Manafianheris & Aghdaei, 2012; Noor et al., 2010; Parand & Rad, 2012; Yomba, 2009; Zahra & Hussain, 2011), homogeneous balance method (Lei et al., 2002) and the differential transform method (Finkel, 2010; Khan et al., 2012; Moon et al., 2007). Adomian Decomposition Method (ADM) was used to deal effectively with a large number of problems such as linear/nonlinear, deterministic/stochastic, etc. (Achouri & Omrani, 2009; George Adomian, 1994; Kaya & El-Sayed, 2003). The main advantages of ADM include rapid convergence rate, straight forward method for both linear/nonlinear problems, avoidance of linearization and perturbation, efficiency to handle moving boundary condition, etc. Dehghan and Salehi (2011) applied Variational Iteration Method (VIM) and Adomian decomposition method (ADM) to obtain approximate solution of Eikonal equation. VIM requires estimation of Lagrange multiplier whereas ADM requires estimation of polynomial. Smarda (2010) modified ADM to investigate singular initial value problems, which allows obtaining analytical solution for specific classes of singular initial value problems. Qin and Sun. (2011) solved a steady state model of a tubular packed bed catalytic reactor in two dimensions, viz. radial and axial direction using ADM for incompatible boundary conditions. Rach et al. (2013) proposed a new modification for ADM to compute the solution's Taylor series expansion. The effectiveness of the proposed algorithm was demonstrated for the higher order inhomogeneous nonlinear initial value problems. Hosseini and Jafari (2008) discussed nonsingular and singular third-order ordinary differential equation with standard ADM and modified ADM using Maple 8. The main advantage of the proposed technique is that it is more efficient than the standard ADM for higher-order system. Duan (2015) suggested a new algorithm for calculating Adomian polynomial and a new modified ADM for boundary value problem (BVP), particularly the second-order nonlinear ordinary differential equation (ODE). Modified Adomian polynomial technique doesn't require the differentiation operator to deal with nonlinear term as involved in estimation of standard Adomian polynomial. Pue-on.P and Viriyapong (2012) presented a modified ADM for the third order ODE which can be applied to both singular and nonsingular problem. Qin and Sun (2014) used ADM to get approximate analytical solution for a shrinking core model for the release of a lithium-iron-phosphate electrode having moving boundary condition. This investigation shows that ADM is a well-organized method to deal with moving boundary problems.

Qin and Sun (2009) used a two dimensions mathematical model of a packed bed electrode with non-standard boundary conditions using symbolic computation in MATLAB. Al-Sawoor and Al-amr (2012) investigated a fast reversible reaction-diffusion system by using ADM and VIM. The comparative analysis shows that both methods are efficient but VIM requires less calculation efforts with respect to Adomian polynomial. Ganji et al.(2007) implemented the VIM to find the approximate analytical solution of generalized Hirota-Satsuma coupled KdV equation, Kawahara and FkdV equation and compared its results with ADM. El-Wakil et al. (2006) used ADM for three different types of the diffusion-convection-reaction equations such as Black-Scholes equation, in financial market option pricing and Fokker-Plank equation and the results were verified with VIM. Yassien (2014) solved a seventh order integro-differential equation by modified ADM. The merit of the proposed method is that it can be applied without transformation of boundary conditions. Rabie and Elzaki (2014) investigated a system of nonlinear partial differential equation (PDE) using ADM and modified ADM. The modified ADM uses infinite series for the linear unknown function. Lin (2014) solved a double singular boundary value problem of second order by a modified ADM which differs from traditional ADM with respect to integrating factor. More reliable and efficient results were obtained by the proposed method. Ramana and Raghu Prasad (2014) modified ADM to solve the parabolic equation. The modified ADM offers a good choice for dynamic study over long period of time. The results of study were compared with numerical solution in MATLAB. Kaliyappan and Hariharan (2015) proposed a way of computing Adomian polynomial using symbolic programming in MATLAB, however, the used programming is lengthy and requires efficient knowledge of MATLAB whereas standard Adomian polynomial requires only differentiation and integration commands of MATLAB. Mohamed (2009) obtained the approximate solution of the unsteady state flow of a polytrophic gas in two dimensions using ADM. The results were compared with the exact solution to prove the reliability and effectiveness of the ADM. Sevukaperumal and Rajendran (2013) studied the bio-reduction of acetophenone in an upflow packed bed reactor. The approximate analytical solution of the nonlinear model was acquired using modified ADM. Singh and Kumar (2011) modified standard ADM by clubbing it with Laplace transform method to overcome the situation of oscillation in results. However, application of Laplace transform restricted its utilization to linear case only. Jebari et al. (2012) applied modified ADM to obtain the approximate numerical solution of the nonlinear diffusion equation with convection term. Manseur and Cherruault (2005) solved adaptive control problem by ADM. The solution was obtained in series form in the form of the unknown parameters. The desired objective function was obtained in terms of unknown parameters which can be minimized by any classical optimization technique. Qin et al.

(2014) obtained an approximate solution of two-phase Stefan problem which describes the pure metal solidification process. They suggested that ADM is a good and easy method to deal with moving boundary value problem. Duan and Rach (2011) proposed a new modification of the ADM to a different class of multi-order and multi-point nonlinear boundary value problem. This modification has an advantage to undetermined coefficient within the recursive scheme for computing in respect to traditional ADM.

The traditional analytical approaches for solving nonlinear distributed parameter model are Fourier series, similarity transformation, etc., which are not easy to use. Adomian decomposition method (ADM) is a methodology to obtain the approximate analytical solution of linear or nonlinear and deterministic or stochastic model equations. It is capable to solve the equations in a few steps manually. To encounter with nonlinear term, polynomial-based algorithm is used which is capable to break down the nonlinearity easily and in a systematic manner to solve the nonlinear system of PDEs. The word semi-analytical emphasizes that the methodology is analytical in nature but has been implemented using MATLAB.

In this work, Adomian decomposition method has been applied for solving unsteady state fixed bed reactor problem, which is the novelty of this work. We try to present both analytical and numerical approaches in a clear and systematic manner to make the work accessible to many who work in this field. The classical ADM along with multistage Adomian decomposition method (MADM) has been analyzed. To carry out the error analysis to measure the performance of the MADM, a method of lines (MOL) technique has been applied. The main emphasis of the study is to develop a less computationally intensive semi-analytical solution approach to solve nonlinear complex distributed parameter model.

2.2 Modeling of Fixed Bed Reactor

A case study for investigating a heterogeneous, non-adiabatic fixed bed reactor has been chosen in which a pseudo first order irreversible, endothermic reaction takes place. The hydrolysis of ethyl acetate is carried out using Amberlyst-15 as a solid catalyst. The diluted solution of reactant ethyl acetate enters the reactor with concentration, C_{A0}, and temperature, T_0. The kinetic and reactor sizing data for this study has been taken from the literature (K.R.Ayyappam, A.P.Toor, R.Gupta , A.Bansal, 2009). In this study, axial dispersion of heat and mass is considered. Heat is transferred to the reacting medium through the wall by using hot water circulation as a hot medium. After applying mass and energy balances, the following equations are obtained:

$$\frac{\partial C_A}{\partial t} = D_{AB}\frac{\partial^2 C_A}{\partial z^2} - v\frac{\partial C_A}{\partial z} - kC_A \tag{2.1}$$

$$\frac{\partial T}{\partial t} = \frac{k_{mix}}{\rho\, C_P}\frac{\partial^2 T}{\partial z^2} - v\frac{\partial T}{\partial z} - \frac{(k\Delta H)}{(\rho\, C_P)}C_A + \frac{A_s U}{V\rho\, C_p}(T_J - T) \tag{2.2}$$

Initial conditions (IC): $C_A(z, t=0) = C_0$, $T(z, t=0) = T_0$ (2 .3)

Boundary conditions:

$$\frac{dC_A}{dz}(z = L, t) = 0 = \frac{dT}{dz}(z = L, t) \tag{2.4}$$

$$\frac{\partial C_A}{\partial z}(z = 0, t) = \frac{v}{D_{AB}}(C_A - C_A^{in}),\ \frac{\partial T}{\partial z}(z = 0, t) = \frac{v\rho C_p}{k_{mix}}(T - T^{in}) \tag{2.5}$$

The system state vector representation can be written as

$$\begin{bmatrix} \dot{C}_A \\ \dot{T} \end{bmatrix} = \begin{bmatrix} D_{AB}\frac{\partial^2}{\partial z^2} - v\frac{\partial}{\partial z} - k, & 0 \\ \frac{-k\Delta H}{\rho\, C_P}, & \frac{k_{mix}}{\rho\, C_P}\frac{\partial^2}{\partial z^2} - v\frac{\partial}{\partial z} - \frac{A_s U}{V\rho\, C_P} \end{bmatrix} \begin{bmatrix} C_A \\ T \end{bmatrix} + \begin{bmatrix} 0 \\ \frac{A_s U}{\rho V C_P} \end{bmatrix} T_J \tag{2.6}$$

$$\dot{z} = f\, z + g\, u \tag{2.7}$$

where $z = [C_A, T]^T$ is the system state vector

$$f \equiv \begin{bmatrix} D_{AB}\frac{\partial^2}{\partial z^2} - v\frac{\partial}{\partial z} - k, & 0 \\ \frac{-k\Delta H}{\rho\, C_P}, & \frac{k_{mix}}{\rho\, C_P}\frac{\partial^2}{\partial z^2} - v\frac{\partial}{\partial z} - \frac{A_s U}{V\rho\, C_P} \end{bmatrix} \tag{2.8}$$

$$g = \begin{bmatrix} 0 \\ \dfrac{A_s U}{\rho V C_P} \end{bmatrix} \tag{2.9}$$

Numerical solution of the fixed bed reactor has been carried out by the method of lines which transforms the system of PDE to the coupled system of ODE by spatial discretization and the resulting system is solved by Runge-Kutta fourth order method.

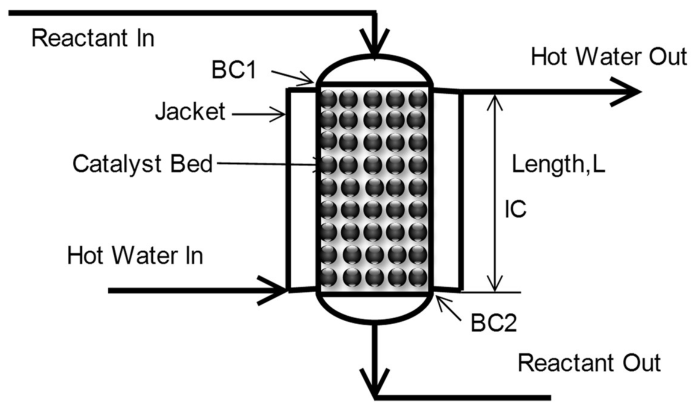


Figure 2. 1: Schematic diagram of the fixed bed reactor.

2.3 Adomian Decomposition Method (ADM)

Consider a nonlinear differential equation in operator form as:

$$Lu + Ru + Nu = g \tag{2.10}$$

where g is the source term and u is the required output solution of the system. L is the linear differential operator. The selection of L should be such that it can be easily inverted for simplification of the calculation. R is the highest derivative operator along with nonlinear term operator N. Taking inverse operator L^{-1} to both sides of the equation 10 yields,

$$u = -L^{-1}[Ru] - L^{-1}[Nu] + L^{-1}[g] + IC \tag{2.11}$$

where $L^{-1}(.) = \int_0^t (.)dt$

After further simplification,

$$u = -L^{-1}[Ru] - L^{-1}[Nu] + f \tag{2.12}$$

where the term f is generated from the summation of inverted source term and the given initial condition (IC) which is assumed to be known. In this method, the approximate series solution can be written as

$$u = \sum_{i=0}^{n} u_i \quad . \tag{2.13}$$

Therefore, decomposition of the nonlinear term N[u] into a polynomial series can be written as

$$N[u] = \sum_0^n A_n \tag{2.14}$$

where A_n represents a polynomial corresponding to $(u_{0\,,}u_1, u_2 \ldots \ldots, u_n)$ and called Adomian polynomial. Let us consider that the nonlinear term has a single variable, N[u] = F(u), then required polynomial can be obtained for F(u) using general formula

$$A_n = \frac{1}{n!}\frac{\partial^n}{\partial\lambda^n}[F(\textstyle\sum_{i=0}^{n} u_i\, \lambda^i)]_{\lambda=0}, \text{ where i = 0, 1, 2… n} \tag{2.15}$$

where λ is a grouping parameter. In real computational practice, we need to trim the decomposition series into a few steps, i = 1, 2… k. The selection of higher order component, u_n, for series solution, $n > k$, does not contribute in the calculation of the A_n .

A single variable Adomian polynomial formula for the simple nonlinear term, N[u] = F(u) from A_0 to A_2 can be written here for convenient reference as

$$\left.\begin{aligned} A_0 &= F(u_0) \\ A_1 &= u_1 F'(u_0) \\ A_2 &= u_2 F'(u_0) + \frac{1}{2!}u_1^2 F''(u_0) \end{aligned}\right\} \tag{2.16}$$

It is important to mention that to formulate recursive scheme, ADM laid emphasis in the selection of zeroth component, u_0, which is not included under recursive scheme.

$$\left.\begin{aligned} u_0 &= f \\ u_{k+1} &= -L^{-1}[Ru_k] - L^{-1}[Nu_k],\ k \geq 0 \end{aligned}\right\} \tag{2.17}$$

To enhance the convergence rate of the ADM, the methodology as discussed by Wazwaz et al.(2013) has been followed. This is called a noise term phenomenon which is generally encountered in inhomogeneous PDE. As suggested by this author, the initial condition (IC) should be included in the zeroth term while the rest of the term should be included in the first term, if any. However, the identification of the zeroth term, u_0, and term generating from source term should be known.

$$\left.\begin{aligned} u_0 &= f \text{ (Initial condition term)} \\ u_1 &= g1(source\ generated\ term) - L^{-1}[Ru_0] - L^{-1}[Nu_0] \\ u_{k+1} &= -L^{-1}[Ru_k] - L^{-1}[Nu_k],\ k \geq 0 \end{aligned}\right\} \tag{2.18}$$

The approximate series solution is $u = \sum_0^n u_n$. Convergence rate of the ADM is fast and only few terms in summation may be able to provide a practical approximate solution. The convergence and stability of the ADM have been discussed in (Abbaoui & Cherruault, 1994; Babolian & Biazar, 2002; Cherruault & Adomian, 1993).

2.4 Multistage ADM

It is known that ADM has capability to solve a wide class of problems including Elliptic, Navier-Stokes, Lotkta-Volterra, etc. but it has some drawbacks. Repaci (1990) has mentioned that the series solution can be rapidly convergent only for the small range but beyond that range, the convergence rate is too slow and summation of the selected series terms is unable to provide an accurate solution. The multistage ADM has been implemented successfully by researchers (J.-S. Duan, Rach, Wazwaz, Chaolu, & Wang, 2013; González-Parra, Arenas, & Jódar, 2009).

To design a controller, there is a necessity to study the transient behavior of the fixed bed reactor over a large period of time. In such a case, classical ADM is unable to provide useful solution. The overcome this drawback, a new approach was introduced by Adomian (1984). He suggested to discrete the time span [0, T], into m intervals of equal width, h = T/m.

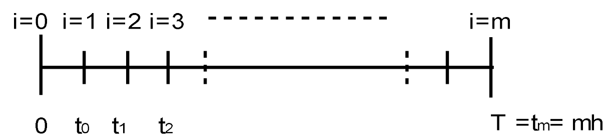


Figure 2. 2: Schematic representation of time discretization.

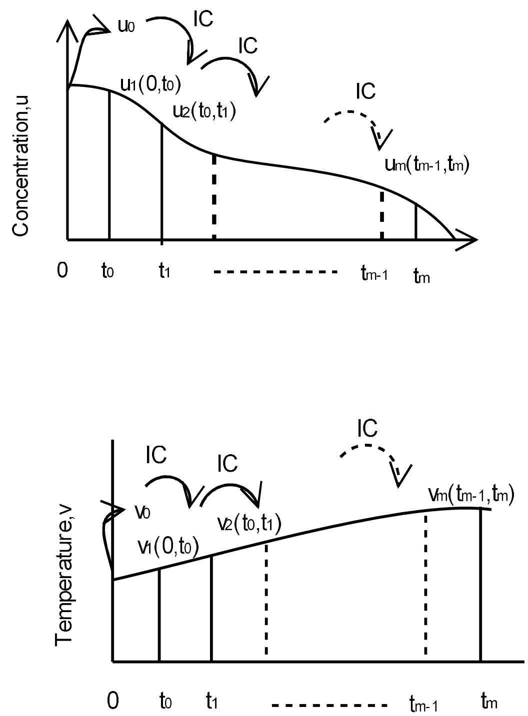


Figure 2. 3: Schematic representation of the MADM to concentration and temperature profiles

.

Initially ADM is applied to get the approximate solution u_1, v_1 on the interval $(0, t_0)$ by utilizing initial condition u_0, v_0, respectively. Forgetting approximate solution over the next interval (t_0, t_1), u_1 and v_1 are used as initial conditions for obtaining successive series components u_2 and v_2, respectively. This sequence of process is repeated over the next interval up to the final time interval under study. The mathematical representation of concentration and temperature summation series are as follows:

$$u = u_0 + u_1(0, t_0) + u_2(t_0, t_1), \dots \dots \dots, +u_m(t_{m-1}, t_m) \qquad (2.19)$$

$$v = v_0 + v_1(0, t_0) + v_2(t_0, t_1), \dots \dots \dots, +v_m(t_{m-1}, t_m) \qquad (2.20)$$

where u = concentration and v = temperature.

2.5 Application to Fixed Bed Reactor Problem

In this section, three methods; ADM, MADM and method of lines (MOL) have been applied to study the transient behavior of the fixed bed reactor. To demonstrate use of the semi-analytical approximate solution, the mathematical model of the fixed bed reactor has been solved. The modeling equations (2.1 and 2. 2) can be written in convenient as,

$$u_t = D_{AB}u_{xx} - v_e u_x - k_0 exp(-\frac{E}{Rv})\,\mathrm{u} \qquad (2.21)$$

$$v_t = \propto u_{xx} - v_e v_x - \beta k_0\, exp\left(-\frac{E}{Rv}\right) u + \gamma(T_j - v) \qquad (2.22)$$

where $\propto = \frac{k_{mix}}{\rho C_P}, \beta = \frac{\Delta H}{\rho C_P}\ \ and\ \gamma = \frac{A_s U}{V \rho C_P}$

2.5.1 Semi-analytical Approximate Solution by ADM

In this section, analysis by ADM is performed for the solution of nonlinear system of parabolic PDE which are obtained by material and energy balance around the fixed bed reactor. Define the differential operator and its inverse as

$$L_t(.) = \frac{d}{dt}(.),\ L_t^{-1}(.) = \int_0^t (.)dt\ \ and\ L_{xx}(.) = \frac{d^2}{dx^2}(.) \qquad (2.23)$$

The equations 2.21 and 2.22 can be written in standard operator form as

$$L_t u = D_{AB} L_{xx} u - v_e L_x u - k_0 \sum_0^n A_n \quad (2.24)$$

$$L_t v = \propto L_{xx} v - v_e L_x v - \beta k_0 \sum_0^n A_n + \gamma (T_j - v) \quad (2.25)$$

Above set of equations can be solved in both t- and x-directions. For convenience from calculation point of view, t-direction solution is relatively easy and requires only initial condition to solve. Applying the operator $L_t^{-1}(.)$ to both sides of equations (2.24) and (2.25) yields

$$u = u(0,x) + L_t^{-1}[D_{AB} L_{xx} u] - v_e L_t^{-1}[L_x u] - k_0 L_t^{-1}[\textstyle\sum_0^n A_n] \quad (2.26)$$

$$v = v(0,x) + \propto L_t^{-1}[L_{xx} v] - v_e\, L_t^{-1}[L_x v] - \beta k_0 L_t^{-1}[\textstyle\sum_0^n A_n] + \gamma L_t^{-1}[(T_j - v)]$$

(2.27)

Given initial condition (IC): u (0,x) = C_0, v (0,x) = T_0 from equation (2.3)

$$u = C_0 + L_t^{-1}[D_{AB} L_{xx} u] - v_e L_t^{-1}[L_x u] - k_0 L_t^{-1}[\textstyle\sum_0^n A_n] \quad (2.28)$$

$$v = T_0 + \propto L_t^{-1}[L_{xx} v] - v_e\, L_t^{-1}[L_x v] - \beta k_0 L_t^{-1}[\textstyle\sum_0^n A_n] + \gamma L_t^{-1}[(T_j - v)]$$

(2.29)

The zeroth and first components of the series summation are as follows

$$\left.\begin{aligned} u_0 &= C_0 \\ v_0 &= T_0 \end{aligned}\right\} \quad (2.30)$$

$$\left.\begin{aligned} u_1 &= L_t^{-1}[D_{AB} L_{xx} u_0] - v_e L_t^{-1}[L_x u_0] - k_0 L_t^{-1}[A_0] \\ v_1 &= \propto L_t^{-1}[L_{xx} v_0] - v_e\, L_t^{-1}[L_x v_0] - \beta k_0 L_t^{-1}[A_0] + \gamma L_t^{-1}[(T_j - v_0)] \end{aligned}\right\} \quad (2.31)$$

The recursive schemes are as follows

$$u_{k+1} = L_t^{-1}[D_{AB} L_{xx} u_k] - v_e L_t^{-1}[L_x u_k] - k_0 L_t^{-1}[\textstyle\sum_0^n A_n] \quad (2.32)$$

$$v_{k+1} = \propto L_t^{-1}[L_{xx} v_k] - v_e\, L_t^{-1}[L_x v_k] - \beta k_0 L_t^{-1}[\textstyle\sum_0^n A_{n]} + \gamma L_t^{-1}[(-v_k)] \quad (2.33)$$

This system of equations has one nonlinear term identified as: $F(u,v) = exp\left(-\frac{E}{Rv}\right)u$. Note that the Adomian polynomial for the nonlinear term must be determined before using recursive steps. The identified nonlinear term is two variables equation and the required Adomian polynomial for A_0 to A_2 can be written as

$$A_n = \frac{1}{n!}\frac{d^n}{d\lambda^n}[F(\sum_{i=0}^{k}(u_i\lambda^i) * exp(-\frac{E}{Rv_i\lambda^i})]_{\lambda=0} \quad (2.34)$$

$$\left.\begin{aligned} A_0 &= F(u_{0,}v_0) = u_0 exp(-\frac{E}{Rv_0}) \\ A_1 &= \frac{d}{d\lambda}[(u_0 + u_1\lambda)exp(-\frac{E}{R(v_0 + v_1\lambda)})]_{\lambda=0} \\ A_2 &= \frac{1}{2}\frac{d^2}{d\lambda^2}[(u_0 + u_1\lambda + u_2\lambda^2)exp(-\frac{E}{R(v_0 + v_1\lambda + v_2\lambda^2)})]_{\lambda=0} \end{aligned}\right\} \quad (2.35)$$

Finally sum up all the component steps of the series to get the final approximate solution. For computational purpose, one has to truncate the summation of the series up to certain number of steps which may influence the correctness of the approximate analytical solution.

$$u = \sum_{i=0}^{k} u_i \quad \text{and} \quad v = \sum_{i=0}^{k} v_i \quad (2.36)$$

A MATLAB code for solving the equations (2.30) to (2.35) was written using symbolic notation. This code is used for developing the correct approximation analytical solution of the equations to avoid manual errors. For numerical solution, ode45 solver in MATLAB was chosen.

In this study, time discretization step was considered as 0.1 s and the number of space discrete intervals for MOL was taken as 100. In Figure 2.4, concentration profile computed by 2-step ADM is compared with that obtained by MOL for a short span of time [0, 60 s]. It is clearly observed that after 10 s, the ADM approximate solution is deviated from its numerical solution. The same trend can also be observed from Figure 2. 5 for temperature but the ADM solution deviates beyond 20 s._In this study, the concentration and the temperature of the ethyl-acetate have been measured at the exit point of the fixed bed reactor. The operating parameters are constant throughout in this study which are as follows:

Inlet feed temperature = 303.15 K

Inlet feed concentration of the ethyl-acetate = 0.001 mol/m^3

Feed rate of the aqueous solution of the ethyl-acetate = 0.0034 m/s

Jacket temperature = 333.15 K

Amount of the Amberlyst-15 catalyst = 64 g

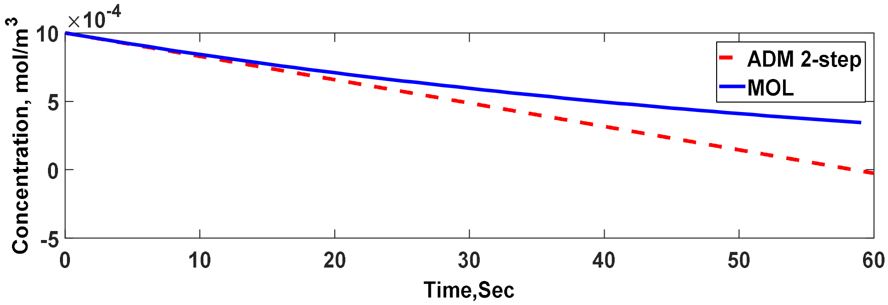


Figure 2. 4: Comparison of concentration profiles between 2-step ADM and MOL up to 60 s (Maximum absolute % error = 86.50).

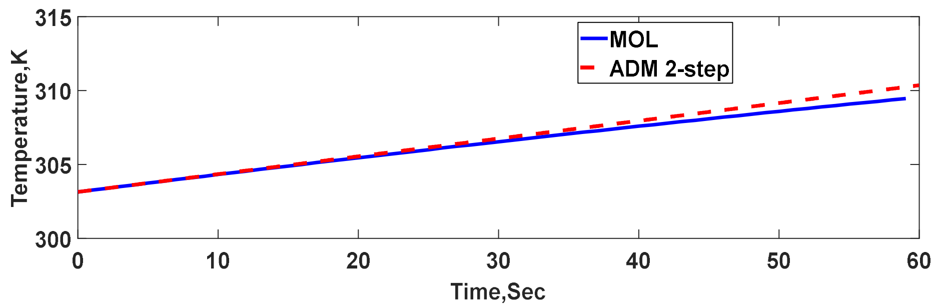


Figure 2. 5: Temperature profiles comparison between 2-step ADM and MOL up to 60 s (Maximum absolute % error = 0.288).

