ISTANBUL TECHNICAL UNIVERSITY ★ GRADUATE SCHOOL OF SCIENCE ENGINEERING AND TECHNOLOGY

TUNING METHODS FOR FUZZY IMC PID CONTROLLER: MULTI-REGION SELF TUNING AND PREDICTIVE PEAK OBSERVER

M.Sc. THESIS

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İSTANBUL TEKNİK ÜNİVERSİTESİ ★ FEN BİLİMLERİ ENSTİTÜSÜ

BULANIK IMC PID KONTROLÖR İÇİN AYAR YÖNTEMLERİ: ÇOK BÖLGELİ ÖZ AYAR YÖNTEMİ VE ÖNGÖRÜLÜ TEPE GÖZLEMLEYİCİSİ

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HAZİRAN, 2012

Arzu DEMİR, a M.Sc. student of ITU Institute of Science and Technology student ID 506091025, successfully defended the thesis entitled "Tuning Methods For Fuzzy IMC PID Controller: Multi-Region Self Tuning and Predictive Peak Observer" which she prepared after fulfilling the requirements specified in the associated legislations, before the jury whose signatures are below.

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Date of Submission : 04 May 2012
Date of Defense : 13 June 2012

To my beloved family,

FOREWORD

Firstly and foremost, I would like to express my deep appreciation and thanks to Dr Hikmet İSKENDER and Prof. Dr. İbrahim EKSİN for their patient guidance, support and helpful leading during the conduction of this thesis.

Also, I would like to present my grateful thanks to my father Mr. Hikmet DEMİR, my mother Ms. Dilek DEMİR, my sister Ms. Ebru DEMİR and especially my beloved Ender ÇAYIR for being with me in my good and bad times when I needed the most, for empathizing me their love throughout my life and for believing and supporting me in my education life.

May 2012 Arzu DEMİR

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ABBREVIATIONS

P	**:** Proportional
PI	**:** Proportional Integral
PID	**:** Proportional Integral Derivative
IMC	**:** Internal Model Control
RD	**:** Reactive Distillation
FOPDT	**:** First Order Plus Dead Time
SOPDT	**:** Second Order Plus Dead Time
PB	**:** Positive Big
AZ	**:** Approximately Zero
NS	**:** Negative Small
PM	**:** Positive Medium
ISE	: Integrated Square of Error
ITAE	**:** Integrated Time Weighted Absolute Error
ISTE	**:** Integrated Time Weighted Square Error

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TUNING METHODS FOR FUZZY IMC PID CONTROLLER: MULTI-REGION SELF TUNING AND PREDICTIVE PEAK OBSERVER

SUMMARY

In this study, two different methods for fuzzy IMC PID controller are proposed: multi-region self tuning method and model based predictive peak observer method. Performance of a new concept that couples Fuzzy IMC PID controller with Predictive Peak Observer method will be investigated. Fuzzy IMC PID controller with some self tuning strategies will be analyzed and these will be compared with Predictive Peak Observer method.

Firstly, a number of process models were examined in order to investigate their representation for the concerning reboiler process reaction curve. Models were generated by using the collected graphical data in specific equations that differ for each kind of model structure. According to comparative results given in related section, 3 term second order plus dead time process model was chosen the best option to define the reboiler reaction curve.

According to the model of reboiler process transfer function, classical and fuzzy IMC PID controllers were designed and applied to another processes. Reboiler process transfer function and controller design calculations made for this process and were demonstrated as primary model example. According to the results of the primary process model and a few different processes with varying transfer functions, Fuzzy IMC PID controller has advantages over classical controllers but for highly delay dominant systems, it has certain drawbacks.

