INTERNAL MODEL CONTROL FOR NONLINEAR DYNAMIC PLANTS USING U-MODEL

BY

MOHAMMED HASEEBUDDIN

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This thesis, written by **MOHAMMED HASEEBUDDIN** under the direction of his thesis advisor and approved by his thesis committee, has been presented to and accepted by Dean of Graduate Studies, in partial fulfillment of the requirements for the degree of **MASTER OF SCIENCE IN SYSTEMS ENGINEERING**.

Thesis Committee

Dr. Muhammad Shafiq (Advisor)

Dr. Fouad M. Al-Sunni (Member)

Dr. Onur Toker (Member)

Dr. Umar M. Al-Turki
(Chairman, Department Of Systems Engineering)

Dr. Mohammad Abdulaziz Al-Ohali
(Dean of Graduate Studies)

Date

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THESIS ABSTRACT

Name: **MOHAMMED HASEEBUDDIN**

Title: Internal Model Control for Nonlinear Dynamic Plants using U-model

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A model based control strategy called the Internal Model Control (IMC) is popular in industrial process control applications due to its fine disturbance rejection capabilities and robustness. The tracking of the reference signals is a requirement in many applications. To accomplish tracking, the IMC structure requires the inverse of the plant. The determination of inverse of large class of nonlinear plants poses difficulties due to lack of a general modeling framework for nonlinear plants. In this thesis, we use the control oriented model called the U-model in the IMC structure for a wide class of stable single-input single-output nonlinear plants. This structure simplifies the design and implementation of the controllers. Learning rate parameter is introduced in the inverse finding computational algorithm to improve the convergence and stability properties. A fine tracking technique is used to further improve the tracking properties of the closed-loop system. An adaptive IMC scheme based on U-model for nonlinear dynamic plants is developed. The use of secant method for the computation of the inverse of U-model has been proposed. Computer simulations and real-time experiments are done to show the effectiveness of the proposed methods.

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خلاصة الرسالة

الاسم : محمد حسيب الدين
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تحكم النموذج الداخلي هو اسم لاستراتيجية تحكم ذات شعبية في تطبيقات التحكم ف بالعمليات الصناعية وذلك لقدراتها الرائعة في رد الإزعاج ولتمكنها تتبع الإشارة المرجعية متطلب كثير من التطبيقات وإجراء عملية التتبع فإن تحكم النموذج الداخلي لتطلب معكوس المصنع. تحديد المعكوس لفئة كبيرة من المصانع غير الخطية يتسم بالصعوبة لعدم وجود إطار لنمذجة المصانع الخطية.

في هذه الرسالة يستخدم نموذج U في تحكم النموذج الداخلي لفئة كبيرة من المصانع المستقرة ذات المدخل والمخرج الوحيدين. هذا التركيب يبسط بتصميم وتنفيذ المتحكمات. معدل التعلم أدخل إلى خوارزمية إيجاد المعكوس لتحسين خواص التقارب والاستقرار أستخدم أسلوب تتبع خواص التتبع لنظام مغلق الصروة. تم تطوير طريقة تحكم نموذج U.

تم إيضاح فاعلية الطرق المقترحة باستخدام المحكاة الحاسوبية وتجارب الزمن الحقيقي.

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CHAPTER 1

Introduction

1.1 Overview

High performance is always the design target in industrial control applications. Many control strategies were proposed and aimed to realize this goal. Among them a model based control strategy called the 'Internal Model Control' (IMC) is very popular and continues to enjoy widespread popularity in industrial control applications due to its fine disturbance rejection capabilities and robustness [2,13,21,25,40,46,61,65].

The IMC structure is composed of the explicit model of the plant and a stable feed-forward controller. The IMC controller guarantees the internal stability of the closed-loop and parameters of the controller can be tuned online easily without disturbing stability of the system. Most of the industrial processes are open-loop stable. If the plant is unstable then using standard robust control techniques the plant is stabilized and the internal model controller is designed for the overall closed-loop system [11, 58, 66]. The incorporation of the inverse of plant model in the feed-forward path can be implemented to achieve asymptotic tracking in IMC structure [14].

Internal model control (IMC) is a powerful controller design strategy for linear systems described by transfer function models. For open-loop, stable systems, the IMC approach provide a very simple parameterization of all stabilizing controllers. The IMC factorization procedure provides valuable insights into the inherent control limitations presented by particular models. Due to the IMC structure, integral action is included implicitly in the controller. Moreover, plant/model mismatch can be addressed via the design of a robustness filter. Unfortunately, virtually all real processes are nonlinear. Some are sufficiently linear in the region of operation so that conventional PID controllers provide adequate performance. But, for highly nonlinear processes, conventional feedback controllers must be detuned significantly to ensure stability. Therefore, performance is often severely degraded. Model based control strategies for nonlinear processes usually require local linearization and linear controller design based on the linearized model. This approach, however, may not be successful when the process is highly nonlinear or deviates significantly from the operating point around which the model is linearized. For batch and semi-batch processes, it is difficult to define an operating point for linearization. If reasonably accurate nonlinear models are available for processes, control strategies in which the nonlinear process model serves as the basis for the controller design can be expected to yield significantly improved performance [25, 40].

Most often, the IMC controllers are designed for the linearized models and then implemented on the true nonlinear plants. The discrepancy in the model and the true plant gives rise to the poor performance of the closed-loop system, whenever the system is excited by a signal away from the selected operating point for the linearization of the plant [42]. Recent advances in the nonlinear control theory and practice have shown that properly designed nonlinear controllers give better performance for wide range of operation [62]. An explicit model of the system is necessary for designing the IMC controller as well. Due to the inherent complexity of nonlinear systems, the development of a general nonlinear extension of IMC has serious difficulties. Except for simple single-input single-output systems, the IMC factorization procedure has no well-defined nonlinear analog [32]. Also, very few tools exist for the design and analysis of robust nonlinear controllers. Furthermore, linear IMC is based on transfer function models, while nonlinear systems are usually described by nonlinear state-space models. Despite these difficulties, the linear IMC scheme has been extended to its non-linear version by different approaches [2,4,6,8,9,18,25,26,30,46,49,50,52,59].

For nonlinear plants, the IMC structure can be extended to nonlinear models [18, 27]. As the IMC design involves a stable and causal approximation of the inverse of the plant, in general however, the inversion of nonlinear models is more involved and analytical solutions may not exists such that solutions have to be found numerically. The tracking of the reference signals is a requirement in many applications [17]. To accomplish tracking, the IMC structure requires the inverse of the plant. The determination of inverse of large class of nonlinear plants poses difficulties due to lack of a general modeling framework for nonlinear plants.

The identification and digital control of linear systems is largely based on the linear difference equation model which relates sampled output signals to sampled inputs. Numerous parameter estimation routines and controller synthesis procedures have been developed based on this description which provides a concise representation of both the process and the feedback controller [22]. When the system is nonlinear, however, the traditional system descriptions are based on the functional series such as the Volterra or Weiner series [41]. Whilst these provide an adequate representation for a wide class of nonlinear systems, several hundred parameters are often required to characterize even simple nonlinear systems. The excessive computational effort required to estimate the unknown parameters, the difficulty of interpreting the results and the necessity to use special input signals are further disadvantages of functional series methods. The usefulness of these system descriptions for identification and control purposes is therefore limited and alternative representations are required. In the field of nonlinear modeling, the nonlinear autoregressive moving average with exogenous inputs (NARMAX) representation [36] has attracted considerable interest both in theory and applications. The NARMAX model yields an input-output representation of a non-linear system where the current output is obtained by means of a non-linear functional expansion of lagged inputs, outputs and noise terms. Depending on how the functional expansion is represented and parameterized, different model structures are derived. In particular, polynomial models have been extensively used, because they are linear-in-the-parameters models and the polynomial terms are often amenable to a direct physical interpretation. Furthermore, the Hammerstein, Weiner, bilinear and several other well-known linear and nonlinear models sets are special classes of the NARMAX model. However designing controllers based on NARMAX models which represent a wide class of nonlinear plants is difficult because they lack a maneuverable structure [48].

To improve robustness, the effects of process model mismatch in the IMC structure should be minimized. In addition, control performance and the controller simplicity are also important for practical applications. Recently proposed control-oriented model for a class of nonlinear plants called U-model [69], simplifies the computation of the approximate inverse system of the nonlinear plant numerically. Originally, finding of the inverse model is converted to the computation of the zeros of the nonlinear plant. The problem can be solved using well-established numerical techniques such as the Newton-Raphson method [10].

In this thesis, the use of, control-oriented model called the U-model, in the IMC structure for stable single input single output (SISO) nonlinear dynamic plants is proposed. We introduce the learning rate parameter in the inverse finding computational algorithm called the Newton-Raphson algorithm to improve the convergence and stability properties. Adaptive inverse control is used to further improve the tracking properties of the closed-loop system. A new IMC structure wherein the model of the plant is replaced by the plant delay is introduced. Adaptive IMC strategy based on U-model for nonlinear dynamic plants is proposed. Computation of the inverse of U-model for nonlinear dynamic plants using the secant method is proposed.

1.2 Problem Statement

In this thesis, the problem of tracking of an input reference signal incase of stable single input single output (SISO) nonlinear dynamic plants is considered. The NARMAX (non-linear autoregressive moving average with exogenous inputs) representation of such plants is given as:

$$y(t) = f[y(t-1),....,y(t-n),u(t-1),....,u(t-n),e(t),....,e(t-n)] \tag{1.1}$$

where $y(t)$ and $u(t)$ are the output and input signals of the plant respectively at discrete time instant t, n is the order of the plant, $f[.]$ is a nonlinear function and $e(t)$ represents the error due to measurement, noise, model mismatch, uncertain dynamics, plant variation etc. The objective is to synthesize $u(t)$ such that $y(t)$ tracks the desired input reference signal $r(t)$, while the plant parameters are unknown or time varying. A perfect control/tracking is possible without feedback, if the control scheme is developed based on the exact model of the process. In practice, however, process-model mismatch is common, the process model may not be invertible and the system is often affected by unknown disturbances.

1.3 Objectives of the Thesis

The objectives of this thesis are the following:

1. To develop an internal model control (IMC) strategy based on the control-oriented model called the U-model for stable SISO nonlinear dynamic plants.
2. To introduce a learning rate parameter in the Newton-Raphson algorithm used to compute the inverse of U-model of stable SISO nonlinear dynamic plants in the proposed IMC strategy.
3. Simulating the developed IMC strategy to test its effectiveness to control the following nonlinear plants:
    - i Hammerstein model
    - ii Laboratory scale liquid level system

iii Continuous stirred tank reactor

4. Real time implementation of the developed IMC strategy to control the speed of brush DC motor.
5. To compare the developed IMC strategy with an existing technique discussed in [37] for control of SISO nonlinear plants.
6. To achieve fine tracking using the adaptive inverse controller in the IMC structure.
7. To develop a new IMC structure wherein the model of the plant to be controlled is replaced by the plant delay.
8. Simulating the developed IMC structure involving the plant delay to control the following nonlinear plants:

   i Hammerstein model

   ii Laboratory scale liquid level system

   iii Continuous stirred tank reactor

9. To develop an adaptive IMC strategy based on U-model for stable nonlinear dynamic plants.
10. Real time implementation of the developed adaptive IMC strategy based on U-model for position tracking of a single-link robot manipulator driven by a brush dc motor.
11. To develop an algorithm to compute the inverse of U-model of stable SISO nonlinear dynamic plants in IMC strategy using Secant method.

1.4 Thesis Organization

The remainder of this thesis is organized as follows: In chapter 2, literature review in the areas of internal model control, system modeling, adaptive control, neural networks is presented. In chapter 3, the control strategies, the U-model concept, the incorporation of the inverse system in the internal model control structure, the computation of the inverse of nonlinear plants using Newton-Raphson method is described and the computer simulation results for different nonlinear plants are presented. A comparison of the developed IMC strategy with an existing technique for control of nonlinear plants is given. In chapter 4, fine tracking technique in the IMC structure is presented and a new IMC structure based on U-model is proposed. In chapter 5, adaptive IMC strategy based on U-model is presented and real time experimental results are illustrated. In chapter 6, the computation of the inverse of nonlinear plants using Secant method in the IMC structure is discussed and simulation results are presented. Conclusions and recommendations for future research are given in chapter 7.

CHAPTER 2

Literature Review

2.1 Literature Review

In 1982, Garcia C.E. and Morari M. [21] first defined the internal model control (IMC) structure for single-input single-output (SISO), discrete-time systems. Several new stability theorems for IMC were proved and it was concluded that the IMC structure allows a rational design procedure where in the first step the controller is selected to give perfect control. In the second step a filter is introduced which makes the system robust to a specified model-plant mismatch.

Leontaritis I.J. and Billings S.A. [36] in 1985 derived the recursive input-output models for both deterministic and stochastic nonlinear multivariable discrete-time systems. The models were derived based on assumptions that the system is finitely realizable and the linearized system has maximum possible order around the equilibrium point. It was shown that the recursive nonlinear input-output models are valid only in some restricted region of operation around the equilibrium point. This work was extended to create prediction error input-output models for multivariable nonlinear stochastic systems and these models were referred to as NARMAX models.

Economou C.G. et al. [18] in 1986 developed a nonlinear IMC by employing an approximate inverse of the model, using local linear approximation. A first step towards a practical approach to the synthesis of nonlinear feedback controllers was attempted.

Calvet J. and Arkun Y. [9] in 1988 used an IMC scheme to implement their state-space linearization approach for non-linear system with disturbances. This method requires state feedback. A systematic procedure was given to structure the control system in the presence of measured and unmeasured disturbances and a technique to reconstruct the control signal to eliminate the nonlinear/linear mismatch due to constraints was introduced.

Kravaris C. [31] discussed the SISO nonlinear processes and their control with nonlinear static state feedback and developed the concept of placing poles at the process zeros to nonlinear systems. It was shown that the class of input/output linearizing state feedback laws places poles at the process zeros in a nonlinear process which will lead to natural stability condition for input/output linearizing state feedback.

Alvarez J. et al. [4] in 1989 proposed a tracking and regulation scheme for discrete time non-linear systems. The scheme allows to track a specified trajectory with a dynamics specified by a tracking reference model and it was shown that the effect of disturbances on the process output can also be eliminated, with a dynamics imposed by a regulation model.

Billings S.A. and Chen S. [7] derived parameter estimation algorithms, based on an extended model, a global data model and a threshold model formulation for identifying severely nonlinear systems. It was shown that in each case an integrated structure determination and parameter estimation algorithm based on an orthogonal decomposition of the regression matrix can be derived to provide procedures for identifying parsimonious models of unknown systems with complex structure.

Sales K.R. and Billings S.A. [53] in 1990 introduced a minimum-variance self-tuning algorithm based on the NARMAX model. It was shown that the NARMAX based controller is more generally applicable and using NARMAX structure is a more practical approach than using functional series or block structured models. Performance analysis of the controller was discussed in terms of a cumulative loss function and high-order correlation functions of the system input, output and residual sequences.

Kravaris C. and Daoutidis P. [32] addressed the problem of synthesizing nonlinear state feedback controllers for second-order nonminimum phase nonlinear systems. A class of control laws were developed that make the closed loop system equivalent, under an appropriate coordinate transformation, to a nonlinear first order all-pass in series with a linear first order lag.

Hunt K.J. and Sbarbaro D. [26] in 1991 proposed a novel technique of directly using artificial neural networks for the adaptive control of nonlinear systems. The use of nonlinear function inverses was investigated and IMC was used as the control structure.

Henson M.A. and Seborg D.E. [25] employed a non-linear filter to derive a non-linear IMC for SISO systems. The controller was designed to provide nominal performance, and a nonlinear filter added to make the controller implementable and to account for plant-model mismatch. The new approach eliminated the assumption of full state feedback inherent in most input-output linearization schemes.

Kulkarni B.D. et al. [34] proposed a methodology based on the similarity between the model and its inverse, for designing a nonlinear IMC controller for SISO systems.

Zhu Q.M. et al. [68] introduced an adaptive nonlinear control scheme which was based on the use of the Hammerstein model, such that the resulting control algorithm is a nonlinear form of generalized predictive control. The key contribution was the use of a novel, one-step simple root solving procedure for the Hammerstein model being a fundamental part of the overall tuning algorithm.

In 1996, Datta A. and Ochoa J. [13] combined adaptation with an internal model control structure to obtain an adaptive internal model control scheme possessing theoretical provable guarantees of stability. The adaptive IMC scheme was designed for open-loop stable plants using the traditional certainty equivalence approach of adaptive control and it was shown that using a series–parallel identification model, for a stable plant, one can adapt the internal model on-line and guarantee stability and asymptotic performance in the ideal case.

Kalkkuhl J. and Liceaga-Castro E. [29] presented a two-degrees of freedom output feedback controller for nonlinear SISO systems where the plant to be controlled was represented by a discrete-time input-output (NARX) model. As a difference to conventional internal model control the approach was based on geometric methods and a modification of the control structure suitable for unstable plants was also given.

In 1997, Brown M.D. et al. [8] proposed a nonlinear internal model control based on local model networks which represents nonlinear dynamical systems by a set of locally valid sub-models across the operating range.

Choi C.-H. and Kim H.-C. [11] proposed a robust adaptive controller based on the

IMC structure for stable plants. A stable high order model for the stable plants using the RLS algorithm and its stable reduced order model is calculated using the ordered real Schur form method. The stable adaptive IMC controller is designed for the reduced order model and is augmented by the low-pass filter such that the closed loop stability for the higher order model is ensured.

Patwardhan S.C. and Madhavan K.P. [46] in 1998 proposed a non linear IMC controller that can handle a larger class of non-linear system, including the singular systems that exhibit change in the sign of the steady sate gain. The construction of the model inverse was achieved through inversion of successive quadratic approximation of the non-linear model operator. The controller synthesis problem was formulated as minimization of 2-norm of single step prediction error.

Harnefors L. and Nee H.-P. [24] applied the IMC method to control the current of ac machine. The result is synchronous-frame proportional integral controllers, the parameters of which are expressed directly in certain machine parameters and the desired closed-loop bandwidth which simplifies the control design procedure.

Yamada K. [66] proposed a design method for anti-windup servo control based on IMC structure by using the idea of internal perturbed model control and considered the reason that the error offset appears in internal model control with input saturation.

Datta A. and Xing L. [15] developed a systematic theory for the design and analysis of adaptive internal model control schemes. The ubiquitous certainty equivalence principle of adaptive control is used to combine a robust adaptive law with robust internal model controllers to obtain adaptive internal model control schemes with provable guarantees of stability and robustness.

Wang Q.G. et al. [60] proposed a modified internal model control scheme with simplified design and implementation. The key is to select an appropriate desired closed loop transfer function and design controller of low order form such that the closed loop transfer function is equal to the product of the controller and the plant transfer function.

Kambhampati C. et al. [30] used recurrent neural networks within the IMC strategy for control of nonlinear plants. It was shown how an inverse controller can be produced from a neural network model of the model, without the need to train an additional network to perform the inverse control.

In 1999, Artemis T. et al. [5] proposed an inverse model based real-time control for nonlinear model. The feedback controller is designed using the IMC structure, especially modified to handle systems described by ordinary differential and algebraic equations. The IMC controller is obtained using optimal control theory.

Xing L. and Datta A. [35] proposed a continuous time decentralized adaptive model controller for the control of $N \times N$ multi-input multi-output system with unknown parameters. By treating the MIMO system as an interconnection of N single-input single-output linear subsystems with weak interactions, robust adaptive internal model controllers are designed for each isolated subsystem.

Hu Q. and Rangaiah G.P. [49] proposed an adaptive internal model control for a class of minimum-phase input-output linearizable non-linear systems with parameter uncertainty.

The IMC for non-linear systems was developed directly from the input-output linearization. The parameter adaptation for the IMC is based on process and model outputs and the state variables predicted by the model only.

Suzuki R. et al. [57] proposed a two-degrees-of-freedom control design method by combining with the IMC design which constructed the compensator using the inverse system as a feed forward part and the LQ control.

Silva G.J. and Datta A. [55] considered the design and analysis of a discrete-time H_2 optimal robust adaptive controller based on the IMC structure. The certainty equivalence principle of adaptive control is used to combine a discrete-time robust adaptive law with a discrete-time H_2 internal model controller to obtain a discrete-time adaptive H_2 internal model control scheme with provable guarantees of stability and robustness.

In 2000, Ma Z. et al. [37] presented a nonlinear self-tuning controller, which is based on Hammerstein model. A class of nonlinear systems, which can be suitable modeled with a Hammerstein model, are effectively controlled by the proposed algorithm by combining a general self-tuning method with a feedforward compensation strategy. The nonlinear parts are accommodated in the control law design so that they are compensated effectively.

Tayebi A. and Zaremba M.B. [58] in 2000 proposed an iterative learning controller for repetitive SISO linear time invariant systems in an IMC structure. The iterative learning control part is introduced to iteratively improve the transient behavior of the control system, particularly in the presence of regular repetitive output disturbances. For a certain choice of the IMC and the iterative learning control filters, the condition of convergence to zero of the tracking error is nothing but the robust performance condition for the IMC structure was shown.