To further investigate the accuracy, a 3-step ADM solution was also considered. As shown in Figure 2.6, a perfect matching for temperature profile is obtained. In Figure 2.7, at approximately 60s, there is large change in concentration with respect to initial concentration (approximately, 62 %) in comparison to the temperature (approximately, 1.65%). However, the strong nonlinearity is present in temperature profile than the concentration profile. The addition of one more component to 2-step ADM does not help much to concentration profile as compared to temperature. The prediction of the concentration is approximated correct up to 20 s but gets deviated later on. Similarly, from Figures 2.8, 2.9, 2.10, 2.11, 2.12 and 2.13, it is clear that merely increasing the number of series components does not work for studying the system for longer period of time. All these figures clearly demonstrate weakness of the classical ADM which put a serious threat to its application in modeling for longer period of time. Because of overlapping concentration and temperature profiles in time span [0, 60s], it has been further increased to [0,100s] for better investigation. Figure 2.13 depicts that merely increase in the no. of series components doesn't able to provide a stable solution in case of the standard ADM. The main weakness of the standard ADM is that it works fine only near to initial conditions (ICs) irrespective of taken no. of series components. The similar fact reveals from Figure 2.10.

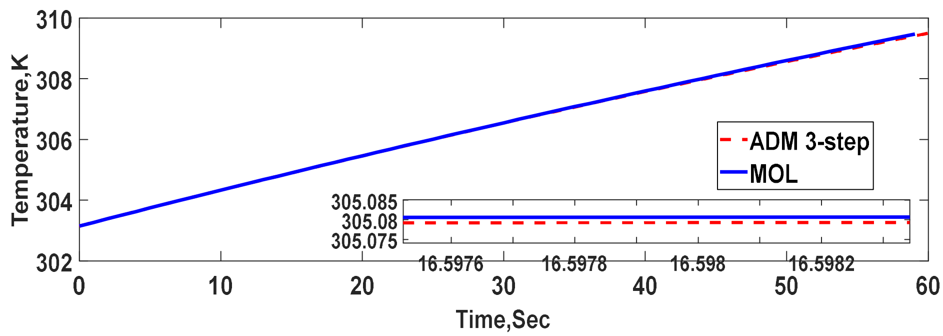


Figure 2. 6: Temperature profiles comparison between 3-step ADM and MOL up to 60 s (Maximum absolute % error = 0.0097).

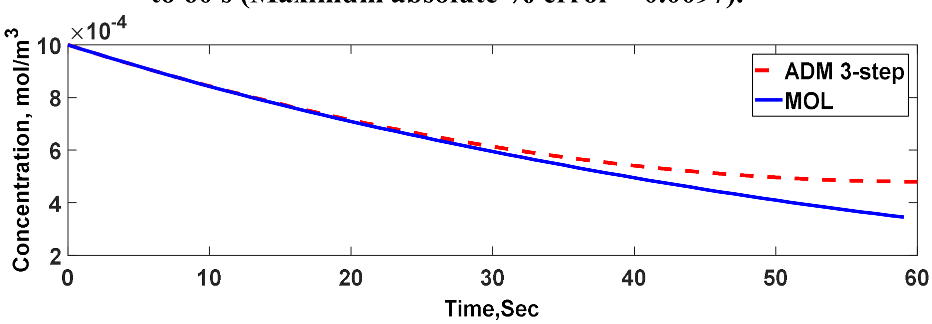


Figure 2. 7: Concentration profiles comparison between 3-step ADM and MOL up to 60 s (Maximum absolute % error = 39.028).

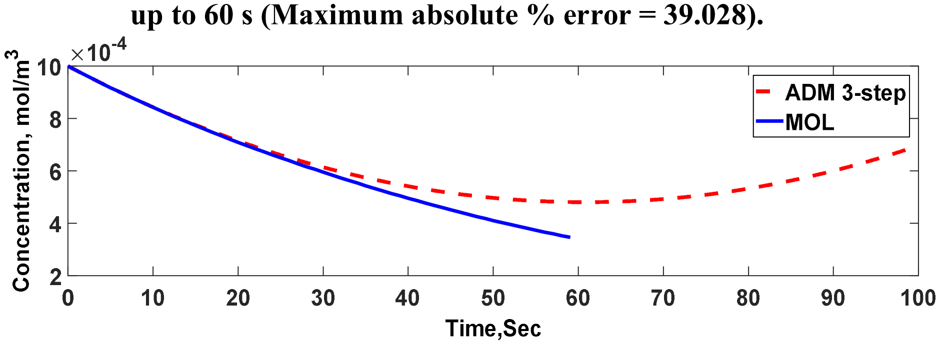


Figure 2. 8: Comparison of concentration profiles between 3-step ADM and MOL up to 100 s(Maximum absolute % error = 99.86).

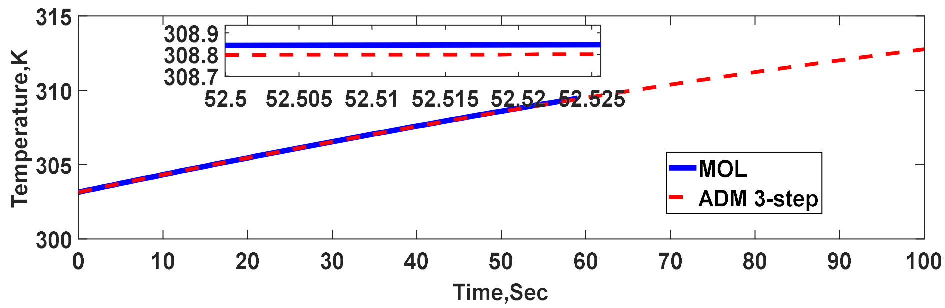


Figure 2. 9: Temperature profiles comparison between 3-step ADM and MOL up to 100 s(Maximum absolute % error = 0.0097).

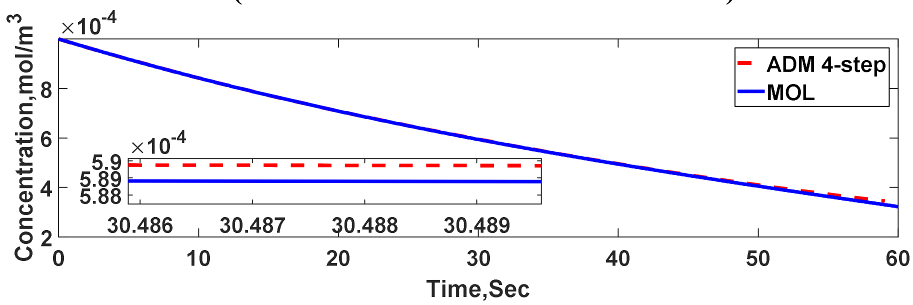


Figure 2. 10: Concentration profiles comparison between 4-step ADM and MOL up to 60 s (Maximum absolute % error = 7.097).

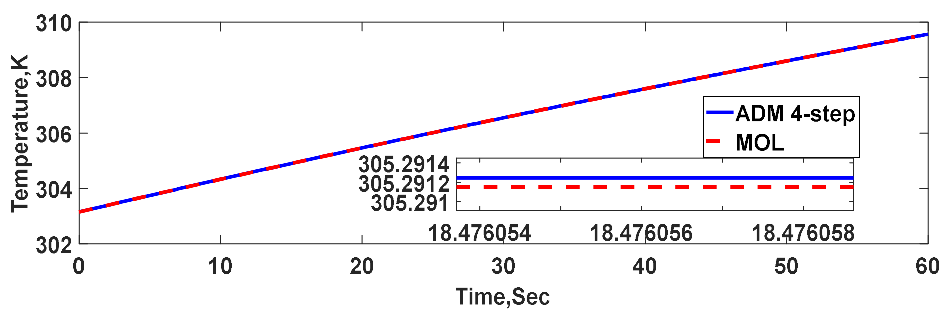


Figure 2. 11: Temperature profiles comparison between 4-step ADM and MOL up to 60 s (Maximum absolute % error = 0.032).

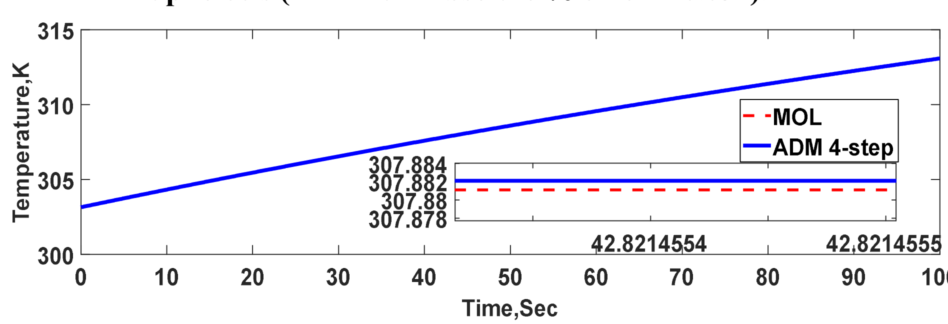


Figure 2. 12: Temperature profiles comparison between 4-step ADM and MOL up to 100 s (Maximum absolute % error = 0.029).

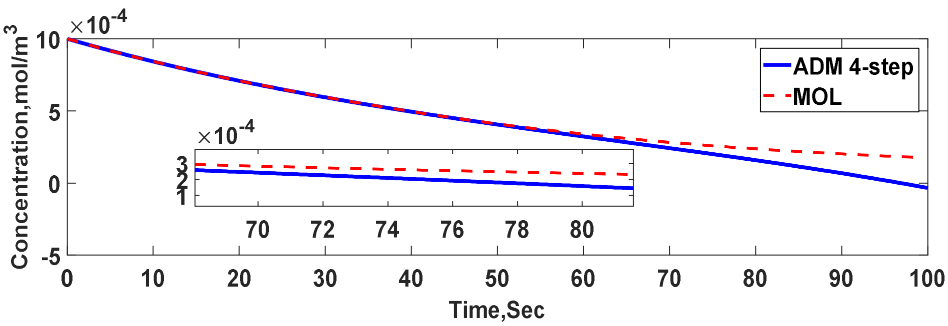


Figure 2. 13: Concentration profiles comparison between 4-step ADM and MOL up to 100 s (Maximum absolute % error = 80.74).

2.5.2 Semi-analytical Solution by MADM

The fairly accurate solutions of a common nonlinear resistor-nonlinear capacitor circuit model problems by multistage ADM have been used by Fatoorehchi et al. (2015). The multistage scheme for ADM in this section is a new exploration to distributed parameter model of fixed bed reactor. Consider [0, T], the required time range for the study of the transient behavior of the fixed bed reactor using initial conditions. The selected time range must be divided into m subintervals of the equal length. The procedure to evaluate u and v by MADM can be described as follows: First of all, set C_0, T_0 as the initial conditions for the system of equations. Start the counter variable i from 1. Thereafter, repeat the below calculations for m times

$$\left.\begin{aligned} t_{i-1} &= (i-1)h \\ t_i &= ih \\ u_0 &= C_0 \\ v_0 &= T_0 \end{aligned}\right\} \quad (2.37)$$

$$
\left.
\begin{aligned}
u_1 &= L_t^{-1}[D_{AB}L_{xx}u_0] - v_e L_t^{-1}[L_x u_0] - k_0 L_t^{-1}[A_0] \\
v_1 &= \propto L_t^{-1}[L_{xx}v_0] - v_e L_t^{-1}[L_x v_0] - \beta k_0 L_t^{-1}[A_0] + \gamma L_t^{-1}[(T_j - v_0)] \\
u_2 &= L_t^{-1}[D_{AB}L_{xx}u_1] - v_e L_t^{-1}[L_x u_1] - k_0 L_t^{-1}[A_1] \\
v_2 &= \propto L_t^{-1}[L_{xx}v_1] - v_e L_t^{-1}[L_x v_1] - \beta k_0 L_t^{-1}[A_1] + \gamma L_t^{-1}[(-v_1)] \\
&. \\
&. \\
u_{k+1} &= L_t^{-1}[D_{AB}L_{xx}u_k] - v_e L_t^{-1}[L_x u_k] - k_0 L_t^{-1}[A_k] \\
v_{k+1} &= \propto L_t^{-1}[L_{xx}v_k] - v_e L_t^{-1}[L_x v_k] - \beta k_0 L_t^{-1}[A_k] + \gamma L_t^{-1}[(-v_k)]
\end{aligned}
\right\} \quad (2.38)
$$

$$C_0 = \sum_{i=0}^{k+1} u_i$$

$$T_0 = \sum_{i=0}^{k+1} T_i$$

It is worth to mention that the accuracy of the MADM can be enhanced either by selecting a small step size or by adding more number of terms to the series solution. However, choosing a small step size increases the number of iterations to achieve the desired accuracy whereas calculating more number of component terms of the series solution requires more analysis for calculating a new term.

2.5.3 Numerical Solution by Method of lines (MOL)

Method of lines is a widely used numerical method for obtaining numerical solution of parabolic type control related problems. MOL uses transformation of a system of PDE to a system of coupled ODEs in time domain by utilizing finite difference approximation for spatial derivative.

For converting the system to a finite difference form, a central difference expression which is accurate to the order of h^2 for the derivative is used (Cutlip, 1999).

$$\frac{dC(i)}{dt} = D_{AB}\frac{C(i+1) - 2C(i) + C(i+1)}{h^2} - v\frac{C(i+1) - C(i-1)}{2h} - k_0 \exp(-\frac{E}{RT(i)})\, C(i) \tag{2.39}$$

$$\frac{d\,T(i)}{dt} = \frac{k_{mix}}{\rho C_P}\frac{T(i+1) - 2T(i) + T(i+1)}{h^2} - v\frac{T(i+1) - T(i-1)}{2h} - k_0\frac{\Delta H}{\rho C_P}\exp(-\frac{E}{RT(i)})\, C(i) + \frac{UA_s}{V\rho C_P}(T_J - T(i)) \tag{2.40}$$

where i = 1 to N is the node number, N is the total number of interior node points and h is the discretization spacing defined as h = L/(N+1), L is the length of the fixed bed reactor. Therefore, entry point, x = 0, corresponds to the node point i = 1 and exit point, x = L, corresponds to the node point i = N+2. Thus x = (i-1)h. The equation system is a set of 2N non-linear coupled ODEs for N dependent variables. Similarly, the corresponding boundary conditions (BCs) are converted into its finite difference form.

Figure 2.14 shows that 2-step MADM is good to approximate the concentration transient solution. The temperature profile is shown in Figure 2.15 and the error in prediction is shown within zoom window. To further elaborate the effect of number of steps on the accuracy, a 3-step MADM solution of concentration and temperature profiles are plotted as shown in Figures 2.16 and 2.17, respectively. Figures 2.18 and 2.19 show that there is a marginal improvement in the accuracy of temperature mapping while considerable improvement in concentration mapping.

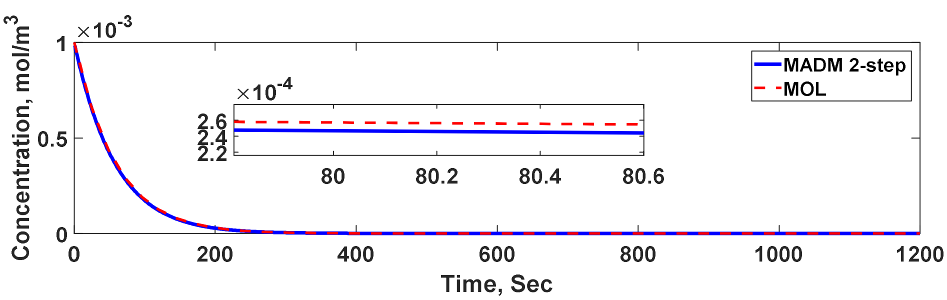


Figure 2. 14: Concentration profiles comparison between 2-step MADM and MOL up to 1200 s (Maximum absolute % error = 7.334).

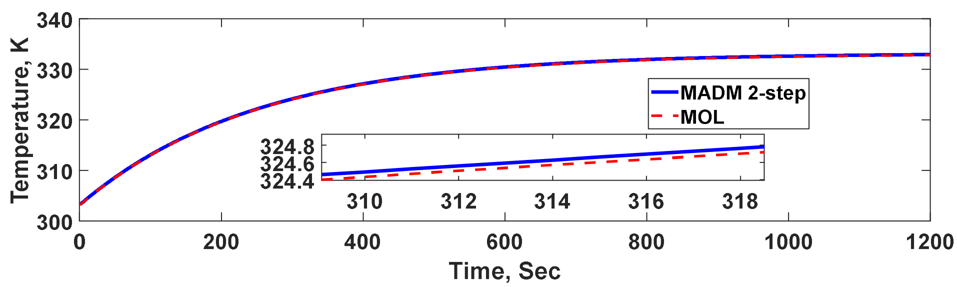


Figure 2. 15: Temperature profiles comparison between 2-step MADM and MOL for up to 1200 s (Maximum absolute % error = 0.0331).

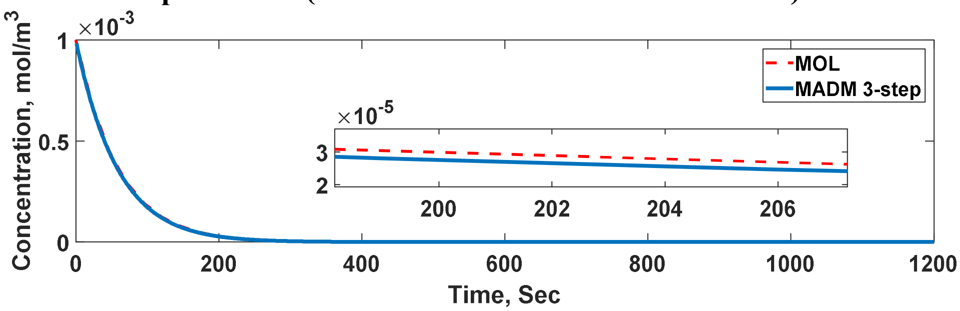


Figure 2. 16: Comparison of concentration profiles for 3-step MADM and MOL up to 1200 s (Maximum absolute % error = 7.329).

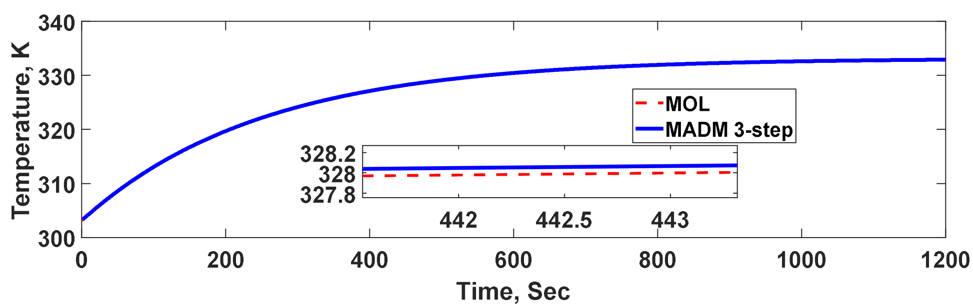


Figure 2. 17: Temperature profiles comparison between 3-step MADM and MOL up to 1200 s (Maximum absolute % error = 0.0331).

Similarly, further increase in the number of the components in series solution from 3-step to 4-step for both the concentration and temperature are shown in Figures 2.18 and 2.19. It is clearly demonstrated from these Figures that no further noticeable changes are observed. But further reduction in time discretization requires a high computation load along with larger memory which restricts the utilization of small-time step.

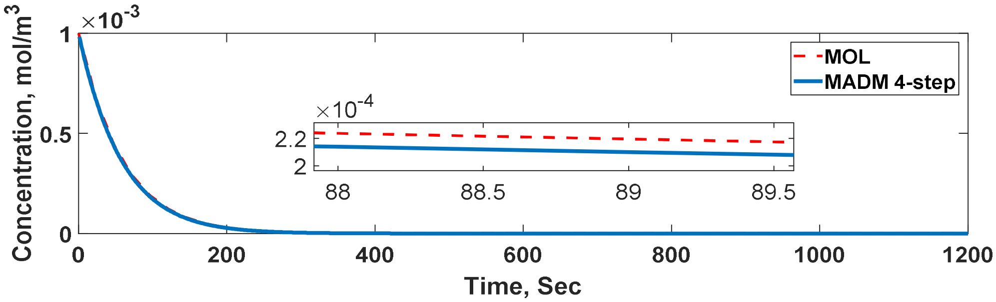


Figure 2. 18: Concentration profiles comparison between 4-step MADM and MOL up to 1200 s (Maximum absolute % error = 7.329).

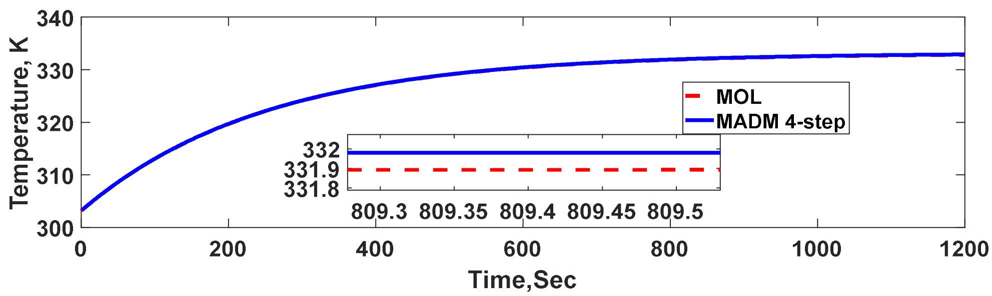


Figure 2. 19: Temperature profiles comparison between 4-step MADM and MOL up to 1200 s (Maximum absolute % error = 0.0331).

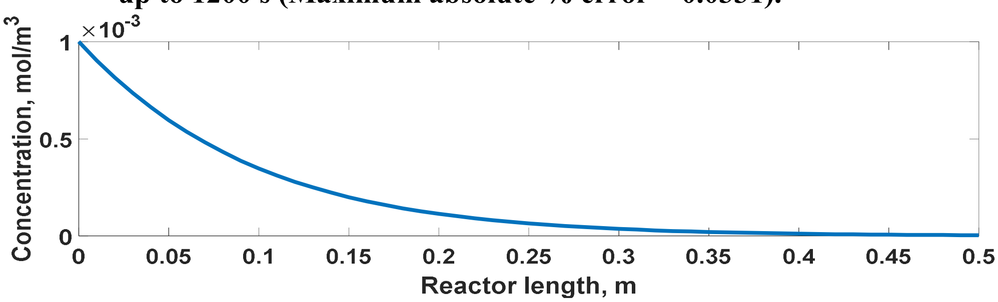


Figure 2. 20: Concentration profile of ethyl-acetate along the length of the fixed bed reactor.

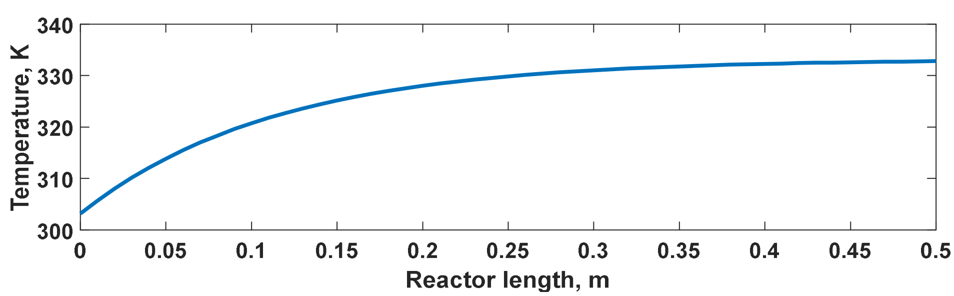


Figure 2. 21: Temperature profile of the mixture along the length of the fixed bed reactor.

To understand the consumption pattern of the reactant ethyl-acetate, Figure 2.20 has been plotted. From the figure it is depicted that the concentration has been reduced smoothly along the length of the reactor and an approximately length of 0.45 m, the reactant gets fully consumed. It is clear from Figure 2.21, the reactor achieves thermal equilibrium state at a length of 0.45m, approximately and this fact is also justified from Figure 2.20. At thermal equilibrium state, the driving force reduces to zero and at this position (L= 0.45 m), the reactant is approximately consumed fully.

2.6 Conclusions

A multistage Adomian decomposition method (MADM) has been used to obtain semi-analytical approximate solution of a fixed bed reactor problem. This approach provided a better alternative to other classical analytical methods and the traditional numerical methods. The transient behavior of fixed bed reactor has been determined using MADM in MATLAB. The performance of the used method depends upon the number of truncated steps and discretization of the time span. The desired accuracy can be achieved by selecting four numbers of truncated series components and 0.1 s time as discretization step for economy of the computation. A comparison with the numerical method of lines has been performed to show error. The obtained results show the satisfactory performance of the MADM to study the dynamic behavior of nonlinear distributed parameter model of the fixed bed reactor. This method can also be applied to similar problems as well as for process control systems.

Chapter 3: Chattering Free Sliding Mode Control with Observer Based Adaptive Radial Basis Function Neural Network for Temperature Tracking in Fixed Bed Reactor

Chapter 3 : Chattering Free Sliding Mode Control with Observer Based Adaptive Radial Basis Function Neural Network for Temperature Tracking in Fixed Bed Reactor

3.1 Introduction

Fixed bed reactor is a time-varying nonlinear system mostly used for catalytic reactions in chemical industries. The temperature trajectory of the fixed bed reactor has drawn significant attention of chemical engineers in the past few decades (Jung-hwan Park, 1995). Recently, attention has been focused on application of sliding mode control (SMC) in chemical engineering due to its robust design that is based on a sliding surface tagged with Lyapunov stability theorem (Zhao, Zhu, & Dubbeldam, 2015). Lyapunov theorem is used to examine the stability of the fixed bed reactor. The distinguished merit of SMC is its capability to deal with system uncertainties. The fixed bed reactor system is a complex nonlinear system whose dynamic parameters are difficult to know precisely (Boubaker & Babary, 2003). Many times, it is possible that a correct mathematical model cannot be formulated accurately because of uncertainty existing in real system (López, Guerra, & Machuca, 2012). SMC is a subsystem of Variable Control Structure (VCS) in which a switching control law enforces the states of nonlinear system to reach the specified surface. Once the states arrive at the surface, controller forces the system states to slide along the surface until it converges towards the origin (Y. Zhang, 2012).

It is common practice in engineering to find a model of dynamic system either by experimental or simulation method. Identification of the model which is based on input-output data may be classified as parametric and non-parametric. Parametric model is important from control engineering point of view. However, the mapping of nonlinear plant is quite difficult with linear function due to its nonlinear behavior. This chapter focuses on the application of combined approach of Radial-basis-function (RBF) and neural networks (NNs). It is proved that RBF networks having one hidden layer are able to do universal approximation due to its nonlinear behavior (J. Park & Sandberg, 1991). The optimization of identified model is employed by least square technique on the measured error between plant and model. However, the overall task is to describe fine model based on input-output data (T & Shin, 1994).

SMC are also gaining popularity in bioprocess engineering. It was designed for continuous fermentation process with uncertain parameters (Zlateva, 1997). However, the control design is based on direct nonlinear model and online measurement of the state variable. The chattering phenomenon is minimized using derivative control input in place of control input. Other type of the control strategy, like binary control system approach, has also been used to stabilize for fermentation process. This approach uses directly the nonlinear model along with knowledge of microbiology (Zlateva, 2000) .