In the analysis of design parameters of fuzzy IMC PID controller section, it is concluded that smaller α and larger β section makes the system response faster but causes some overshoot while larger α and smaller β provides more sluggish response but smaller settling time with much less overshoot. In order to achieve the best possible result, a serious of trials all of that concerns to different α-β combinations were conducted for the process under investigation. The transient part of α=1 and β=21.72 system and steady state performance of α=10 or 5 and β=21.72 system is planned to be combined to make system response rise fast and settle well. As it is seen β should be constant at 21.72 but α should be selected a value between 1 and 10. It can be concluded as α value gets bigger gradually, rise time increases, so response slows down too early but overshoot decreases.

In Double Step Adjustment of Alpha section, because of the system response needs to be kept fast until a specified ratio of ultimate response is achieved, EIR (Error Input Ratio) is defined and α is kept minimum until the specified ratio, after the specified ratio α begins to increase gradually. This allows system response stay fast as long as possible and begin to slow down when it is about to reach the set point. Double step self tuning fuzzy IMC PID controller gives better results compared to its non-self tuning type but these results cannot be generalized for all kinds of processes.

Therefore, the step response of the process controlled by non-self-tuning controller is examined and first overshoot peak value is observed. By dividing this value with input value, a new ratio parameter is defined as OSR. The results of processes with this overshoot-input ratio based self tuning fuzzy IMC PID controllers are quite well when they are compared to ones with non-self tuning fuzzy IMC PID controllers. But It is seen that as R ratio increases, settling time increases and for the processes with controllability ratio greater than 0.33, oscillations starts to increase.

Multi-region self tuning fuzzy IMC PID controllers are proposed for the processes with high controllability ratio. Self tuning rule base table was obtained by partitioning the controllability ratio R in to three portions which means 0.33 for each in partitioning of 0-1 range. After that, rules in each three sections were replaced with fuzzy “if – then” rules in order to soften the transient zone behaviors along rule boundaries and also along partitioned portion boundaries. The final results showed that proposed multi region self tuning rules improved step response performance of Fuzzy IMC PID controller by providing it with the proper self tuning strategies for each kind of process behavior.

Another proposed strategy is model based peak observer method for Fuzzy IMC PID controllers. In this method, it is treated before the system reaches its peak point based on its process model. The adjustments of PID controller parameters are found by trial and error method. According to the results of the primary process and the other kinds of processes a comparison was made based on the performance indexes such ITAE and ITSE, rise time, settling time, overshoot and steady state error. It can be easily said that the proposed peak observer method improved the response performance of fuzzy IMC PID controller.

BULANIK IMC PID KONTROLÖR İÇİN AYAR YÖNTEMLERİ: ÇOK BÖLGELİ ÖZ AYAR YÖNTEMİ VE ÖNGÖRÜLÜ TEPE GÖZLEMLEYİCİSİ

ÖZET

Bu çalışmada, bulanık IMC PID kontrol ediciler için iki farklı ayar yöntemi önerilmektedir: çok bölgeli öz ayar yöntemi ve model öngörülü tepe gözlemleyicisi yöntemi. Bulanık IMC PID kontrol edici ile tepe gözlemleyicisi yöntemlerinin performansları incelendi. Bulanık IMC PID kontrol edici için önerilen bazı öz ayarlama yöntemleri analiz edildi ve bunlar model öngörülü tepe gözlemleyicisi yöntemi ile karşılaştırıldı.

Öncelikle, ilgili reboiler proses reaksiyon eğrisini tanımlamak için birçok model incelenmiştir. Modeller, prosesin grafik dataları farklı model yapıları için değişen denklemlerde kullanılarak oluşturulmuştur. İlgili bölümde verilen karşılaştırma sonuçlarına göre, 3 parametreli ikinci dereceden ölü sistemli proses modeli reboyler reaksiyon eğrisinin tanımlamak için en iyi model seçilmiştir.