Xie W.F. and Rad A.B. [65] presented a fuzzy adaptive internal model controller for open-loop stable plants. The control scheme consists of a dynamic model and a model-based fuzzy controller. Fuzzy dynamic model which serves as the internal model is identified online by using the input and output measurement of the plant. Based on the identified fuzzy model, the fuzzy controller is designed.

Rivals I. and Personnaz L. [52] proposed a design procedure of neural internal model control systems based on a model reference controller for stable processes with delay. It was shown that the controller is obtained by cascading the inverse of the model which is deprived from its delay with a rallying model which imposes the regulation dynamic behavior and ensures the robustness of the stability.

In 2001, Hu Q. and Rangaiah G.P. [50] proposed an internal model control with feedback compensation, which consists of a nonlinear model control and an error feedback loop, to achieve disturbance attenuation and offset-free performance. The matching conditions for the uncertainties of nonlinear systems are not necessary, and the adjustable parameters can be easily be tuned to satisfy the particular specification. The underlying theoretical approach for the feedback compensation is the Lyapunov stability theory.

Alleyne A. and Tharayil M. [3] proposed a semi-active IMC for SISO linear time invariant systems that have a passive characteristic. The passivity of the open loop system is utilized to determine a controller that acts in a semi-active fashion for disturbance rejection. The key idea is the combination of the internal model principle with a semi-active actuation approach to supply disturbance attenuation without adding any power to the system. The disturbance itself effectively supplies the energy necessary for the control system to attenuate it.

Wang Q.G. et al. [61] proposed a scheme called partial internal model control (PIMC), which is capable of controlling both stable and unstable processes. In this scheme, a process model is expressed as the sum of the stable and the antistable parts and only the stable part of the process model is used as the internal model. The process stable part is cancelled by the internal model and the remaining antistable part is stabilized and controlled with a primary controller.

Abdullah A. et al. [1] in 2002 designed the servo controller for a dual-stage actuator in hard-disk drive using the IMC approach. The designed method provided robustness of the micro-actuator loop required to overcome the problem of uncertainties in the model of the micro-actuator.

Matausek M.R. et al. [39] presented an approach to the design and tuning of two degrees of freedom linear digital controllers wherein the controller structure is directly obtained from the model used and fewer parameters are to be adjusted to obtain high closed –loop performance.

Alexander F. et al. [2] discussed the extension of the IMC scheme to local linear neuro-fuzzy models. It was shown that the well developed linear design techniques can easily be adapted to these type of models and the IMC structure can be converted into standard control loop where the resulting controller is mainly a PI or PID controller and the IMC approach can be utilized to design and tune conventional controllers.

Bel Hadj Ali S. et al. [6] proposed the use of an artificial neural network in IMC both as process model and as controller, for a class of nonlinear systems with separable nonlinearity. It was shown that an IMC with a neural network controller, in which the linear part of the plant and its inverse are replaced by neural networks, cancels the effects of nonlinear dynamics and measured disturbances.

Shafiq M. and Riyaz S.H. [54] in 2003 proposed an adaptive IMC scheme based on adaptive finite impulse response filters, which can be designed for both minimum and non-minimum phase systems in the same fashion. The internal model of the plant is estimated by the recursive least square algorithm and the inverse of the system by the least mean square. The closed loop is designed such that the system from the reference input to plant output can be approximately represented by a pure delay and the effect of process zeros on the output is compensated using the adaptive finite impulse response filters which avoid the cancellation of the non-cancelable zeros of the plant.

Wright R.A. and Kravaris C. [64] proposed a systematic approach for the synthesis of decoupling controllers in the presence of sensor and actuator dead-times. The method is in state-space and can be applied for both linear and nonlinear systems. The given system is put in lower block triangular form through rearranging and partitioning and the control law is derived that ensures that the closed-loop system is input-output linear and decoupled, with dead-times equal to the smallest ones that satisfy the feasibility conditions.

Boubaker O. and Barbary J.P. [43] introduced SISO and MIMO variable structure controls of a class of nonlinear and time varying distributed parameter systems. Theoretical proof of distributed parameter systems convergence for SISO and MIMO distributed variable structure control laws was developed.

Gutman P.-O. [47] presented the concept of adaptive robust control of SISO linear time-invariant systems and is applicable in very general framework, such as nonlinear and multi-variable plants and for very general uncertainty structures. It was shown that the control is switched between robust controllers that are based on plant uncertainty sets that take into account not only the currently estimated plant model set but also the possible jumps and drifts that may occur until the next time the controller can be updated.

Miller D.E. [12] proposed an alternative approach to adaptive control, which yields a linear periodic controller. In this approach rather than estimating the plant or compensator parameters, the control signal is estimated during the estimation phase if the plant parameters were known and in the control phase a suitably scaled version of the estimate is applied.

Srinivas P. et al [56] designed a robust non-linear controller based on the input/output linearization and multi objective H_2 / H_∞ synthesis, for non-square multivariable nonlinear systems and are subject to parametric uncertainty. A nonlinear state feedback is synthesized that approximately linearizes the systems in an input/output sense by solving a convex optimization problem. It is shown that the procedure is applicable for minimum phase systems that are input/output linearizable.

Mahmudov N.I. and Zorlu S. [38] studied the complete controllability of a semi-linear stochastic system assuming controllability of the associated linear system. It was also shown that a nonlinear stochastic system is locally null controllable provided that the corresponding linearized system is controllable.

Zhang X. and Nair S.S. [67] developed analytical details for a robust adaptive control strategy that combines control and on-line adaptive learning for a class of nonlinear systems and derived the condition to guarantee stable learning for the strategy. The guidelines for design parameter selection were provided.

Sontag E.D. [19] showed, under suitable technical assumptions, that if a system adapts to a class of external signals, in the sense of regulation against disturbances or tracking signals then the system must necessarily contain a subsystem which is capable of generating all the signals and further showed that there is no prior requirement for the system to be partitioned into separate plant and controller components.

Hannah M. and Torres-Torriti M. [23] presented an approach to the construction of stabilizing feedback for strongly nonlinear systems. The approach is independent of the selection of a lyapunov type function, but requires the solution of a nonlinear programming satisficing problem stated in terms of the logarithmic coordinates of flows.

Piroddi L. and Spinelli W. [48] analyzed the problem of structure selection for polynomial NARX models, with focus on the simulation performance of the identified models and proposed a new algorithm which employs a combination of two factors namely a pruning mechanism to keep the model dimension small during iterations, and a simulation error based criterion for regression selection.

Toivonen H.T. et al. [59] applied internal model control to design scheduled controllers based on linearized plant models obtained by velocity-based linearization. When the velocity–form linear parameter varying model is applied in the conventional IMC structure, the control system does provide elimination of steady state offsets. This problem is resolved by modifying the IMC structure in such a way that the elimination of steady state offsets is achieved subject to a condition on a tuning filter only.

In 2004, Kravaris C. et al. [33] developed a systematic method to arbitrarily assign the zero dynamics of a nonlinear system by constructing the requisite synthetic output maps. The proposed approach emphasized the algorithmic construction of minimum-phase synthetic output maps that induce stable zero dynamics for the original nonlinear system. These output maps are made statically equivalent to the original output maps and could be directly used for non-minimum phase compensation purposes.

Kaya I. [28] proposed a method based on relay auto-tuning of a plant to find parameters for its control using a Smith predictor. In this method a Smith predictor configuration is represented as its equivalent internal model controller (IMC) which provides the parameters of the PI or PID controller to be defined in terms of the desired closed-loop time constant, which can be adjusted by the operator and the parameters of the process model.

CHAPTER 3

IMC strategy using U-model for Nonlinear Dynamic plants

In this chapter, concept of the control-oriented model called the U-model is presented. The use of this U-model in internal model control (IMC) structure for a wide class of nonlinear plants is proposed. The computation of the inverse of U-model using Newton-Raphson method is explained. Computer simulation and real-time experimental results are given to show the effectiveness of the proposed IMC strategy. A comparison of the proposed IMC strategy with nonlinear self-tuning controller discussed in [37] is presented.

3.1 Introduction to U-model

The main difficulty for nonlinear control system design lies in the lack of a general modeling framework for nonlinear plants, which allows the synthesis of control input for the plant to be performed analytically and effectively. Several models like the NARMAX model, Hammerstein, Weiner, bilinear and several other well-known models for representing the nonlinear plants exists but the difficulty occurs when controlling a plant based on these models because of lack of a maneuverable structure.

A newly parameterized model called the U-model is a control-oriented model used to represent a wide range of nonlinear discrete time dynamic plants [69]. It is more general compared to other parameterizing approaches and exhibits a polynomial structure in terms of the control term. The nonlinear algebraic equations obtained using the U-model are also polynomials, which are easier to solve to get the controller output whereas other models lead to complex non-linear algebraic equations.

To obtain the U-model, consider single-input single-output (SISO) nonlinear dynamic plants with a NARMAX (nonlinear autoregressive moving average with exogenous inputs) representation of the form as follows:

$$y(t) = f[y(t-1),....,y(t-n),u(t-1),....,u(t-n),e(t),....,e(t-n)] \qquad (3.1)$$

where $y(t)$ and $u(t)$ are the output and input signals of the plant respectively at discrete time instant t, n is the order of the plant, $f(.)$ is a nonlinear function and $e(t)$ represents the error due to measurement noise ,model mismatch, uncertain dynamics, plant variation.

The U-model is obtained by expanding the nonlinear function $f(.)$ of equation (3.1) as a polynomial with respect to $u(t-1)$ as follows:

$$y(t) = \sum_{j=0}^{M} \alpha_j(t) u^j(t-1) + e(t) \qquad (3.2)$$

where M is the degree of model input $u(t-1)$, $\alpha_j(t)$ is a function of past inputs and outputs $u(t-2),....,u(t-n), y(t-1),....,y(t-n)$ and errors $e(t),......,e(t-n)$.

To apply linear control system design methodologies to the nonlinear model a further transformation is applied as follows:

$$y(t) = U(t) \tag{3.3}$$

where, $U(t) = \Phi[u(t-1)] + e(t) = \sum_{j=0}^{M} \alpha_j(t) u^j(t-1) + e(t)$.

The expression of equation (3.3) is defined as the U-model.

3.1.1 Advantages of U-model

1. The control-oriented U-model is more general than other parameterizing approaches, such as the polynomial NARMAX model, the Hammerstein model etc.
2. The sampled data representation of many non-linear continuous time systems can be of the form as follows:

$$y(t) = \sum_{j=0}^{M} \alpha_j(t) u^j(t-1)$$

3. The U-model exhibits a polynomial structure in the current control u(t-1).
4. Due to its polynomial structure, the nonlinear algebraic equations, which need to be solved to obtain the output value of the controller, are also polynomials in u(t-1), unlike other models which lead to complex non-linear algebraic equations.

3.2 Internal Model Control

One of the most popular control strategies in industrial process control is the Internal Model Control (IMC) strategy, because of its simple structure, fine disturbance rejection capabilities and robustness. This control strategy can be used for both linear and non-linear systems. The IMC design is lucid for the following reasons:

- It separates the tracking problem from the regulation problem.
- The design of the controller is relatively straightforward.

The IMC strategy is especially suitable for the design and implementation of the open-loop stable systems and many industrial processes happen to be intrinsically open-loop stable. The IMC has the general structure as shown in figure 3.1.

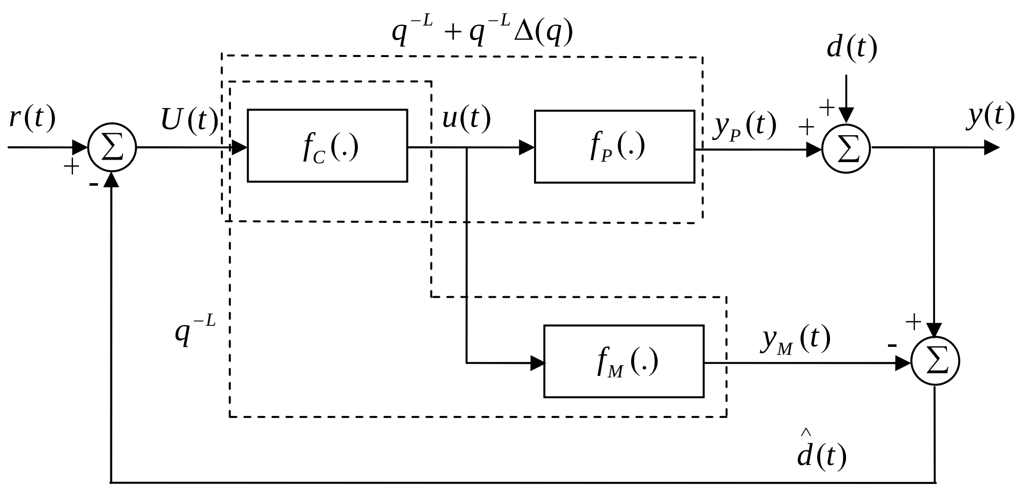

Figure 3.1: IMC Structure

In figure 3.1, $r(t)$ is the reference signal, $d(t)$ is an unknown disturbance affecting the system, $f_C(.)$ represents the controller, $f_P(.)$ and $f_M(.)$ represents the process and its model respectively. The controller output $u(t)$ is fed to both the process and its model. The process output $y(t)$ is compared with the output of the model $y_M(t)$ and the resulting signal $\hat{d}(t)$ represents the tracking error, which is given by

$$\hat{d}(t) = y(t) - y_M(t) \tag{3.4}$$

If $d(t)$ is zero, then $\hat{d}(t)$ is a measure of the difference in behavior between the process and its model. If $f_P(.) = f_M(.)$, then $\hat{d}(t)$ is equal to the unknown disturbance. Thus, $\hat{d}(t)$ may be regarded as the information that is missing in the model $f_M(.)$ and can therefore be used to improve control effort. This is given by subtracting $\hat{d}(t)$ from the reference signal $r(t)$ and the resulting control signal is given by

$$u(t) = f_C([r(t) - \hat{d}(t)]) \qquad (3.5)$$

The controller $f_C(.)$ is obtained using the Newton-Raphson algorithm discussed in section 3.4 of this chapter.

If the model is exact representation of plant i.e. $f_M(.) = f_P(.)$ and the controller the inverse of the model i.e. $f_C(.) = [f_M(.)]^{-1}$,then $q^{-L} + q^{-L}\Delta(q)$ can be regarded as the delay along the path from the input $U(t)$ to the plant output $y(t)$, and q^{-L} the delay along the path from the input $U(t)$ to the output of the model of the plant $y_M(t)$, where q^{-1} is the backward shift operator and $\Delta(q)$ represents the plant uncertainty, then from figure 3.1, we get

$$y(t) = [q^{-L} + q^{-L}\Delta(q)]U(t) \qquad (3.6)$$

$$y_M(t) = q^{-L}U(t) = U(t - L) \qquad (3.7)$$

$$U(t) = r(t) - \hat{d}(t) \qquad (3.8)$$

On substituting equation (3.6) and (3.7) in equation (3.4) we have

$$\hat{d}(t) = q^{-L}\Delta(q)U(t) \tag{3.9}$$

Using equation (3.6), (3.8), and (3.9) and on further simplification the overall closed loop function for the system in figure 3.1 for $L = 1$, is obtained as follows:

$$y(t) = r(t-1)[1+\Delta(q)] - r(t-2)[\Delta(q)+\Delta^2(q)] \tag{3.10}$$

If $|\Delta(q)| << 1$, in equation (3.10), then $y(t) \approx r(t-1)$. This means approximate tracking objective is accomplished.

3.2.1 Properties of Internal Model Control

Property P1 (Dual Stability): Assume that the plant and the controller are input-output stable and that the model is a perfect representation of the plant. Then the closed-loop system is input-output stable.

Property P2 (Perfect Control): Assume that the inverse of the operator describing the plant model exists, that this inverse is used as the controller, and that the closed-loop system is input-output stable with this controller. Then the control will be perfect.

Property P3 (Zero Offset): Assume that the inverse of the steady state model operator exists, that the steady state controller operator is equal to this, and that the closed-loop system is input-output stable with this controller. Then offset free control is attained for asymptotically constant inputs.

3.3 Computation of Inverse of Nonlinear Plants using Newton-Raphson Method

Most widely used methods for solving the nonlinear equations is the Newton-Raphson method because it is more rapidly convergent compared to other methods. In general the Newton-Raphson method has the form as follows:

$$x_{n+1} = x_n - \frac{f(x_n)}{f'(x_n)} \quad , \quad n = 1,2,3,.....$$

where, $f(x_n)$ is a nonlinear equation.

Consider figure 3.1, a general inverse controller using the U-model of equation (3.3) can be given as follows:

$$U(t) = r(t) - y(t) + y_M(t) \tag{3.11}$$

where $r(t)$ is the reference signal, $y(t)$ and $y_M(t)$ are the system and plant model outputs respectively as shown in figure 3.1. The controller output $u(t-1)$ can be found using the Newton-Raphson algorithm recursively with $U(t)$ as a root solver. The algorithm is given as follows:

$$\begin{aligned} u_{i+1}(t-1) &= u_i(t-1) - \frac{\Phi[U_i(t-1)] - U(t)}{d\Phi[u(t-1)]/du(t-1)} \\ &= u_i(t-1) - \left.\frac{\sum_{j=0}^{K} \alpha_j(t) u_i^j(t-1) - U(t)}{d[\sum_{j=0}^{K} \alpha_j(t) u^j(t-1)]/du(t-1)}\right|_{u^j(t-1)=u_i^j(t-1)} \end{aligned} \tag{3.12}$$

where the subscript i is the iteration index.

The value of future unknown term $e(t)$ contained in $U(t)$ is set to zero and the terms $e(t-1),.....,e(t-n)$ are estimated at each sampling instant from equation (3.2) as follows:

$$\hat{e}(t-1)=\sum_{j=0}^{K}\hat{\alpha}_j(t)u^j(t-1)-y(t) \qquad (3.13)$$

where $\hat{\alpha}_j(t)$ is an estimate of $\alpha_j(t)$, which is calculated using $\hat{e}(t-1),.....,\hat{e}(t-n)$. Substituting equation (3.13) in equation (3.12), results in an iterative formula for calculating the controller output as follows:

$$u_{i+1}(t-1)=u_i(t-1)-\left.\frac{\sum_{j=0}^{K}\hat{\alpha}_j(t)u^j(t-1)-U(t)}{d[\sum_{j=0}^{K}\hat{\alpha}_j(t)u^j(t-1)]/du(t-1)}\right|_{u^j(t-1)=u_i^j(t-1)} \qquad (3.14)$$

It may be possible that in equation (3.14),

$$\frac{d[\sum_{j=0}^{K}\hat{\alpha}_j(t)u^j(t-1)]}{du(t-1)}\approx 0$$

or there exists no real root of the polynomial. To deal with such problems [68] proposed an improved computation for the traditional Newton-Raphson algorithm. We incorporate a learning rate parameter $0<m\leq 1$ in equation (3.14) to decrease the rate of convergence and thereby increasing the stability of the system. The resulting equation is given as follows:

$$u_{i+1}(t-1) = u_i(t-1) - m \left. \frac{\sum_{j=0}^{K} \hat{\alpha}_j(t) u^j(t-1) - U(t)}{d[\sum_{j=0}^{K} \hat{\alpha}_j(t) u^j(t-1)] / du(t-1)} \right|_{u^j(t-1) = u_i^j(t-1)} \tag{3.15}$$

3.4 Simulation Results

To show the effectiveness of the proposed IMC strategy, computer simulation results for control of nonlinear plants are given in this section.

3.4.1 Control of Hammerstein Model

Consider the following Hammerstein model

$$\begin{aligned} y(t) &= 0.5y(t-1) + x(t-1) + 0.1x(t-2) \\ x(t) &= 1 + u(t) - u^2(t) + 0.2u^3(t) \end{aligned} \tag{3.16}$$

The equivalent U-model of equation (3.16) is given by

$$y(t) = \alpha_0(t) + \alpha_1(t)u(t-1) + \alpha_2(t)u^2(t-1) + \alpha_3(t)u^3(t-1) \tag{3.17}$$

where,

$$\begin{aligned} \alpha_0(t) &= 0.5y(t-1) + 1 + 0.1x(t-2) \\ \alpha_1(t) &= 1 \\ \alpha_2(t) &= -1 \\ \alpha_3(t) &= 0.2 \end{aligned} \tag{3.18}$$

Simulation results obtained using the proposed IMC strategy for the Hammerstein model are shown in figure 3.2 and figure 3.3. Figure 3.2 shows that the plant output converges to the desired output and the peak overshoot is small. Figure 3.3 indicates that the control input is bounded. In this simulation $m = 0.085$ is selected. For the purpose of comparison, the results obtained using the pole placement controller discussed in [69] are shown in figure 3.4 and figure 3.5. Figure 3.4 shows that plant output converges to the desired output with a large peak overshoot. The control input is shown in figure 3.5. This means proposed controller is capable of reducing the peak overshoot. It can also be observed from figure 3.3 and figure 3.5 that the control input synthesized using the proposed method is less active.