It is well-known that unmodeled dynamics exist in various practical nonlinear systems. There are many factors responsible for it such as measurement noise, modeling errors, external disturbances, modeling simplifications, etc. (Kwan, 1995). Closed-loop system performance can deteriorate significantly if the designed controller is not robust against such problems. Therefore, various approaches were examined to deal with such systems with unmodeled dynamics (López et al., 2012). To overcome this problem, online tuning is one of the possible alternatives. Adaptation of the controller parameters is simple, fast and precious. Soons et al.(2008) analyzed the tuning method with respect to the stability of the system under closed loop condition. The main reasons for emerging SMC techniques are their robustness to parameter variation and external disturbance. It has been used in many practical applications, but not explored much in chemical engineering. Mostly the feedback controllers' performance relies on exact model information and measuring device. It is difficult to obtain an accurate model of real processes such as fixed bed reactors. To overcome this difficulty, an intelligent control is needed to design a robust SMC (Kaynak & Yu, 2001). Kobayashi and Tsuda (2011) applied SMC scheme for robust control in space robot where the target was to capture the spacecraft motion while the parameters were unknown. It uses saturation function to avoid the chattering phenomena; the acquired results prove the feasibility.

Broomhead and Lowe (1988) were the first researchers who used RBF in the design of NNs. There are in general two classes of NNs which have received much attention of researchers in recent years (Parthasarathy, 1990): multilayer and recurrent NNs. Multilayer NNs have been widely used in pattern recognition (David J, 1988; Sejnowski, 1988) and recurrent NNs have been used in optimization problems

(Hopfield & Tank, 1985; Rauch & Winarske, 1988). RBFNN has been widely used because it has characteristic of global optimization, best approximation, simple network structure, and fast training learning capability (Fu, Liu, Liu, & Gao, 2016). Ferreira and Pinho (1998) focused on the asymptotic power of RBFNN in the sup norm. Wilkinson and Meade (2016) proposed a mesh-free numerical solver for differential equations, which was acquired from machine learning technique using RBFNN. This technique was different from traditional solver techniques which require grids, volume or meshes. The tired length training process is required with sigmoid artificial neural network (ANN) which has been reported by researchers (Alexandridis, Sarimveis, & Bafas, 2003; Maciej, 2010). Gaussian function is a special type of RBF, which is radially symmetric and its function value decreases monotonically in both directions as x moves away from the center (Azlan, 2016). Although there are different NN architectures used for designing control systems but RBF networks present some more advantages which have better approximation characteristics (Alexandridis, Stogiannos, Loukidis, Ninos, & Zervas, 2014). The traditional NNs have the common problem that they produce static network i.e. the dynamic behavior does not vary with time. Therefore, a static NN is not adequate to provide an accurate prediction for long time period. Due to this reason, an RBF modeling training technique has been used, which has property to adjust the network parameters as per demand (Alexandridis et al., 2003). Shah and Meckl (1995) proposed a control structure of RBF neural network for the control of the fixed bed reactor. The NN consisting of RBF has Gaussian function and is trained online to learn the dynamics of the fixed bed reactor. Application of Lyapunov theorem ensures the global stability of the system. The control structure has the capability to reduce the tracking error to near zero. Feng et al.(2008) focused a tracking control problem related to a free-floating space robot in a task space, which considered the model uncertainty and external disturbance. They suggested utilization of RBFNN in place of discontinuous part of SMC to reduce the chattering. The proposed algorithm is validated with simulation results. Han et al. (2018) designed a terminal iterative learning control scheme for nonlinear system such as train station control and batch reactor system using NN. The simulation results show the effectiveness of the proposed algorithm. Climenti et al (2018) proposed a closed loop control scheme for better quality of nitrile rubber. They derived a simple model of the reactor used for the production of nitrile rubber. The developed model was used for the designing a soft sensor and later on for the development of a suboptimal control law. Predicting results suggest that the chemical composition can be altered as per need. Tao et.al. (2016) proposed SMC based on RBF for deburring of industrial robotics. It compared the traditional SMC with the SMC based on RBF for robotic joint position tracking and proved the superiority of SMC-RBF to learn uncertain control actions. The major concern of AK et al.(2015) was to provide a scheme which did not take into consideration the system's parameters to compute the equivalent control. To calculate gain, fuzzy logic was used. A real-time comparison between PID controller and the proposed scheme was tested on the Manutecg-r15 industrial robot manipulator and suggested that the proposed scheme can be utilized in trajectory control for robotic system. Paris (1965) had suggested a technique to remove the hot spot in externally cooled fixed bed reactor. He proposed a jacket design by dividing it into many sections and also suggested a reaction model. First few sections had a low flow rate of cooling media so that the reaction could be propagated by achieving a desired temperature. The next consecutive sections had high coolant flow rate to control the high reaction rate. For transient control in power plant, a fast valving technique has been seen as effective and economic techniques by Chen et al. (1995). However, in the presence of strong nonlinearity in the system, the conventional methodology for designing the fast valving controller cannot provide a good control system. They demonstrated a new technique to control fast valving using RBF. From online test, the designed controller structure has proved its effectiveness and robustness. Tse and Shin. (1994) approximated the dynamics and static equations of stochastic nonlinear systems and also measured the variables based on RBFNN. Krzyiak (1995) derived analytical expression for optimal RBF and gave the optimal rate of convergence. Das et al. (1998) proposed a new technique using RBF regarding measurement of neural activity filed of biological neurons which plays a major role in computational neuroscience research. The problem becomes worst due to presence of high noise level and uneven spatial distribution. The results suggest the fruitfulness of the applied technique.

Adaptive control scheme is suitable for the systems in which the model parameters change with time. Mccullough (1992) shows some light on nonlinear systems for which there the accurate models do not exist. Mei and Yu (2017) proposed a combined approach of state observer, disturbance observer and RBFNN to develop neural feedback control for the robot manipulator. Jiang et al. (2017) used integral approximation and model block approach methods with RBFNN adaptive control in manipulator trajectory tracking. Bhatia and Belarbi (2018) used fuzzy system for modeling of Continuous Stirred Tank Reactor (CSTR) and developed model reference adaptive control using adaptive RBFNN scheme. The simulation results show the good modeling and control of temperature in CSTR. Du et al. (2018) proposed the application of RBFNN based adaptive PID scheme for control of Dissolved Oxygen (DO) in activated sludge system. A comparison in the performance of traditional PID and RBFNN-PID shows that the RBFNN-PID scheme gives good control of DO concentration in activated sludge system. Su et al. (2017) discuss a four order nonlinear underactuated system in which they designed the sliding mode decoupling subsystem combined with RBFNN adaptive control to the underactuated system successfully. Emran et al. (2017) proposed an adaptive NN control system design for small quadrotors to follow the desired trajectory despite uncertainty and actuator saturation. Cui and Tian (2016) showed an adaptive control using a single parameter RBF algorithm for the manipulator. The simulation results showed good tracking performance. A Model Reference Adaptive Sliding Mode Control (MRASMC) using RBFNN was proposed to control the single-phase active power filter. It not only provides assurance of globally stability but also the compensatory current to track the harmonic current perfectly (Fang, Fei, & Ma, 2015). Sun et al.(2016) suggested a neural network control scheme based on RBF for biped robots for balancing and posture control. To encounter with uncertainties, neural networks are used to approximate the unknown function. Full state feedback control and output feedback control are considered in this study.

In this chapter, a Chattering Free Sliding Mode Control (CFSMC) technique embedded with observer based adaptive RBFNN is used to design an intelligent controller for a model reference temperature trajectory. The steady-state analysis, effect of different operating parameters, and space discretization are discussed. The main emphasis of this chapter is to design a control structure of RBF neural network for online identification of nonlinear system and apply the gradient descent method for updating weights to predict mapping of the nonlinear term in the reaction kinetics of the fixed bed reactor due to Arrhenius law. One of the main approaches of this study is to find nonlinear function by neuro-identification (W. Yu & Li, 2001). The number of neuron numbers has been optimally found. To reduce the main drawbacks of SMC, i.e.

chattering and requirement of high gain value, an algorithm based on hybrid controller has been proposed. To evaluate performance of the hybrid controller, a comparison with PID controller has been made. Furthermore, an Integral Time Weight Absolute Error (ITAE) analysis has been carried out to prove its robustness against external disturbance, load variation, variation in key parameters and model mismatch. From the best of authors' knowledge, no such study of the fixed bed reactor for the reaction of hydrolysis of ethyl acetate using amberlyst-15 as a solid catalyst has been carried out. This study adds value to "off the shelf" methods in process control.

3.2 Temperature Control of Fixed Bed Reactor

3.2.1 Process Details and Mathematical Model

This study investigates temperature control of non-adiabatic fixed bed reactor in which a pseudo first order, irreversible, endothermic reaction is carried out. A mathematical model of the reactor is formulated with material and energy balances, reaction rate and transport characteristics (Jung-hwan Park, 1995; Wu & Huang, 2003).

Hydrolysis of ethyl acetate has been studied in the fixed bed reactor. A one-dimensional model has been considered along the length of the reactor. Mass transfer resistance and pore-diffusion control have been ignored. Many models for solid-liquid kinetics were proposed and experimentally verified by several researchers (Erdem & Cebe, 2006; Mittal, Nair, & Deshmukh, 2015; Sharma, Toor, & Wanchoo, 2014; Nisha Singh, Kumar, & Sachan, 2013; Suryawanshi, Shinde, & Nagotkar, 2014; Toor, Sharma, Kumar, & Wanchoo, 2011; Toor, Sharma, Thakur, & Wanchoo, 2011) but this study uses only a power model which requires only few parameters. The reaction system can be represented as

$$CH_3COOC_2H_5(A) + H_2O(B) \xrightarrow{k} CH_3COOH + C_2H_5OH \tag{3.1}$$

Two liquid phase reactants react in presence of solid porous catalyst, which is amberlyst-15 that is a well-known catalyst in various esterification and hydrolysis reactions (Delgado, Sanz, & Beltrán, 2007). Ayyappan et al. (2009) mention that less work has been carried out in hydrolysis of ethyl acetate in a fixed bed reactor.

Axial dispersion has been assumed along the length of the fixed bed reactor. Radial gradient of concentration and temperature has been neglected. As per

Dudukovic and Felder (1983), for packed bed, the axial dispersion can be ignored for first-order reaction system if,

$$\frac{L}{d_P} \geq \frac{100}{p} \frac{N_{Da}^2}{N_{Bo}} \tag{3.2}$$

where N_{Da} is Damkohler number defined as $kC_A^{n-1}L/v$, N_{Bo} is Bodenstein number defined as vd_p/v_oD_{AB}, L is length of reactor, d_p is particle diameter, and p is percent deviation from ideal plug flow behavior. In the present study (N_{Da} = 4.324 x10^3, void fraction, v_o = 0.3, N_{Bo} =1.884 x10^3 , L= 0.50 m, d_p = 2.1x10^{-4}m, p=100) this condition is not satisfied, therefore, axial dispersion is considered. As per Pabby et al. (2015), concentration gradient in radial direction can be neglected when the following condition is satisfied.

$$\frac{d_P^2}{4D_{AB}} \leq \frac{L\rho}{\mu} \tag{3.3}$$

In our case (d_p = 2.1x10^{-4} m, D_{AB} = 2 x10^{-9} m^2/s, L= 0.50 m, ρ = 982.320 kg/m^3, μ = 4.744 x10^{-4} kg/m-s), this condition is satisfied.

The following equations are obtained on carrying out mass and energy balance:

$$\frac{\partial C_A}{\partial t} = D_{AB}\frac{\partial^2 C_A}{\partial z^2} - v\frac{\partial C_A}{\partial z} - kC_A \tag{3.4}$$

$$\frac{\partial T}{\partial t} = \frac{k_{mix}}{\rho C_P}\frac{\partial^2 T}{\partial z^2} - v\frac{\partial T}{\partial z} - \frac{(k\Delta H)}{(\rho C_P)}C_A + \frac{A_s U}{V\rho C_p}(T_J - T) \tag{3.5}$$

Initial conditions: $C_A(z, t = 0) = C_{A0}$, $T(z, t = 0) = T_0$ (3.6)

Boundary conditions:

$$\frac{dC_A}{dz}(z = L, t) = 0 = \frac{dT}{dz}(z = L, t) \tag{3.7}$$

$$\frac{\partial C_A}{\partial z}(z = 0, t) = \frac{v}{D_{AB}}(C_A - C_A^{in}), \frac{\partial T}{\partial z}(z = 0, t) = \frac{v\rho C_p}{k_{mix}}(T - T^{in})$$

(3.8)

The system state vector representation can be written as

$$\begin{bmatrix} \dot{C}_A \\ \dot{T} \end{bmatrix} = \begin{bmatrix} D_{AB}\dfrac{\partial^2}{\partial z^2} - v\dfrac{\partial}{\partial z} - k, & 0 \\ \dfrac{-k\Delta H}{\rho\, C_P}, & \dfrac{k_{mix}}{\rho\, C_P}\dfrac{\partial^2}{\partial z^2} - v\dfrac{\partial}{\partial z} - \dfrac{A_s U}{V\rho\, C_P} \end{bmatrix} \begin{bmatrix} C_A \\ T \end{bmatrix} + \begin{bmatrix} 0 \\ \dfrac{A_s U}{\rho V C_P} \end{bmatrix} T_J \tag{3.9}$$

$$\dot{z} = f(z,t)\, z + g(z,t)\, u + d(z,t) \tag{3.10}$$

where z=$[C_A,T]^T$ is the system state vector and

$$f(z) = \begin{bmatrix} D_{AB}\dfrac{\partial^2}{\partial z^2} - v\dfrac{\partial}{\partial z} - k, & 0 \\ \dfrac{-k\Delta H}{\rho\, C_P}, & \dfrac{k_{mix}}{\rho\, C_P}\dfrac{\partial^2}{\partial z^2} - v\dfrac{\partial}{\partial z} - \dfrac{A_s U}{V\rho\, C_P} \end{bmatrix} \tag{3.11}$$

$$g(z) = \begin{bmatrix} 0 \\ \dfrac{A_s U}{\rho V C_P} \end{bmatrix} \tag{3.12}$$

To solve the above system of equations, method of lines (MOL) technique has been used. MOL technique transforms the governing equations to a system of coupled ordinary differential equations (ODE) in time by utilizing finite difference approximation for spatial derivatives. For converting the system to a finite difference form, central difference expression has been employed (Subramanian & White, 2000).

$$\frac{dC_i}{dt} = D_{AB}\frac{C_{i+1} - 2C_i + C_{i-1}}{h^2} - v\frac{C_{i+1} - C_{i-1}}{2h} - kC_i \tag{3.13}$$

$$\frac{dT_i}{dt} = \frac{k_{mix}}{\rho C_P}\frac{T_{i+1} - 2T_i + T_{i-1}}{h^2} - v\frac{T_{i+1} - T_{i-1}}{2h} - \frac{\Delta H}{\rho C_P}kC_i + \frac{UA_s}{V\rho C_P}\left(T_J - T_i\right) \tag{3.14}$$

where i = 1 to N is the node number, N is the total number of interior node points and h is the discretization spacing defined as $h = L/(N+1)$, L is the length of the fixed bed reactor. Entry point, x = 0, corresponds to the node point i = 1 and exit point, $x = L$, corresponds to the node point $i = N+2$. Thus, $x = (i-1)h$. The equation system is a set of $2N$ nonlinear coupled ODEs for N dependent variables. Similarly, the corresponding Boundary Conditions (BCs) are converted into its finite difference form (Cutlip, 1999).

With the help of BCs, the values of C_{A0}, T_0, C_{N+2}, and T_{N+2} are eliminated from the equations. The optimum number of discretization points is obtained by comparing the final transient and steady-state solution. In this study, jacket temperature, T_J, has been used as a manipulated variable to control the outlet temperature of reactor. It is assumed that due to high flow rate governed by pump, jacket temperature is considered uniform. It is assumed that there is no temperature drop between two ends of the jacket. A MATLAB code was written to solve the above system of equations. Table 3.1 contains all parameter values which are used to carry out simulation.

Table 3. 1: Model parameters and operating conditions (Ayyappan et al., 2009)**.**

Kinetic data and model parameters		Initial condition
$E = 41140\ J.mol^{-1}K^{-1}$	$D_0 = D_i + 0.004m$	$C_{A0} = 0.0001\,mol.m^{-3}$
$k_0 = 0.0875m^6 g^{-1} mol^{-1} s^{-1}$	$v = 0.0034\ m.s^{-1}$	$T_0 = 303.15\ K$
$R = 8.314 J.mol^{-1}.K^{-1}$	$D_{AB} = 2\times10^{-9} m^2 s^{-1}$	
L= 0.50 m	$k_{mix} = 0.6371 Wm^{-1}K^{-1}$	
$D_i = 0.025m$	$C_{pmix} = 75.42860\ Jmol^{-1}K^{-1}$	
$U = 800\ Wm^{-2}K^{-1}$	$\rho_{mix} = 982.320\,kg.m^{-3}$	

3.2.2 Fixed Bed Reactor Control Problem Formulation

The reactor control problem formulation consists of monitoring and control of outlet temperature corresponding to first order transfer function temperature trajectory as setpoint change. The manipulated variable used by the controller is jacket temperature. The total dead time in the temperature control loop is the sum of the jacket transport lag, the dead time due to imperfect mixing, and other smaller contributing factors. The dead time due to the jacket displacement can be reduced by increasing the pumping rate.

In general, in the temperature control strategy inside the reactor, the reaction mixture temperature is sensed, and the flow of heat-transfer medium to the reactor jacket is manipulated. But this scheme is considered to be unsatisfactory for many practical situations because of the reactor nonlinearity and dynamic characteristics. This “once-through” method of heating is undesirable also from economic point of view. Another disadvantage of this arrangement is the variable heating residence time of the hot water within the jacket as the flow rate changes. This causes the dead time of the jacket to vary, which in turn demands the updating of the control loop tuning constants as the load varies. In addition to this, when the water flow is low, the Reynolds number will drop off significantly which in turns will reduce the heat-transfer efficiency. The low water velocity can also result in fouling of the heat transfer surfaces of the jacket and reactor under run of prolonged condition.

To overcome all the mentioned facts, the jacketed hot water flow was kept constant at 30 ml/min which was the maximum flow that could be achieved by the peristaltic pump and jacketed temperature was considered as a manipulating variable. The constant flow rate of the pump keeps the constant time lag. The time lag significance of the jacketed, electrical heater, and the reactor has been evaluated. In this study, the following data have been used:

i) The volume of liquid reactant inside the reactor, $V_R = 6.63 \times 10^{-03}$ m^3
ii) The volume of hot water inside the jacket, $V_j = 5.70 \times 10^{-03}$ m^3
iii) The volume percentage of the liquid reactant in the reactor with respect to the jacketed hot water = 11.67 %
iv) The time lag of the jacket = 1.78 minutes
v) The time lag of the reactor = 1.67 minutes

The volume of the liquid reactant is 11.67 % volume of the jacketed hot water. In the tightly fixed bed reactor, lesser space is available for reactant to flow in respect to continuous stirred tank reactor. Due to that reason the time response of the reactor is much lesser concerning the time response of the jacket. In this study, the five seconds sampling time was chosen by running many experiment trials to keep the thought in mind for prolonging run with lesser computational load. From the data, it was being observed that the time lag of the jacket and reactor were lesser than 2 minutes and it is being reported by B.G.Liptak (2006) that this should be kept below 2 min to neglect the effect of time lag. Therefore, there were no need to considered theses negligible time lags into our study.

It is required to ensure that the controller enforces the outlet temperature of the fixed bed reactor to follow the desired change. In this study, temperature trajectory is considered as a first-order transfer function model, which is smoother and more desirable than sharp step change because every practical system takes some time to change itself. The fixed bed reactor has inherently nonlinear complex dynamics. It is well known that operating conditions often change with time, which enhances the complexity in the behavior of real fixed bed reactor and under such environment; it is difficult to obtain satisfactory performance by using a conventional PID controller. With the changing dynamics it is not recommended to tune the controller repeatedly and this task is also impracticable with unknown system or changing system dynamics in the presence of uncertainty and unmeasured disturbance along with model mismatch. Therefore, for a process engineer, it is a challenging task to design a chattering free, robust controller, which has the capability to track the outlet temperature of the fixed bed reactor having process uncertainty, load variation, variation in key parameters, measurement noise and model mismatch.

Practically, every measurement system has some noise. These disturbances in temperature measurement may influence the reactor dynamics and ultimately the controller performance. This study focuses on designing a CFSMC when the dynamics of complex nonlinear fixed bed reactor is not known exactly or has disturbances. To deal with nonlinear complex dynamics, observer-based adaptive RBFNN technique has been applied with CFSMC having three layers neural network system. CFSMC has a good capability to discard the unwanted effects of the disturbances in an efficient manner. It is assumed that outlet reactor concentration and temperature can be the measured parameter. Figure 3.1 shows the complete control setup diagram along with fixed bed reactor. The reactor outlet temperature is measured and compared with a set point temperature trajectory and appropriate control action is taken place by jacket temperature through CFSMC.

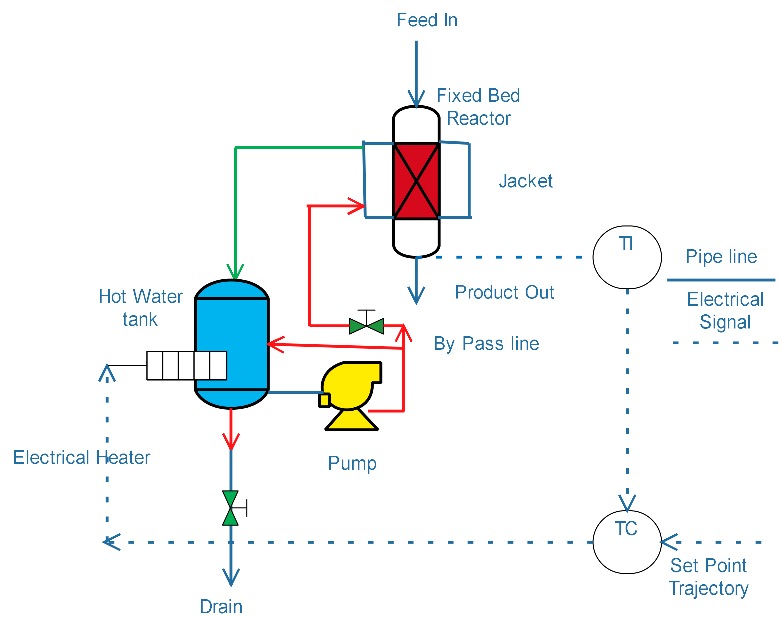


Figure 3. 1: A schematic diagram of a fixed bed reactor control.

To match the simulation with real-time results, a practical constraint has been applied on control input and input rate. The possible variation in the jacketed tape heater's temperature is allowed between 160 °C to 30 °C. The heating rate is found to be 0.5 °C/s based upon experimental observation using 5 kW of electric heater. The initial steady state temperature is considered to be 30 °C.

3.2.3 Analysis of Steady-state Behavior and Effect of Operating Parameters

The reaction kinetics and other operating parameters have been taken from Ayyappan et al. (2009). The reactor of length 0.5 m and diameter of 50 mm was chosen for study. The inlet feed temperature was considered to be 303.15 K and velocity, $v = 0.0034$ m/s. The results are shown in Figures 3.2—3.6. From Figure 3.2, it is seen that the concentration of the reactant decreases and rate of concentration change slows down along the length of the reactor. Jacket temperature (333.15 K) has been considered to be higher than inlet temperature (303.15 K) in this case. Therefore, the conversion increases slightly as the feed velocity decreases due to enhancement in retention time. The feed velocity does not affect the reaction rate but it affects the reaction time, therefore, the temperature profile is affected slightly as shown in Figure 3.3. From

Figures 3.2 and 3.3, it is also obvious that the reactant ethyl acetate is consumed at approximate reactor length of 0.25 m whereas the temperature of mixture remaining in the stream continuously rises. The possible reason for this is that there is temperature driving force between jacket and reactor temperatures. It is obvious from the temperature profile that it is the lowest at the inlet (same as the feed temperature) and approached to jacket temperature along the reactor length. For lower velocity, the temperature is observed to increase faster than that at higher velocity, which is in agreement with the results obtained by Song and Dang (2014). Due to endothermic nature of the reaction, temperature gradient goes down in the initial stage as heat is absorbed during the reaction and the absorption of heat is overcome by supplying adequate heat through jacket. To demonstrate the reduction in the temperature due to endothermic reaction at initial state, the jacket temperature was taken equal to the feed temperature as shown in Figure 3.4. It is clearly seen that the lower temperature is obtained in the axial direction. The reactor temperature profiles have been shown for several feed velocities. At lower velocity, the reactant stays longer in contact with catalyst to carry out reaction which ultimately consumes more heat than supplied and finally temperature falls down.

Figure 3.5 and 3.6 show the effect of feed temperature on the concentration and the temperature profile. The feed temperature affects the reaction rate whereas it does not affect the retention time. The different feed temperatures show the different reactor temperature profiles. The reactor temperature rises due to adequate supply of energy when the jacket temperature is higher than the feed temperature. The different changes in the feed inlet temperature are 30, 25, 20, 15, 10, and 5 degree Celsius. From Figure 3.5, it is crystal clear that the reactant has been consumed all approximately, it means that there are only products left behind, that are acetic acid and ethyl alcohol along with the left-out water. From the reactor length 0.25 m onwards, there is no reaction conversion taking place, and only heating of the products and water is taking place. After residence time of 1.960 minute (0.4/.0034*60), thermal equilibrium state has been established.

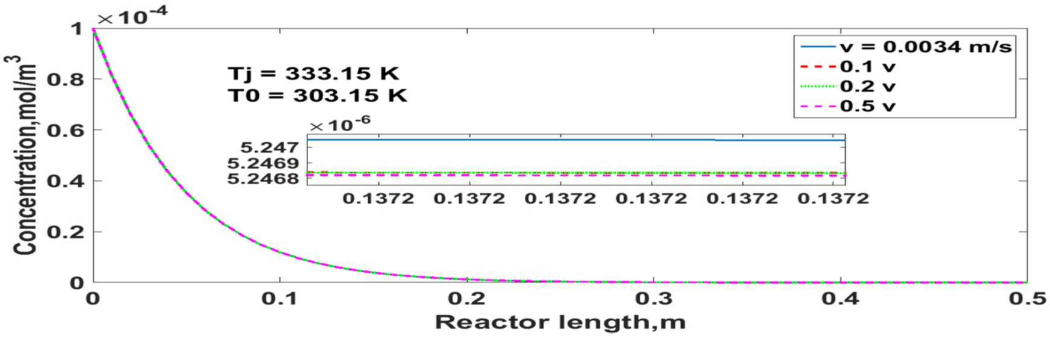


Figure 3. 2:Effect of the feed velocity on the concentration in case of jacket temperature higher than the inlet feed temperature.