Reboyler proses transfer fonksiyonunun modeline göre, klasik ve bulanık IMC PID kontrol ediciler tasarlandı ve başka prosesler için uygulandı. Reboyler transfer fonksiyonu ve kontrol edicinin tasarım hesaplamaları bu prosese göre yapıldı ve bu ana model örneği olarak gösterildi. Ana proses modelinin ve farklı transfer fonksiyonlarına sahip proseslerin sonuçlarına göre, bulanık IMC PID kontrolörün klasik kontrol edicilere göre avantajları var ama yüksek zaman gecikmeli sistemler için, belirgin dezavantajları vardır.

Bulanık IMC PID kontrol edicinin dizayn parametrelerinin analizi kısmında, büyük α ve küçük β'nın daha yavaş cevap verip, daha az aşımla ve daha az yerleşme zamanıyla oturduğu gözlenirken, küçük α ve büyük β'nın sistem cevabını hızlandırdığı ama aşıma sebep olduğu gözlemlenmiştir. Mümkün olan en iyi sonucu bulmak için, incelenen proseste farklı α-β kombinasyon denemeleri yapılmıştır. $\alpha=1$ ve $\beta=21.72$ olan sistemin yükselme bölümüyle, $\alpha=10$ veya 5 ve $\beta=21.72$ olan sistemin yatışkın bölümünün, sistemin daha hızlı yükselip, daha iyi yerleşmesi için birleştirilmesi planlanmıştır. Görüldüğü üzere β değerinin 21.72'de sabit kalması fakat α'nın 1 ile 10 arasında seçilmesi gerekmektedir. Buradan, α değerinin yükseldikçe, yükselme zamanının arttığı bu yüzden cevabın daha geç oturduğu ama aşımın azaldığı gözlemlenmiştir.

Alfanın çift adım ayarlama yönteminde, sistem cevabının belirli bir oranda en yüksek cevaba ulaşıncaya kadar hızlı tutulması gerektiği için, EIR (Hata Giriş Oranı) tanımlanmıştır ve alfa belirli bir orana kadar sabit tutulmuştur. Tanımlanan orandan sonra, alfa zamanla artmaya başlar. Bu sistem cevabının mümkün olabildiğince hızlı kalmasını sağlar ve alfa referans değere yakınlaştıkça yavaşlamaya başlar. Çift adım öz ayarlama yöntemli bulanık IMC PID kontrol ediciler öz ayarlaması olmayan sistemlerle karşılaştırıldığında daha iyi sonuçlar verir fakat bu sonuçlar her tip proses

için genellenemez. Bu yüzden, öz ayarlamasız sistemde prosesin basamak yanıtı incelenir ve ilk aşım yaptığı nokta gözlemlenir. Bu değer referans değere bölünerek OSR oranı tanımlanır. Bu aşım-referans oranına dayalı öz ayarlamalı bulanık IMC PID kontrol edicilerin sonuçları oldukça iyi bulunmuştur. Ama kontrol edilebilirlik oranının (R=L/(L+T)) arttıkça yerleşme zamanının azaldığı ve kontrol edilebilirlik oranının 0.33'ten küçük olan sistemlerde, salınımların artmaya başladığı gözlemlenmiştir.

Çok bölgeli öz ayar yöntemli bulanık IMC PID tip kontrol ediciler yüksek kontrol edilebilirlik oranı olan prosesler için tasarlanmıştır. Öz ayar yöntemi kural tablosu kontrol edilebilirlik oranı R'nin 0-1 arasında her biri 0.33ê denk gelen 3 eşit parçaya bölünmesiyle elde edilmiştir. Daha sonra bu üç bölümdeki kurallar bulanık "eğer-öyleyse" kurallarıyla yer değiştirilmiştir böylece yükselme bölgesinin davranışı kural sınırları boyunca yavaşlatılıyor. En son sonuçlar önerilen çok bölgeli öz ayar yöntemli kuralların, bulanık IMC PID kontrol edicinin basamak yanıtını her proses tipi için düzgün öz ayarlama stratejileri sağlayarak geliştirdiğini göstermiştir.