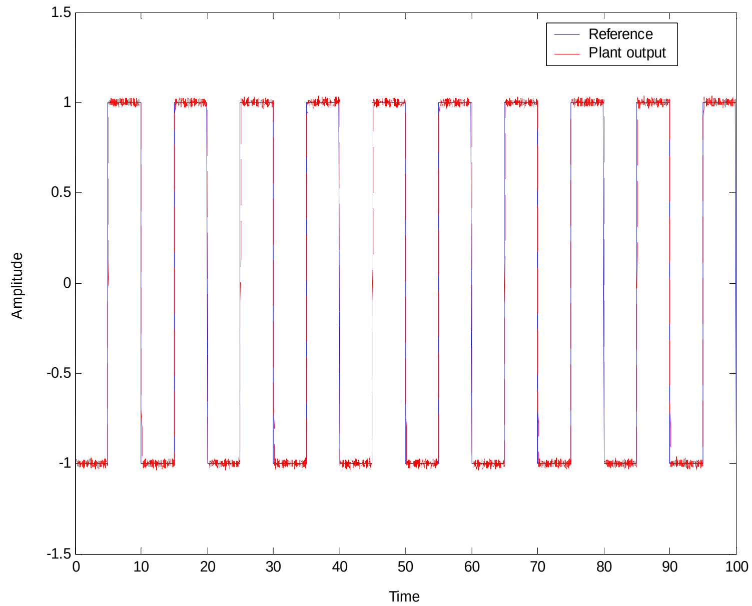

Figure 3.2: System response of Hammerstein model using proposed IMC strategy

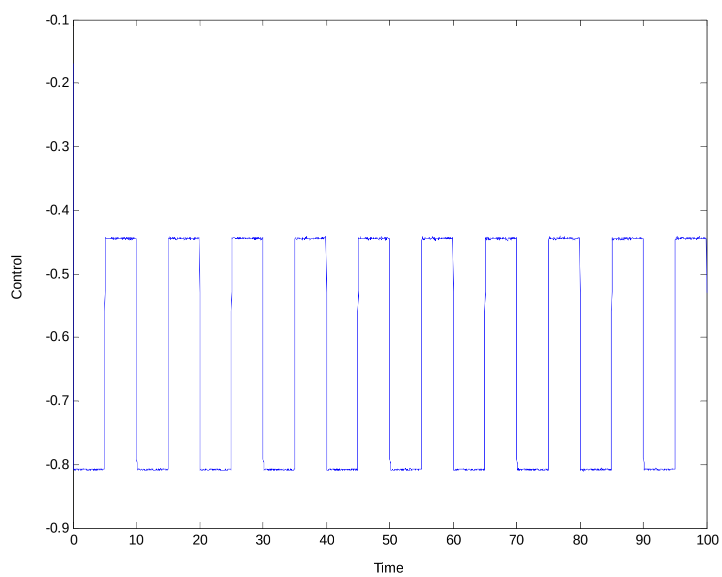

Figure 3.3: Control signal for the Hammerstein model incase of proposed IMC strategy

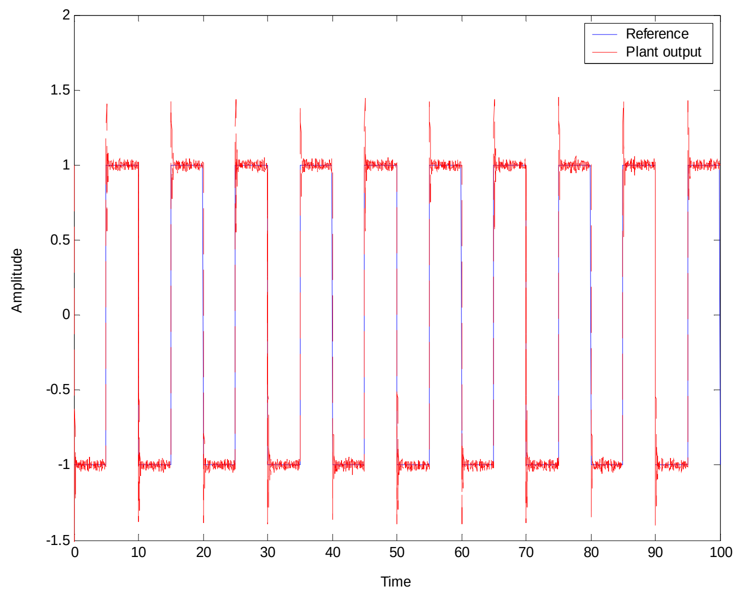

Figure 3.4: System response of Hammerstein model using pole Placement controller

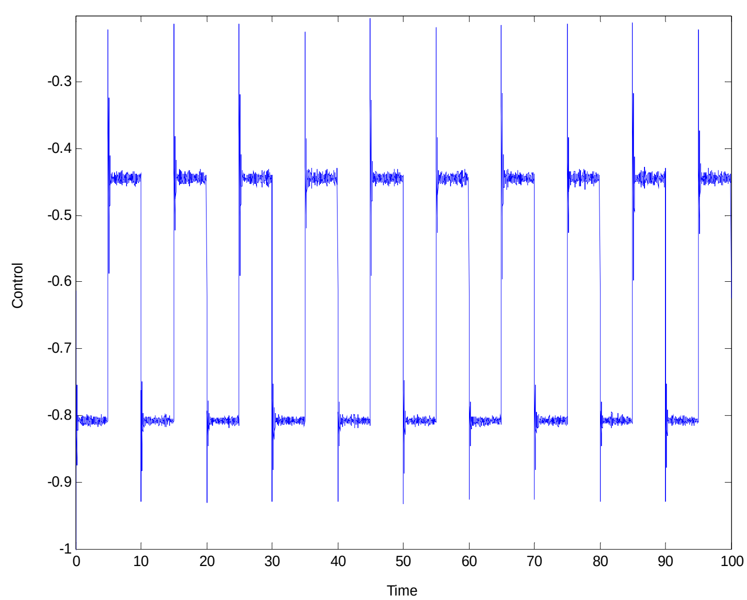

Figure 3.5: Control signal for Hammerstein model incase of pole placement controller

3.4.2 Control of a Laboratory Scale Liquid Level system

The proposed IMC strategy is applied to control a laboratory scale liquid level system represented by the following nonlinear model:

$$\begin{aligned}
y(t) &= 0.9722y(t-1) + 0.3578u(t-1) - 0.1295u(t-2) - 0.3103y(t-1)u(t-1) \\
&- 0.04228y^2(t-2) + 0.1663y(t-2)e(t-1) - 0.03259y^2(t-1)y(t-2) \\
&- 0.3084y(t-1)y(t-2)u(t-2) + 0.2939y^2(t-2)e(t-1) \\
&+ 0.1087y(t-2)u(t-1)u(t-2) + 0.4770y(t-2)u(t-1)e(t-1) \\
&+ 0.6389u^2(t-2)e(t-1) + e(t)
\end{aligned} \tag{3.19}$$

The equivalent U-model of equation (3.18) is given as follows:

$$y(t) = \alpha_0(t) + \alpha_1(t)u(t-1) + e(t) \tag{3.20}$$

where

$$\begin{aligned}
\alpha_0(t) &= 0.9722y(t-1) - 0.04288y^2(t-2) + 0.1663y(t-2)u(t-2) \\
&+ 0.2573y(t-2)e(t-1) - 0.03259y^2(t-1)y(t-2) - 0.3513y^2(t-1)u(t-2) \\
&+ 0.3084y(t-1)y(t-2)u(t-2) + 0.2939y^2(t-2)e(t-1) - 0.1295u(t-2) \\
&+ 0.6389u^2(t-2)e(t-1)
\end{aligned} \tag{3.21}$$

$$\alpha_1(t) = 0.3578 - 0.3103y(t-1) + 0.1087y(t-2)u(t-2) + 0.4770y(t-2)e(t-1)$$

In this simulation a square signal is chosen to be the desired reference signal and the noise sequence is Gaussian. The output of the plant converges to the reference signal using the proposed IMC strategy as shown in figure 3.6. The corresponding control signal is shown in figure 3.7.The results obtained using the pole placement controller are depicted in figure 3.8 and figure 3.9.A comparison of figures 3.6 and figure 3.8 shows the effectiveness of the proposed IMC strategy.

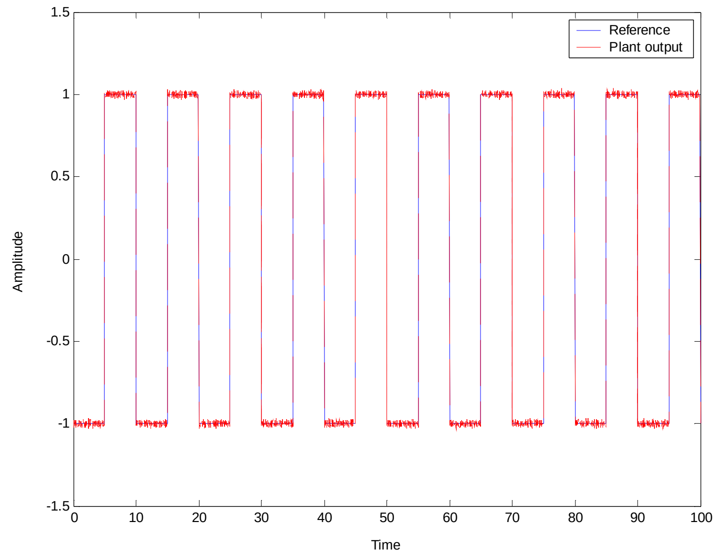

Figure 3.6: System response of laboratory scale liquid level system using IMC strategy

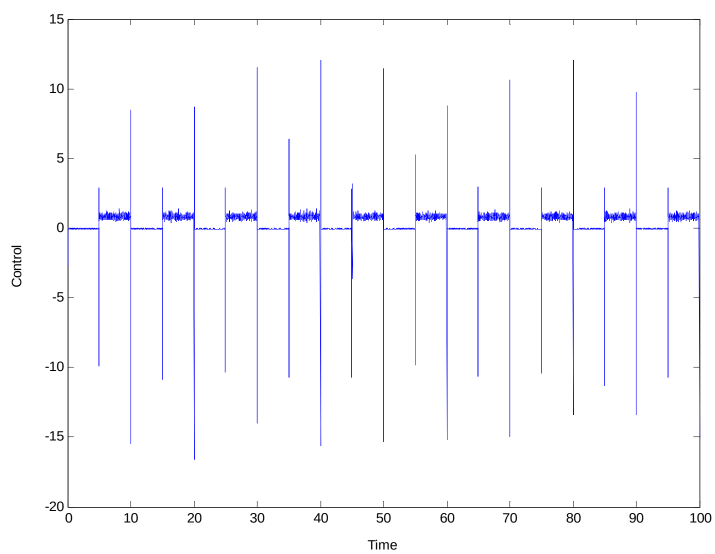

Figure 3.7: Control signal for the laboratory scale liquid level system in case of IMC strategy

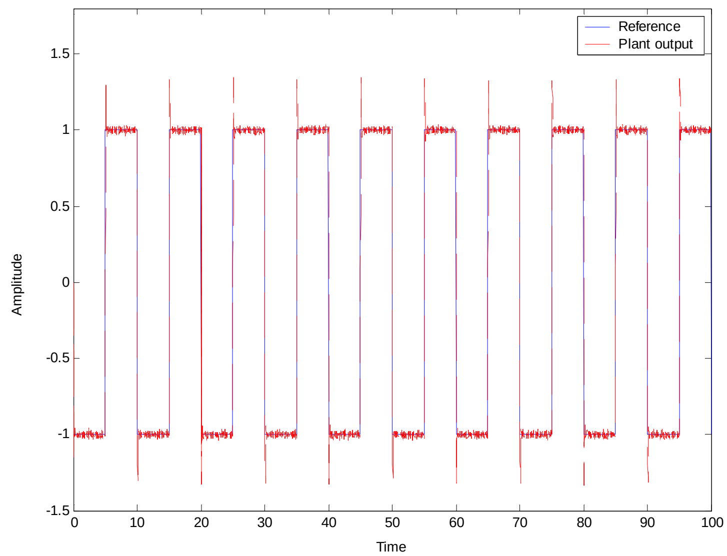

Figure 3.8: System response of liquid level system using pole placement controller

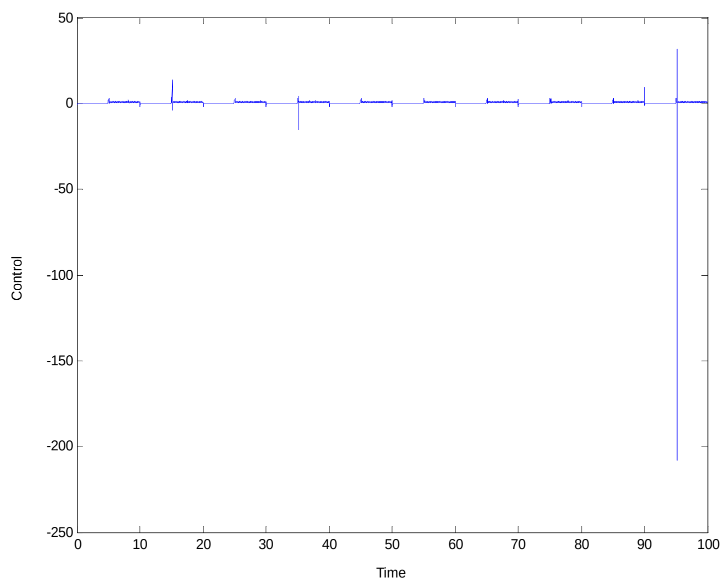

Figure 3.9: Control signal for liquid level system using pole placement controller

3.4.3 Control of Continuous Stirred Tank Reactor (CSTR)

In this section the simulation results of control of a continuous stirred tank reactor are discussed. The nonlinear model of the continuous stirred tank reactor when the sampling time is chosen as 0.05 seconds is as follows.

$$\begin{aligned} y(t+1) &= 0.8606y(t) - 0.0401y^2(t) + 0.0017y^3(t) - 0.000125y^4(t) + 0.0464u(t) \\ &- 0.045y(t)u(t) + 0.0034y^2(t)u(t) - 0.00025y^3(t)u(t) - 0.0012u^2(t) + \\ &0.0013y(t)u^2(t) - 0.0001458y^2(t)u^2(t) + 0.00002083u^3(t) - 0.00002083y(t)u^3(t) \end{aligned} \tag{3.22}$$

The equivalent U-model of equation (3.19) is given as follows:

$$y(t) = \alpha_0(t) + \alpha_1(t)u(t-1) + \alpha_2(t)u^2(t-1) + \alpha_3(t)u^3(t-1) \tag{3.23}$$

where

$$\begin{aligned} \alpha_0(t) &= 0.8606y(t-1) - 0.0401y^2(t-1) + 0.0017y^3(t) - 0.000125y^4(t-1) \\ \alpha_1(t) &= 0.0464 - 0.045y(t-1) + 0.0034y^2(t-1) - 0.00025y^3(t-1) \\ \alpha_2(t) &= -0.0012 + 0.0013y(t-1) - 0.0001458y^2(t-1) \\ \alpha_3(t) &= 0.00002083 - 0.00002083y(t-1) \end{aligned} \tag{3.24}$$

The output response of the system using the proposed IMC strategy is as shown in figure 3.10 and the corresponding control signal is shown in figure 3.11.For purpose of comparison the results obtained using the pole placement controller discussed in [69] are also presented in figure 3.12 and figure 3.13. It can be seen from the figures 3.10 and 3.12 that the proposed IMC controller performs better tracking than the pole placement controller.

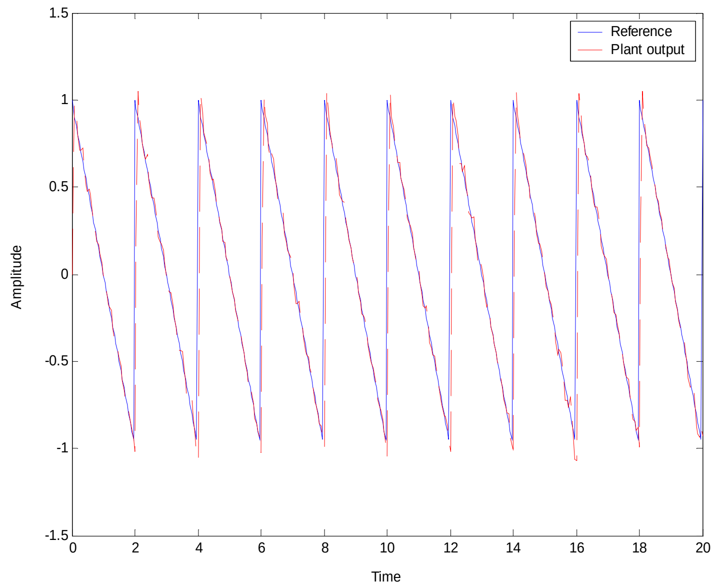

Figure 3.10: System response of CSTR using IMC strategy

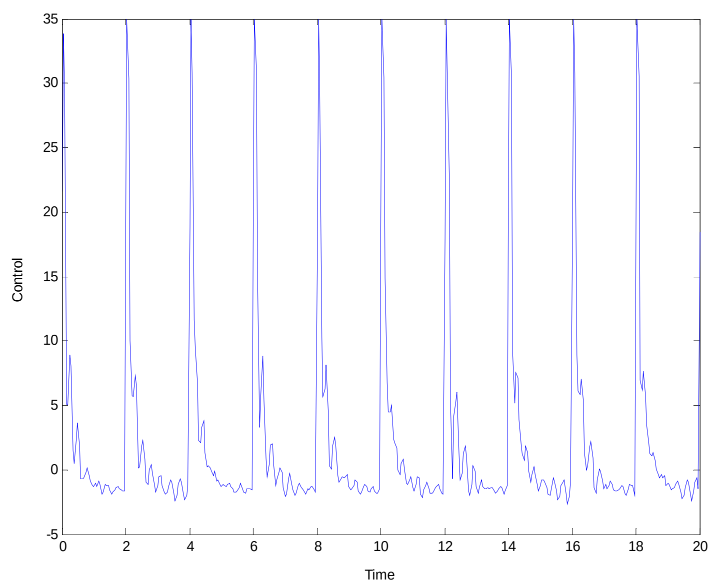

Figure 3.11: Control signal for CSTR using IMC strategy

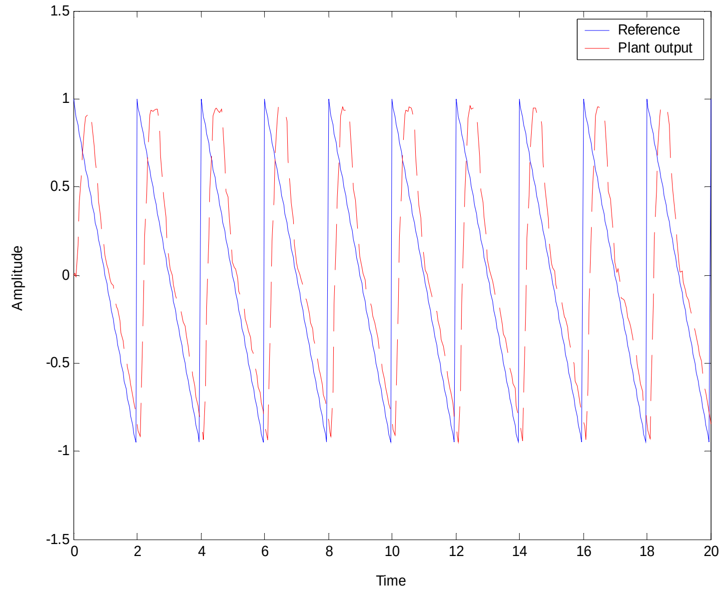

Figure 3.12: System response of CSTR using pole placement controller

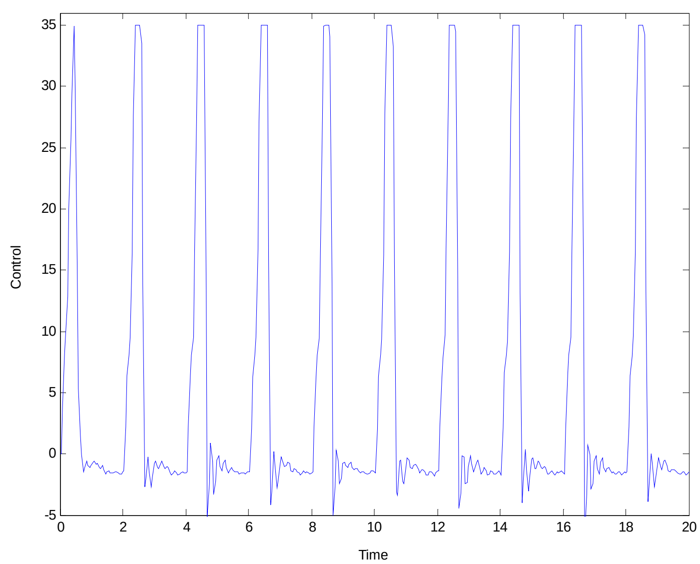

Figure 3.13: Control signal for CSTR using pole placement controller

3.4.4 Control of Hammerstein model with discrepancy in model and plant parameters

In practice, the plant parameters may have some uncertainties and the model parameters may not be exactly equal to the plant parameters. We choose the parameters for the U-model to be different than the plant parameters. The parameters chosen for the U-model and the controller design in this simulation are shown in equation (3.25) instead of the parameters given in equation (3.18).

$$
\begin{aligned}
\alpha_0(t) &= 0.4312y(t-1) + 1.62 + 0.3752x(t-2) \\
\alpha_1(t) &= 1.213 \\
\alpha_2(t) &= -0.713 \\
\alpha_3(t) &= 0.2375
\end{aligned}
\tag{3.25}
$$

The response of the system using the proposed IMC scheme is shown in figure 3.14 and the corresponding control signal is shown in figure 3.15. The results obtained using the pole placement controller [69] are shown in figure 3.16 and figure 3.17. It can be seen that the proposed IMC scheme gives better tracking properties compare to the pole placement controller.