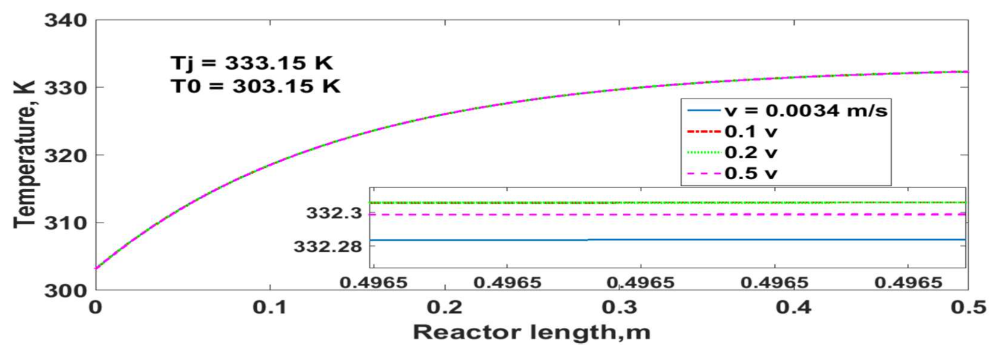


Figure 3. 3: Effect of feed velocity on the temperature profile in case of jacket temperature higher than the inlet feed temperature.

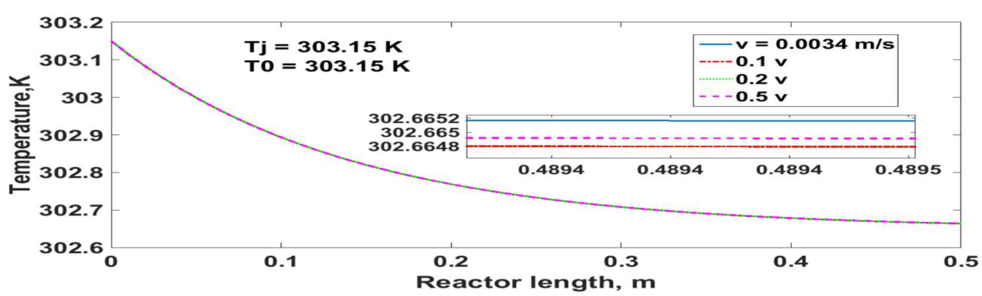


Figure 3. 4: Effect of the feed velocity on the temperature in case of jacket temperature equal to the inlet feed temperature.

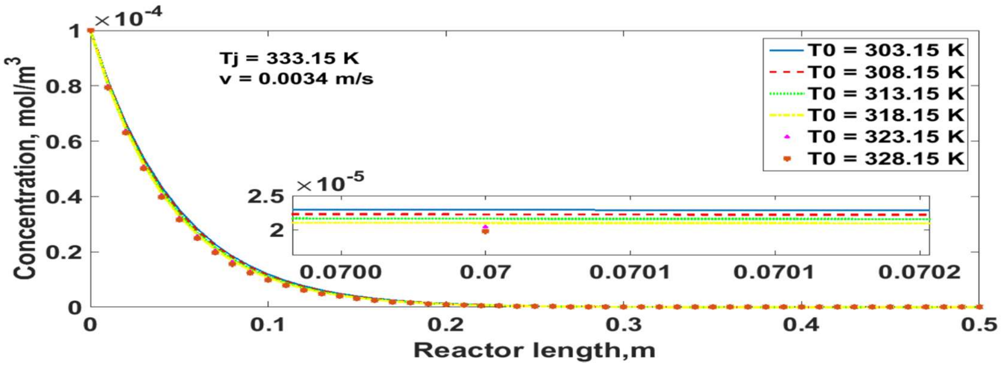


Figure 3. 5: Effect of the feed temperature on the concentration.

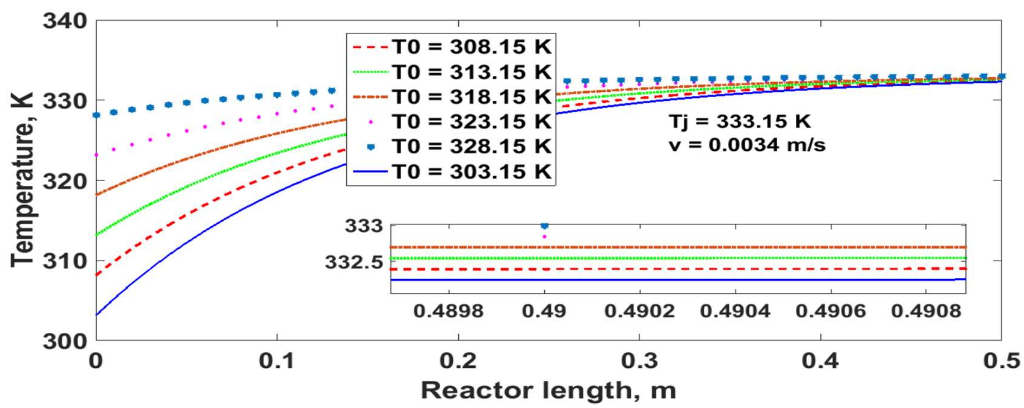


Figure 3. 6: Effect of the feed temperature on the reactor temperature.

3.2.4 RBF Neural Network

RBF has mainly three layers arranged in series from input to output through one hidden layer having RBF as an activation function. The relation between inputs to hidden layer is nonlinear, but linear between hidden to output layer. The weights of hidden function were adjusted by descent gradient algorithm. The calculation of weights involves two important parameters: learning rate and momentum rate. By selecting suitable values of these parameters, it is possible to map the desired function (Vecci, Piazza, & Uncini, 1998).

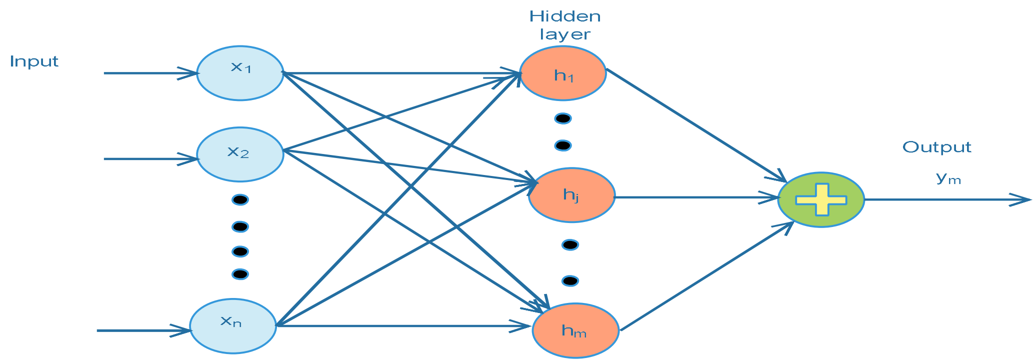


Figure 3. 7: Structure of neural network embedded with RBF.

In Figure 3.7, the first layer represents an input layer, X= $[x_1 \ldots x_n]^T$. The middle layer is called hidden layer with RBF, H = $[h_1 \ldots h_j]^T$, where h_j is Gaussian function. Gaussian profiles are utilized to approximate peak shapes observed. A Gaussian curve is characterized by peak position, peak height and peak width. Commonly, the half width is used (Jagannathan, S., F. L. Lewis, 1994):

$$h_j = \exp\left(- \frac{\left\| X - C_j \right\|^2}{2 b_j^2} \right) \tag{3.15}$$

where $\boldsymbol{C}_j = [c_{j1}, \ldots\ldots, c_{jn}]$ is the center vector of neural set j. The width vector of Gaussian function is $\mathbf{B} = [b_1, b_2, \ldots\ldots.. b_m]^T$, where $b_j > 0$. The weight vector of the output is $\mathbf{w} = [w_1, w_2, \ldots w_m]^T$. The neural network output is a linear summation of product of weight and radial basis function as an activated function in the hidden layer.

$$y = w_0 + w_1 h_1 + w_2 h_2 + w_3 h_3 + \ldots..+ w_m h_m \tag{3.16}$$

$$y = w_0 + \sum_{j=1}^{m} w_j h_j \tag{3.17}$$

where w_j and h_j are the weight vector and radial basis function in the hidden layer, respectively.

3.2.5 Identification Algorithm for Nonlinear Term due to Arrhenius Law

In this study, model reference RBF neural network technique is applied with adaptive weight algorithm as shown in Figure 3.8.

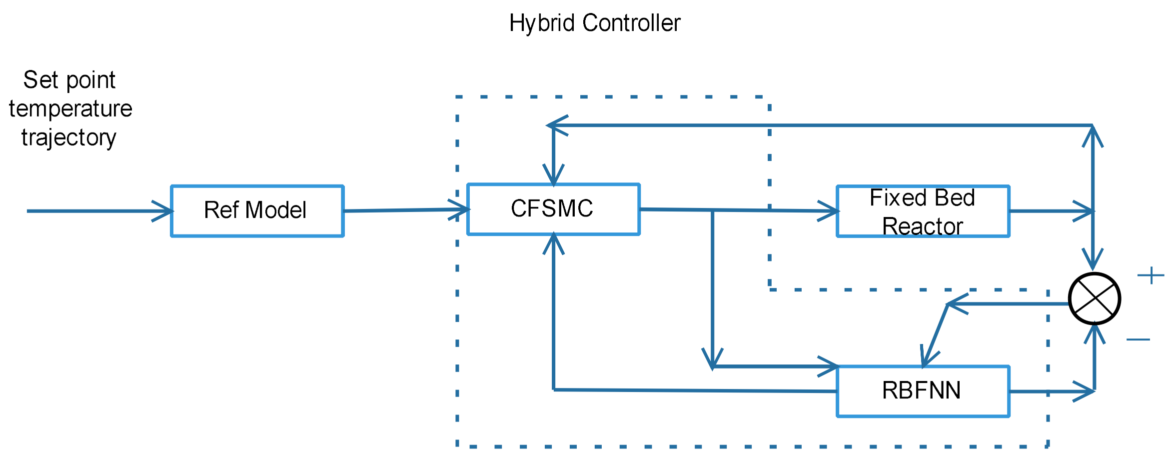


Figure 3. 8: Structure of high gain observer based adaptive RBFNN model reference CFSMC

To evaluate the performance of RBF at any moment of progressive time for further improvement, the performance index function is

$$J = \frac{1}{2}(y(t) - y_m(t))^2 \tag{3.18}$$

RBF is optimized by minimizing the mean square error. The parameters are updated with descent gradient method as follows:

$$\Delta w_j(t) = -\eta \frac{\partial E^1}{\partial w_j} = \eta\big(y(t) - y_m(t)\big)h_j \tag{3.19}$$

$$w_j(t) = w_j(t-1) + \Delta w_j(t) + \alpha(w_j(t-1) - w_j(t-2)) \tag{3.20}$$

where η , α are learning rate and momentum rate, respectively. The sensitivity of the fixed bed reactor is the ratio of outlet temperature to controller input signal, which is also called Jacobian matrix (C. Chen & Chang, 1996):

$$\frac{\partial y(k)}{\partial u(k)} \approx \frac{\partial y_m(k)}{\partial u(k)} = \sum_{j=1}^{m} w_j h_j \frac{c_{ji-u(k)}}{b_j^2} \tag{3.21}$$

3.2.6 Design of CFSMC using Model Reference High Gain Observer based Adaptive RBFNN

To design SMC, a sliding surface is considered. Let S (t) be the sliding surface represented as :

$$S(t) = \lambda_1 e(t) + \lambda_2 \int_0^t e(t)dt \tag{3.22}$$

where, $e(t)$ is tracking error (=T_d - T), $\lambda_1, \lambda_2 > 0$ are tuning parameters of the system. The time derivative of S should be zero.

$$\left.\begin{aligned} \dot{S} &= 0 = \lambda_1 \dot{e} + \lambda_2 e \\ \lambda_1(\dot{T}_d - \dot{T}) &+ \lambda_2(T_d - T) = 0 \end{aligned}\right\} \tag{3.23}$$

By substituting in equation (3.5) and solving, the equivalent control law is

$$u_{eq}(t) = \frac{(\dot{T}_d - \frac{k_{mix}}{\rho C_p}\frac{\partial^2 T}{\partial z^2} + v\frac{\partial T}{\partial z} + \frac{\Delta H}{\rho C_p} k\, C_A) + \lambda_2(T_d - T)/\lambda_1}{1/\tau} + T \tag{3.24}$$

where $\tau = \dfrac{V\rho\, C_P}{UA_s}$ and u_{eq} (t) = T_J.

Adaptive RBFNN has been used to approximate the nonlinear term

$$fx = k_0 \exp\left(\frac{-E}{RT}\right) \tag{3.25}$$

The identification scheme of fx using adaptive RBFNN has been presented in section 3.5. Equations (3.13) and (3.14) can be written as

$$\left.\begin{aligned} \frac{dC_i}{dt} &= D_{AB}\frac{C_{i+1} - 2C_i + C_{i-1}}{h^2} - v\frac{C_{i+1} - C_{i-1}}{2h} - fxC \\ \frac{dT_i}{dt} &= \frac{k_{mix}}{\rho C_P}\frac{T_{i+1} - 2T_i + T_{i-1}}{h^2} - v\frac{T_{i+1} - T_{i-1}}{2h} - \frac{\Delta H}{\rho C_P} fxC + \frac{UA_s}{V\rho C_P}(T_J - T_i) \end{aligned}\right\} \tag{3.26}$$

The input to NN is selected as $x = [e]$ and the resulted output of RBFNN is as follows

$$\widehat{fx} = W^T h(x) \tag{3.27}$$

where $h(x)$ is the Gaussian function of the NN. The success of mapping depends upon the proper selection of the weight, center and width vectors. In this study, center and width vectors are fixed whereas weight vectors are updated online using gradient descent method. The design equation of the high gain observer is,

$$\left.\begin{aligned}
\frac{d\widehat{C_i}}{dt} &= D_{AB}\frac{\hat{C}_{i+1}-2\hat{C}_i+\hat{C}_{i-1}}{h^2} - v\frac{\hat{C}_{i+1}-\hat{C}_{i-1}}{2h} - \widehat{fx}C - \frac{l(leng\quad of\ l+1-i)}{\epsilon^i}(C-\widehat{C_i}) \\
\frac{d\hat{T}_i}{dt} &= \frac{k_{mix}}{\rho C_P}\frac{\hat{T}_{i+1}-2\hat{T}_i+\hat{T}_{i-1}}{h^2} - v\frac{\hat{T}_{i+1}-\hat{T}_{i-1}}{2h} - \frac{\Delta H}{\rho C_P}\widehat{fx}\,C + \frac{UA_s}{V\rho C_P}(T_J-\hat{T}_i) - \\
&\frac{l(lengt\quad of\ l+1-i)}{\epsilon^i}(T-\widehat{T_i})
\end{aligned}\right\} \tag{3.28}$$

where C_i, T_i are the system state vectors, $\hat{C}_i, \widehat{T_i}$ are the estimated state vectors. The l vector is Hurwitz polynomial parameter matrix which is solely responsible for providing stable solution.

$$\left.\begin{aligned}
l &= [\lambda^7\ 7\lambda^6\ 21\lambda^5 35\lambda^4\ 35\lambda^3\ 21\lambda^2\ 7\lambda\ 1] \\
\epsilon &= 0.1\ and\ \lambda = 1.1
\end{aligned}\right\} \tag{3.29}$$

The purpose of observer is such that $lim_{\epsilon\to 0}\,\hat{C} = C,\quad lim_{\epsilon\to 0}\,\hat{T} = T$.

Define the observing sliding mode surface as

$$\hat{S}(t) = \lambda_1\hat{e}(t) + \lambda_2\int_0^t \hat{e}(t)dt \tag{3.30}$$

where $\hat{e}(t)$ is the observer tracking error $= (\widehat{T_d} - \hat{T}), \lambda_1, \lambda_2 > 0$ are tuning parameters of the system.

Based on the above-described sliding surface, the designed feedback control term is as follows:

$$\widehat{u_1}(t) = -k \times \hat{S}(t) \times \tau \tag{3.31}$$

and the robust control term along with equivalent control term is

$$\widehat{u_2}(t) = -\beta \times \tau \frac{\hat{S}(t)}{|\hat{S}|+\varepsilon} \tag{3.32}$$

$$\hat{u}_{eq}(t) = \frac{(\dot{T}_d - \frac{k_{mix}}{\rho C_p}\frac{\partial^2 \hat{T}}{\partial z^2} + v\frac{\partial \hat{T}}{\partial z} + \frac{\Delta H}{\rho C_p} k \hat{C}_A) + \lambda_2 (T_d - \hat{T}) / \lambda_1}{1/\tau} + \hat{T} \tag{3.33}$$

The final control law is $\hat{u}(t) = \widehat{u_{eq}}(t) + \widehat{u_1}(t) + \widehat{u_2}(t)$ (3.34)

But by simulation it is found that the main cause of chattering in traditional SMC is u_{eq} due to which the practical implementation of SMC scheme becomes difficult to physical system such as circulating pump. In this study, the final control element is electrical heater which receives the electrical signal as a control input. To overcome the above-mentioned situation, $\widehat{u_{eq}}$ part is neglected which is responsible for wear and tear of final control element. In addition, it also reduces the high gain requirement for SMC which is again a critical problem when applied with bounded control input to real-time system.

It is noted that the system of partial differential equations (3.4 and 3.5) turns into first-order system of ODEs after space discretization by MOL technique. Once the error reaches the surface, the value of $S(t)$ becomes constant and to keep the value constant, $dS(t)/dt$ must be equal to zero in finite time.

To check the stability condition of the observer based adaptive RBFNN, a Lyapunov function candidate is selected:

$$V = \frac{1}{2}\widehat{S^2} \tag{3.35}$$

From Lyapunov theorem, it is well known that if

$$\dot{V} \le 0 \tag{3.36}$$

the system states will be forcefully driven and move towards the sliding surface and remain there until it reaches the origin asymptotically.

$$\dot{V} = \hat{S} \times \dot{\hat{S}} \tag{3.37}$$

After simplification, the following expression is obtained.

$$= S[\lambda_1(\dot{T}_d - W) + \lambda_2(T_d - \hat{T})] + (\hat{S} - S)[\lambda_1(\dot{T}_d - W) + \lambda_2(T_d - \hat{T})] - k_1\lambda_1\hat{S}^2 \quad (3.38)$$

where $W = \frac{k_{mix}}{\rho C_P}\frac{\partial^2 T}{\partial z^2} - v\frac{\partial T}{\partial z} - \frac{(k\Delta H)}{(\rho C_P)}C_A - \frac{A_s U}{V\rho C_p}T$

$$\leq |S|[\lambda_1|(\dot{T}_d - W)| + \lambda_2|(T_d - \hat{T})|] + |(S - \hat{S})|[\lambda_1|(\dot{T}_d - W)| + \lambda_2|(T_d - \hat{T})|] - k_1\lambda_1|\hat{S}^2|$$

Due to convergence and perfect mapping, the terms $|(\dot{T}_d - W)|, |(T_d - \hat{T})|$ and $|(\hat{S} - S)|$ are very small. Therefore, it can be written as

$$\dot{V} \leq -k_1\lambda_1|\hat{S}^2| < 0, \text{ where } k_1 > \lambda_1 > 0 \quad (3.39)$$

Figure 3.8 represents the simulation diagram of the CFSMC with high gain observer based adaptive RBFNN. The system first identifies the plant model and the appropriate control action is governed by the CFSMC to track the desired temperature trajectory.

3.3 Results and Discussion

A fixed bed reactor has been investigated in this section whose dynamics is described by equations 3.4 and 3.5. The feedback gain considered is 5 .The desired temperature tracking of the fixed bed reactor is assumed to be given by first-order transfer function, $G(s) = 1 / (0.2s+1)$. In this section, a hybrid control technique using sliding mode control and high gain observer based adaptive RBFNN are studied in the presence/absence of external disturbance, measurement noise, load variation, variation in key parameters and model mismatch. To quantify the performance of the designed controller, an integral time weight absolute error (ITAE) analysis has been carried out. ITAE is estimated as per following equation:

$$\text{ITAE} = \int_0^t |e| t dt \quad (3.40)$$

The complete solution scheme for design and its implementation in step-by-step manner is shown in Figure 3.9.

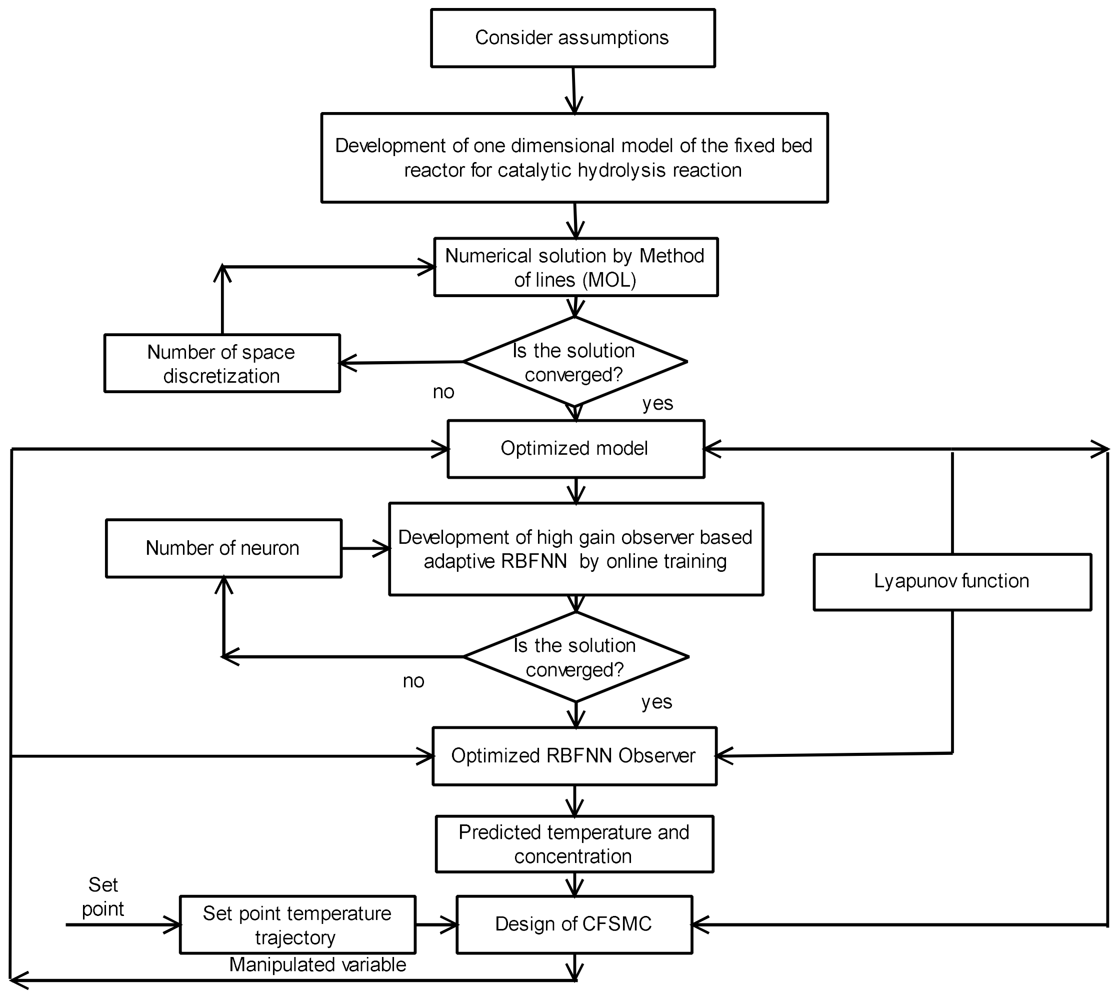
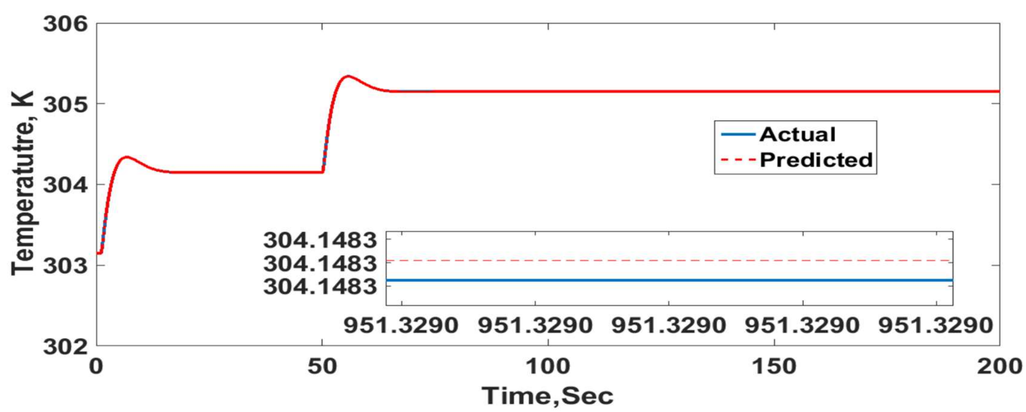
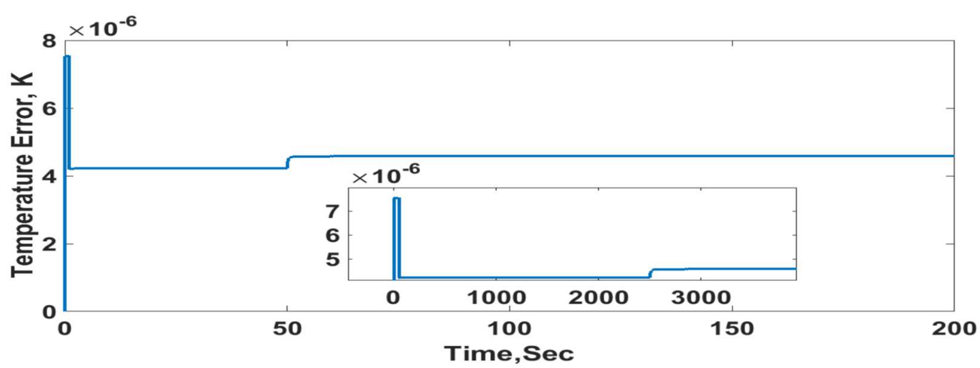


Figure 3. 9: Scheme of the proposed algorithm

3.3.1 Mapping of Concentration and Temperature with High Gain Observer based Adaptive RBFNN

High gain observer based adaptive RBFNN technique has been tested with the desired temperature trajectory, which is the first order transfer function as described earlier. From Figure 3.10, it can be clearly observed that the actual temperature is successfully mapped by the observer based RBFNN. The results show that the observer based adaptive RBFNN has quite extraordinary capability to predict the nonlinear model, like, fixed bed reactor. Figure 3.10 also shows the mapping error of the observer for the temperature and concentration. It is clear from the figures that mappings are perfect. Figure 3.11 shows the estimation of nonlinear term *fx* by adaptive RBFNN. The estimation is good and the *fx* error is quite low. Figure 3.12 shows the effect of neuron numbers on the mapping of nonlinear term *fx*. It is quite clear that eight numbers of neuron is good to map the highly nonlinear term fx. In selection of the suitable numbers of neuron, computational load and simulation runtime is an important aspect to consider. This figure also shows that the adaptive RBFNN, which has only one hidden layer with eight number of neurons embedded with RBF, is sufficient to map the nonlinear term *fx* with the reduction of computation load as compared to multilayer feed forward neural network.