Diğer önerilen öz ayarlama yöntemi bulanık IMC PID kontrol ediciler için model öngörülü tepe gözlemleyicisi yöntemidir. Bu metotta, sisteme proses modelin tepe noktasına ulaşmadan müdahale ediliyor. Proses modelinin cevabı ve bir önceki adımdaki cevabı karşılaştırılarak referans değerden küçük olması durumunda hesaplanan yeni değer bulanık IMC PID kontrol edicinin parametrelerine geliyor ve burada deneme-yanılma yöntemi ile bulunan parametrelerle çarpılarak kontrol ediciye veriliyor. Verilen basamak değişme göre, model öngörülü tepe gözlemleyicisi yönteminin ilk aşımı ve salınımları azalttığı, yükselme zamanını arttırdığı ve yerleşme zamanını azalttığı görülmüştür.

Ana prosesimiz ve diğer proseslerin önerilen iki metot ile kontrolleri sonucunda, performans göstergeleri ITAE ve ISTE, yükselme zamanı, yerleşme zamanı, aşım ve ofseti içeren bir karşılaştırma yapıldı. Buna göre kolaylıkla önerilen tepe gözlemleyicisi yönteminin bulanık IMC PID cevabının performansını geliştirdiği söylenebilir.

1. INTRODUCTION

Reactive Distillation (RD) is the combination of reaction and distillation in a single vessel [1]. Reactive distillation has received a tremendous industrial interest over the last years. Many publications have been made regarding the design of such columns, however, concentrating on the steady state behavior [2, 3, and 4].

Due to the interaction of reaction and distillation in one single apparatus, the steady-state and dynamic operational behavior of RD can be very complex. Therefore, suitable process control strategies have to be developed and applied, ensuring optimal and safe operation. This is another very important area of current and future research and development [5].

Distillation columns have been extensively studied, and research has been completed in some sense [6]. But the control of a distillation column can be split into two different problems: steady state control and dynamic control. Steady state control comprehends the rejection of disturbances, and it is usually realized by industrial PID controllers. These controllers are adjusted to operate around specifically operation points obtained from linearized process models. When a change in the operations conditions occurs, dynamic control is necessary. In this case, predictive controllers are used to generate set points to the PID controllers [7].

Classical P, PI, PD and PID type controllers are most commonly used ones in process industries today. Since their design strategies and online tuning methods have been identified in great proportions during historical progress, substitution of a classical controller in to any control scheme is treated to be the fastest and most convenient way of composing a successful control loop [8].

During the historical progress of control studies, classical controllers have been applied to many control systems and all these applications provided these controllers with largely determined design techniques and tuning strategies. In literature there are lots of design and tuning techniques proposed for classical controllers all of which are results of hundreds of theoretical and practical control study experiences.

Thus, classical P, PI, PD and PID type controllers have generally been the most trusted solution to control any given process scheme.

On the other hand, it is known that, classical controllers owe their success to mathematical equations that are based on generalized relationships between process parameters and controller parameters. Thus, their performance is not generally appropriate for processes showing extraordinary behavior. For example, high order systems and processes with large time delay are not being able to be controlled properly by a classical controller in general [8]. Under this complex environment, it is well-known that the fuzzy controller can have a better performance due to its inherent robustness. Thus, over past three decades, Fuzzy PID (FPID) controllers have been widely used for industrial processes. Despite the fact that industry shows greater interest in the applications of FPID, it is still a highly controversial topic. One reason is that the fundamental theory for the analytical tuning methods of FPID is still missing. The tuning mechanism of scaling factors and the stability analysis are difficult task due to the complexity of nonlinear control surface that is generated by FPID controllers. If the nonlinearity can be suitably utilized, FPID controllers may show better performance than classical PID controllers [9].

Recently proposed design strategy for FPID controllers based on Internal Model Control (IMC) technique [10] shows great potential for further improvement. But while it provides enhanced control performance for some sort of processes, it still has certain drawbacks for very high time delay processes and some high order processes.