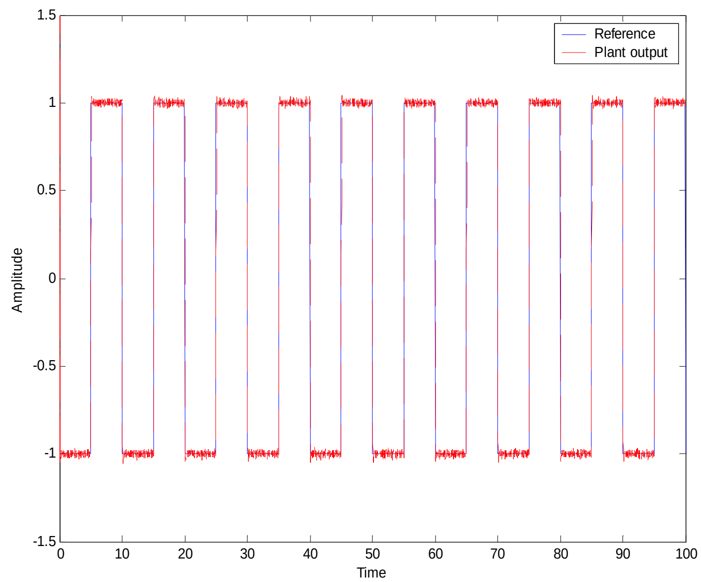

Figure 3.14: System response of the Hammerstein model using the proposed IMC scheme

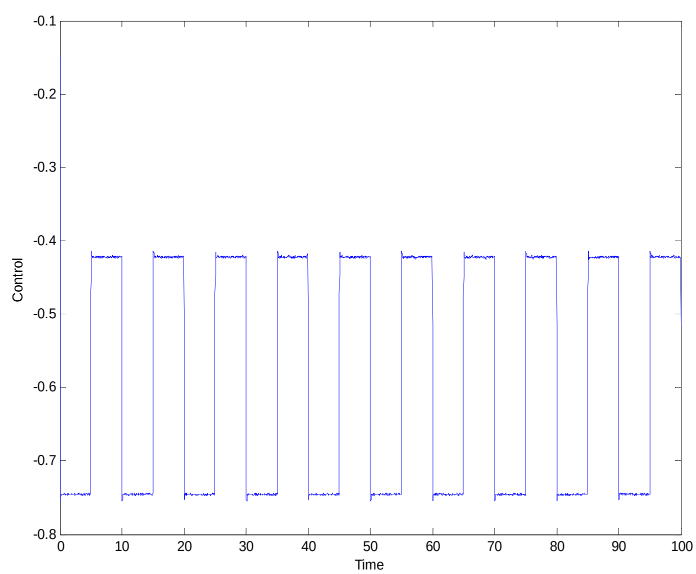

Figure 3.15: Control signal for the Hammerstein model incase of proposed IMC scheme

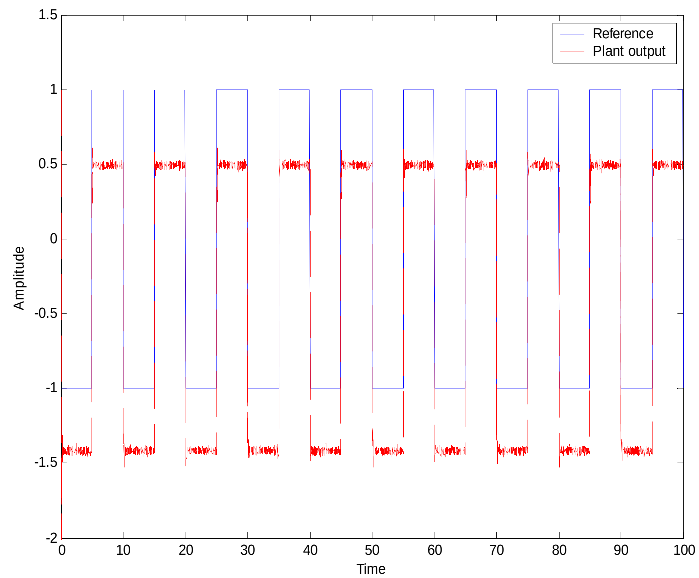

Figure 3.16: System response of the Hammerstein model using the pole placement controller

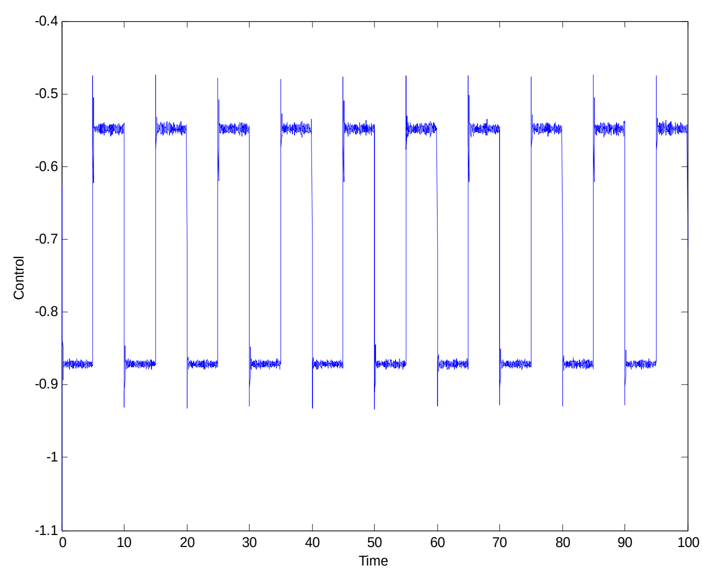

Figure 3.17: Control signal for the Hammerstein model incase of pole placement controller

3.4.5 Control of Liquid Level system with discrepancy in model and plant parameters

In this simulation, the parameters chosen for the U-model of the plant and for the controller design are given in equation (3.26) which is different from that of the plant parameters given in equation (3.21).

$$\begin{aligned}\alpha_0(t) &= 0.972y(t-1) - 0.04285y^2(t-2) + 0.166y(t-2)u(t-2) \\ &+ 0.257y(t-2)e(t-1) - 0.0325y^2(t-1)y(t-2) - 0.351y^2(t-1)u(t-2) \\ &+ 0.308y(t-1)y(t-2)u(t-2) + 0.293y^2(t-2)e(t-1) - 0.1295u(t-2) \\ &+ 0.6389u^2(t-2)e(t-1)\end{aligned} \tag{3.26}$$

$$\alpha_1(t) = 0.357 - 0.310y(t-1) + 0.108y(t-2)u(t-2) + 0.4770y(t-2)e(t-1)$$

The simulation results carried out using the proposed IMC strategy are shown in figures 3.18 and 3.19 and the results obtained by the pole placement controller discussed in [69], are shown in figures 3.20 and 3.21. It can be seen from the figures that proposed IMC scheme performs well compared to the pole placement controller.

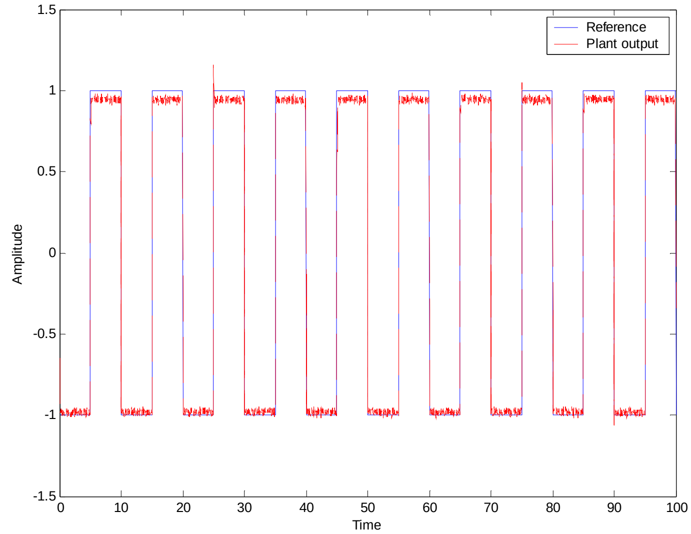

Figure 3.18: System response of the liquid level system using the proposed IMC scheme

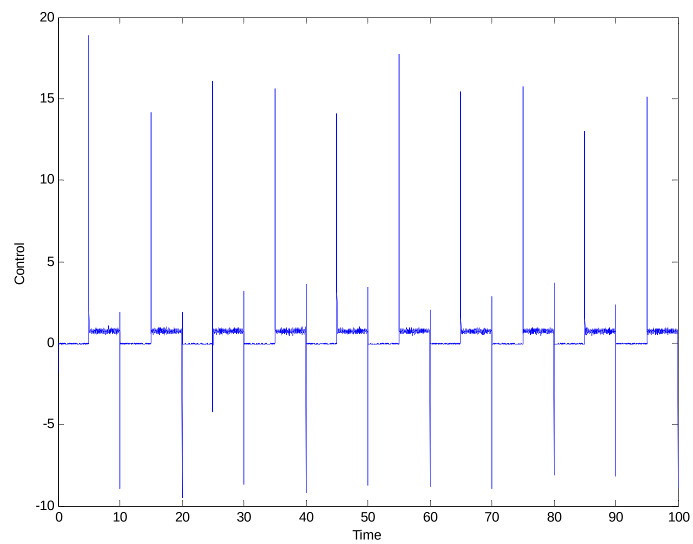

Figure 3.19: Control signal for liquid level system incase of proposed IMC scheme

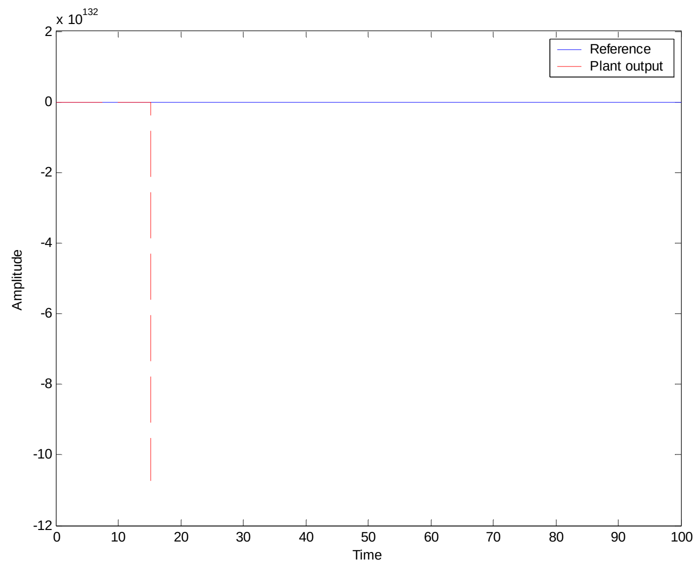

Figure 3.20: System response of the liquid level system using the pole placement controller

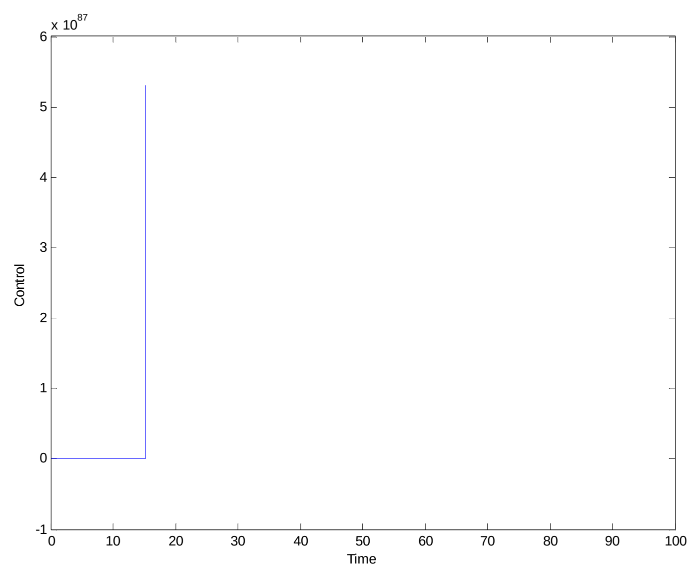

Figure 3.21: Control signal for liquid level system incase of pole placement controller

3.4.6 Control of CSTR with discrepancy in model and plant parameters

In this simulation, the parameters given in equation (3.27) are chosen for the U-model of the plant and for the controller design which are different from that of the plant parameters given in equation (3.24).

$$\begin{aligned}
\alpha_0(t) &= 0.84y(t-1) - 0.04y^2(t-1) + 0.001y^3(t-1) - 0.0001y^4(t-1) \\
\alpha_1(t) &= 0.04 - 0.04y(t-1) + 0.003y^2(t-1) - 0.0002y^3(t-1) \\
\alpha_2(t) &= -0.001 + 0.001y(t-1) - 0.0001y^2(t-1) \\
\alpha_3(t) &= 0.00002 - 0.00002y(t-1)
\end{aligned} \tag{3.27}$$

The simulation results obtained using the proposed IMC strategy are shown in figures 3.22 and 3.23 and the results obtained by the pole placement controller discussed in [69], are shown in figures 3.24 and 3.25.It is evident from the figures that the proposed IMC scheme performs better compared to the pole placement controller.

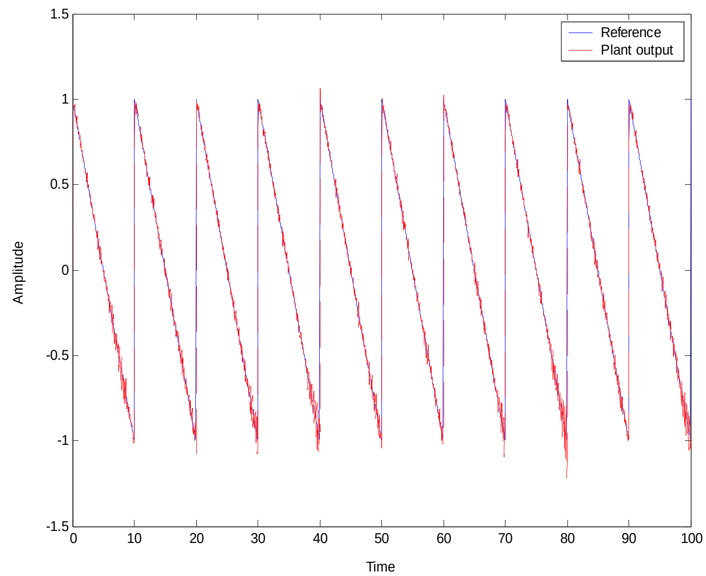

Figure 3.22: System response of CSTR using IMC scheme

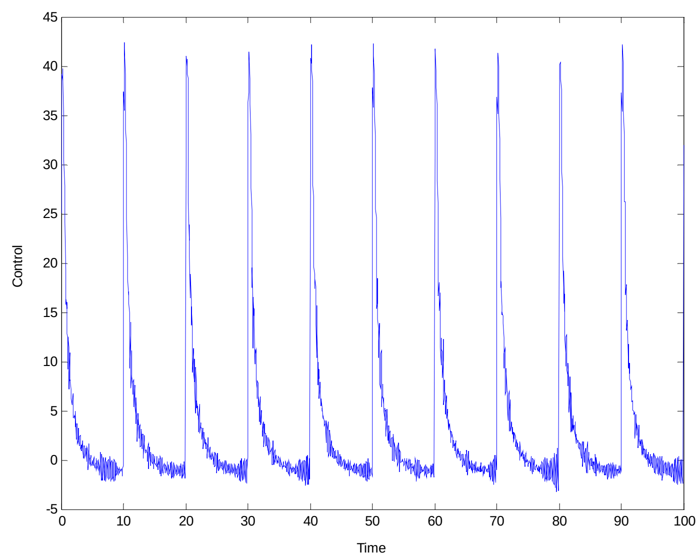

Figure 3.23: Control signal for CSTR using IMC scheme

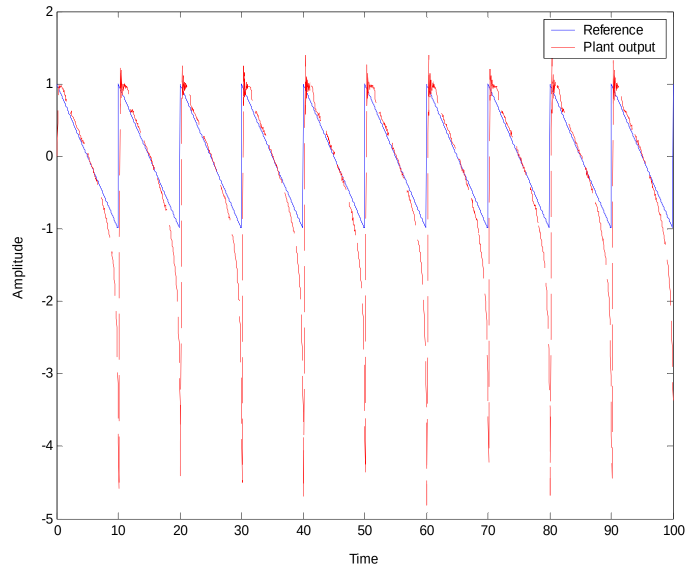

Figure 3.24: System response of CSTR using pole placement controller

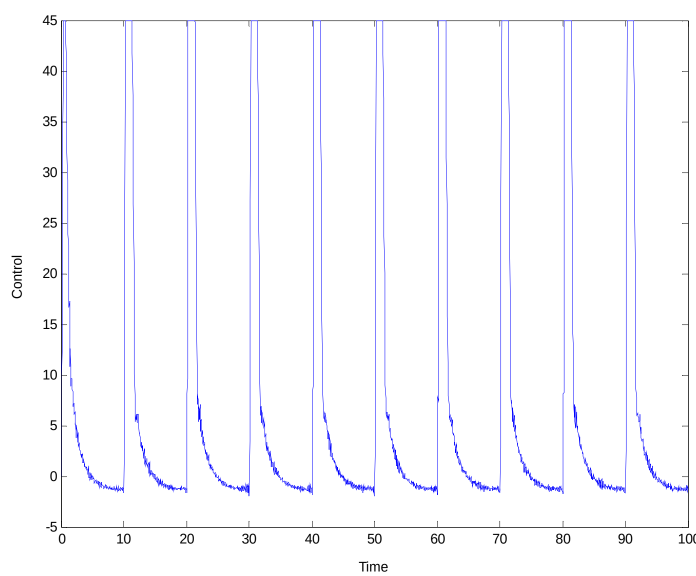

Figure 3.25: Control signal for CSTR using pole placement controller

3.5 Real-Time Implementation

The proposed IMC scheme is implemented in real-time to control the speed of a brush direct current motor as shown in figure 3.26.

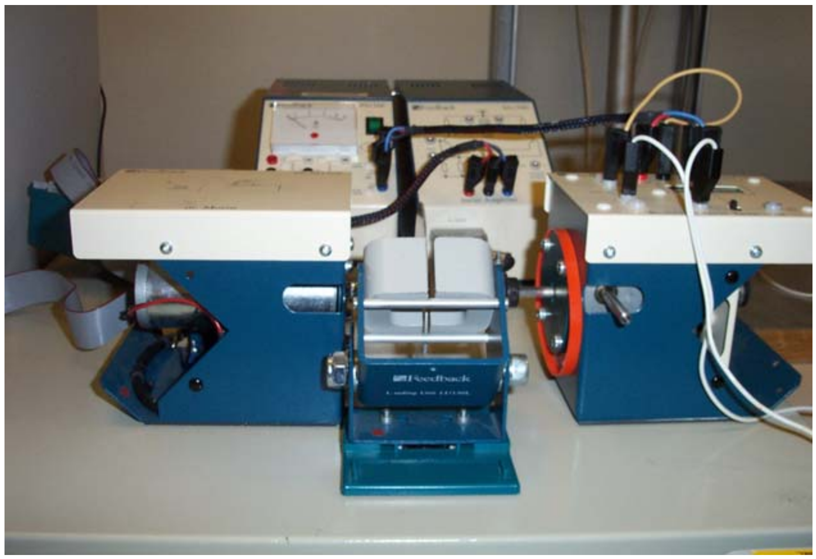

Figure 3.26: Speed Control of brush DC motor

In this experiment, standard IBM PC-type Pentium III is used for the computation in real time. Data acquisition is accomplished by Advantech card PCI-1711 and the controller is implemented in Simulink real-time windows target environment. The sampling interval of 0.01 seconds is selected. The brush DC motor (Crouzet 8285002) has a maximum speed of 3200 revolution per minute, which can be achieved by exciting the motor by 24 volts DC. Speed is measured by using a tachometer, which provides a voltage proportional to the speed of the motor. Servo amplifier is used to provide variable voltage (control input) for the excitation of the motor.