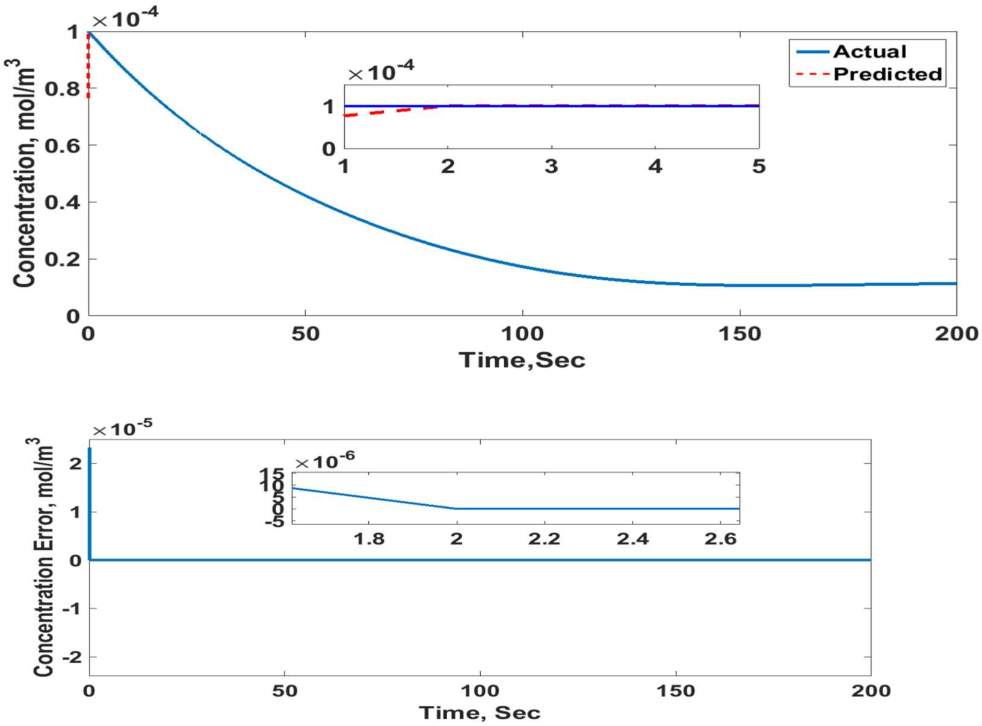


Figure 3. 10: Estimation of temperature and concentration with error by high gain observer based adaptive RBFNN.

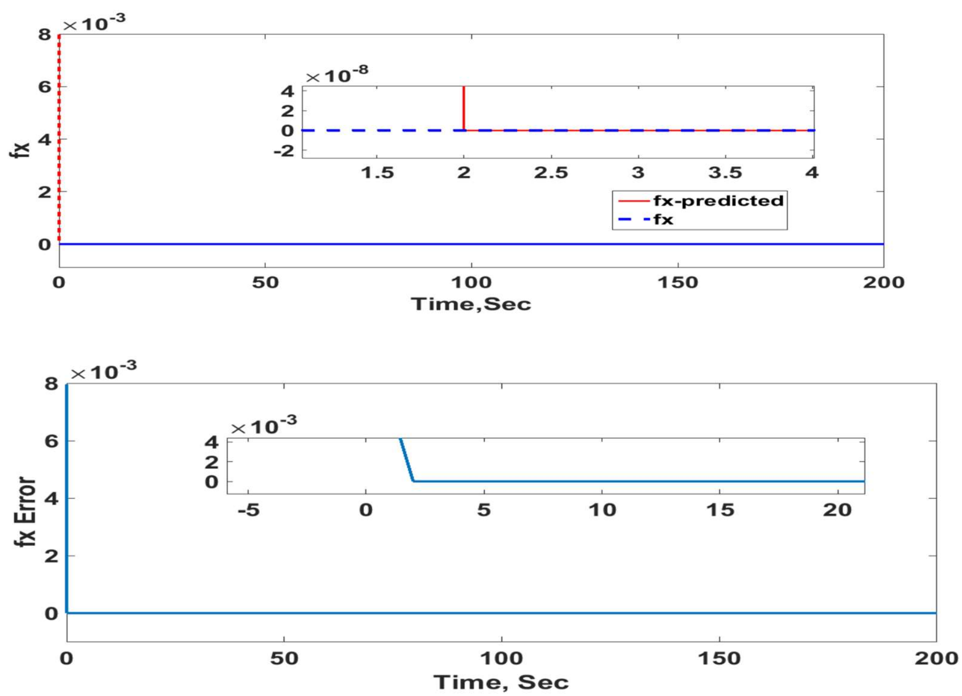


Figure 3. 11: Estimation of non-linear term due to Arrhenius law and its estimation error.

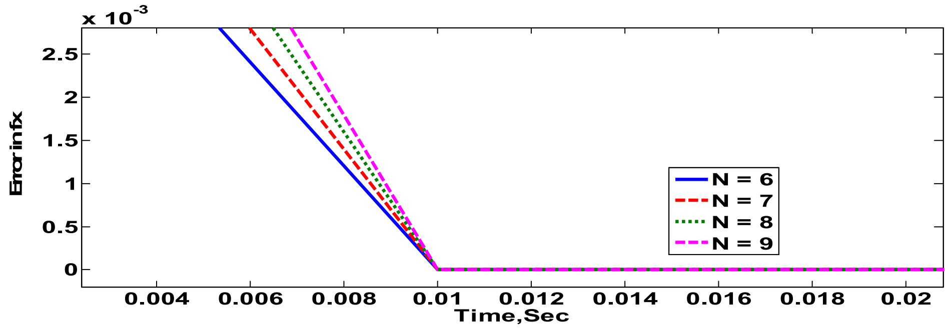
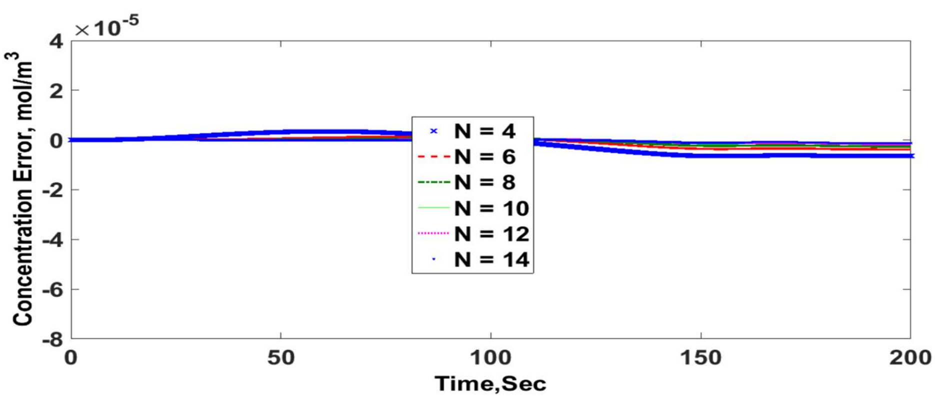


Figure 3. 12: Effect of the neuron numbers on *fx* error by adaptive RBF neural network.

3.3.2 Effect of Space Discretization Step

Figure 3.13 demonstrates the effect of space discretization step to get the numerical solution. In this study, one hundred space discretization steps are considered as a good accurate solution for comparison. This figure demonstrates the effect of step size on modeling error of temperature and concentration profile. It is clear that decreasing step size enhances the performance. But presence of heavy computation load and runtime might make it difficult to run on real-time system. To keep that thought in mind, it is found that the selection of eight number of space discretization steps is reasonably good.



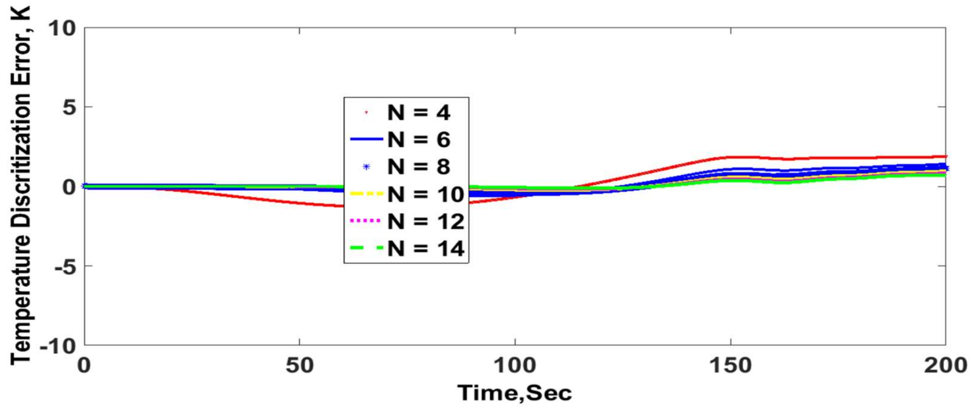
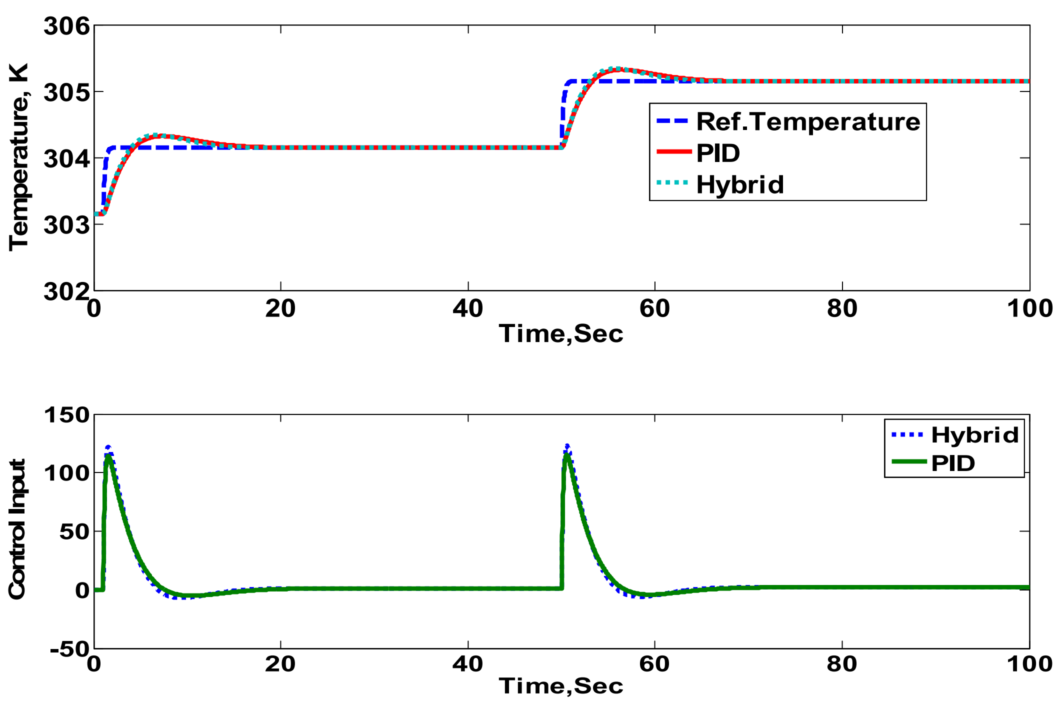


Figure 3. 13: Effect of the number of node points on concentration and temperature.

3.3.3 Performance of Hybrid Controller

To enhance the performance, manual tuning is carried out. For fair comparison between the designed and PID controller, manually tuning is adjusted so that both controllers show equal performance up to time span of 10 s. The model is monitored with respect to outlet concentration and temperature when a first-order model output is set as a reference temperature trajectory.



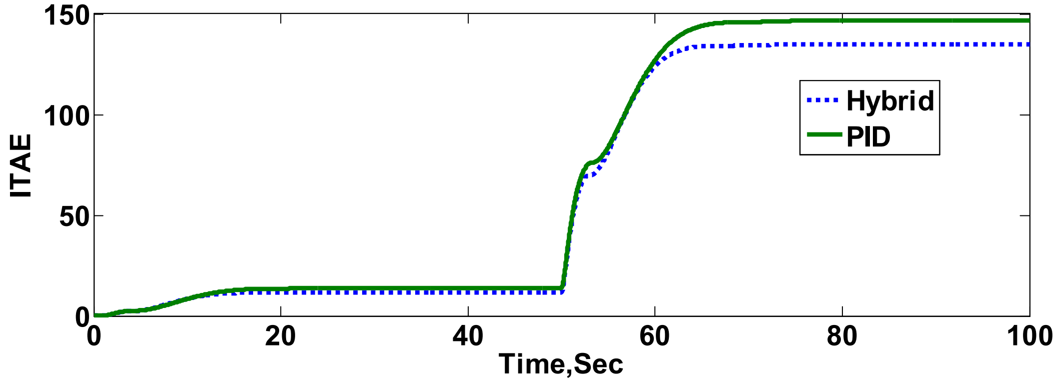


Figure 3. 14: A performance comparison between hybrid and PID controller with control input (deviation variable) and ITAE under the condition of perfect model

The tuning parameters of the controller are as follows:

$$\left.\begin{aligned} &\lambda_1 = 1,\ \lambda_2 = 0.5 \\ &\beta = 0.1,\ \ \varepsilon = 0.1 \end{aligned}\right\} \tag{3.41}$$

The transfer function of PID controller is

$$G(s) = 140 + \frac{30}{s} + 15s \tag{3.42}$$

Figure 3.14 shows a performance comparison between the PID and the hybrid controller for first-order transfer function model as a temperature tracking trajectory. The hybrid controller performance evaluation has been carried out with low gain k = 5. All operating parameters values were kept constant throughout this study. It is noted that simple conventional SMC technique, which is mostly opted for simple system is unable to serve the purpose due to strong nonlinearity and therefore is not much use to control reactor. It is also clear from Figure 3.14 that controller has small response time but a slightly more overshoot in respect to PID controller for tracking the desired set point temperature trajectory. One possible reason may be use of very low gain value in comparison to PID controller which is using value 28 times higher. Selecting a sliding surface, one can reach sliding surface. The negligence of the equivalent control part enhances the performance of the CFSMC and follows temperature tracking superior than PID controller. Figure 3.14 also depicts that the control signal does not show chattering phenomena.

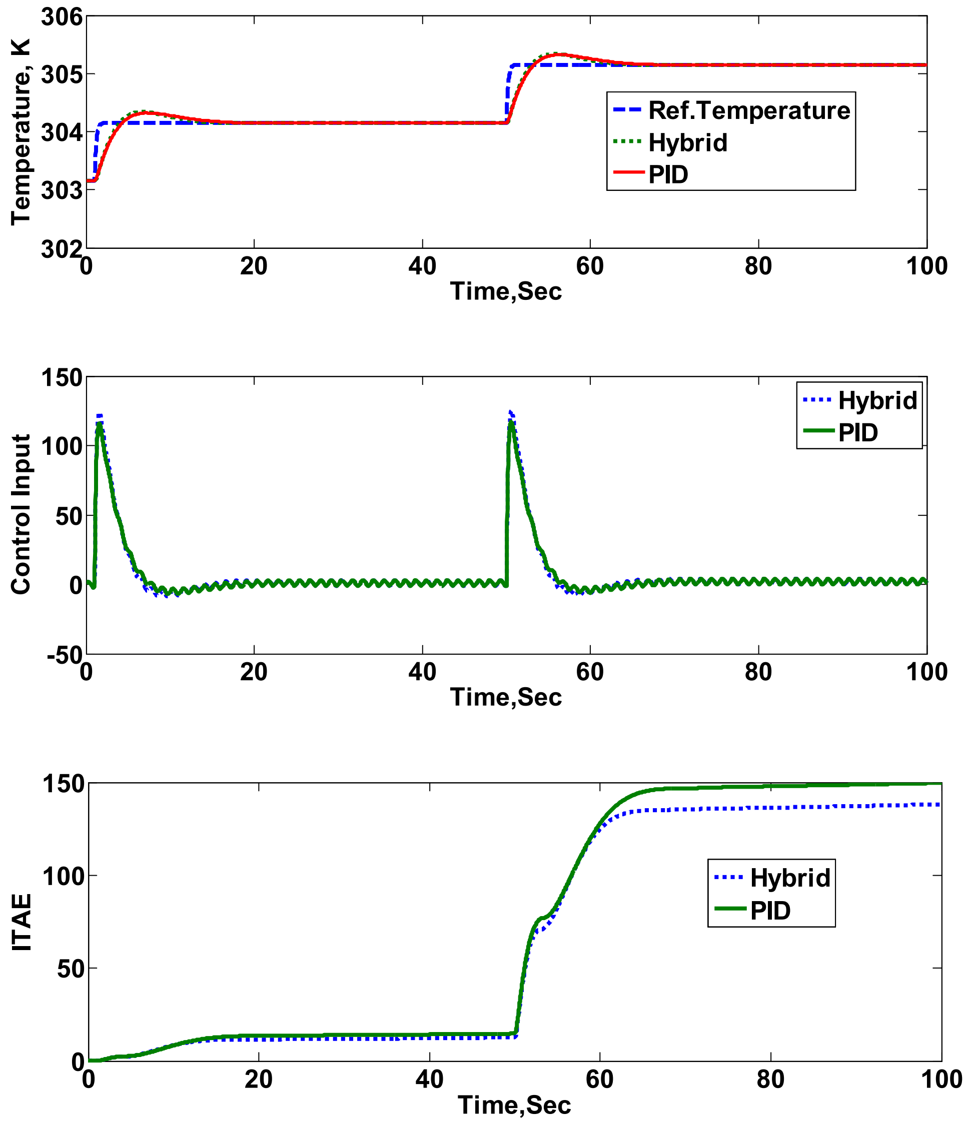
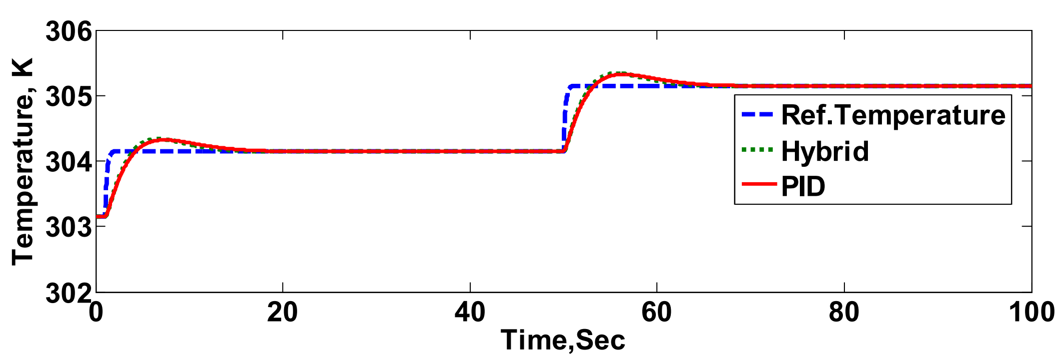


Figure 3. 15 : A performance comparison between hybrid and PID controller for continuously varying load with control input (deviation variable) and ITAE.

In addition, the performance of hybrid controller is judged against continuously varying load of 2 sin(5t). The addition of the load is through control input to plant. Figure 3.15 depicts that the control input is stable without chattering and requires less value of gain in respect to PID controller. The performance of the hybrid controller is better than PID.

The performance of the designed controller is verified against variation in key parameters such as reaction rate constant and activation energy, which are critical parameters of the hydrolysis reaction system and wrongly measurement of these parameters can deteriorate the performance of the controller. As suggested by Chen (2014), there are +100% changes given in the value of frequency factor and -20 % changes in the activation energy. The designed controller is robust to these changes as shown in Figure 16. Results reveal that by giving the known variations in the reaction rate constant and activation energy, the controller performance shows no longer rise time to track the desired response and takes no longer time to settle down as compared to that for the case of perfect model. Furthermore, this simulation study also emphasizes on the facts that the conventional method of removing chattering phenomena is not generally successful when system has strong nonlinearity. The development of undesirable chattering phenomena is taken place by utilizing sign function in reaching phase, which is also responsible to reduce the life of final control element. Similarly, other commonly used function is the saturation function in which a small boundary thickness around the selected surface is built and within this boundary layer, system state is continuously switched and marched forward until it reaches the origin. To suppress the effect of chattering further, the use of hyperbolic function has proven a better choice (Sinha, 2016) but not much effective for a distributive nonlinear model.

It is generally a tradeoff between reduction in chattering and controller performance. The precise balance is based on user’s choice. However, the negligence of equivalent control term provides a better choice to retard chattering behavior without much deterioration in the controller performance.



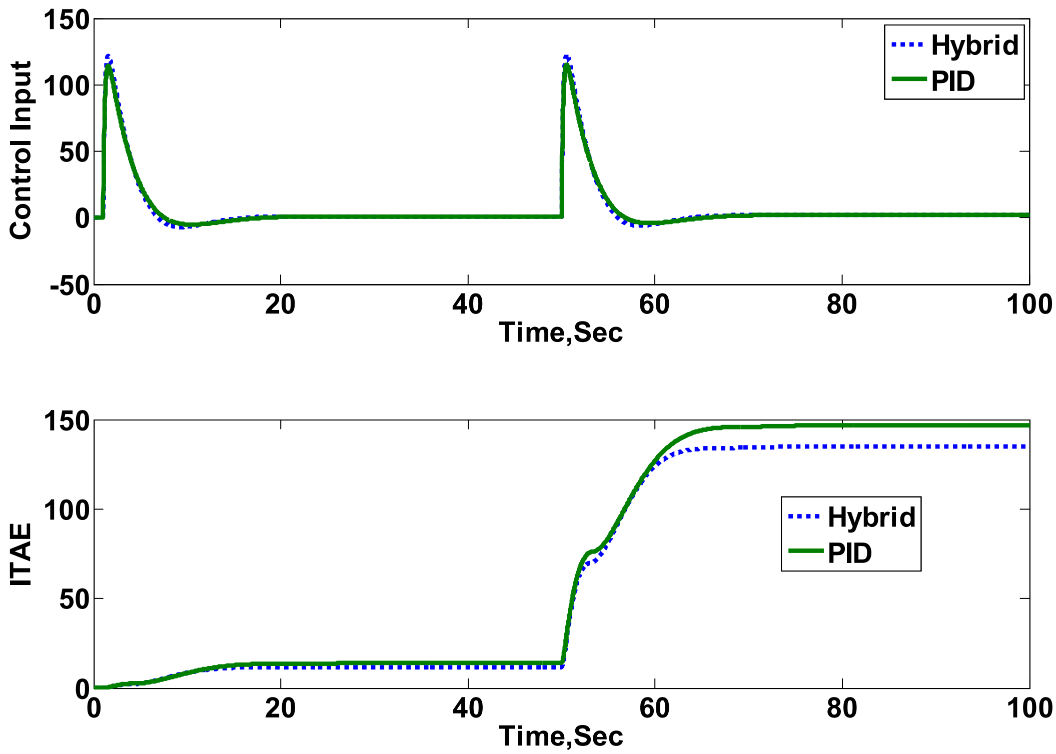


Figure 3. 16: A performance comparison between hybrid and PID controller for +100 % change in the value of frequency factor and -20 % change in the value of activation energy with control input (deviation variable) and ITAE.

3.3.4 Effects of External Disturbance

The performance of the designed controller is also verified in the presence of external disturbance and measurement noise. The value of switching gain is kept constant. For performance evaluation, a repetitive unmeasured disturbance $d(t) = 0.1\sin(0.2t)$ was added to the modeling equation 3.5 as suggested by Chen (2014). Figure 3.17 depicts that hybrid controller has no visible chattering signal even in the presence of such strong disturbance and also shows good disturbance rejection as compared to PID controller.

To illustrate one step further, the effect of noise in temperature measurement of controller performance has been investigated. For this, zero mean random numbers with standard deviation of 0.5 were added to reactor outlet temperature. To suppress the effect of unwanted noise, the value of gain was not reduced as suggested by Chen (2014); the hybrid controller still showed small overshoot initially as before. Figure

3.18 shows the controller performance under such noisy measurement. Therefore, the designed hybrid controller is able to retard the effect of unmeasured disturbance up to acceptable level.

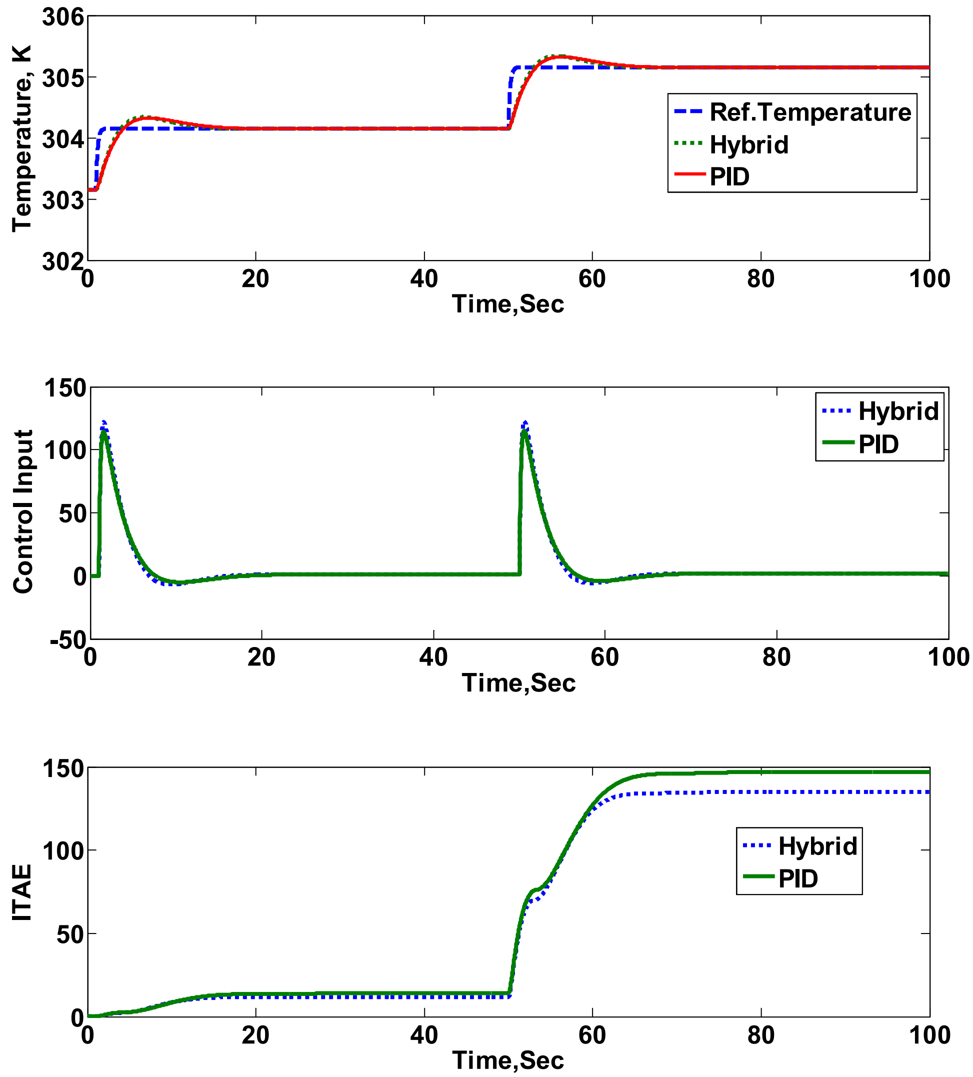


Figure 3. 17: A performance comparison between hybrid and PID controller in presence of periodic disturbance with control input (deviation variable) and ITAE.