The idea of IMC may have originated from the time delay compensator proposed by Smith. But as general conception involved in a design control system, it was proposed by [11]. In a single-variable and multi-variable continuous system, it has attracted a variety of researches and applications [12, 13] and has been extended into discrete systems [14]. Morari had given a complete design procedure of IMC and analyzed the stability and robustness of linear IMC in theory [12, 15].

The main characteristic of IMC is that it has a simple structure and fewer parameters to be tuned on-line and is for tuning. Especially, it has significant effectiveness in improving robustness and control performance of systems with a long time delay [16].

Decentralized PI control structures for reactive distillation columns have been considered [17, 18 and 19]. PI controls and linear model predictive control have applied to a dynamic simulation of an ETBE reactive distillation column using the (L, V) configuration [20]. The linear model predictive controller used first-order plus dead time models for each of its input/output models.

In this study, IMC tuned FPID controller and classical PID controller performances are compared for a variety of processes one of which is the process model generated for a reboiler equipment of a reactive distillation column. So, some self tuning strategies for Fuzzy IMC PID controllers are proposed in this study. Multi-Region self tuning strategy is improved and predictive peak observer method is adapted to Fuzzy IMC PID controller. The effectiveness of these tuning algorithms is compared with non-self tuning counterpart.

2. DISTILLATION PROCESS

In this study, vapor phase temperature profile among the Reboiler of a reactive distillation process is observed. The concerning reactive distillation process produces acetate esters from fusel alcohols. Feed stream of the reactive distillation column is fusel oil that is composed of 16% water, 17.12% ethyl alcohol, 1.86% n-propyl alcohol, 4.04% isobutyl alcohol, 60.99% isoamyl alcohol. This feed stream gives esterification reaction with glacial acetic acid. The flow sheet of ideal reactive distillation column is shown in Figure 1. Since esterification reaction is “an equilibrium reaction, one of the products water and ester compounds should be removed from product mixture. In process of producing acetates from fusel oil, removal of light esters such as propyl acetate and ethyl acetate together with the water coming from feed stream and reaction product stream is determined to be the best method [21].