The discrete-time model for the brush DC motor discussed in [51] is used in this experiment which is given as follows:

$$\begin{aligned}\omega_r(n+1) &= K_1\omega_r(n) + K_2\omega_r(n-1) + K_3\left[sign\{\omega_r(n)\}\right]\omega_r^2(n) \\ &+ K_4\left[sign\{\omega_r(n)\}\right]\omega_r^2(n-1) + K_5 v_a(n) + K_6\end{aligned} \tag{3.28}$$

where $v_a(t)$ is the time-varying motor terminal voltage and $\omega_r(t)$ is the motor speed. $K_1, K_2, K_3, K_4, K_5,$ and K_6 are constants expressed in terms of motor parameters. If T_s is taken as the sampling period, then $K_1, K_2, K_3, K_4, K_5,$ and K_6 are given as follows:

$$K_1 = \frac{2L_a J + T_s(R_a J + L_a B) - T_s^2(R_a B + K_E K_T)}{L_a J + T_s(R_a J + L_a B)}$$

$$K_2 = -\frac{L_a J}{L_a J + T_s(R_a J + L_a B)}$$

$$K_3 = -\frac{T_s(vL_a + R_a T_s)}{L_a J + T_s(R_a J + L_a B)}$$

$$K_4 = \frac{T_s v}{L_a J + T_s(R_a J + L_a B)}$$

$$K_5 = \frac{K_T T_s^2}{L_a J + T_s(R_a J + L_a B)}$$

$$K_6 = -\frac{T_F R_a T_s^2}{L_a J + T_s(R_a J + L_a B)}$$

where

$R_a =$ Armature resistance in ohms

$B =$ Viscous constant in N.m/k r/min

$K_T =$ Torque constant in N.m/A

$v =$ Load torque constant in N.m.s^2

$L_a =$ Armature inductance in mH

$J =$ Rotor inertia in kg.m^2

$T_F =$ Frictional constant in N.m

$K_E =$ Voltage constant in V.s/rad

The equivalent U-model of equation (3.28) is given as follows:

$$\omega_r(n) = \alpha_0(n) + \alpha_1(n) v_a(n-1)$$

where

$$\alpha_0(n) = K_1\omega_r(n-1) + K_2\omega_r(n-2) + K_3\left[sign\{\omega_r(n-1)\}\right]\omega_r^2(n-1)$$
$$+ K_4\left[sign\{\omega_r(n-1)\}\right]\omega_r^2(n-2) + K_6$$

$$\alpha_1(n) = K_5$$

3.5.1 Speed control of DC motor with constant load

In this experiment the load on the DC motor was kept constant and the proposed IMC strategy was applied to control the speed of the DC motor. The experimental results are shown in Figures 3.27 and 3.28. Figure 3.27 shows that the speed of the shaft of motor converges to the desired speed and Figure 3.28 shows control input to the plant which is bounded.

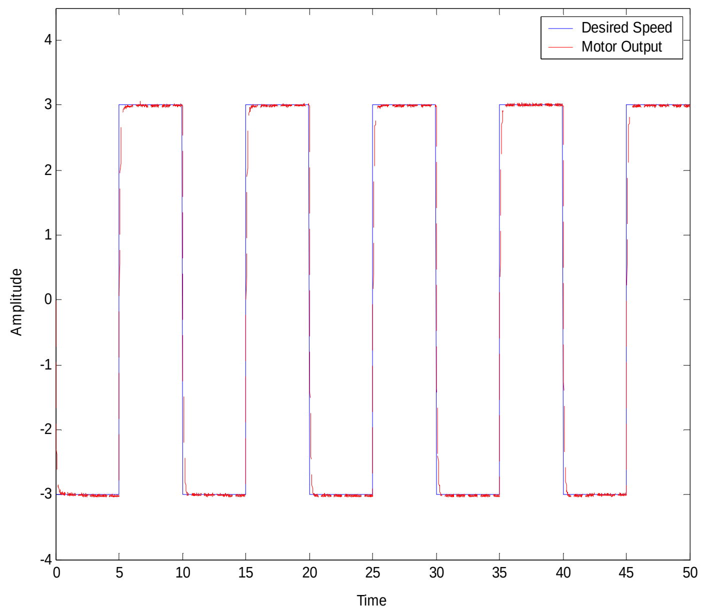

Figure 3.27: Speed control of DC motor with constant load

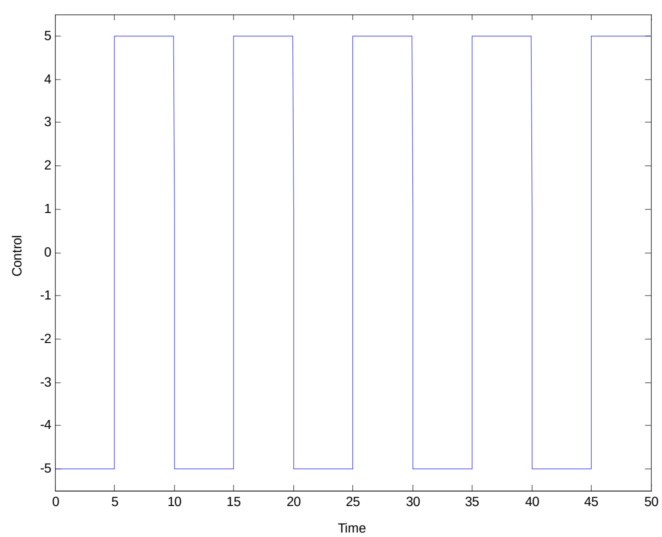

Figure 3.28: Control signal for speed control of DC motor with constant load

3.5.2 Speed control of DC motor with varying load

When the load on the motor is varied, the dynamics of the motor changes. In order that the model represents the plant exactly the parameters of the model has to be updated for any change in the dynamics of the plant. To accomplish this, adaptive normalized least mean square filter is used.

Adaptive filters are used for plant modeling, for plant inverse modeling and to do plant disturbance canceling. The form of adaptive filter comprises a tapped delay line, variable weights whose input signals are the signals at the delay-line taps, a summer to add the weighted signals, and an adaptation process that automatically seeks an optimal impulse response by adjusting the weights. In addition to the usual input signals, another input signal, the desired response, must be supplied during the adaptation process to generate the error signal. The same input is applied to the adaptive filter as to the unknown system to be modeled. The output of the unknown system provides the desired response for the adaptive filter. The weights of the adaptive filter are adjusted by an automatic algorithm to minimize the mean square error. When the weights converge and the error becomes small, the impulse response of the adaptive filter will closely match a sampled version of the impulse response of the unknown system. The LMS adaptive Filter implements an adaptive FIR filter using the stochastic gradient algorithm known as the normalized Least Mean-Square (LMS) algorithm given as follows:

$$y(n) = \hat{\omega}^{H}(n-1)u(n)$$

$$e(n) = d(n) - y(n)$$

$$\hat{\omega}(n) = \hat{\omega}(n-1) + \frac{u(n)}{a + u^H(n)u(n)} \mu e^*(n)$$

where

n is the current algorithm iteration

$u(n)$ The buffered input samples at step n

$\hat{\omega}(n)$ The vector of filter tap estimates at step n

$y(n)$ The filtered output at step n

$e(n)$ The estimation error at step n

$d(n)$ The desired response at step n

μ The adaptation step size

The Simulink block diagram for controlling the speed of the dc motor with varying load is as shown in figure 3.29 wherein adaptive normalized least mean square filter is used for updating the parameters of the U-model of the plant and a similar filter is used to update the parameters of the controller. The experimental results obtained for the speed control of DC motor while the load on the motor is varying are shown in figures 3.30 and 3.31.Figure 3.30 shows the desired speed, the output of the motor and the output of the model of the motor. It can be seen from the figures that the speed of the motor converges to the desired speed while the load on the motor is varied and the control signal is bounded.

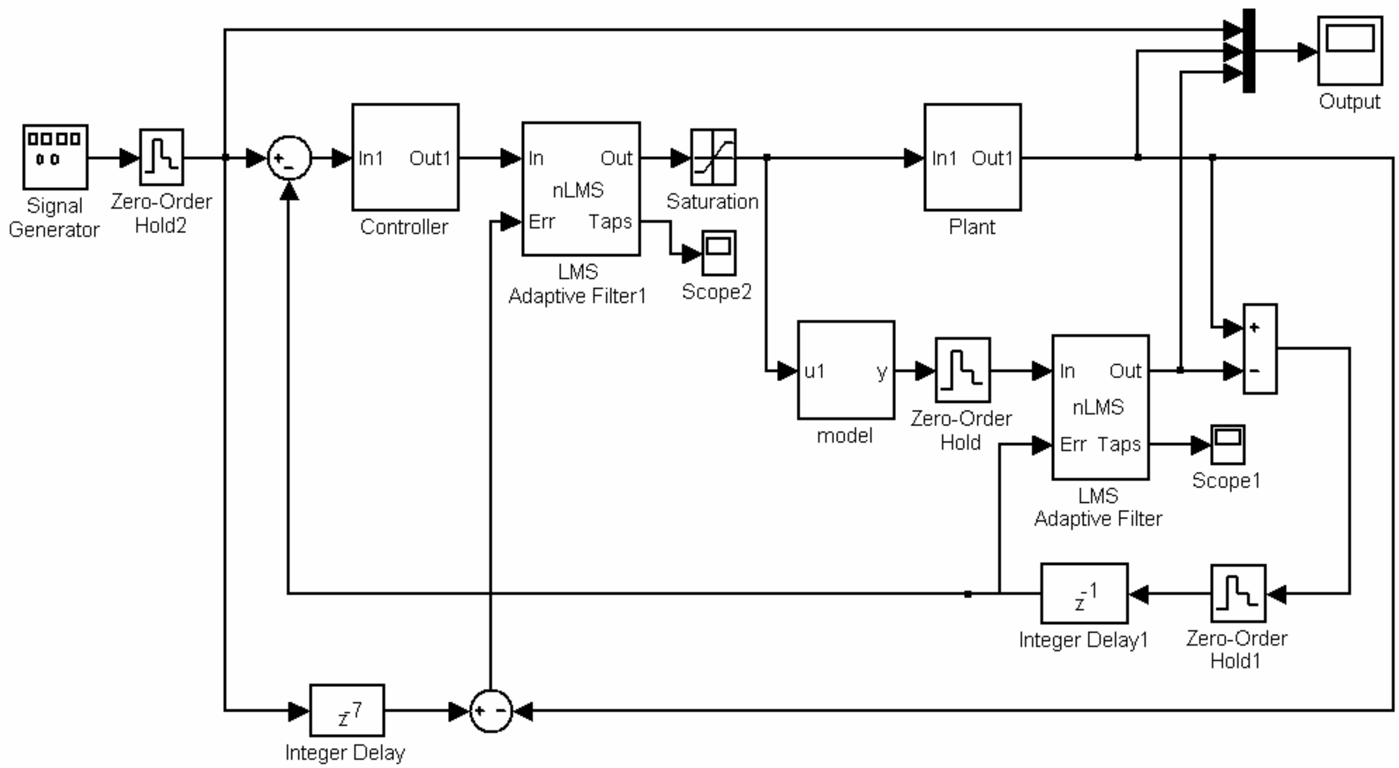

Figure 3.29: Simulink diagram for Speed control of DC motor with varying load

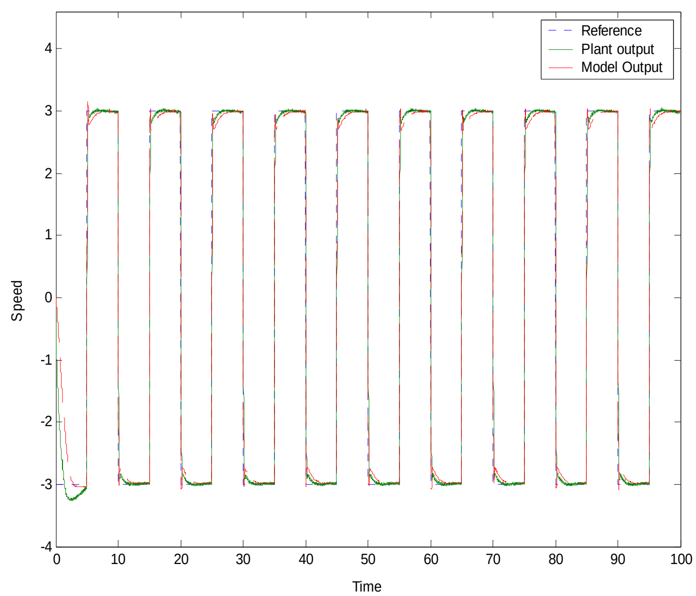

Figure 3.30: Speed control of DC motor with varying load

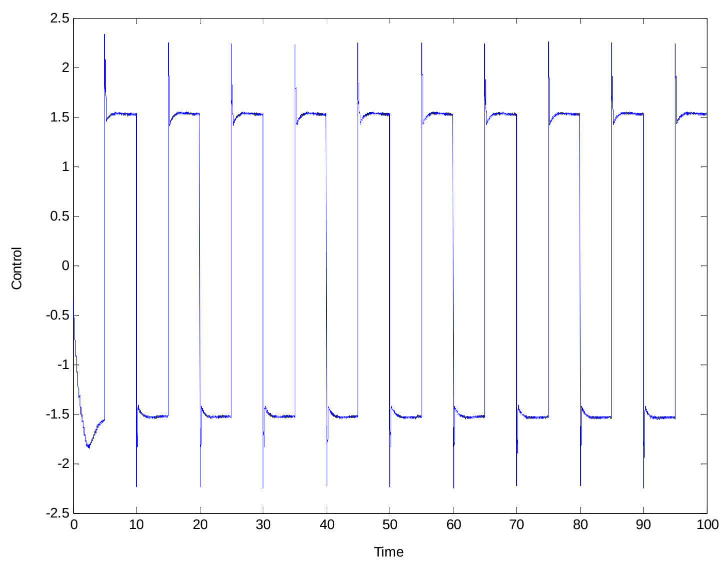

Figure 3.31: Control signal for DC motor with varying load

3.6 Comparison of developed IMC strategy with Nonlinear Self-Tuning Controller

A nonlinear self-tuning controller discussed in [37] is compared with the developed IMC strategy and computer simulation results are presented in this section.

The following nonlinear Hammerstein model is considered for the purpose of comparison

$$y(t) = ay(t-1) + b_0 x(t-1) + b_1 x(t-2)$$
$$x(t) = u(t) + k_1 u^2(t) + k_2 u^3(t)$$

where

$a = -0.3, b_0 = 0.2, b_1 = 0.1, k_1 = 0.2, k_2 = 0.5$

The simulation results obtained using the nonlinear self-tuning controller is shown in figures 3.32, 3.33, & 3.34, and that obtained using the proposed IMC strategy is shown in figures 3.35, 3.36. It is evident from the figures 3.32 and 3.35 that the proposed IMC strategy performs better in tracking the reference signal compared to the nonlinear self-tuning controller.

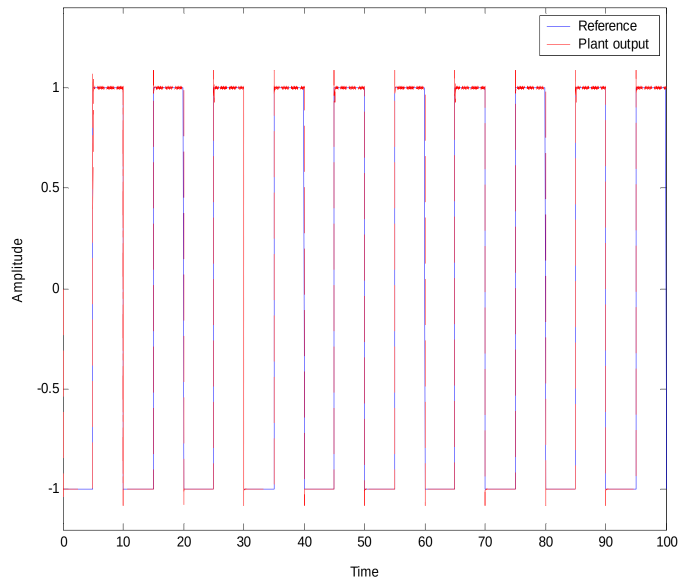

Figure 3.32: System response using nonlinear self-tuning controller

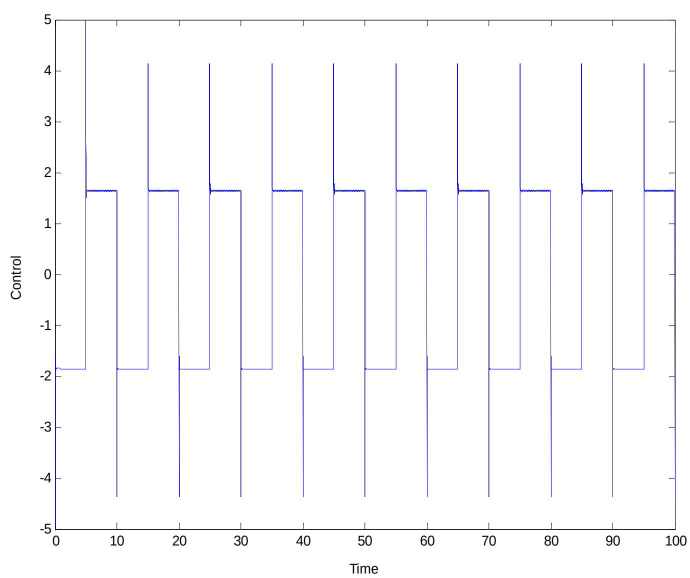

Figure 3.33: Control signal using nonlinear self-tuning controller

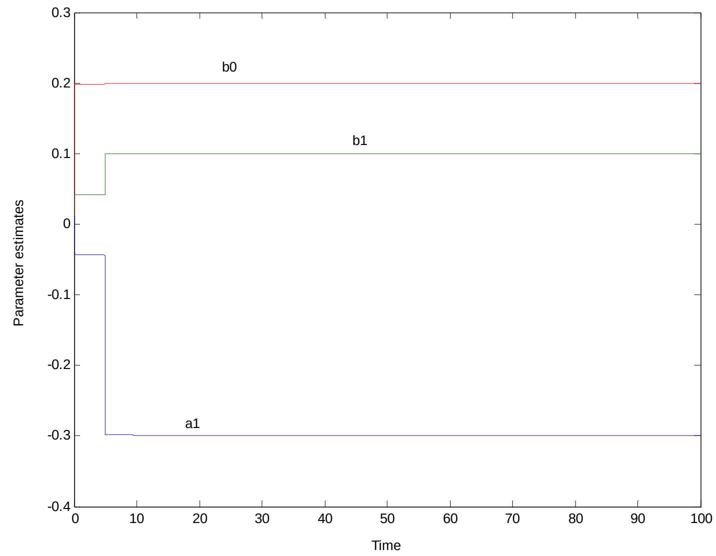

Figure 3.34: Parameter estimates for nonlinear self-tuning controller

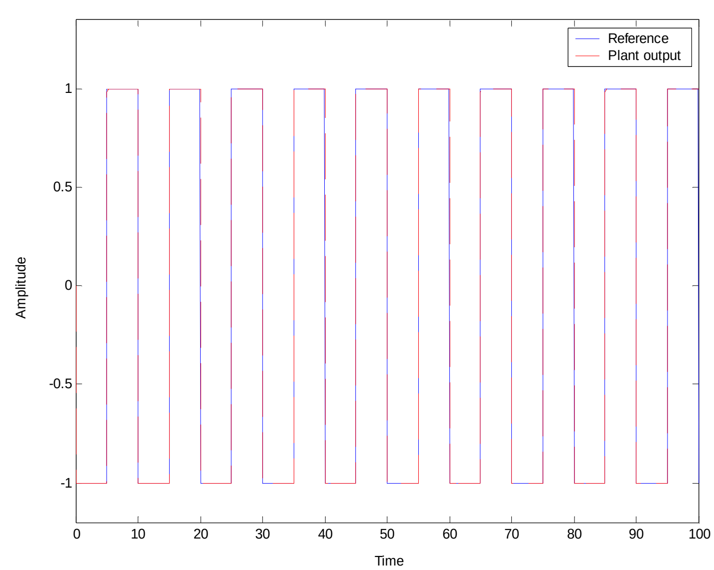

Figure 3.35: System response using IMC strategy

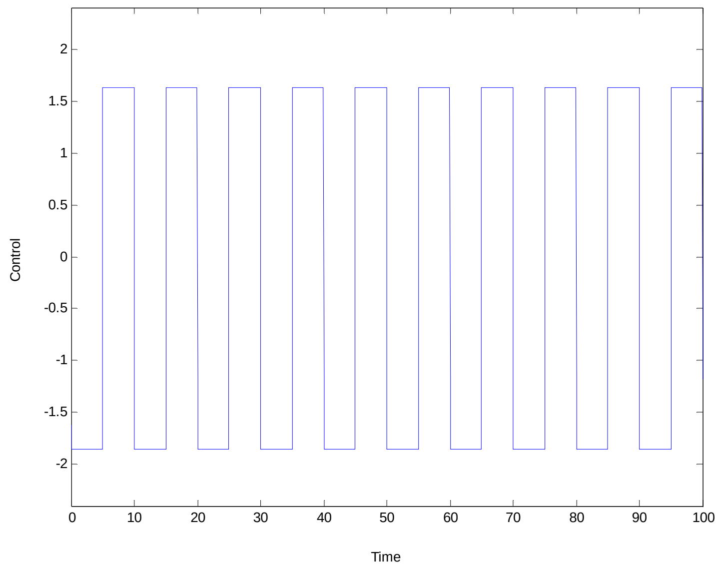

Figure 3.36: Control signal using IMC strategy

CHAPTER 4

Fine tracking in IMC and a new IMC structure based on U-model

In this chapter, we propose fine tracking in IMC using adaptive inverse controller based on the IMC strategy presented in chapter3. A new IMC structure is also proposed wherein the model of the plant to be controlled is replaced by the plant delay.