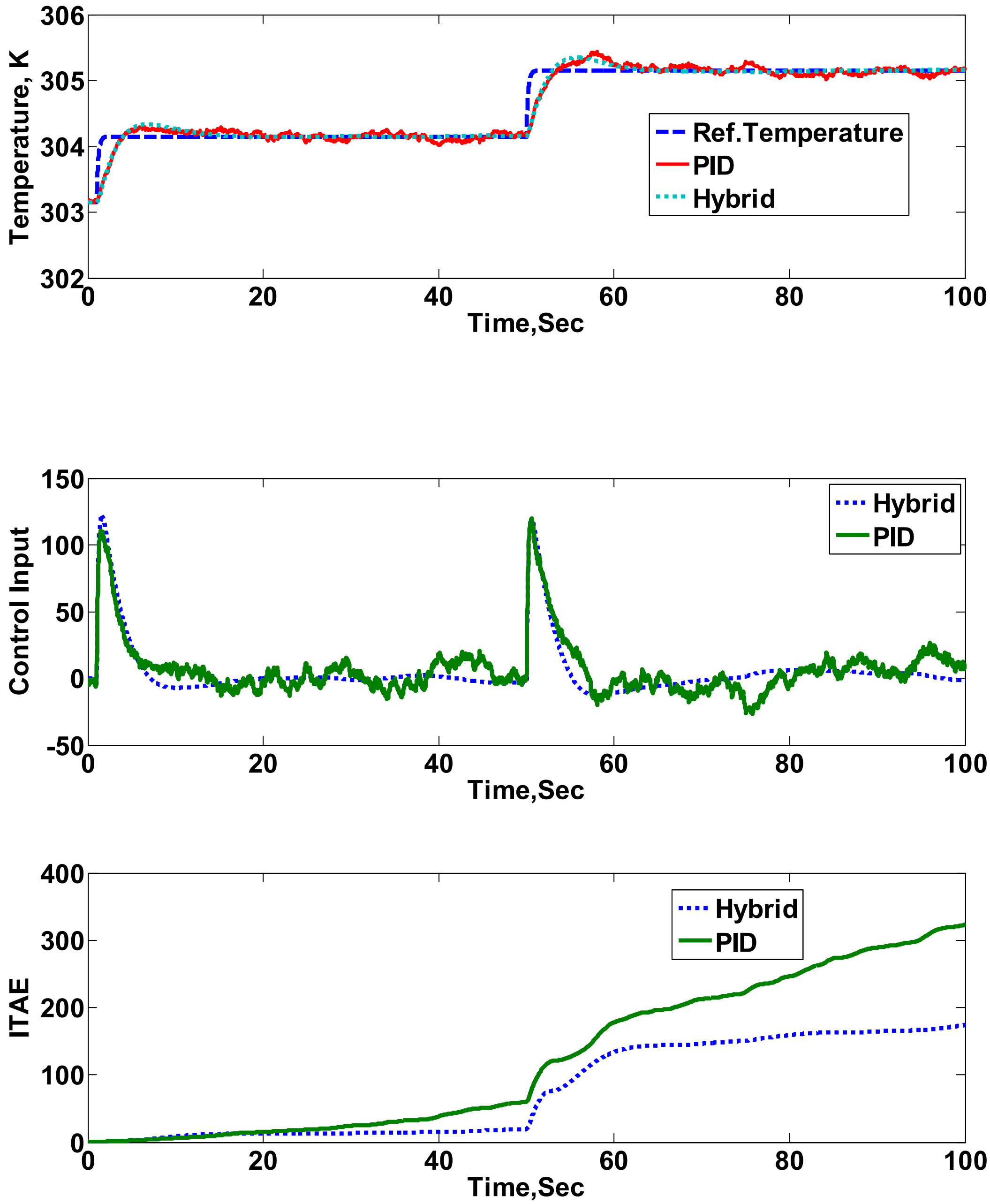


Figure 3. 18: A performance comparison between hybrid and PID controller in presence of measurement noise with control input (deviation variable) and ITAE.

3.3.5 Model Mismatch

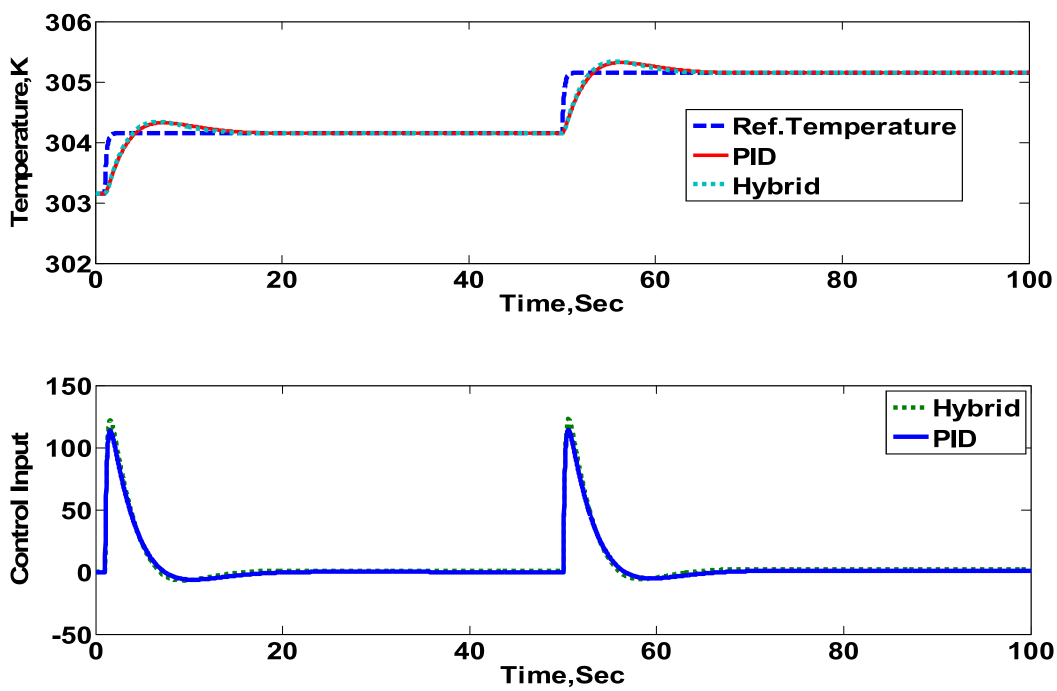
The performance of the designed hybrid controller under un-modeled dynamic condition is also investigated, which might be possible when dealing with a complex system such as the fixed bed reactor. For this, a model mismatch of $d(z, t)$ is added to right-hand side of the modeling equations (3.4) and (3.5) of the fixed bed reactor (C. Chen, 2014). In this study, it is considered that the model uncertainties are Δf and Δg in f and g, respectively. To quantify values of uncertainty; the suggested equation is as follows:

$$d(z,t) = \Delta f(z,t) + \Delta g(z,t) \tag{3.43}$$

$$\Delta f(z,t) = \begin{bmatrix} -.001 \quad C_A \\ 0.2 \end{bmatrix} \tag{3.44}$$

and

$$\Delta g(z,t) = \begin{bmatrix} 0 \\ 1 \end{bmatrix} u \tag{3.45}$$



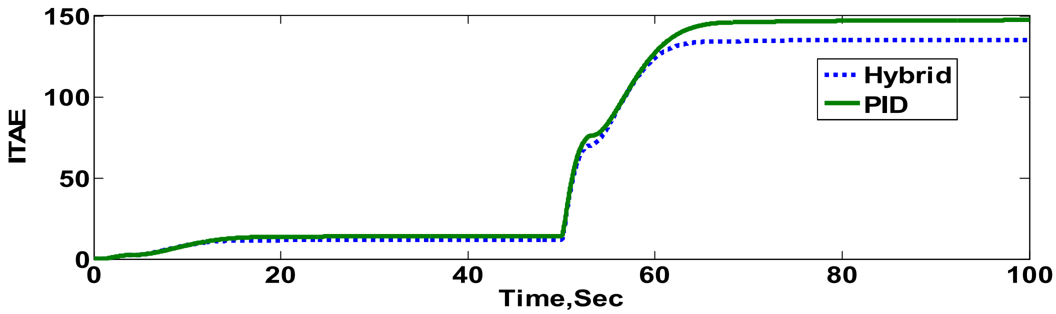


Figure 3. 19: A performance comparison between hybrid and PID controller in presence of model mismatch with control input (deviation variable) and ITAE.

As suggested by Chen (2014), a model mismatch was incorporated into the rate law equation in terms of a reaction rate constant and activation energy. Figure 3.19 illustrates how the designed hybrid controller has robustness to overcome against model mismatch. It is seen from this figure that the control has a slightly larger overshoot and less settling time for temperature tracking comparatively.

3.4 Conclusions

This study studies design of a hybrid controller using high gain observer based adaptive radial basis function neural network (RBFNN) applied in a fixed bed reactor for hydrolysis of ethyl acetate. The performance of the hybrid controller has been analyzed with and without presence of unmeasured external disturbance, variation in frequency factor and activation energy, load variation, and model mismatch for the temperature tracking. The adaptive RBFNN was used to predict the nonlinear term. The high gain observer with adaptive RBFNN was used to predict the states of the system. The design parameters of the observer were estimated using Hurwitz polynomial. The inlet feed temperature and velocity were varied to see the effect in the fixed bed reactor operation. The outlet temperature was observed to be higher when the jacket temperature was selected to be higher than feed temperature whereas the outlet temperature got lower when the jacket temperature was kept at lower temperature. Eight numbers of neurons and eight space discretization steps were found suitable for the study by many simulations runs. However, during optimization of these parameters, computational load and efficient feasibility for run on real-time system was also kept in mind. For the removal of chattering behavior, the equivalent control term was neglected which had advantages not only in terms of chattering free control signal but also in terms of low feedback gain. To match the simulation with real time, a practical constraint was applied on control input and input rate. The maximum possible variation in jacket temperature was allowed between 160 °C to 30 °C. CFSMC with high gain observer based adaptive RBFNN was found to be robust to external disturbance and model mismatch. Adaptive RBFNN was used to approximate the nonlinear term of the reactor kinetics arising due to Arrhenius law with only eight numbers of neurons embedded with RBF as an activation function. The center and width vector were assumed to be constant and the weight vector was determined by the gradient descent method. The application of Lyapunov theorem guaranteed the stability of the numerical simulation results. A comparison with PID shows that the designed controller has a good performance. The results illustrate that the hybrid controller is good controller in the presence of uncertainty, load variation, measurement noise, and model mismatch.

Chapter 4: Temperature Control of Real-time Identified Fixed Bed Reactor by Adaptive Sliding Mode Control Equipped with Arduino in MATLAB

Chapter 4 : Temperature Control of Real-time Identified Fixed Bed Reactor by Adaptive Sliding Mode Control Equipped with Arduino in MATLAB

4.1 Introduction

Rapid advancement in the field of control has an impact on all the major disciplines. Modeling and system identification are used in many different ways in industrial control system. Modeling is a way of studying the behavior of a complex industrial system such as fixed bed reactor and the reactor identification may be used to improve the accuracy of the model or to trace parameters in a model of the fixed bed reactor. Uncertainty in the developed model can provide the basis for advanced robust control. However, the reactor identification knowledge can be used in an effective design of adaptive control systems. The identification of black-box and gray-box model put a constraint on the utilization of knowledge of physical and chemical processes and at the same time enforces the application of simple mathematical forms to capture the behavior of real systems. There is a considerable growth in various fields, including theory, modeling strategy, and system identification techniques.

Fixed bed reactor is a widely used unit in the process industries, which needs to be controlled in order to improve productivity. One of the most common controllers used in industries to control hydrolysis of Ethyl Acetate (EA) reaction is PID controller in which jacket temperature is changed by manipulating the jacket water flow rate. Fixed bed reactor is difficult to model perfectly; therefore, to overcome this difficulty, open loop identification of the process is carried out by assuming the discrete first order plus unit delay model. The closed-loop identification technique is more subtle to noise in comparison to the open loop technique. However, application of open loop identification technique is restricted to a stable system. In closed-loop system, after initial open loop identification, model parameters may change with the changing dynamics of the system, which is responsible for the deterioration of the designed fixed parameter controller's performance. A simple solution to this problem is the development of adaptive control.

Teng and Song (2014) proposed a Predictive Functional Control (PFC) scheme for temperature control of a batch reactor with heating and cooling provisions. They developed process model to design a controller for the situation where online measurement was not possible easily. They implemented real-time implementation of PFC in MATLAB. Chew-Hernandez et al. (2004) applied a Minimum Error Profile (MEP) algorithm to control temperature of an auto-thermal reactor equipped with internal countercurrent heat exchanger. An extended Kalman filter was used by them to estimate the states of the reactor by measurement at various points along the length of the reactor. The combination of MEP with LQR shows superiority in the performance when a sinusoidal disturbance affects inlet feed. Tahir et al.(2018) proposed a real-time process control and monitoring scheme for the production of ether using a continuous flow micro-reactor. The combination of MPC and Principal Component Monitor Analysis (PCA) provides a good robust control for the process. Besides control, the proposed PCA monitor scheme is able to detect process/reaction faults. Panjapornpon et al. (2018) implemented a real-time control of CO_2 absorption in a bench scale bubble column reactor. Main emphasis of the designed I/O linearized controller was to get maximum CO_2 absorption efficiency at the optimized pH. A performance comparison with PI controller was shown by them. Kaluri et al. (2018) predicted the proximity of Lean Blow Out in combustion systems using real-time temperature measurements in chemical reactor network. Sinha and Mishra (2018) suggested a control scheme, which ensures the stability of CSTR under closed loop condition. The designed event-driven sliding mode control is used to control temperature and concentration only when the predefined conditions are no longer valid. This approach reduces the computational load in comparison to traditional SMC. Amini et al. (2018) proposed an adaptive second order Discrete Sliding Mode Control (DSMC) and results showed that the tracking performance can be improved up to 90 % in comparison to first order discrete SMC. However, the overall improvement is 25 % when shifted from Single-input Single-output (SISO) to Multi-input Multi-output (MIMO) system. Anastasov (2002) investigated the effect of the operating parameters to hot spot formation using oxidation of O-xylene into phthalic anhydride in the fixed bed catalyst. They developed a two-dimensional heterogeneous mathematical model and validated with pilot plant data for two different states of the solid catalyst. Wang et al. (2006) used ANN to determine the heat transfer rates of shell and tube heat exchanger based on the availability of limited experimental data. Wagner and Mannschott (1994) developed a simple linear relation between kinetic average temperature and thermal power reactor. They suggested that the average kinetic temperature can be used as a chemical sensor for the temperature measurement in a fixed bed reactor. Petre et al. (2008) proposed a robust adaptive control strategy to analyze bioprocess inside a fixed bed reactor. The control strategy consists of linearized control law coupled with internal observer and assumed that both bacterial growth and flow rates are time averaging and have uncertainty but bounded one. Dochain et al. (1994) focused on the design of adaptive linearized controller using concentration measurement at the exit of the fixed bed reactor. The unknown kinetics was estimated online and used in the control law. Miller et al. (2004) suggested nonlinear and linear flow model for fluidized bed boiler. However, the developed nonlinear model was a lumped parameter model. They obtained a linearized model experimentally for designing a control system. The chemical reactor network was used in the production of various combustion reactions (Hao, 2014). Lee and Lee (1985) designed an online optimization scheme for exothermic reaction system inside a fixed reactor. They developed an adaptive control for temperature control of the partial oxidation of n-butane to maleic anhydride. To monitor the system online, they interfaced a microcontroller showing that the reaction control was driven inside an optimum region. Kuen et al. (2010) demonstrated an integration of an online process model identification using Recursive Least Square (RLS) scheme and an adaptive IMC to control the biodiesel trans-esterification reactions in biodiesel reactor. Westerink et al. (1990) suggested that one-dimensional mathematical model is quite reasonable to predict the hotspot formation inside a tubular reactor. Srihawan et al.(2018) proposed a real-time scheme to deal simultaneously with pH and level control of solution in a tank. They designed a linearized feedback controller for trajectory tracking. Experimental investigation demonstrated the effectiveness of their proposed scheme. Charfeddine and Lassaad (2015) presented the comparison of simulation between gain scheduling and SMC schemes on CSTR. Both the schemes tracked well the desired trajectory but authors did not comment on the superiority of the designed controllers. Pyrhonen et al. (2016) proposed a linearized-based gain scheduling Composite Non-linear Controller

(CNF) for exothermic reaction in CSTR. A simulation study was carried out by them to show the comparison among the proposed scheme to traditional gain scheduling cascade control and gain scheduling MPC. Miguel et al.(2017) developed Divide and Conquer (D&C) approach for real-time temperature control of a three-phase electric air heating furnace. Linearized models were identified for different operating ranges. A set of 12 PI and PID controllers was designed by them and switching among the controllers was used by gain scheduling technique. Gain scheduling is an adaptive control technique, but it has some disadvantages in comparison to the proposed technique. For gain scheduling technique, it is necessary to determine typical operation points and optimize the parameters at all the operation points through simulation and experiments (Jin & Wang, 2014) **.**The second problem is the proper selection of the scheduling variable, which is selected by the rule of thumb that may vary gradually and that must arrest nonlinearities of the plant. The third major difficulty is its real-time implementation through scheduling function due to which the gains are varied as a function of the scheduling variable.

Raghaven (1992) suggested a three-tier reactor scheme for controlling highly exothermic reaction. It consists of inbuilt cooling, online detection of runaway reaction precursor along with re-stabilization of temperature and pressure releasing system through venting. Fixed bed reactor dealing with exothermic/endothermic reactions, generally, shows a parametrically sensitive behavior under certain range of operating conditions. The slight variations in the reactor input values can cause a large variation at reactor outlet. Under such situation, temperature along the length of the reactor decreases/increases which finally can affect the catalyst activity and conversion. Therefore, to deal safely with fixed bed reactor, a tightened dynamically temperature control technique should be applied.

Dostal et al. (2011) developed a continuous-time nonlinear model of the CSTR. The designed controller consists of two parts that is static and dynamic parts. Simulation tests were performed for consecutive exothermic reaction. Dostal et al.(2015) designed an adaptive LQ control for a tubular chemical reactor in which consecutive exothermic reaction was taken place. Cascade control design consists of two control loops: primary and secondary. The primary loop was used to control the concentration of main product whereas the secondary loop was used to control the reactant temperature inside the reactor. Vojtesek and Dostal (1996) suggested an adaptive control scheme for controlling a nonlinear tubular reactor. The performance of the designed controller can be altered by a suitable value of root. Larger values of the root helped much to respond faster at the cost of overshoot. Bouhtouri et al. (2006) proposed a tracking scheme to track the set point temperature trajectory of a nonlinear distributed parameter model of the tubular reactor in which an exothermic reaction was taken place. Hallager et al. (1984) applied a self-tuning control scheme to control a nonlinear distributed fixed bed reactor. They used a dynamic quantity interaction to select model structure and control strategy. Jarupintusophon et al. (1994) proposed a technique which consisted of two phases. First phase heating was initiated by adaptive control algorithm in which overshoot was yielded at the end of the phase. This overshoot was supervised by predictive control in the second phase. The controller task in the second phase was to overcome the overshoot. Vojtesek and Dostal (2015) did the simulation study of the CSTR to find out the working zone. They used polynomial based and pole placement technique to design adaptive control. However, their scheme had undesirable non-minimum phase and overshoot. They further suggested the implementation of control configuration to overcome the demerits. Prabhu and Bhaskaran (2013) used RLS algorithm to identify the process parameter and pole placement scheme to find the controller parameters. The implementation of MRAC is complex in comparison to self-tuning control. Mhaskar et al. (2004) proposed a two-level scheme for PID controller tuning. In the first level, conventional tuning method was applied to trace out the upper and lower bound of k, τ and D parameters worked as constraints in optimization. In the second level, sum of square technique on plant output and control output was used to optimize the PID parameters using nonlinear model. The simulation results revealed that the proposed methodology helps to improve the performance. Kosanovich et al. (1995) developed a linearized feedback adaptive control structure with full states. One known state temperature was used to control CSTR tightly. For available state, a nonlinear observer was used. The success of the developed scheme depends upon the dynamics of the jacket and on the limitation of manipulated variable. Eom and Chwa (2016) proposed a chattering free Adaptive Integral Sliding Mode Control (AISMC) for a nuclear reactor to deal with system uncertainty. A comparison through simulation between AISMC and ISMC was carried out by them to show the effectiveness. Martı´nez-Guerra et al. (2004) designed a robust observer to predict heat transfer in

CSTR. The considered model was unstructured with noisy measurement; the simulation results were found to be satisfactory. Xia et al. (2010) proposed a linear sliding surface and a reaching phase controller having a discrete system with input delay. A Linear Matrix Inequality was used to derive a condition which guaranteed system stability. To deal with uncertainty, a new reaching phase controller scheme was proposed. Shtessel (2008) proposed a discrete sliding mode control observer to predict the nonlinear system states with system uncertainties; the results of simulation study are promising. Zlateva (1997) designed a sliding mode control for continuous fermentation process. The main emphasis of the problem was to control the substrate concentration by measuring it online; the simulation investigation showed the fine performance. Chen (2014) proposed a simple model based SMC scheme for robust temperature trajectory tracking of a batch reactor. For non-availability of all states, the author designed an observer-based SMC with the assumption that only temperature was available for measurement. He compared the controller performance between Globally Linearized Control (GLC) and SMC and found the latter better than GLC.

Generally, the identification of processes is performed off-line. With the development of computers as powerful tools, it is easy nowadays to identify the system online. Recursive identification algorithms are used for real-time identification because it is designed in simple and easy to use way. Most commonly used PID controller is not able to compensate for most of the complexities develop to these processes. Uppal et al.(1974) described dynamic behavior for a single first-order reaction in stirred tank reactor for various values of the parameters. They developed many analytical relations based upon the system parameters for the prediction of the results of similar environmental condition. Ray (1981) illustrated that PID control alone was not capable to deal against parametric sensitive and nonlinear oscillation which encounters in process reaction system. Most of applied control methods to a nonlinear problem are typically based on linearization of a process which is valid around a specific operating state.

In recent years, adaptive control has gone through significant development. The main reason for its application is to solve controller design problem where process characteristics are not known precisely or change with time. In 1960, there were two major areas emerging out for adaptive system: first, Model Reference Adaptive System

(MRAS) in which the controller parameters modify themselves according to the desired performance. The second was Self-Tuning Controller (STC) in which adaptation once occurred in the beginning state of control and then remains fixed (Bobal, Böhm, JFessl, & Machacek, 2005). Many control methodologies have been proposed by academic control experts but a few of them have been implemented in industries. Less number of papers has been published on adaptive control directly to real system due to its complex structure.

This chapter is devoted to real-time identification and implementation of ASMC using data acquisition card Arduino in MATLAB environment. The purpose of this chapter is to demonstrate that low order models for the control related process dynamics can be identified in a straight forwarded manner on the basis of experimental input-output data**.** To the best of our knowledge, no such study has been carried out using Arduino in MATLAB to control fixed bed reactor. This controller has been designed to control temperature of the fixed bed reactor in real-time environment in which hydrolysis of ethyl acetate takes place in the presence of heterogeneous catalyst Amberlyst-15.

4.2 **Problem Statement**

The concentration of EA reactant in the exit stream should be the lowest for which a temperature trajectory is required to follow. Since hydrolysis of EA using Amberlyst-15 wet as a solid catalyst is an endothermic reaction, heating of the reactor is required. The heating operation of the process is shown in Figure 4.1. The heating medium is the hot water which is circulated through the jacket with the help of a computer operated peristaltic pump. The required heating rate is controlled by regulating the electrical signals to the jacketed tape heater.

In the presence of inherently nonlinear dynamics and different operating conditions, control of the fixed bed reactor by the conventional linear controller is quite difficult. In addition to this, determining fine-tuning parameters of the controller is a time-consuming task. The situation becomes worse by the presence of process uncertainties, unmeasured disturbance, and model mismatch. To overcome these difficulties, the application of advanced and robust control technique is a must. Many advanced control techniques are difficult to implement on the real complex system such as fixed bed reactor and requires skilled manpower. The Simulink based data acquisition is used by process control engineers and researchers. It provides a common platform to perform simulation and real-time work with the fixed bed reactor which is simple, flexible and less expensive than the industrial control system. However, sampling time and discretization capabilities are restricted in comparison to expensive industrial control.

In this study, temperature measurement at different positions along the length of the reactor is considered as a measuring variable whereas temperature of the jacketed tap heater is considered as the manipulated variable under the constraint of 0 to 130 °C. The control objective in this study is to bring the fixed bed reactor temperature as close as possible to the setpoint trajectory. To maintain feed temperature to the reactor corresponding to set point temperature trajectory, a PID controller has been designed for feed heater along with anti-windup and anti-derivative kick which has been applied with a bounded upper limit of 250 °C for safety concern. Temperature of the fixed bed reactor has been controlled by the proposed ASMC. The studied reaction system is endothermic due to which a favorable selected reactor temperature trajectory is considered as

$$T = 50+4\exp(-5\times10^{-3}t) \tag{4.1}$$

where t is in s.

4.3 Controller Design

SMC enforces the system to reach a sliding surface, s and remain on it. The controller system will have sliding merit only if it has directional property towards sliding surface. To move the system states to the sliding surface and keep there, the control action is needed. Consider the control action as

$$u = u_{s1} + u_{eq} + u_a + u_{s2} \tag{4.2}$$

where $u_{s2}= 0$ under the condition $s \to 0$. The value of s depends upon the following;

$$u_{s2} = -ksat(s), \text{where } sat(s) = \begin{Bmatrix} \text{sign}(s), |s| > \varepsilon \\ \frac{s}{\epsilon}, |s| < \varepsilon \end{Bmatrix} \tag{4.3}$$

where ε is the boundary thickness around the selected surface s and k is feedback gain which ensures the tracking in finite time along with the stability of the system. The aim of switching control, u_{s2}, is basically to provide the direction to the state variable under different operating conditions. The equivalent control action, u_{eq}, describes the value of control action required to keep the states of the system on the sliding surface once system states have been reached. The adaptive control action, u_a is used to find the most recent value of the parameter after online identification process so that a complete control action can take place.