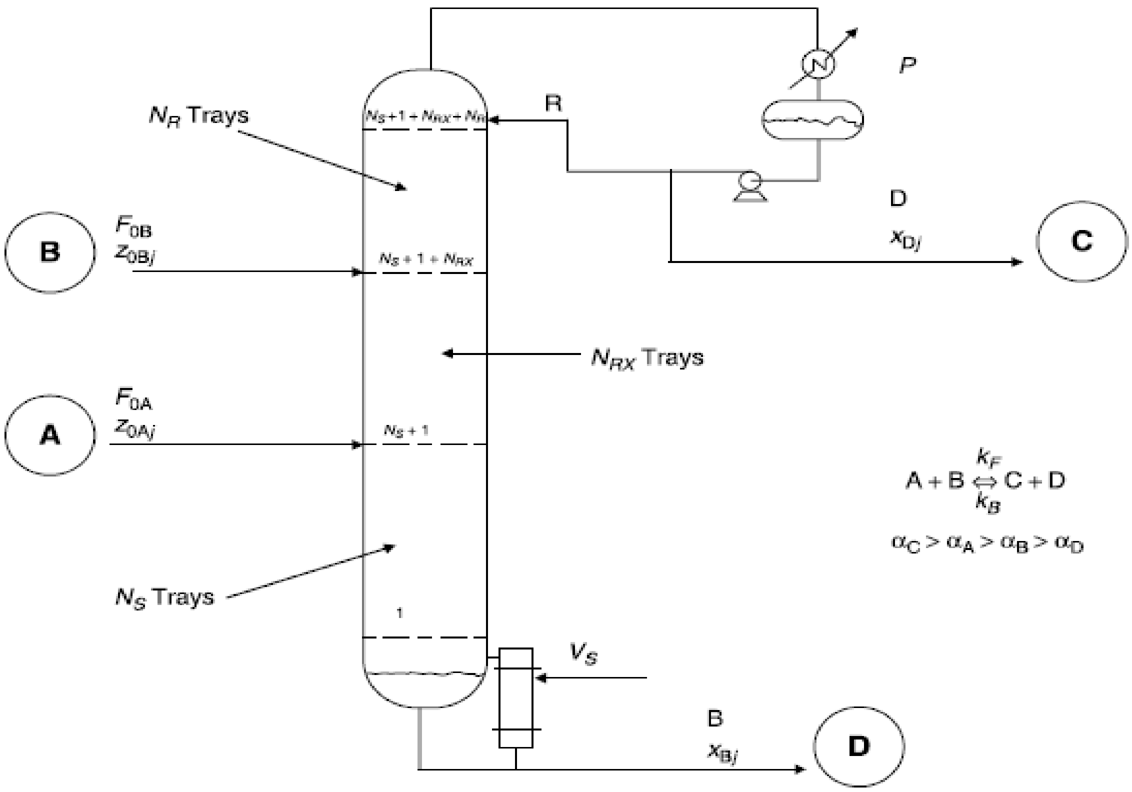

Figure 3.1 : Ideal Reactive Distillation Column

The temperature of the reboiler of the column increases and decreases according to the amount of heating power exerted to the system. As a result of experimental studies, Tanrıverdi [21] obtained temperature vs. heat data of the reboiler system. The graphical representation of system response is given in Figure 1. Tanrıverdi and İskender [22] studied on the relevant process to analyze the performance of a double slope PID controller which introduced different proportional, derivative and integral gains for positive and negative step actions [22].

İskender and Tanrıverdi [23] also investigated the performance of a self tuning controller on same reboiler system. As a conclusion of their studies, it is particularly mentioned that, the temperature at the top of the reactive distillation column should be kept between 79 °C and 87 °C. Since the water content of distillate stream seems to disappear for temperatures less than 79 °C, the column flow regime is interrupted. On the other hand, the column temperature at the top should be kept less than 87°C to prevent bottom product components from passing in to top product stream [24].

Cebeci [25] also performed a series of studies on the same reactive distillation reboiler process and made observations about performance of an IMC Based Dual Phase PID controller in controlling reboiler temperature. Dual phase PID controller concept introduces determination of two different sets of controller parameters for both the vapor and the liquid phases of the reboiler content [25].

In this study, performance of a new concept that couples Fuzzy IMC PID controller with Predictive Peak Observer method will be investigated. Fuzzy IMC PID controller with some self tuning strategies will be analyzed and these will be compared with Predictive Peak Observer method.

3. BASICS AND DESIGN PRINCIPLES OF IMC AND FUZZY IMC PID CONTROLLERS

3.1 PID CONTROL

The PID controller which consists of proportional, integral and derivative elements is widely used in feedback Control of industrial processes. A PID controller is a controller that includes elements with those three functions. The PID controller was first placed on the market in 1939 and has remained most widely used controller in Process Control until today [26].

The basic structure of conventional feedback control systems is shown in Figure 3.1. In this figure, the process is object to be controlled. The purpose of the control is to make the process variable y follow the set-point value r. To achieve this purpose, the manipulated variable u is changed at the command of the controller. The error e is defined by e=r-y. The compensator C(s) is the computational rule hat determines the manipulated variable u based on its input data, which is the error e in the case of Figure 3.1. Three elements of PID controller produce outputs with the following nature:

P element: proportional to the error at the instant t, this is the present error.

I element: proportional to the integral of the error up to the instant t, which can be interpreted as the accumulation of the past error.

D element: proportional to the derivative of the error at the instant t, which can be interpreted as the prediction of the future error.