4.1 Fine-Tracking using Adaptive Inverse Controller

To improve the tracking properties in IMC structure a fine tracking technique is proposed.

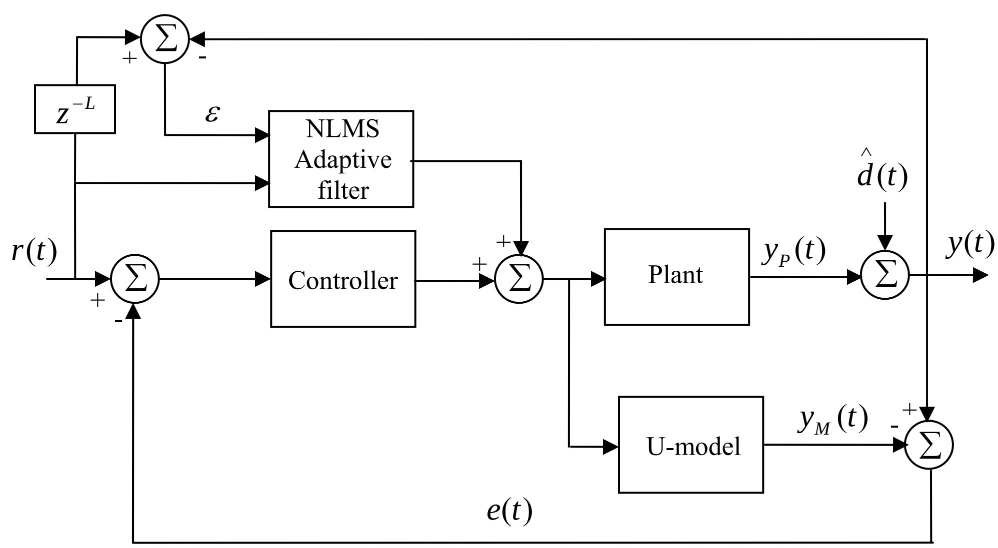

Figure 4.1: Fine Tracking in IMC using adaptive inverse controller

In this technique a normalized least mean square filter is used as an adaptive inverse controller as shown in figure 4.1.The computation of the inverse of the U-model of the plant is done using the Newton-Raphson algorithm as discussed in chapter 3. The tracking error ε between the output $y(t)$ of the plant to be controlled and the input reference signal $r(t)$ is fed to the adaptive normalized least mean square filter along with the desired reference signal $r(t)$ as shown in figure 4.1.The filtered output of the normalized least mean square adaptive filter which represents the information missing in the control signal is added to the controller output to improve tracking.

4.2 Simulation Results

In this section, simulation results of nonlinear plants using the proposed fine tracking technique are presented. To show the effectiveness of the proposed fine tracking technique, a comparison of the tracking error obtained using the fine tracking and that obtained without using the fine tracking technique is given.

4.2.1 Fine Tracking in Hammerstein Model

The Hammerstein model and its equivalent U-model discussed in section 3.4.1 are used in this simulation. The tracking error obtained using the fine tracking technique is shown in figure 4.2 and tracking error obtained without using the fine tracking technique is shown in figure 4.3.A comparison of the error plots shows that using the proposed fine tracking technique the tracking error is minimized.

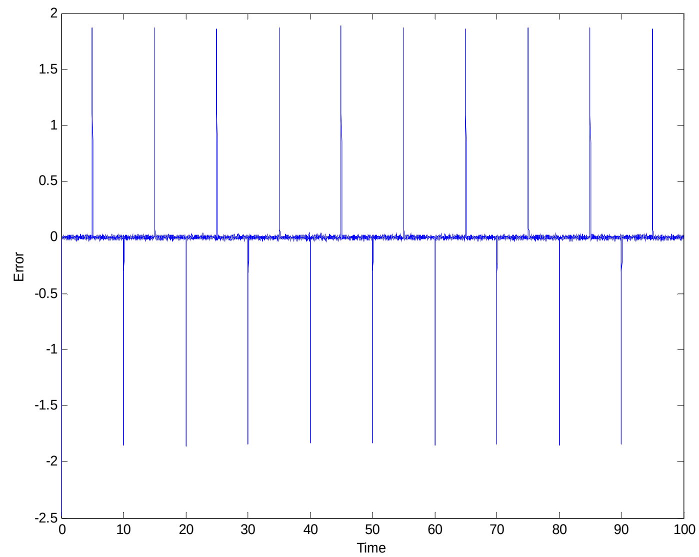

Figure 4.2: Tracking Error in Hammerstein model using fine tracking

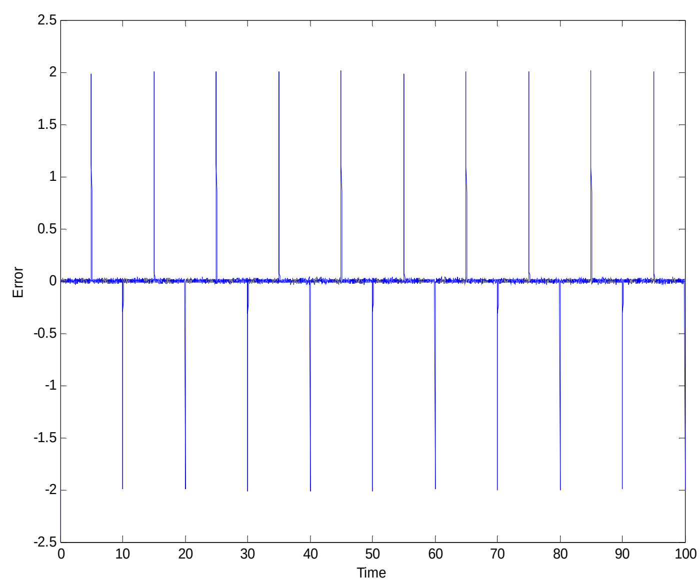

Figure 4.3: Tracking error in Hammerstein model without using fine tracking

4.2.2 Fine-Tracking in Laboratory Scale Liquid Level system

The laboratory scale liquid level system and its equivalent U-model discussed in section 3.4.2 are chosen in this simulation. The plots of the tracking error with and without using the fine tracking technique are as shown in figures 4.4 and 4.5 respectively.

4.2.3 Fine-Tracking in continuous stirred tank reactor (CSTR)

In this simulation, the CSTR and its equivalent U-model discussed in section 3.4.3 is chosen. The plots of the tracking error with and without using the fine tracking technique are shown in figures 4.6 and 4.7 respectively. It can be seen from the error plots that the fine tracking technique reduces the tracking error significantly.

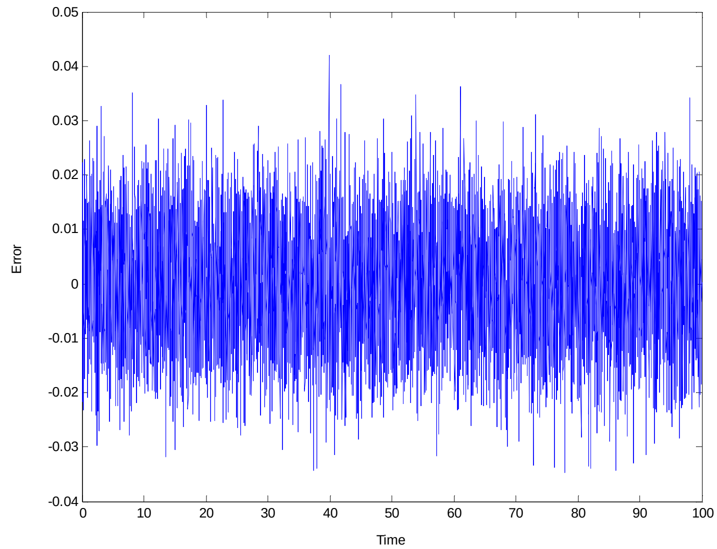

Figure 4.4: Error plot for liquid level system using fine tracking

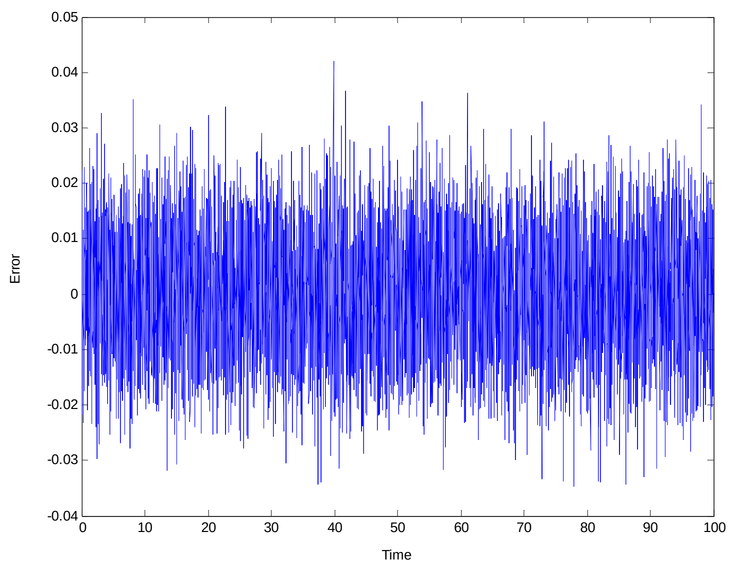

Figure 4.5: Error plot for liquid level system without using fine tracking

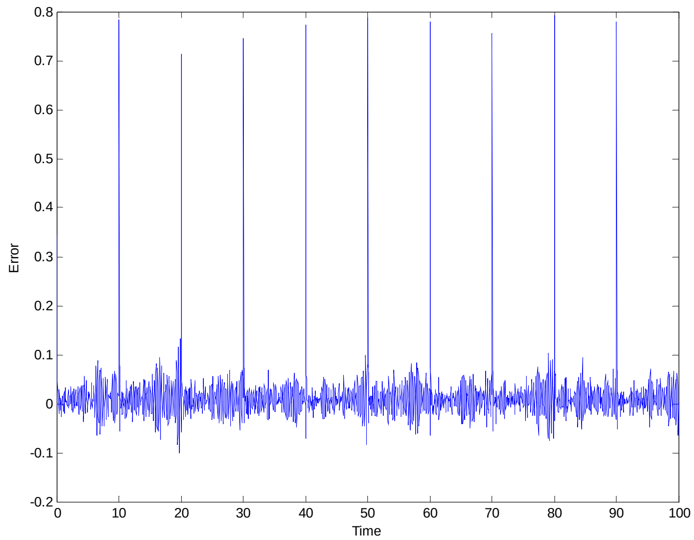

Figure 4.6: Error plot for CSTR using fine tracking

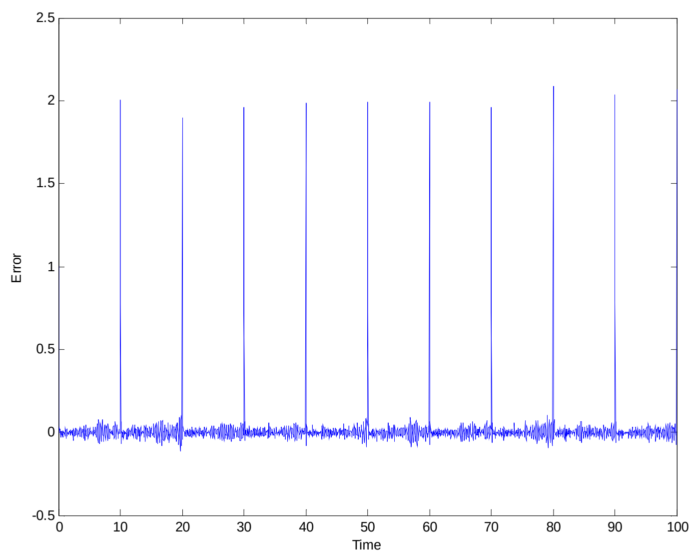

Figure 4.7: Error plot for CSTR without using fine tracking

4.3 A new IMC structure based on U-model

A new IMC structure based on U-model is proposed. Consider the general IMC structure shown in figure 4.8. As the controller performs the inverse computation of the

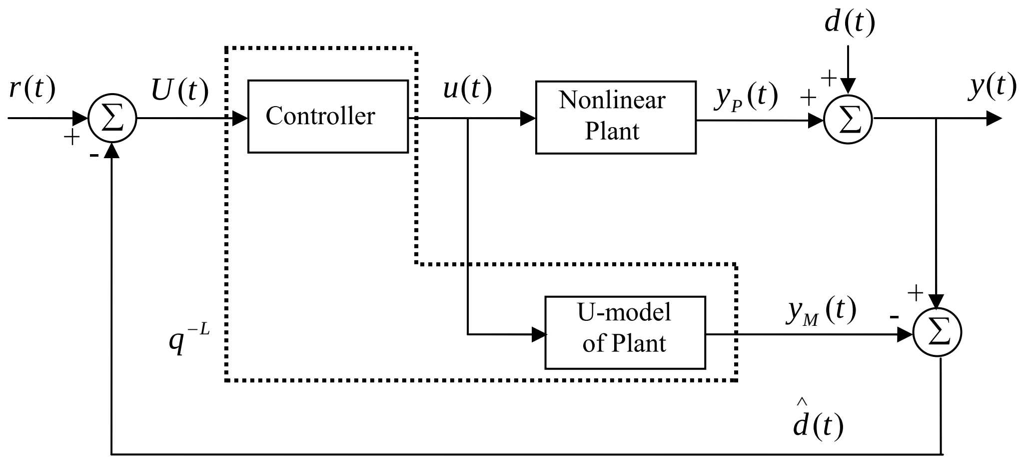

Figure 4.8: General IMC Structure

U-model, the controller and the U-model of the nonlinear plant together contribute a delay q^{-L} as shown by the dotted line in figure 4.8.Hence the U-model of the nonlinear plant can be replaced by a delay which leads to a new IMC structure as illustrated in figure 4.9.

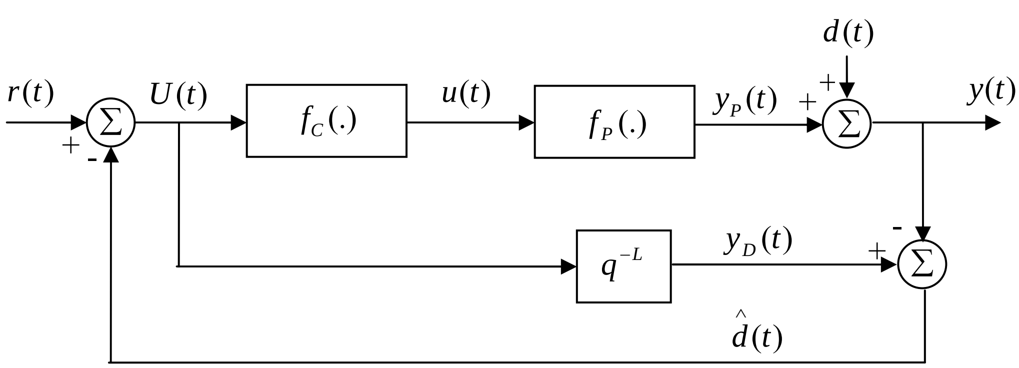

Figure 4.9: Proposed IMC structure based on U-model

In the proposed IMC structure shown in figure 4.9, the value of the delay is chosen such that it is greater than the plant delay. The computation of the inverse of the plant is done using the Newton-Raphson method based on the U-model of the plant known apriori. In figure 4.9, $r(t)$ is the reference signal, $d(t)$ is an unknown disturbance affecting the system, $f_C(.)$ represents the controller, $f_P(.)$ represents the process to be controlled. The signal $\hat{d}(t)$ represents the tracking error, which is given by

$$\hat{d}(t) = y_D(t) - y(t) \tag{4.1}$$

If $d(t)$ is zero in and the controller the inverse of the plant i.e. $f_C(.) = [f_P(.)]^{-1}$, then $q^{-L} + q^{-L}\Delta(q)$ can be regarded as the delay along the path from the input $U(t)$ to the plant output $y(t)$, where $\Delta(q)$ represents the plant uncertainty, then from figure 4.9, we get

$$y(t) = [q^{-L} + q^{-L}\Delta(q)]U(t) \tag{4.2}$$

$$y_D(t) = q^{-L}U(t) = U(t-L) \tag{4.3}$$

$$U(t) = r(t) - \hat{d}(t) \tag{4.4}$$

On substituting equation (4.2) and (4.3) in equation (4.1) we have

$$\hat{d}(t) = q^{-L}U(t) - [q^{-L} + q^{-L}\Delta(q)]U(t) \tag{4.5}$$

Using equation (4.2), (4.4), and (4.5) and on further simplification the overall closed loop function for the system in figure 4.9 for $L = 1$, is obtained as follows:

$$y(t) = r(t-1)[1+\Delta(q)] + r(t-2)[\Delta(q) + \Delta^2(q)] \tag{4.6}$$

If $|\Delta(q)| << 1$, in equation (4.6), then $y(t) \approx r(t-1)$. This means approximate tracking objective is accomplished.

4.4 Simulation Results

In this section, simulation results obtained using the proposed IMC structure for three nonlinear plants are presented.

4.4.1 Hammerstein model

The simulation for the Hammerstein model discussed in section 3.4.1 is performed using the proposed new IMC structure. Figure 4.10, shows the response of the Hammerstein model and the corresponding control signal is shown in figure 4.11.The IMC scheme proposed in chapter 3 is used to find the inverse of the nonlinear plant. The learning rate $m = 0.1$ is chosen in this simulation.

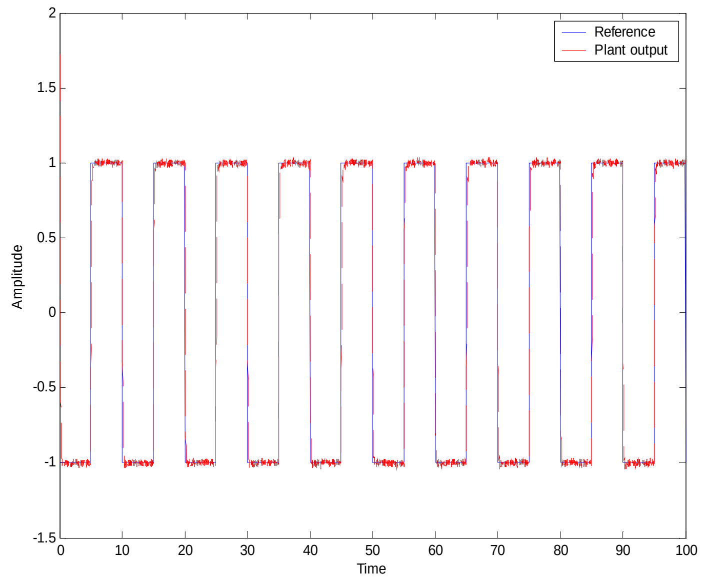

Figure 4.10: System response of Hammerstein model using proposed IMC structure

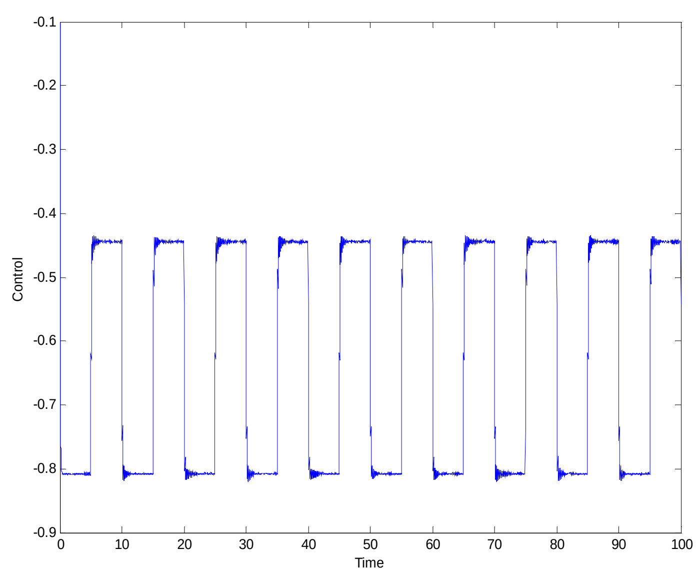

Figure 4.11: Control signal for Hammerstein model using proposed IMC structure

4.4.2 Laboratory scale liquid level system

The model of laboratory scale liquid level system discussed in 3.4.2 is selected in this simulation. The system response and the corresponding control signal are shown in figures 4.12 and 4.13 respectively.

4.4.3 Continuous stirred tank reactor (CSTR)

In this simulation the proposed IMC structure is applied to the CSTR model discussed in section 3.4.3 for tracking of the reference signal. The learning rate $m = 0.3$ is selected. The response of the system and the corresponding control signal is shown in figures 4.14 and 4.15 respectively.