4.3.1 Online Process Identification

Online model identification methodology is not only less energy intensive approach but also more practical feasible technique than offline. Most of the real systems have measurement noise which can corrupt closed loop identification. To overcome this difficulty, initially, the fixed bed reactor was run in open loop state to identify the first order discrete plus unit delay transfer function which was later transformed to equivalent continuous transfer model for further design of the controller. In the closed-loop state, ASMC becomes active, which adapts parameter of the fixed bed reactor when a change is noticed in the environment. To put the limit on the number of data points without throwing away old data points, a recursive scheme with forgetting factor is employed. It advantages to use least square method with exponential forgetting in which the influence of newer data to the parameters estimations is larger than the influence of older data.

4.3.2 Recursive Least Square

In this technique, a first order discrete transfer function plus unit delay model is considered with initial guess of the parameters. For identification purpose, a sampling time of 1 second is considered while for the real-time control, the sampling time of 5 seconds is considered for long run. A unit time delay has been assumed.

To identify the system, a set of input and output data pairs, u (k), y (k), are selected. The simple auto-regressive with exogenous input model is,

$$A(q^{-1})\, y(k) = d^{-1} B(q^{-1})\, u(k) \tag{4.4}$$

Consider a model structure,

$$G(z) = \frac{B(q^{-1})}{A(q^{-1})} = \frac{y(k)}{u(k)} = \frac{b_o d^{-1}}{1 + a_1 q^{-1}} \tag{4.5}$$

which has two unknown parameters, $\theta = [a_1, b_o]^T$; the values of these parameters are to be estimated such that predicted values can match to the actual values.

The proposed model can be written in terms of difference equation

$$y\,(k) = -a_1 y(k-1) + b_0 u(k-1) \tag{4.6}$$

Equation (4.6) is based on the past output, and present and past input to get the current output.

$$\emptyset = [-y(k-1){:}\, u(k-1)]^T \tag{4.7}$$

The equations (4.6) and (4.7) can be written compactly as

$$Y(k) = \emptyset^T \theta \tag{4.8}$$

The data vector $\emptyset$ is known as the regression vector since it is using to regress values of the parameter vector, θ.

Next, we have to find the parameter vector θ such that the predicted model is the true estimate of the actual system. For this, the sum of squared errors is to be minimized, therefore, the cost function to be minimized is:

$$J = \textstyle\sum_{k=1}^{2} (y(k) - \emptyset(k)^T \theta)^2 \tag{4.9}$$

The value of J is not of our interest but the optimum values of the parameter vector, θ, is of use to be calculated from:

$$\theta^* = argmin\, \theta(\textstyle\sum_{k=1}^{2} (y(k) - \varphi(k)^T \theta) \tag{4.10}$$

The final optimum solution is

$$\theta = (X^T X)^{-1} X^T Y \tag{4.11}$$

Define P as the covariance matrix

$$P \stackrel{\text{def}}{=} (X^T X)^{-1} \tag{4.12}$$

The parameter update equation is

$$\theta(k+1) = \theta(k) + K(k+1)(y(k+1) - \varphi(k)^T \theta) \tag{4.13}$$

where gain matrix $K(k+1) = \frac{P(k)\emptyset(k+1)}{1 + \emptyset^T(k+1)P(k)\emptyset(k+1)}$ (4.14)

$$P(k+1) = P(k)[I - \emptyset(k+1)K(k+1)^T] \tag{4.15}$$

4.3.3 Adaptive Sliding Mode Control Design

The identified transfer function is

$$TF = \frac{1.5067\, z^{-1}}{1-0.5025z^{-1}} \tag{4.16}$$

The equivalent continuous transfer function has been obtained using d2c command of MATLAB using sampling time 1 s.

$$TF1 = \frac{2.083\, e^{-s}}{s+0.6882} \tag{4.17}$$

The equivalent proposed transfer functions using Taylor series expansion

$$TF11 = \frac{2.083}{s^2+1.6882s+0.6882} \tag{4.18}$$

Taylor series expansion for delay term of TF1 has been used with zero order hold to acquire second-order transfer function. The obtained transfer function TF11 is responsible for obtaining smooth response.

Consider an equivalent continuous time model as

$$A\ddot{y}(t) + L\dot{y}(t) + My(t) = B\, u(t) \tag{4.19}$$

where *A,* L, M and *B* are the plant parameters that are needed to be determined. Rearranging the above equation, we obtain,

$$A\ddot{y}(t) = -L\dot{y}(t) - My(t) + B\, u\,(t) \tag{4.20}$$

Consider θ to be the parameter whose value changes with time. Assume adaptive parameter

$$\theta\ddot{y}(t) = -L\dot{y}(t) - My(t) + B\, u\,(t) \tag{4.21}$$

In this study, delay time is considered equivalent to a sampling time for identification process which is 1 s. However, the sampling time is 5 s for the rest of the closed-loop control system. It is mentioned that for long run of the process control, sampling time of 5 s is quite feasible.

Write the second order equation (4.20) as a system of first order ordinary differential equations

$$\left.\begin{aligned} & y = x_1, \dot{y} = x_2 \; and \; \ddot{y} = \dot{x_2} \\ & \theta\dot{x_2}(t) = -Lx_2(t) - Mx_1(t) + B\, u\,(t) \end{aligned}\right\} \tag{4.22}$$

Select appropriate sliding surface for the chosen system as

$$
\left.\begin{aligned}
s &= \dot{e} + ce = (\dot{y} - \dot{y_d}) + c(y - y_d) \\
s &= (\dot{x_1} - \dot{x_d}) + ce = x_2 - g,
\end{aligned}\right\} \tag{4.23}
$$

$where\ g = \dot{x_d} - ce$

Time derivative of the sliding surface

$$\dot{s} = \ddot{e} + c\dot{e} = \ddot{y} + c(\dot{y}) = 0 \tag{4.24}$$

After simplification, equivalent control law is

$$u_{eq} = -\frac{[(c - 1.688)\dot{y} - 0.688y]}{2.083} \tag{4.25}$$

To make $\dot{y} \to 0$, c = 1.688 and $u_{eq} = \frac{[0.688y]}{2.083}$

To assure the system stability, select Lyapunov function candidate as

$$L = \frac{1}{2}\theta s^2 + \frac{1}{2\gamma}\bar{\theta}^2 \ > 0 \tag{4.26}$$

For linear system, $\dot{x} = \mathbf{A}x + \mathbf{B}u$, where **A** is 2 × *2* matrix, **B** is *2* × 1 matrix and *u* is control input, a sliding variable can be designed as $s = ce + \dot{e}$. To satisfy the stability condition that $p + c = 0$ is Hurwitz polynomial, the eigenvalue of $p + c = 0$ should have a negative real part, i.e.$c = 1.688 > 0$, where *p* is a Laplace operator. This is the first criteria to fulfill stability by selecting the appropriate sliding surface. It is clear from basic definition of SMC that it has three fundamental mechanisms, namely, hitting/reaching the sliding surface, *s*, staying on the surface, and converging towards the stable equilibrium point i.e. origin, in general. The trajectory chatters within the boundary of sliding manifold and converges toward the origin. After reaching at steady state, trajectory traps in a periodically fluctuating near the origin. The aim of the hitting condition is to make sure that regardless of the position of the initial condition, the corresponding control decision will enforce the trajectory of the system to move toward and eventually attain, within a prescribed boundary. The necessary and sufficient condition for the system to suit the hitting state is that the resulting control action produces a state-variable and a controlled trajectory *s*(*t*>0), which fulfill the following inequality:

$$s\frac{ds}{dt} < 0$$

The above inequality is one of the forms of the Lyapunov second theorem on stability of which the Lyapunov function candidate is $L = \frac{1}{2}\theta s^2 + \frac{1}{2\gamma}\bar{\theta}^2 \; > 0$. The fundamental aspect to design the SMC is to first determine the suitable discontinuous control action for the system so that hitting phase must always be satisfied. The existence condition of the SMC operation can be determined by investigating only the local reachability condition of $s\frac{ds}{dt} < 0$ such that in the domain of $0 < |s| < \varepsilon$, the condition $\lim_{s \to 0+} s \; \frac{ds}{dt} < 0 \; and \; \lim_{s \to 0-} s \; \frac{ds}{dt} > 0$ must be satisfied. In general, the stability of a system is acquired by determining the eigenvalues of the Jacobian of the system at the steady-state. To guarantee that the temperature trajectory is stayed on the sliding surface, the existence condition derived from Lyapunov's second method to find out asymptotic stability must be obeyed. The eigenvalues of continuous approximation model in the present study are -1, -0.6882 and the rank of the controllability matrix is 2, which shows the stability of the system. In the closed loop condition, the stability is governed by Lyapunov function.

Time derivative of Lyapunov function is

$$\dot{L} = \theta \dot{s} s + \frac{1}{\gamma}\bar{\theta} \; \dot{\widehat{\theta}} \tag{4.27}$$

$$\dot{L} = \theta s(\dot{x_2} - \dot{g}) + \frac{1}{\gamma}\bar{\theta}\dot{\widehat{\theta}} \tag{4.28}$$

where $\bar{\theta} = \widehat{\theta} - \theta$

The required condition for stability is

$$\dot{L} = s(u - 0.8104x_2 - 0.3304 \, x_1 - \theta \, \dot{g}) + \frac{1}{\gamma}\bar{\theta}\dot{\widehat{\theta}} < 0 \tag{4.29}$$

The update law is

$$\dot{\widehat{\theta}} = -\gamma s \dot{g} \tag{4.30}$$

The adaptive control law is

$$u_a = \widehat{\theta} \, \dot{g} \tag{4.31}$$

To verify that the selected control law fulfills the condition of stability,

$$\dot{L} = s\left(\widehat{\theta} \, \dot{g} - ks - \eta sat(s) - 0.8104x_2 - 0.3304 \, x_1 - \theta \, \dot{q}\right) + \frac{1}{\gamma}\bar{\theta}(-\gamma s \; \dot{} \;) \tag{4.32}$$

$$\dot{L} = -ks^2 - \eta s sat(s) - s(0.8104x_2 + 0.3304\, x_1) < 0 \quad if\ k\eta \tag{4.33}$$

Finally, the complete control law is $u = u_a + u_{s1} + u_{s2} + u_{eq}$ (4.34)

where feedback control law is $u_{s1} = -ks$ and directional control or switching control law is $u_{s2} = -\eta\ sat(s)$.

To restrict the movement of the predicted value of $\breve{\theta}$ from very large value and also to avoid large control action, an algorithm proposed by L. Xu and B. YaO (2008) has been used.

$$\dot{\breve{\theta}} = proj(-\gamma s\ \dot{}\ ) \tag{4.35}$$

Where

$$proj(-\gamma s\dot{g}) = \begin{bmatrix} 0, & if\ \breve{\theta} \geq \theta_{max}\ and\ \dot{\breve{\theta}} > 0 \\ 0, & if\ \breve{\theta} \leq \theta_{min}\ and\ \dot{\breve{\theta}} < 0 \\ & ,otherwise, \\ \dot{\breve{\theta}} & \end{bmatrix}$$

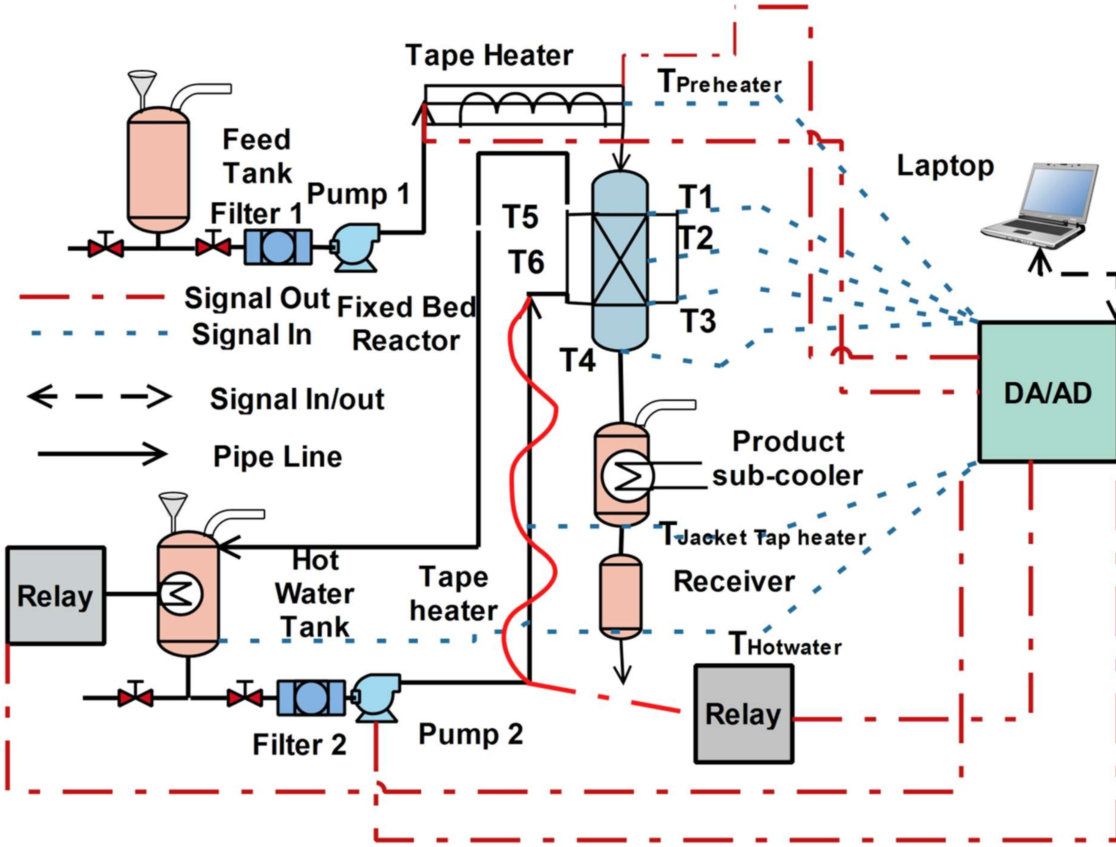


Figure 4. 1: A schematic diagram of computer-controlled fixed bed reactor set up.

4.4 Experimental Setup

4.4.1 DAQ Card and Software

Arduino Mega 2560 board is one of the boards of the Arduino family. The board surface area offers 70 I/O pins, of which, 16 are analog inputs with the other 54 being digital. 15 of the digital pins can handle Pulse Width Modulation (PWM). It also includes four RX/TX serial ports. With regard to the controller, this is the ATmega2560 chip, which operates at 5 volts. The Arduino Mega provides four times more memory than the Arduino Uno, specifically, 256KB of flash memory, 8KB of Static Random-Access Memory (SRAM) and 4KB of Electrically Erasable Programmable Ready-only Memory (EEPROM).

To interact with Arduino board, Simulink is the most widely used feature in MATLAB to acquire the data with the help of the board and plot the data in real time. The Simulink model has a COM number corresponding to the Port number by which Arduino board is connected. As shown in Figure 4.1, the input temperature sensor is K-type thermocouple which is responsible for temperature measurement and transmits through an amplifier. The amplifier is capable of boosting mV signal to 0-5 Volt DC control signal. The received control signal is an analog type and is fed to Arduino analog block. Arduino board consists of a 10-bit Analog-to-Digital Converter (ADC). Its analog input channel reads a voltage between 0 and 5 V and divide that range into 2^{10} =1024 pieces. Therefore, 0-bit value corresponds to 0 V DC and 1023 bits value corresponds to 5 V DC. However, a digital-to-analog signal converter is 8-bit. Approximate analog out signal is produced by PWM pins. The resolution is , $\Delta V = \frac{(V_{max}-V_{min})}{2^N} = \frac{(5-0)}{2^{10}}$ = 0.0049 V and the quantization error = $\mp\frac{0.0049}{2} = \mp 0.002\ V$. Similarly, the resolution in temperature = $\Delta V = \frac{(T_{max}-T_{min})}{2^N} = \frac{(600-0)}{2^{10}} = 0.586$ K and the quantization error = $\mp\frac{0.586}{2} = \mp 0.293\ K$.

No. of bins = 2^N = 1024 or (0-1023)

This quantization error is too small for most practical applications. Notice that we cannot tell the difference between an input of 4.995 V (599.707 K) and 5 V (600 K) – both of these input voltages fall into bin number 1023, and would be assigned the same output voltage. It means that if the assigned voltage is $V_{assigned}$, then the actual voltage might be represented as, V = $V_{assigned} \mp 0.002\ V$.

The controller generates a control signal which regulates the jacket temperature of the fixed bed reactor. For this large system, the control signal can't be applied directly which is merely 5 V DC signal. Therefore, there is a need of additional device to control the real system. The control signal is used as triggering signal to open gateway of the large amount of AC voltage to operate the jacketed tape heater. The applied control signal is used by solid state relay to adjust the voltage of jacketed tape heater. PWM pin of the Arduino board generates a train of pulses. The width of pulse is adjusted as per the values of the control signals. Larger control signal has larger duration pulse.

$$V_{Average} = \frac{T_{on}}{T}\, V = dc\, V \tag{4.36}$$

where dc is duty cycle.

$$0 \leq dc = \frac{T_{on}}{T} \leq 1$$

4.4.2 Materials and Methods

Ethyl Acetate (EA) and Amberlyst-15 were purchased from a local supplier (HPLC grade) in 10 L and 0.5 kg packet, respectively. Amberlyst-15 was converted into acidic form by a simple acidic treatment. First, a catalyst was washed with distilled water two to three times, and then it was dried at atmospheric condition. The dried form of catalyst was dipped in 0.1N hydrochloric solution for one hour. Later on, the catalyst was separated with the help of a mechanical sieve and dried at room temperature for 48 hours. 4 moles % solution of EA in water was prepared and 150-gram catalyst was charged into the fixed bed reactor.

4.4.3 Fixed Bed Reactor

A schematic diagram of the computer controlled fixed bed reactor is shown in Figure 4.1. The fixed bed reactor consists of a 5 cm ID, 16 cm long stainless-steel tube surrounded by another concentric pipe of 7 cm ID as a jacket. The catalyst was placed on a 60-mesh stainless steel screen which was fitted in the bottom of the rector. The catalyst was filled to a depth of about 16 cm. The entrance and exit sections of the reactor were filled with glass beads to reduce dead volume zone and flow mal-distribution. Liquid flow in the jacket and the reactor were kept in counter-current operation. The feed was delivered to the reactor from a 5 liter tank by a computer-controlled pump at 30 ml/min. The feed was preheated by tape heater corresponding to fixed step point temperature trajectory while the required temperature was maintained by circulating hot water through the jacket. The water was heated by immersing an electrical heater of capacity 2 kW in addition to the jacketed tape heater, which was wrapped around inlet pipeline to the jacket. Temperatures were measured at the entrance and exit positions along with three additional locations within the fixed bed reactor. At the reactor outlet, the product was cooled down to ambient temperature as it passed through product sub-cooler. Finally, the cooled product was collected in the receiver at the end. To measure the concentration of acetic acid in the products, gas chromatography analysis was used. All controlling signals were governed by the designed control algorithm with a computer through Arduino board. The flow diagram of the controller implementation on the real system is shown in Figure 4.2.

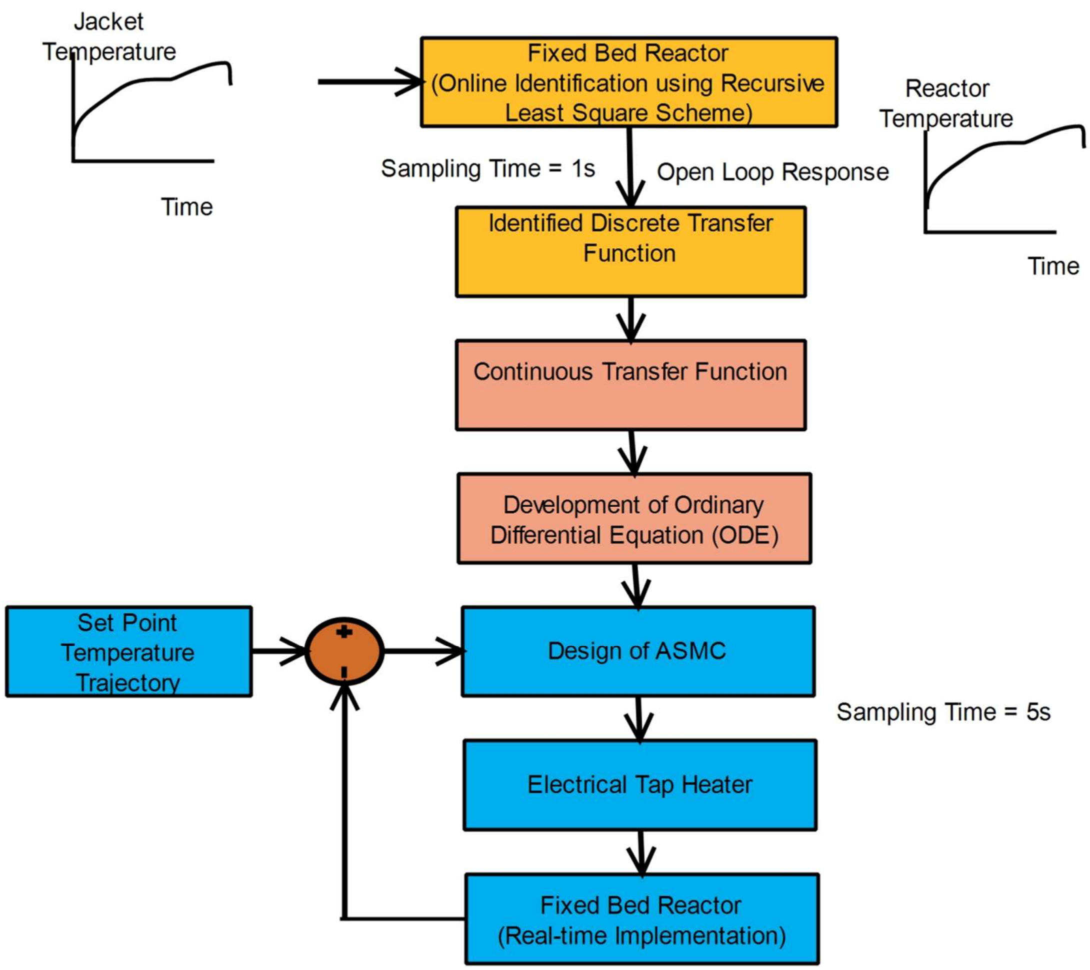


Figure 4. 2: Flow diagram of controller implementation on fixed bed reactor.

4.5 Results and Discussion

This section describes the performance of ASMC with averaging temperature measurement at various position along the length of the reactor. The controller governs the outlet composition via temperature by manipulating jacket temperature. As we know that on-line measurement of concentration is a costly process. For the assurance of the desired concentration of the ethyl-acetate inside the reactor, a tight temperature control scheme has been implemented. The concentration of the reactant is temperature dependent and can change by altering the temperature. By manipulating the temperature, we can indirectly control the composition which we normally adopt at the industrial level. The jacket temperature was manipulated by a tape heater which was wrapped around the inlet pipeline to the jacket. Real-time identification of the system was performed with RLS with forgetting factor. Once the system was identified, the tuning parameters of the system were found by numerical optimization. Arduino did not support MATLAB S-file and variable step size, so fixed step size, h = 0.01, was considered with Newton's formula of first order with sample time, T_s = 5 s. Sample time plays a critical role concerning stability at fixed step size. By examining different real-time control, a sample time of 5 s was found suitable for the job. The main reason behind this was the physical limitation of Arduino board with MATLAB. Arduino board supports only fixed step size numerical computation in MATLAB which is a major constraint to apply in real system. Till date, Arduino board neither supported S-function nor any toolbox of MATLAB. So, we could use only Simulink and MATLAB function file. Due to this limitation, the designed Simulink model got complicated which was quite difficult to load in Arduino memory due to limited memory constraint. To make the control realistic, a constraint on jacket temperature, 0 to 130 °C was applied to the control input which bound the upper and lower limits of the jacket temperature. A PID controller was deployed for regulating the feed temperature corresponding to the fixed set point temperature trajectory. For safety, upper limit of the feed tape heater temperature was considered to be 250 °C. In this study, PID was used to control the feed temperature only. The application of the electric heater is used to boost the heating process as per the varying set-point temperature. The other advantage of the feed preheater is to share the load with jacketed tap heater. The simultaneous working of both the heaters helps in better temperature control. However, during temperature trajectory tracking, attention has been paid to upper permissible limit of the feed and jacketed tap heater. These upper limits are 250 and 130 °C, respectively, as advised by the manufacturer.

During control, the feed flow rate and hot water rate were kept constant at 30 ml/min and 50 ml/min, respectively. To overcome against the chattering phenomena of the SMC, electrical tape heating was used as a manipulated variable. Due to the electrical signal, there is no wear and tear problem of the final control element.

4.5.1 Open Loop Identification

In general, open loop identification is feasible only for a stable system. The reaction system is endothermic, so heat is supplied through jacket which affects the conversion by changing the reactor temperature. The reactor temperature varies along the length of the reactor. The water is preheated by electrical heater of capacity 2 kW in hot water tank other than the tape heater wrapped around inlet pipeline to the jacket. This on/off heater boosts the heating process and saves the initial heating time. Figure 4.3 shows the identified first order discrete system parameters. Real-time identification and temperature tracking plot of the identified transfer function is shown in Figure 4.4. The actual temperature is the temperature of the fixed bed reactor when the jacketed heater is in ON position. The identified temperature is the temperature response based on the identified transfer function model. To obtain a good model, response of the discrete equivalent continuous transfer functions has been plotted in Figure 4.5. The comparison of the step response of the various proposed transfer function is shown in Figure 4.5. From this figure, it is clear that the performance of the selected transfer function, TF11, is reasonably well. During consideration, “the simpler, the better” approach has been considered. The Transfer Function 1 (TF1) can be approximated by Transfer Function11 (TF11) without any major loss in the characteristics using Taylor series. As mentioned earlier that the aim of this study is to develop real-time controller. However, in this case, Taylor series expansion of the actual plant does not deteriorate much the performance of the actual plant.