The conventional PID controller is often described by the following equation:

$$\begin{aligned} U_{PID} &= K_c + K_I \int e \, dt + K_D \dot{e} \\ &= K_c\left(e + \frac{1}{T_i} \int e \, dt + T_d \dot{e}\right) \end{aligned} \tag{3.1}$$

where e is tracking error, K_c is the proportional gain, K_I is the integral, K_D is the derivative gain, and T_i and T_d are the integral time constant and derivative time constant, respectively. The relationships between these control parameters are $K_I=K_c/T_i$ and $K_D=K_cT_d$. [9]

The transfer function of the PID controller (3.1) can be expressed as follows;

$$G_c(s) = K_c \frac{(t_i s + 1)(t_d s + 1)}{s} \tag{3.2}$$

where

$$t_i, t_d = \frac{T_i}{2}\left[1 \mp \left(1 - \frac{4T_d}{T_i}\right)^2\right] \tag{3.3}$$

3.2 INTERNAL MODEL CONTROL (IMC)

The development of IMC had begun since the late 1950s in order to design an optimal feedback controller. The first to utilize the structure of a model parallel to the process is Frank in 1974 [3]. Then, Garcia and Morari had introduced the IMC structure with the distinct theoretical framework and application in a multivariable system [11]. The IMC consist of three parts [10]: (1) Internal Model: to predict the process response in an attempt to adjust the manipulated variable to achieve control objective; (2) Filter: to achieve certain robustness in control design; (3) Control algorithm: to calculate the future values of manipulated variable so that the process output is within the desired value. The general IMC structure is shown in Figure 3.1. The distinguish characteristic of IMC is the process model, ṕ which is parallel to process, p, giving it a disturbance estimation ability. If the process model ṕ is equal to process p, then the estimated disturbance is the actual disturbance d to the system. It is a best practice for the process model to implicitly or explicitly representing the model so that the theoretical perfect control can be achieved. Based on the theory, if the p(s)= ṕ(s) and q(s)= $ṕ^{-1}$(s), by using the minimum phase of the inverse model ṕ(s) and introduce filter to make the controller physical realizable, the IMC controller q, will have the ability to eliminate any deviation from the set point r, hence, achieving the perfect control. [26]

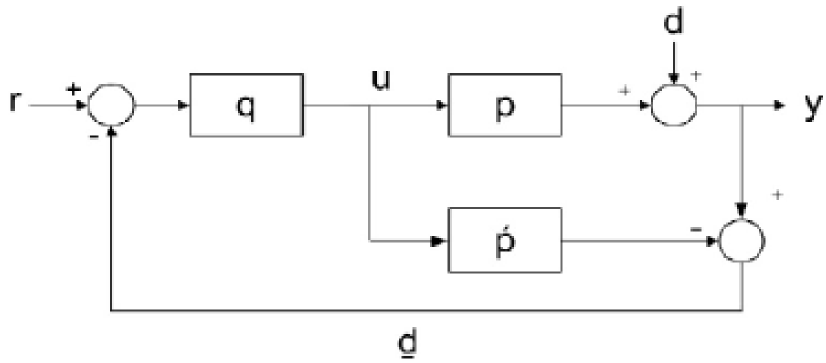

Figure 3.2 : The IMC Structure

It is recognized that IMC have the following criteria’s;

- Dual Stability: By assuming that p= ṕ, that is the process model and the process is identical, and if the controller and the process are stable, then the IMC structure can guarantees the closed loop stability.
- Perfect Control: By assuming that q(s)= $ṕ^{-1}$(s), that is the controller is equivalent to the inverse model and the closed loop system is stable, then there is no output steady-state error for set point variance and disturbance.
- Zero Offset: By assuming that the steady state gain controller is equal to the inverse model gain and the closed loop system in Figure 3.1 is stable, for constant set point and disturbance, there will be no offset.