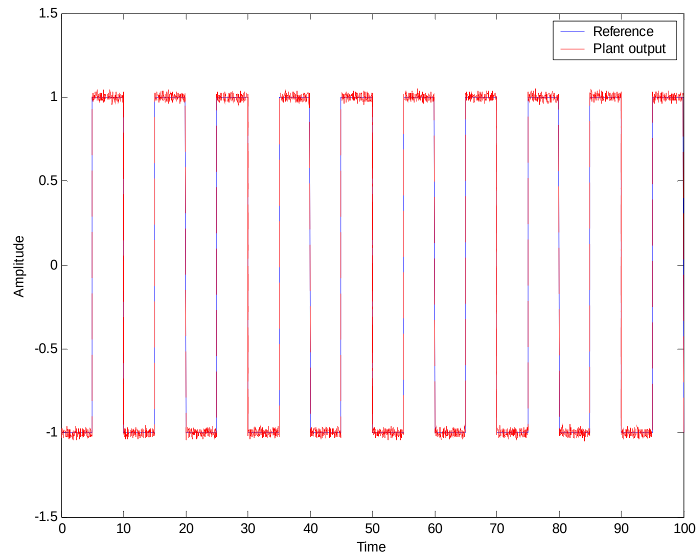

Figure 4.12: System response of liquid level system using proposed IMC structure

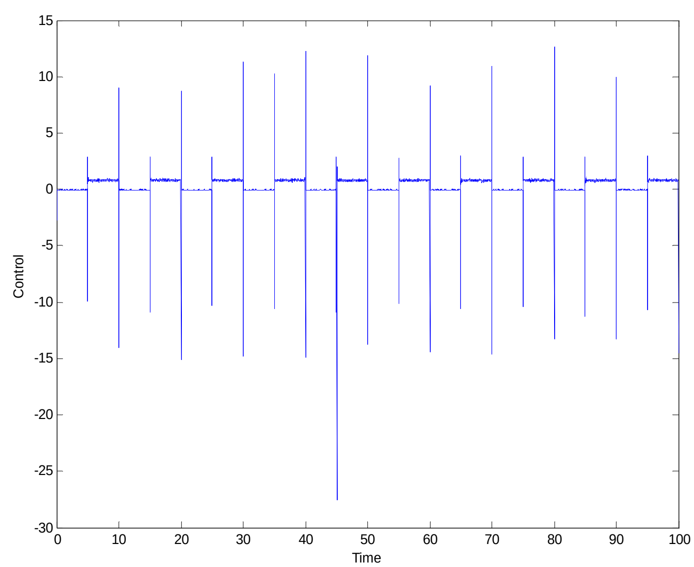

Figure 4.13: Control signal for liquid level system using proposed IMC structure

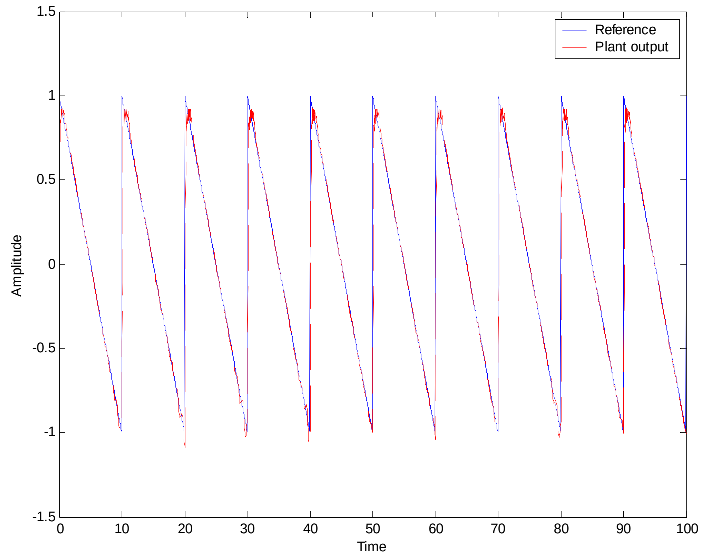

Figure 4.14: System response of the CSTR using proposed IMC structure

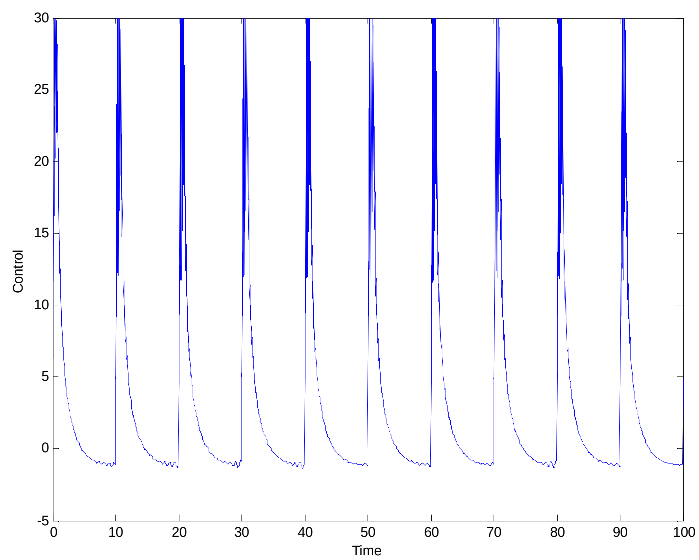

Figure 4.15: Control signal for the CSTR using proposed IMC structure

CHAPTER 5

Adaptive IMC based on U-model for Nonlinear Dynamic plants

5.1 Introduction

Model-based controllers are often essential for effective control of nonlinear processes. Performance and robustness of these controllers are affected by the inevitable modeling errors. In practical applications, models used in the model-based controllers will have uncertainties in parameters and/or unmodeled dynamics. Parameter adaptation is a technique to robustify the model-based controllers.

One of the features of IMC is that it requires an explicit model of the plant to be used as part of the controller. When the plant itself happens to be unknown, or the plant parameters vary with time, no such model is directly available a priori, and identification techniques are to be applied to come up with an appropriate plant model online. The goal of system identification is to develop a mathematical model to describe the relation between the input and the output of the unknown system. In recent years artificial neural network (ANN) has gained a wide attention in control applications [16, 20, 63]. The ANN structure such as the radial basis function provides a nonlinear mapping between the inputs and outputs of a plant without the knowledge of any predetermined model. These characteristics of ANN make the system robust and insensitive to noise, parameter variations, load changes etc.

In this chapter, we propose an adaptive IMC scheme wherein the internal model the "U-model" for the unknown plant is identified on-line using radial basis nonlinear moving average filter. The parameters of this nonlinear filter are learned using the normalized least mean square algorithm. The computation of the inverse of the identified U-model is performed online using the Newton-Raphson method.

5.2 System Identification

System identification is a modeling problem. Given a black box system, the system identification technique helps to develop a mathematical model to describe the relation between the input and the output of the unknown system. If the system under consideration is memoryless, the implication is that the output of this system is a function of present input only and bears no relation to past input. In this situation, the system identification problem becomes a function approximation problem. If the system to be identified is a dynamic system, then the present input $u(t)$ alone is not sufficient to determine the output $y(t)$. Instead, $y(t)$ will be the function of both $u(t)$ and a present state vector $x(t)$. The state vector can be regarded as a summary of all the input in the past. Unfortunately, for many systems, only the input and outputs are observable. In this situation, previous outputs within a time window may be regarded as a generalized state vector. To derive the mapping from $u(t)$ and $x(t)$ to $y(t)$, a sufficient amount of training data is to be gathered and then develop a mapping $y(t) = \varphi(u(t), x(t))$ using a linear model or a nonlinear model such as an artificial neural network structure. Such training process is conducted using online learning. This is illustrated in figure 5.1, where the error $e(t)$ is fed back to the model to update model parameters θ.

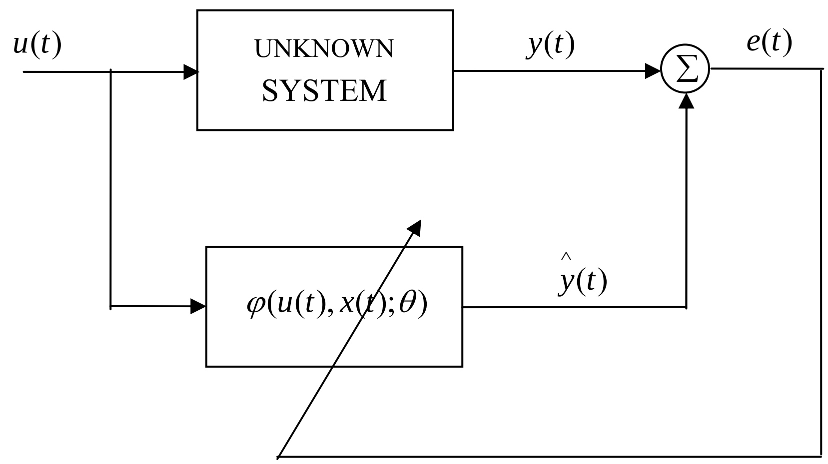

Figure 5.1: Illustration of online dynamic system identification.

With online learning, the mathematical dynamic model receives the same inputs as the unknown system, and produces an output $\hat{y}(t)$ to approximate the true output $y(t)$. The difference between these two quantities will then be fed back to update the mathematical model.

5.2.1 Function Approximation

Assume a set of training samples $\{(u(i), y(i))\}$, where $u(i)$ is the input vector and $y(i)$ is the output vector. The purpose of function approximation is to identify a mapping from x to y, that is,

$$y = \varphi(u)$$

such that the expected sum of square approximation error $E\left\{\left|y - \varphi(u)\right|^2\right\}$ is minimized.

Neural network structure such as the radial basis function is suitable to realize the $\varphi(u)$ function.

5.2.2 Radial Basis Function

A radial basis function has the general form of $f\left(\left\|x - m_0\right\|\right) = f(r)$.Such a function is symmetric with respect to a center point x_0.Radial basis function can be used to approximate a given function. Given a set of points $\{x(k); 1 \le k \le K\}$ and the values of an unknown function $F(x)$ evaluated on these K points $\{d(k) = F(x(k)); 1 \le k \le K\}$, the radial basis function approximates $F(x)$ in the form

$$\hat{F}(x) = \sum_{i=1}^{C} w_i \varphi\left(\left\|x - m_i\right\| / \sigma_i\right)$$

which is a weighted linear combination of a family of radial basis functions such that the sum of square approximation error at these sets of training samples,

$$\sum_{k=1}^{K}\left[d(k) - \hat{F}(x(k))\right]^2$$

is minimized.

The Gaussian radial basis function is most commonly used in the neural network. Its profile function is $\Phi(r) = e^{\left(\frac{-r^2}{\sigma^2}\right)}$. This leads to the radial basis function

$Z(x) = \exp\left(\frac{\|x-\mu\|^2}{\sigma^2}\right)$. In this case, the width parameter is the same as the standard deviation of the Gaussian function.

5.3 Proposed adaptive IMC based on U-model for nonlinear dynamic plants

In order to implement the IMC based controllers, the plant must be known apriori so that the "internal model" can be designed. When the plant itself is unknown, the IMC based controllers cannot be designed. In this case, we propose to retain the same general IMC structure as shown in figure 5.2, and identify the plant online using the radial basis non-linear moving average filter.

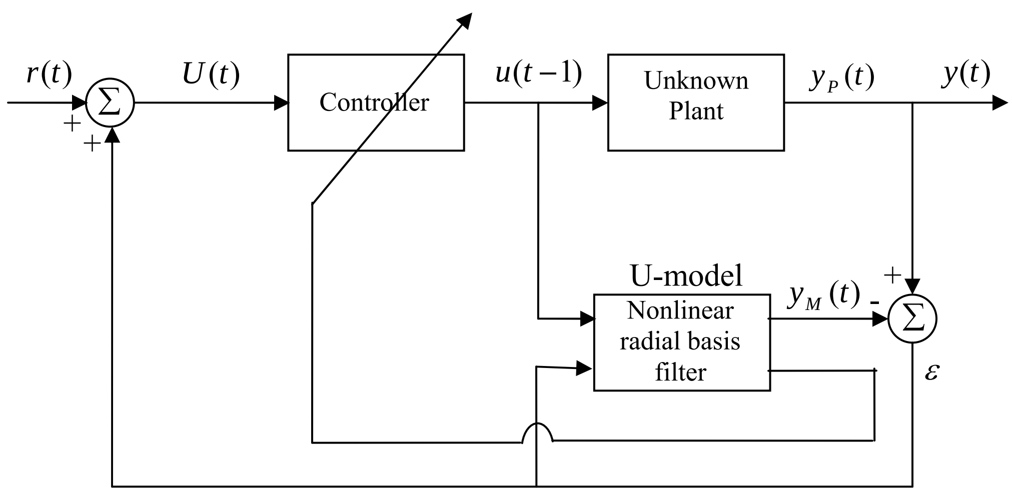

Figure 5.2: Adaptive IMC based on U-model

In fact this scheme is equivalent to the single layer radial basis neural networks. The model for the radial basis nonlinear filter is chosen as follows:

$$y_M(t) = a_1 u(t-1) + \hat{b}_1 \Phi(u(t-1)) + \hat{b}_2 \Phi(u(t-2)) + \dots\dots\dots + \hat{b}_n \Phi(u(t-n)) \qquad (5.1)$$

where the parameter a_1 is selected in advance and the parameters $\hat{b}_1, \hat{b}_2, \dots\dots \hat{b}_n$ are estimated using the normalized least mean square algorithm. Φ can be any function used in neural networks. Here we use the Gaussian radial basis function, as it is more suitable and have been successfully used for several algorithms developed for such type of neural networks. Radial basis neural networks have the universal approximation capabilities [44, 45].This property ensures that radial basis networks will have at least the same capabilities as the well known multilayer networks with sigmoidal nonlinearities.

5.4 Controller Design for the proposed adaptive IMC scheme

The equivalent U-model for the radial basis nonlinear filter of equation (5.1) is given as follows:

$$y_M(t) = \alpha_0(t) + \alpha_1(t) u(t-1) \qquad (5.2)$$

where

$$\alpha_0(t) = \hat{b}_1 \Phi(u(t-1)) + \hat{b}_2 \Phi(u(t-2)) + \dots\dots\dots + \hat{b}_n \Phi(u(t-n))$$

$$\alpha_1(t) = a_1$$

The controller output $u(t-1)$ shown in figure 5.2, can be found using the Newton-Raphson algorithm recursively with $U(t)$ as a root solver as follows:

$$u_{i+1}(t-1) = u_i(t-1) - \left. \frac{\sum_{j=0}^{K} \alpha_j(t) u_i^j(t-1) - U(t)}{d[\sum_{j=0}^{K} \alpha_j(t) u^j(t-1)] / du(t-1)} \right|_{u^j(t-1)=u_i^j(t-1)} \tag{5.3}$$

where the subscript i is the iteration index.

Using the U-model of equation (5.2) which is linear with respect to the control term $u(t-1)$ in equation (5.3), the controller has the simplified form as follows:

$$u(t-1) = \frac{U(t) - \alpha_0(t)}{\alpha_1(t)} \tag{5.4}$$

As shown in figure 5.2, the output of the controller $u(t)$ is fed to both the unknown plant and the radial basis nonlinear moving average filter. The mismatch error ε input to the filter is the difference between the output of the plant $y_P(t)$ and the output of the radial basis nonlinear moving average filter $y_M(t)$ .The filter parameters are updated using normalized least mean square algorithm such that the error ε is minimized. A copy of the filter parameters which are the parameters of the U-model is fed to the controller online and the controller calculates the inverse of the unknown plant using the Newton-Raphson method based on the U-model of the plant. If the plant to be controlled is unstable then it is first stabilized using any known robust control techniques and then the controller scheme proposed here can be applied considering the entire stabilized system as an unknown plant to achieve tracking of the input reference signal.

5.5 Real Time Implementation

The proposed adaptive IMC scheme using the U-model based on the dynamic neural network modeling is implemented for load position tracking in a nonlinear electromechanical system consisting of a brush dc motor driving a one-link robot manipulator as shown in figure 5.3.

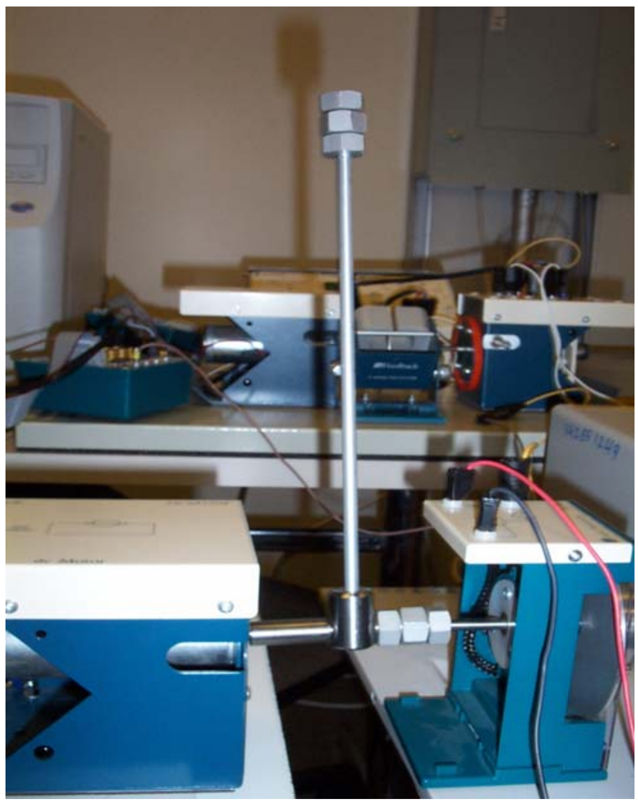

Figure 5.3: Brush dc motor turning a robotic load

In this experiment the unstable nonlinear system is first stabilized and then the U-model of the stabilized system is identified using the radial basis nonlinear moving average filter with four parameters. Standard IBM PC-type Pentium III is used for the computation in real time. Data acquisition is accomplished by Advantech card PCI-1711 and the controller is implemented in Simulink real-time windows target environment. The sampling interval of 0.001 seconds is selected. The brush DC motor (Crouzet 8285002) has a maximum speed of 3200 revolution per minute, which can be achieved by exciting the motor by 24 volts DC. Position of the one link robot manipulator is measured by using a potentiometer, which provides a voltage proportional to the angular position of the shaft attached to the motor. Servo amplifier is used to provide variable voltage (control input) for the excitation of the motor. The Simulink block diagram used in the experiment is shown in figure 5.4.The experimental results are shown in figure 5.5, 5.6, 5.7 and 5.8 to illustrate the performance of the proposed adaptive IMC scheme. It can be seen from figure 4.6, that good load position tracking is achieved despite parametric uncertainty throughout the entire electromechanical system.