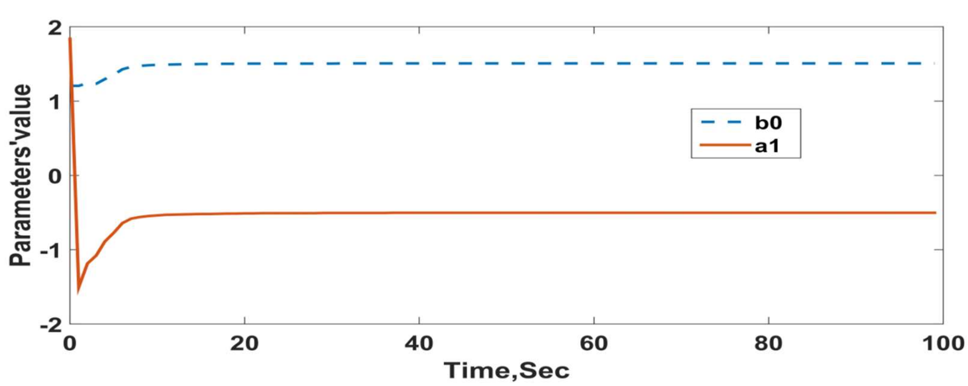


Figure 4. 3: Identified parameters of discrete transfer function.

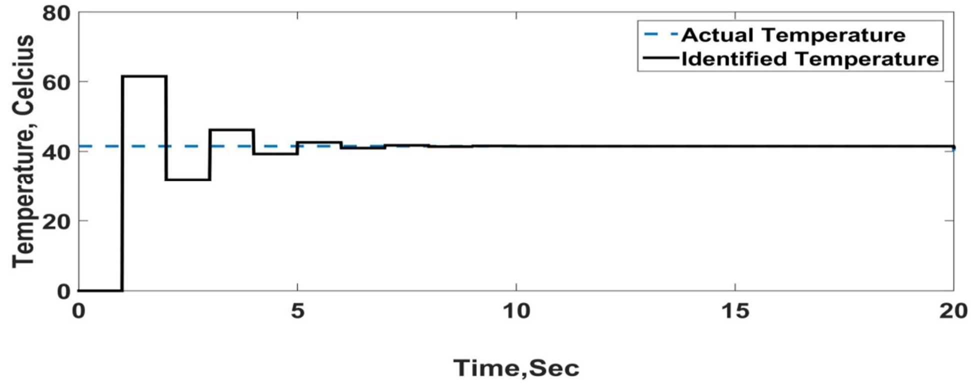


Figure 4. 4: Real-time identification of discrete transfer function model with unit delay.

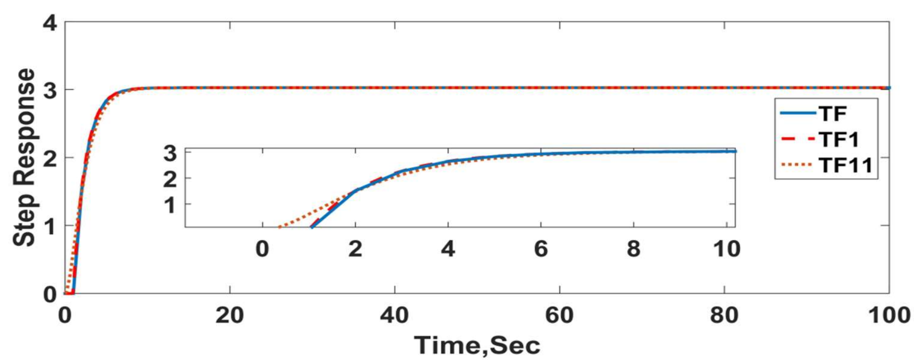


Figure 4. 5: Step response of the identified and its equivalent proposed transfer functions.

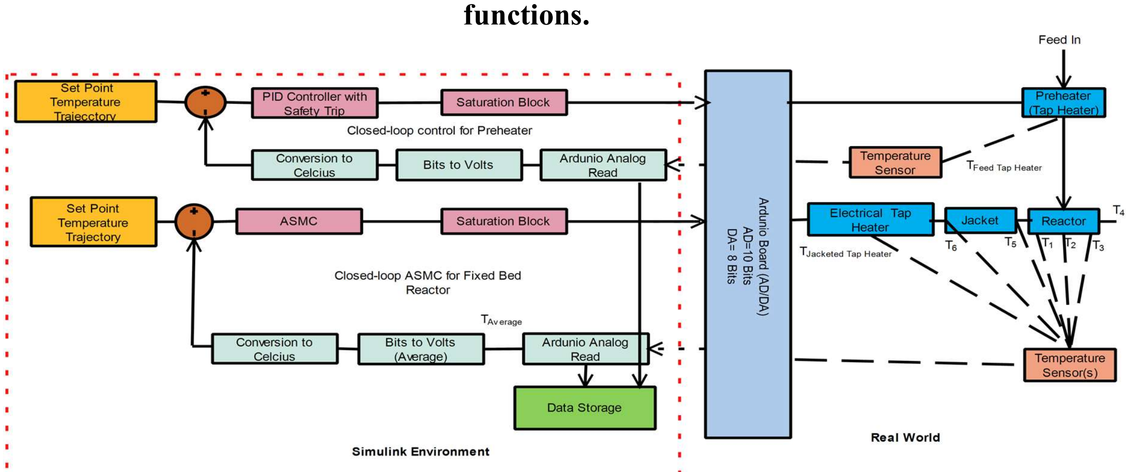


Figure 4. 6: Arduino interface with Simulink® and real fixed bed reactor.

Figure 4.6 shows a Simulink® sketch to interact with Arduino board. Arduino board works as a gate to transfer data from Simulink to the real plant and from the real plant to Simulink interface. The transfer of data is restricted with the capability of the board which is 10 bits from analog to digital and 8 bits from analog to digital as mentioned earlier.

4.5.2 Adaptive SMC

Figure 4.7 illustrates temperature trajectory tracking profile of the reactor. Initially, the system shows a lag of 20 s due to sluggish nature of the heating process but once the error has been determined, an appropriate control action takes place by supplying enough heat to the jacketed hot water. The control action applies full effort and reaches the upper limit of 130 °C and ceases off there. But the control action alters as per the value of error corresponding to the average of zone1/2/3 temperature. At the time t = 50 s, a slight overshoot is seen which is an effect of control action corresponding to initial error while control action comes to the lowest value which can be seen from Figure 4.11 and decreases with progress of time.

Figure 4.8 shows temperature profile of the reactor at various locations. Temperature of zone 1 is the highest (due to proximity to the feed tap heater). After zone 1 temperature, zone 3 temperature is the second highest because it is closer to the jacketed inlet pipeline. The temperature of zone 2 is the smallest. This temperature profile is sluggish with respect to other zone temperatures. However, exit temperature rises despite consuming energy due to the endothermic hydrolysis reaction.

To further investigate the process, Integral Absolute Error (IAE) value is plotted. Figure 4.9 shows the profile of IAE of the system with time. F.G. Martins (2005) reported that the performance evaluation of the controller based on ITAE is a good criterion and this criterion is not very often used because its computer implementation is a difficult task. Working on the same line, IAE criteria have been used in this study to evaluate the performance of the designed controller.

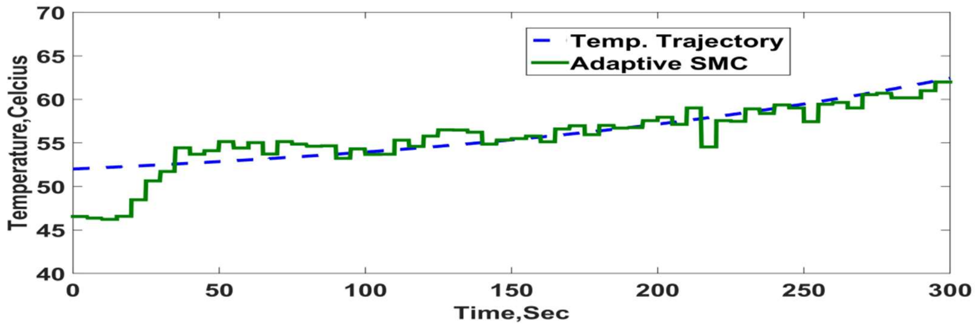


Figure 4. 7: Temperature tracking trajectory of the fixed bed reactor.

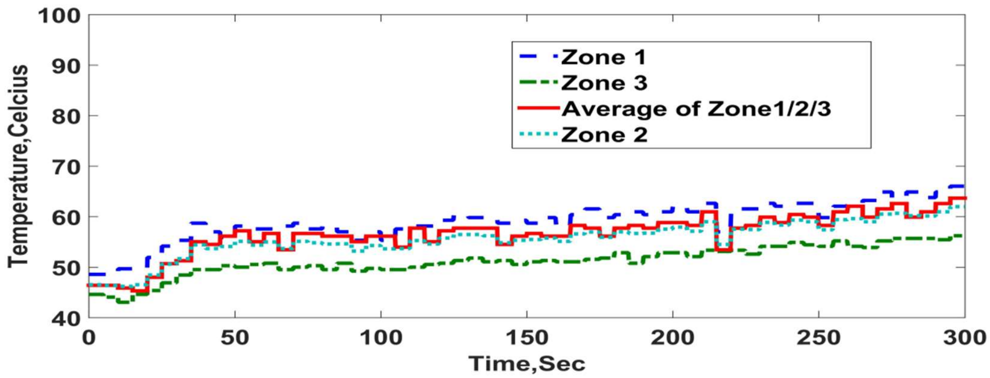


Figure 4. 8: Temperature profiles at various positions within the fixed bed reactor: top (zone 1), middle (zone 2) and bottom (zone 3).

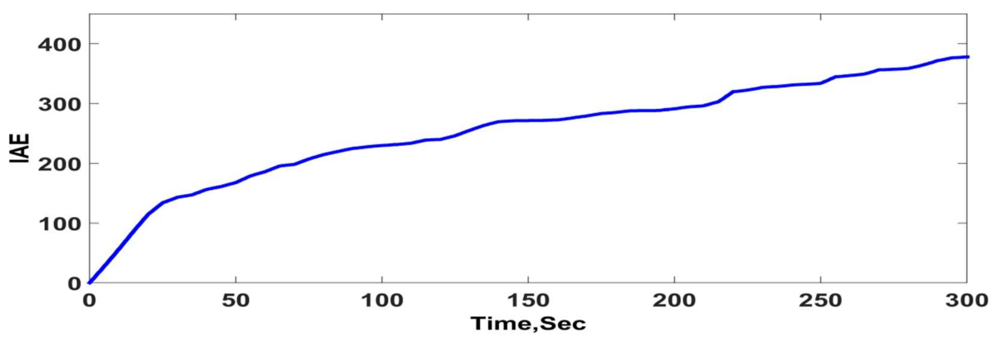


Figure 4. 9: Integral absolute error of the temperature tracking

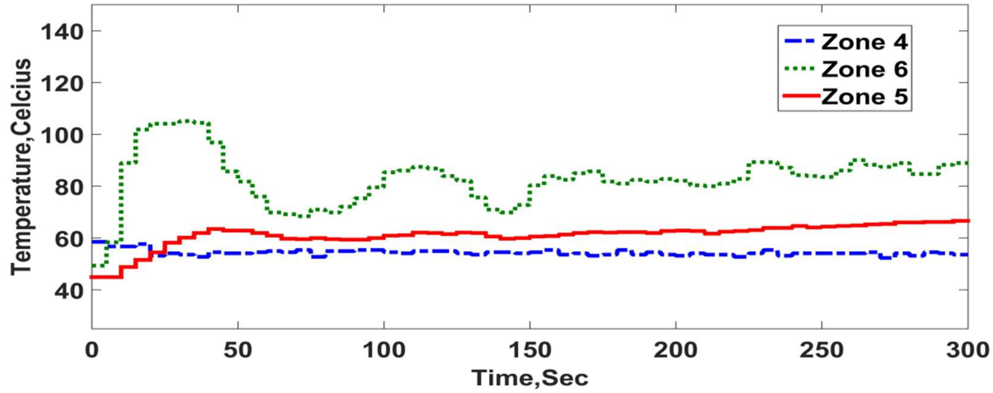


Figure 4. 10: Temperature of jacket inlet (zone 6), jacket outlet (zone 5) and reactor outlet (zone 4).

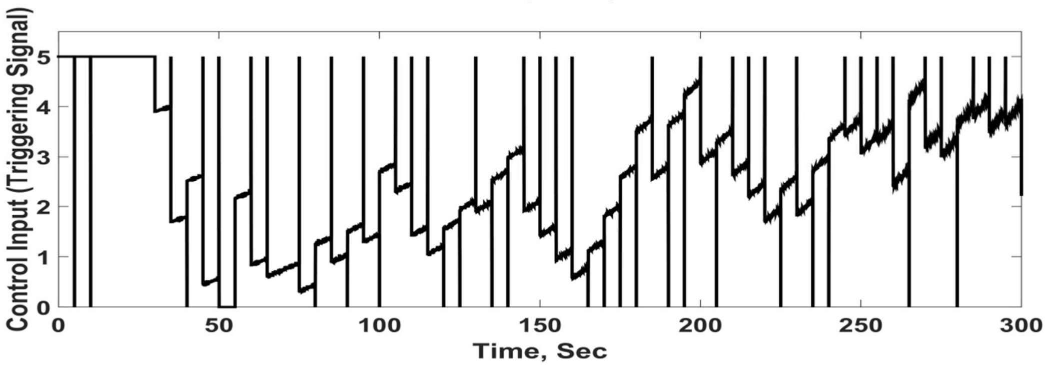


Figure 4. 11:Triggering control input signal in terms of DC voltage.

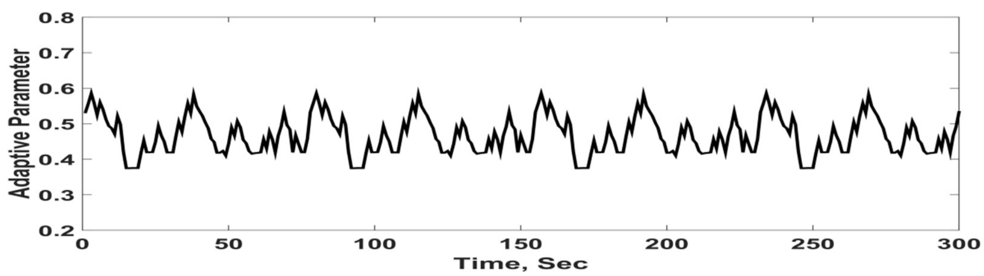


Figure 4. 12: Adaptation of the reactor parameter with time.

Figure 4.10 shows the jacket inlet temperature (zone 6), jacket outlet temperature (zone 5) and reactor outlet temperature (zone 4). Zone 6 temperature shows oscillation with time due to the sense of the manipulated jacketed tap heater temperature which is placed at jacketed inlet pipeline. Zone 5 and 4 show the sluggish response. There is no variation observed in zone 4 temperature due to large surface areas of the product sub-cooler and the receiver. The larger surface area is enough to cool down the product temperature up to the surrounding temperature. Figure 4.11 shows the control input effort to track the temperature trajectory in terms of 0-5 V DC signal.

In this study, the parameter $A=\theta$ is considered as the adaptive parameter of the system which is most likely to change as per the change observed in the system. An alteration of $0.37\ to\ 0.59$ is allowed in the value of θ within which the parameter is continuously monitored. Figure 4.12 depicts the adaptation of the parameter with time. For adaptive parameter value, the signal continuously moves around the actual value of the parameter. If any change is sensed, it will be adapted by the system. As mentioned earlier, the restriction has been applied on the value of θ as suggested by Xu and Yao (2008). Figure 4.13 illustrates the effect of the control action on manipulated variable which is the temperature of the jacketed tape heater having capacity of 2 kW. From Figure 4.13, it is clear that the jacketed tape heater temperature reaches to 100 ºC in a small-time interval of 20 s and remains there up to 20 s and then comes down as per next signal received through the control action.

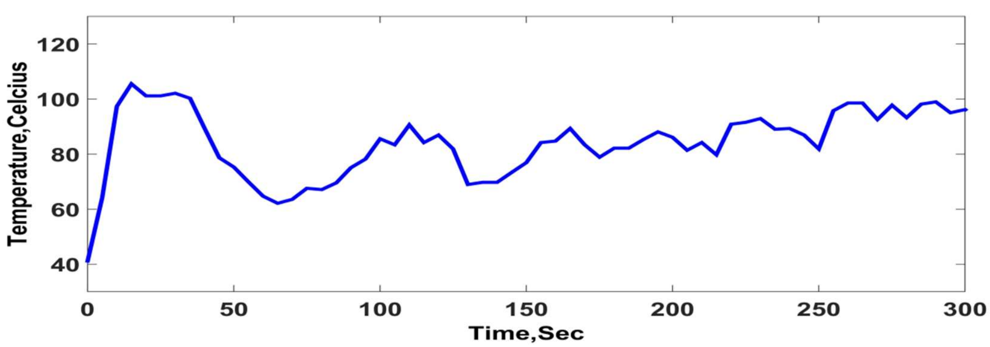


Figure 4. 13: Temperature profile of the jacketed tape heater.

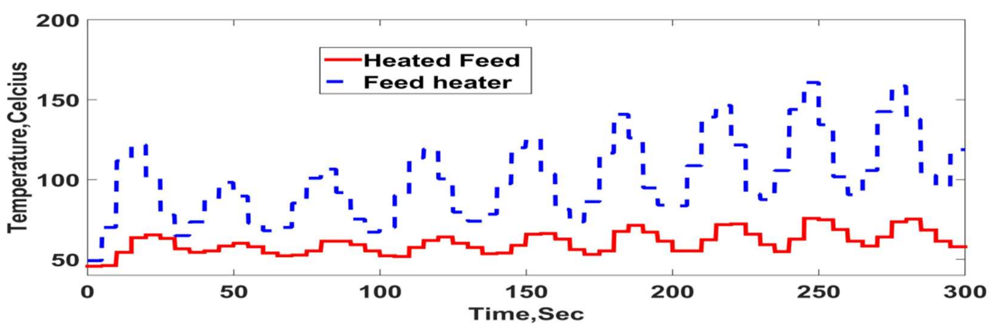


Figure 4. 14: Temperature profiles of the heated feed and feed tape heater.

Figure 4.14 depicts temperature measurement of the heated feed and feed heater of the reactor. To keep the feed temperature corresponding to the setpoint temperature trajectory, a PID controller along with anti-wind and anti-derivative were applied. For safety purposes, the constraint has been applied to the upper limit of PID controller. In any case, upper temperature of the feed tape heater should not go beyond 250 °C. Feed temperature has been considered as a control variable at the inlet point of the reactor while the feed tape heater which is wrapped around the feed inlet pipeline has been considered as a final control element. Figure 4.14 shows the response of the PID controller for tracking of setpoint temperature trajectory of feed.

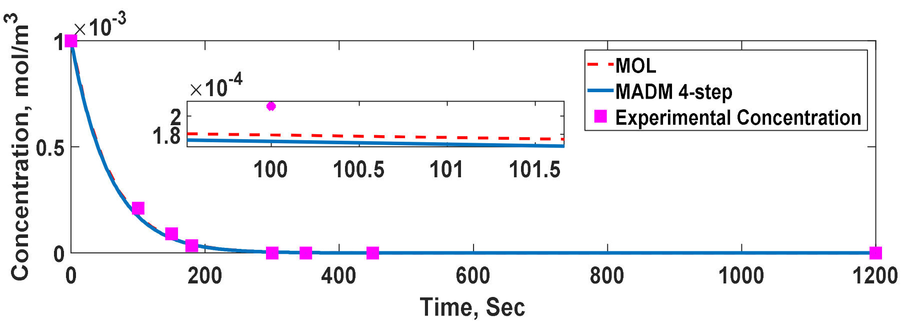


Figure 4. 15: **Comparison of the ethyl-acetate concentration among MOL, MADA 4-step and experimental run.**

Figure 4.15 depicts the comparison between theoretical models' output concentration of the fixed bed reactor using MOL and MADM 4-step with the experimental run. From the figure it is clear that the model's prediction is in good agreement with the experimental observation of the concentration of the ethyl-acetate at the exit condition. To get a good response in agreement demands a balance between agreement and computational load. In this study, to make the things feasible at industrial level, a balance computational load has been adopted.

4.6 Conclusions

The problem of adaptive SMC for a fixed bed reactor has been considered in which different practical aspects such as identification of parameters; development of transfer function, real-time implementation has been discussed. To make the design of the controller simple, a first order plus unit delay transfer function has been identified. An appropriate identification method using recursive least squares with forgetting factor has been selected. The aim of this study was to utilize the advantages of adaptive SMC and online system identification in open loop condition in real time using Arduino as a data acquisition board. The resulting combination has made the fixed bed reactor asymptotically stable and robust in the presence of measurement noise. To overcome the main disadvantage of the SMC, i.e., chattering, jacketed tape heater was selected as final control element which uses electrical control signal. For safety concern, the constraint was applied to the control signal between 0 to 130 °C and the feed tape heater was bounded with the upper limit of 250 °C. Many tests have been conducted to validate the system and a temperature tracking study has been completed in order to know the possibilities of the proposed strategy in the control of other plants. The temperature trajectory tracking by the ASMC is fine despite the presence of electrical measurement noise. The major limitation of this work is Arduino's memory and other limitation is that it does not support MATLAB S-function due to which implementation of complex control algorithm is difficult. The future scope is that above limitations can be overcome by using other software and data acquisition cards.

Chapter 5: Conclusions and Recommendations for Future Work

Chapter 5 : Conclusions and Recommendations for Future Work

5.1 Conclusions

This thesis deals with some significant control problems in a fixed bed reactor. Fixed bed reactors represent an engineering challenge because of their strong nonlinearities, the unsteady operating conditions and the lack of complete state and parameters measurements. Theoretical and experimental aspects of modeling, identification, and control of fixed bed reactors have been tackled. First, the full model of the reactor, involving a system of partial differential equations, has been developed. Then, well-known analytical techniques for nonlinear systems have been applied to get the transient behavior of the reactor. This approached has been developed for a controller design's point of view. This is the very first time to use a semi-analytical solution strategy, i.e. multistage Adomian decomposition method, to study the transient response of the reactor. A multistage Adomian decomposition method (MADM) has been used to obtain semi-analytical approximate solution of a fixed bed reactor problem. This approach may be provided a better alternative to other classical analytical methods and the traditional numerical methods. The transient behavior of fixed bed reactor has been determined using MADM in MATLAB. The performance of the used method depends upon the number of truncated steps and discretization of the time span. The desired accuracy can be achieved by selecting four numbers of truncated series components and 0.1 s time as discretization step for economy of the computation. A comparison with the numerical method of lines (MOL) has been performed to show error. The obtained results show the satisfactory performance of the MADM to study the dynamic behavior of nonlinear distributed parameter model of the fixed bed reactor. This method can also be applied to similar problems as well as for process control systems.

Further, a full state mathematical model has been developed to design an intelligent Adaptive Sliding Mode Control (ASMC) for the temperature control of the fixed bed reactor. Numerical simulation has been carried out in MATLAB using Method of Lines (MOL) approach. The system stability has been assured by Hurwitz polynomial. A hybrid controller using high gain observer based adaptive radial basis function neural network (RBFNN) has been applied in a fixed bed reactor for hydrolysis of ethyl acetate. The performance of the hybrid controller has been analyzed with and without presence of unmeasured external disturbance, variation in frequency factor and activation energy, load variation, and model mismatch for the temperature tracking. The adaptive RBFNN has been used to predict the nonlinear term. The high gain observer with adaptive RBFNN has been used to predict the states of the system. The design parameters of the observer have been estimated using Hurwitz polynomial. The inlet feed temperature and velocities have been varied to see the effect in the fixed bed reactor operation. The outlet temperature has been observed to be higher when the jacket temperature was selected to be higher than feed temperature whereas the outlet temperature got lower when the jacket temperature was kept at lower temperature. Eight numbers of neurons and eight space discretization steps have been found suitable for the study by many simulations runs. However, during optimization of these parameters, computational load and efficient feasibility for run on real-time system has also been kept in mind. For the removal of chattering behavior, the equivalent control term has been neglected which has advantages not only in terms of chattering free control signal but also in terms of low feedback gain. The other intelligent approaches can also be employed.

Next, the full computer control setup of the fixed bed reactor has been developed to control the temperature. It consists of a single jacketed fixed bed reactor, preheated, jacketed tap heater, peristaltic pump, product receiver, and feed tanks. To design an adaptive SMC, some reduced-order models, able to represent the temperature absorbed by the reaction concerning the supply of heat from the jacket. Online experimental procedure, for data generation and model validation, has been carried out. A novel model-based controller-observer algorithm for temperature trajectory control has been presented. This algorithm is based on a linear temperature controller. The performance, in terms of tracking accuracy and robustness to un-modeled dynamics, of the overall scheme has been verified through an experiment set-up and evaluated with the performance using integral absolute error (IAE). The problem of adaptive SMC for a fixed bed reactor has been considered in which different practical aspects such as identification of parameters; development of transfer function, real-time implementation has been discussed. To make the design of the controller simple, a first order plus delay time transfer function has been identified. An appropriate identification method using recursive least squares with forgetting factor has been selected. The aim of this study was to utilize the advantages of adaptive SMC and online system identification in open loop condition in real time using Arduino as a data acquisition board. The resulting combination has made the fixed bed reactor asymptotically stable and robust in the presence of measurement noise. To overcome the main disadvantage of the SMC, i.e., chattering, jacketed tape heater was selected as final control element which uses electrical control signal. For safety concern, the constraint has been applied to the control signal between 0 to 130 °C and the feed tape heater has been bounded with the upper limit of 250 °C. Many tests have been conducted to validate the system and a temperature tracking study has been completed in order to know the possibilities of the proposed strategy in the control of other plants. The temperature trajectory tracking by the ASMC is fine despite the presence of electrical measurement noise.

5.2 Recommendations for Future Work

The major limitation for real-time implementation is with Arduino's memory and other limitation is that it does not support MATLAB S-function due to which implementation of complex control algorithm is difficult. The future scope is that above limitations can be overcome by using other software and data acquisition cards.

In this thesis, a significant contribution is towards building the mathematical model and its semi-analytical solution approach for the design of control problem for distributed parameter systems with special focus on fixed bed catalytic reactor. Some challenges remain in the synthesis of the design of a controller for a fixed bed reactor. The semi-analytical approach studied in chapter 2 used the multistage Adomian decomposition method as a tool to get the solution of a system of the partial differential which was formulated by material and energy balances. This method performs very well for systems, but another similar approach such as reduced differential transform method can also be studied and applied. To deal with non-linearity, other than Adomian polynomial approaches can be used to tackle the nonlinearity. Unfortunately, to get a steady state solution by ADM in case of Danckwarts' boundary conditions is not feasible up to till date. The method proposed in chapter 3 can be extended to intelligent control using other popular techniques such as Fuzzy, Neuro-Fuzzy, etc. The main limitation is associated with the memory of Arduino board when working in MATLAB. MATLAB s-function file doesn’t support Arduino data acquisition board and therefore it is difficult to implement a complex system.

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