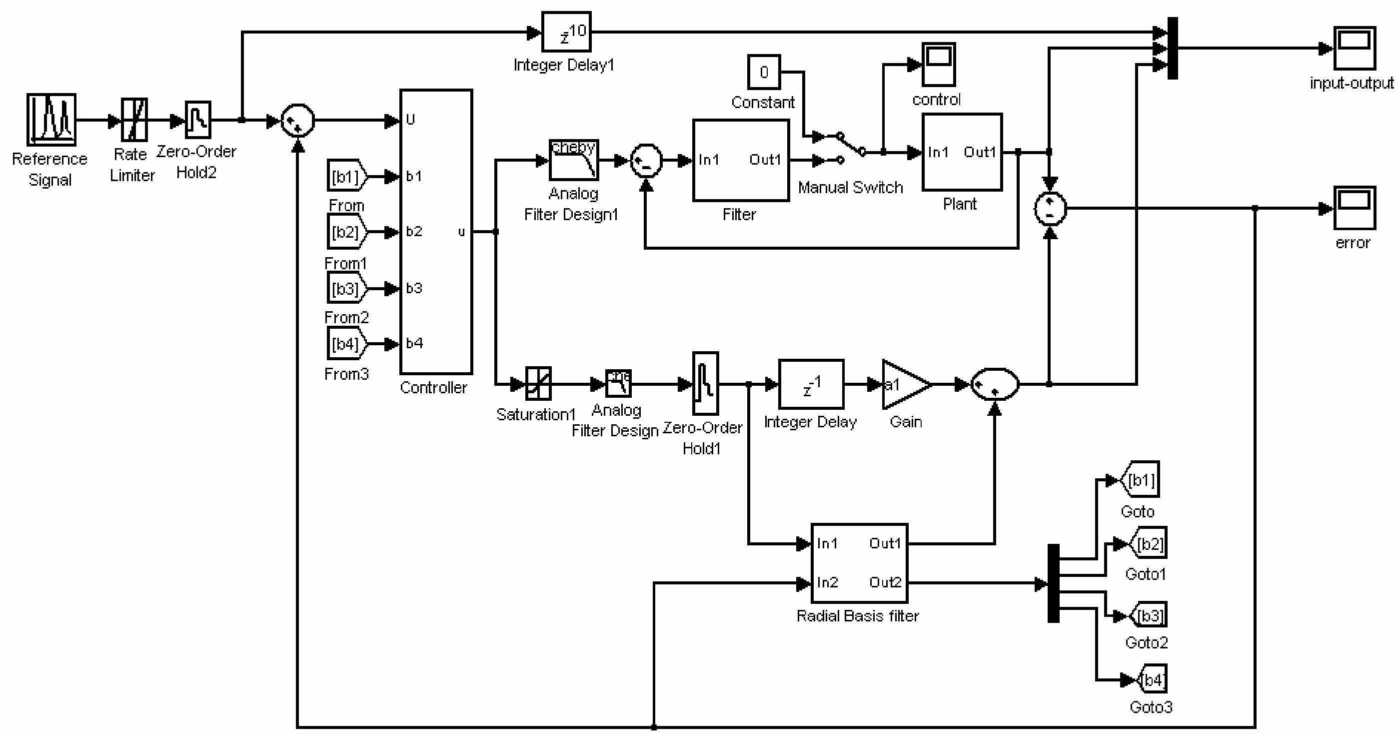

Figure 5.4: Simulink block diagram for position control of one-link robot manipulator

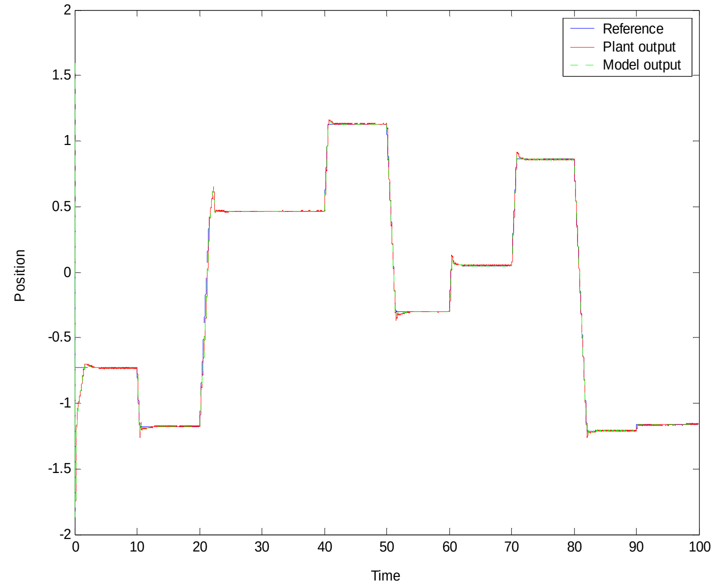

Figure 5.5: Position tracking of one link robot manipulator

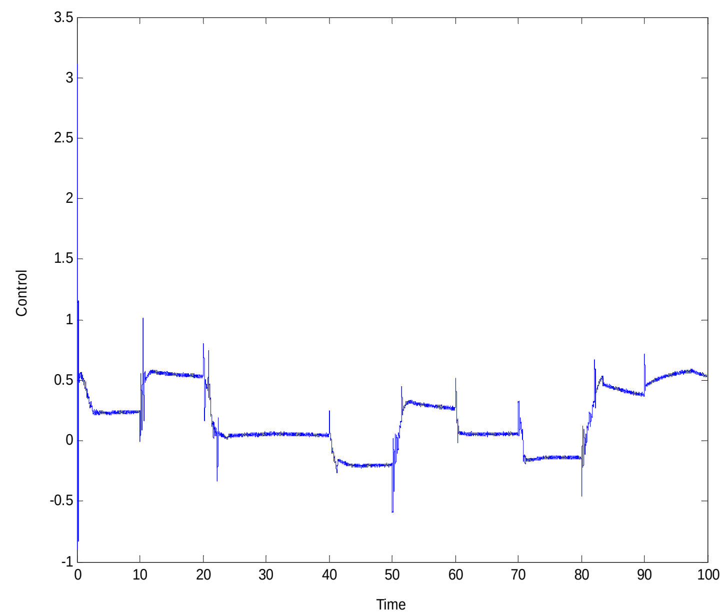

Figure 5.6: Control signal for position tracking of one link robot manipulator

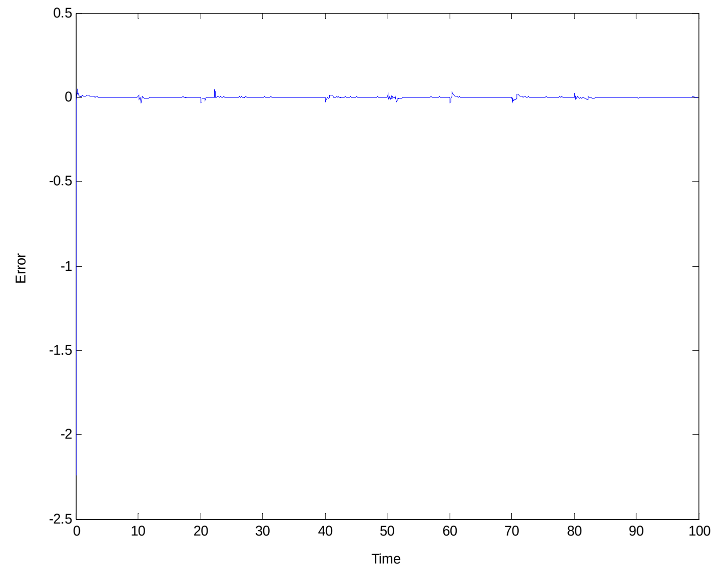

Figure 5.7: Plot of mismatch between the plant and the identified U-model

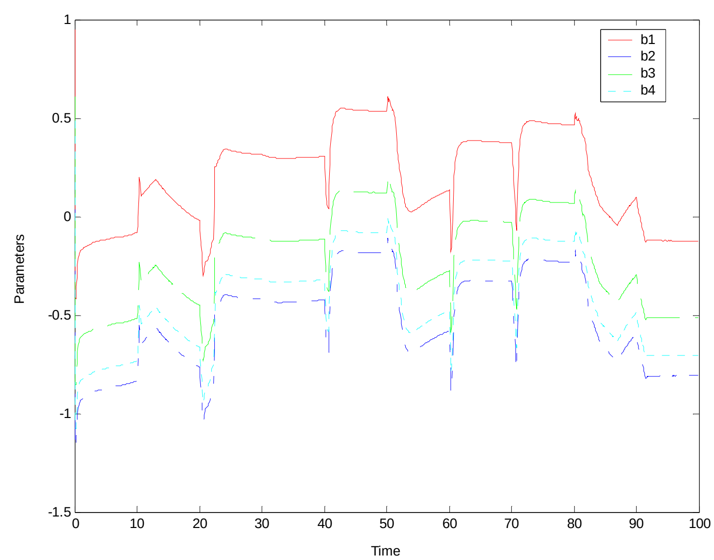

Figure 5.8: Estimation of parameters of U-model

CHAPTER 6

Inverse computation of U-model using Secant method

In this chapter, we propose the use of Secant method for computation of the inverse of U-model for nonlinear dynamic plants in the IMC structure. The advantage of using the Secant method is that it mimics Newton-Raphson's method but avoids the calculation of derivatives.

6.1 Secant Method

If $f(.)$ is a function in $'x'$ whose roots are to be evaluated. Then the Newton-Raphson's iteration defines x_{n+1} in terms of x_n via the formula

$$x_{n+1} = x_n - \frac{f(x_n)}{f^{'}(x_n)} \tag{6.1}$$

In the Secant method, we replace $f^{'}(x_n)$ in equation 6.1 by an approximation that is easily computed. Since the derivative is defined by

$$f^{'}(x) = \lim_{h \to 0} \frac{f(x+h) - f(x)}{h}$$

For small value of h, $f^{'}(x) \approx \dfrac{f(x+h) - f(x)}{h}$

In particular, if $x = x_n$ and $h = x_{n-1} - x_n$, then

$$f^{'}(x_n) \approx \frac{f(x_{n-1}) - f(x_n)}{x_{n-1} - x_n} \tag{6.2}$$

Substituting equation (6.2) in equation (6.1), the result defines the Secant method

$$x_{n+1} = x_n - f(x_n)\left(\frac{x_n - x_{n-1}}{f(x_n) - f(x_{n-1})}\right) \tag{6.3}$$

6.2 Computation of Inverse of Nonlinear Plants using Secant Method

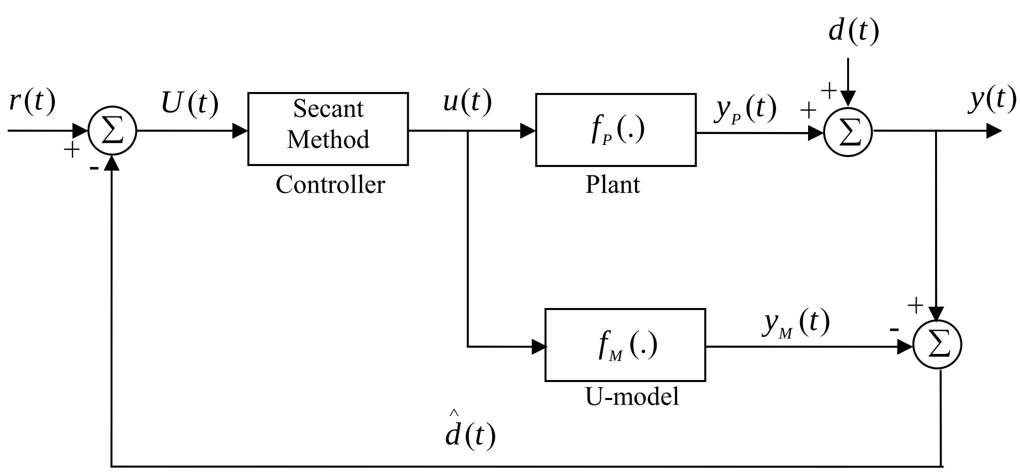

Figure 6.1: Inverse computation of U-model using Secant method

Consider figure 6.1, a general inverse controller using the U-model of equation (3.3) can be given as follows:

$$U(t) = r(t) - y(t) + y_M(t) \tag{6.4}$$

where $r(t)$ is the reference signal, $y(t)$ and $y_M(t)$ are the system and plant model outputs respectively as shown in figure 6.1. The controller output $u(t-1)$ can be found using the Newton-Raphson algorithm (discussed in Chapter 3) recursively with $U(t)$ as a root solver as follows:

$$u_{i+1}(t-1) = u_i(t-1) - m \left. \frac{\sum_{j=0}^{K} \hat{\alpha}_j(t) u^j(t-1) - U(t)}{d[\sum_{j=0}^{K} \hat{\alpha}_j(t) u^j(t-1)] / du(t-1)} \right|_{u^j(t-1)=u_i^j(t-1)} \tag{6.5}$$

$$= u_i(t-1) - m \left. \frac{\Phi\left[u(t-1)\right] - U(t)}{d\Phi\left[u(t-1)\right] / du(t-1)} \right|_{u^j(t-1)=u_i^j(t-1)} \tag{6.6}$$

where

$$\Phi\left[u(t-1)\right] = \sum_{j=0}^{K} \hat{\alpha}_j(t) u^j(t-1)$$

The derivative in the denominator of equation (6.6) can be replaced by an approximation as follows:

$$\frac{d\Phi\left[u(t-1)\right]}{du(t-1)} = \frac{\Phi\left[u(t-1)\right] - \Phi\left[u(t-2)\right]}{u(t-1) - u(t-2)} \tag{6.7}$$

Substituting equation (6.7) in equation (6.6), the result defines the computation of the controller output $u(t-1)$ using the Secant algorithm as follows:

$$u_{i+1}(t-1) = u_i(t-1) - m \left. \frac{\left(\Phi\left[u(t-1)\right] - U(t)\right)\left(u(t-1) - u(t-2)\right)}{\Phi\left[u(t-1)\right] - \Phi\left[u(t-2)\right]} \right|_{u^j(t-1)=u_i^j(t-1)} \tag{6.8}$$

where the subscript $'i'$ in equation (6.8) is the iteration index and $0 < m \le 1$ is the learning rate parameter.

6.3 Simulation Results

Simulation results obtained with the proposed IMC scheme using secant method for control of Hammerstein model given in equation (3.16) are shown in figures 6.2 and 6.3.In this simulation the learning rate $m = 0.07$ is selected and the noise is Gaussian. It can be seen from the figures that the response of the system tracks the reference signal and the control signal is bounded.

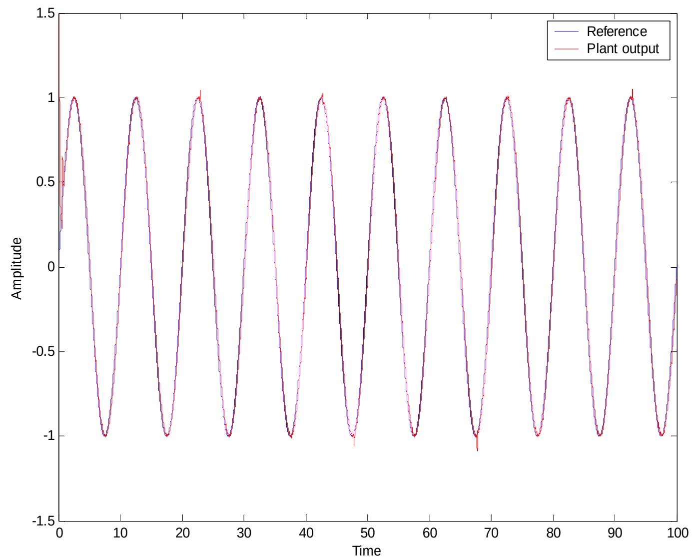

Figure 6.2: System response of Hammerstein model using IMC with secant method

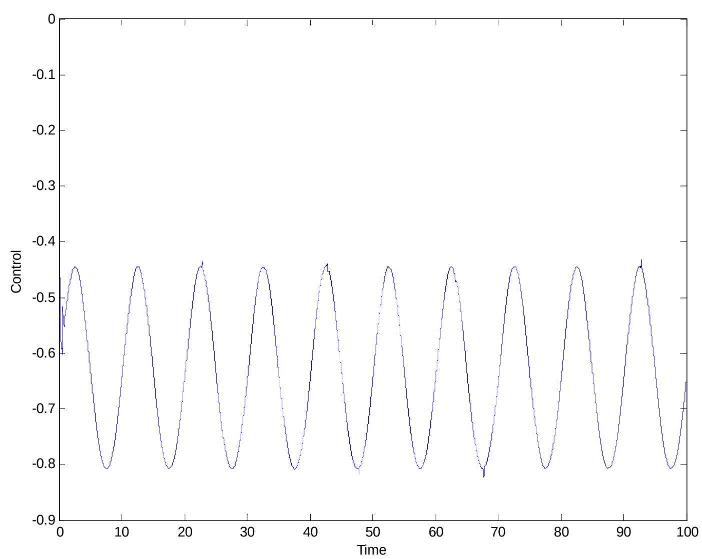

Figure 6.3: Control signal for Hammerstein model using IMC with secant method

CHAPTER 7

Conclusions and Recommendations

This chapter concludes the thesis by presenting the conclusions, summary and recommendations for extending the work carried out in this thesis.

7.1 Conclusions

In this thesis, an internal model control (IMC) strategy using the control oriented model called the U-model discussed in [69] is designed to achieve tracking of the input reference signal for stable single input single output nonlinear dynamic plants. The Newton-Raphson algorithm is used to compute the inverse of the U-model. A learning rate parameter is introduced in this algorithm which decreases the rate of convergence of the algorithm and increase the stability of the overall closed loop system. To test the efficiency of the developed IMC strategy simulations for different nonlinear plants is performed and a comparison of these simulation results with the results obtained using the pole placement controller presented in [69], clearly reveals that the developed IMC strategy performs well. To match the real time situations wherein the parameters of the model may not be exactly the same as that of the plant due to uncertainty in the plant parameters, the parameters of the U-model are chosen to be different from that of the plant and the controller is designed based of this U-model. Simulations are performed for different processes and the results obtained show that the developed IMC strategy performs far better than the pole placement controller technique given in [69].Real time implementation of the developed IMC strategy is done to control the speed of the brush dc motor. Two cases are considered in this experiment, one wherein a constant load is acting on the motor and the one wherein the load acting on the motor is varying. In case of the varying load acting on the motor, an adaptive normalized least mean square filter is used to update the parameters of the U-model as well as the parameters of the controller. The results obtained in both the cases are in good agreement with the expected results. The proposed IMC strategy is compared with the nonlinear self-tuning controller discussed in [37] and simulation results reveal that the proposed IMC strategy performs better.

A fine tracking technique is proposed to minimize the tracking error in the developed IMC strategy. Simulations are carried out for nonlinear processes and a comparison of the tracking errors obtained with and without using the proposed fine tracking technique show that the tracking error is reduced by using the fine tracking technique.

A new IMC structure is developed wherein the model of the plant is replaced with a delay in the general IMC structure. The inverse computation of the plant is carried out based on the U-model of the plant using the Newton-Raphson method. To test the efficiency of the developed IMC structure simulations are performed and the results obtained are in good agreement with the desired results.

An adaptive IMC strategy based on U-model is developed to achieve tracking of the reference input signal when the plant in unknown. In this strategy, the U-model of the plant is identified online using the radial basis non-linear moving average filter and the controller is designed online based on this U-model. The parameters of the U-model are identified using the normalized least mean algorithm. Real time implementation of the developed adaptive IMC strategy is done for position tracking of a one-link robot arm manipulator driven by a brush dc motor to show the effectiveness of the proposed adaptive IMC. The experimental results obtained are as expected.

The secant method is used to compute the inverse of the stable single-input single-output nonlinear dynamic plants in the IMC structure. Simulations are performed based on the developed strategy.

7.2 Summary

The contribution of this thesis can be summarized as follows:

- An internal model control (IMC) strategy was developed using the U-model discussed in [69] to control a wide class of single input single output nonlinear dynamic plants
- A learning rate parameter was introduced in the Newton-Raphson algorithm used to compute the inverse of U-model in the developed IMC strategy to decrease the rate of convergence of the algorithm and thereby increasing the stability of the overall closed loop system
- To test the efficiency of the developed IMC strategy, simulations are carried out for different nonlinear processes and a comparison of these simulation results with the results obtained by using the technique given in [69], revealed that the developed IMC strategy performs well.

- Real time implementation of the developed IMC strategy is done for controlling the speed of the brush dc motor with constant as well as varying load and the results obtained are in good agreement with the desired results.
- To minimize the tracking error in the IMC strategy a fine tracking technique is developed and simulations for nonlinear plants are carried out to test its efficiency. The results illustrate that the tracking error is reduced significantly using the developed fine tracking technique.
- A new IMC structure is developed which do away the use of explicit model of the plant in the general IMC structure and the U-model of the plant is used only in the synthesis of the control signal.
- Simulations for different nonlinear plants are done using the developed new IMC structure and the results obtained are as expected.
- An adaptive IMC strategy based on U-model is developed to achieve tracking in nonlinear dynamic unknown plants.
- Real time implementation of the adaptive IMC strategy based on U-model is done to achieve position tracking of one-link robot manipulator driven by a brush dc motor. The results obtained reveal the effectiveness of the developed adaptive IMC strategy.
- An IMC strategy based on U-model of the plant using the secant method for computation of the inverse of the nonlinear dynamic plants is developed and simulation results are presented.

7.3 Recommendations for future research work

Following are the recommendations for possible research that can be carried out in future based on the work presented in this thesis:

- Extension of the developed IMC strategy using U-model to multi-input multi-output nonlinear dynamic plants.
- To develop a technique to find the exact value of the learning rate parameter introduced in the Newton-Raphson algorithm used for computation of the inverse of nonlinear dynamic plants.
- To extend the developed IMC strategy to be suitable to control the known plants wherein the U-model of the plants is non-minimum phase.
- Extension of the developed adaptive IMC strategy based on U-model to multi-input multi-output nonlinear dynamic plants.

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List of Publications

Following are the list of publications from this thesis:

- Muhammed Shafiq and Mohammed Haseebuddin., Internal model control for nonlinear dynamic plants using U-model., MED'04, 12^{th} Mediterranean Conference on Control and Automation, Turkey, June, 2004.

- Muhammed Shafiq and Mohammed Haseebuddin., Pole placement controller with learning rate for nonlinear dynamic plants., Mechatronics2004, 9^{th} Mechatronics Forum International Conference, pp. 37-44, Turkey, Aug. 30-Sept. 1, 2004.

- Muhammed Shafiq and Mohammed Haseebuddin., Internal model control based on U-model., Proceedings of the 2^{nd} International Industrial Engineering Conference, IIEC-2004, Riyadh, 2004.

- Muhammed Shafiq and Mohammed Haseebuddin., U-model based internal model control for nonlinear dynamic plants., Proceedings of the Institution of Mechanical Engineers (Part 1), Journal of Systems and Control Engineering.

VITA

- **MOHAMMED HASEEBUDDIN**
- Born in Hyderabad, India
- Received Bachelor of Technology Degree in Electronics and Communication Engineering from Jawaharlal Nehru Technological University, Hyderabad, India, in June 2000.
- Worked as a Software Engineer in Wipro Technologies, Hyderabad, India from February 2001 to August 2002.
- Joined Systems Engineering Department, King Fahd University of Petroleum & Minerals, Dhahran, Saudi Arabia, as a Research Assistant in September 2002.
- Received Master of Science Degree in Systems Engineering with Automation and Control Engineering as a major from King Fahd University of Petroleum & Minerals, Dhahran, Saudi Arabia, in May 2004.