3.2.1 Principle of IMC

The basic IMC principle is shown in Figure 3.3a, where P is plant, $\tilde{P}$ is a nominal model of the plant, C is a controller; r and d are the set point and the disturbance, and y and $\hat{y}$ are the outputs of the plant and its nominal model, respectively. [9]

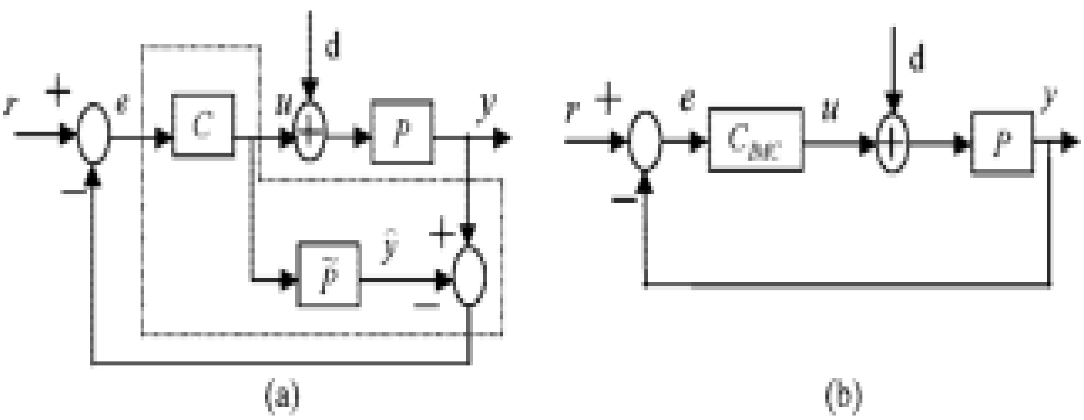

Figure 3.3 : IMC Configuration

The IMC structure is equivalent to the classical single-loop feedback controller shown in Figure 3.3b. If the single-loop controller C_{IMC} is given by

$$C_{IMC}(s) = \frac{C(s)}{1 - C(s)\tilde{P}(s)} \quad \textbf{(3.4)}$$

$$C(s) = \frac{1}{\tilde{P}_{-}(s)} f(s) \quad \textbf{(3.5)}$$

where $\tilde{P} = \tilde{P}_{-}(s)\tilde{P}_{+}(s)$, $\tilde{P}_{-}(s)$ is the minimum phase part of the plant model, $\tilde{P}_{+}(s)$ contains any time delays and right-half-plane zeros, and f(s) is a low-pass filter with steady-state gain of one, which typically has the form

$$f(s) = \frac{1}{(1 + t_c s)^n} \quad \textbf{(3.6)}$$

The tuning parameter t_c is the desired closed-loop time constant and n is the integer to be determined. [27]

3.2.2 Tuning of Fuzzy PID Controller Based on IMC

By first-order Pade approximation, the delay time is approximated as follows:

$$e^{-Ls} = \frac{1 - \frac{L}{2}s}{1 + \frac{L}{2}s} \quad \textbf{(3.7)}$$

Therefore, the $\tilde{\boldsymbol{P}}$ can be factorized as $\tilde{\boldsymbol{P}} = \tilde{\boldsymbol{P}}_{-}(\boldsymbol{s})\tilde{\boldsymbol{P}}_{+}(\boldsymbol{s})$, wher$\tilde{\boldsymbol{P}}_{+}(\boldsymbol{s}) = \boldsymbol{1} - \boldsymbol{Ls}/\boldsymbol{2}$e and

$$\tilde{P}_{-}(s) = \frac{K}{(Ts + 1)\left(1 + \frac{L}{2}s\right)} \quad \textbf{(3.8)}$$

Substituting $\tilde{\boldsymbol{P}}_{-}(\boldsymbol{s})$ into (3.4) and setting n=1 in filter (3.6), one has

$$C_{IMC}(s) = \frac{(Ts + 1)\left(1 + \frac{L}{2}s\right)}{K(1 + t_c s)} \quad \textbf{(3.9)}$$

During the study, all non-self regulating and self regulating fuzzy IMC PID controllers are designed according to the first order models of relating second order processes. The first order models of different second order processes are found from [9].

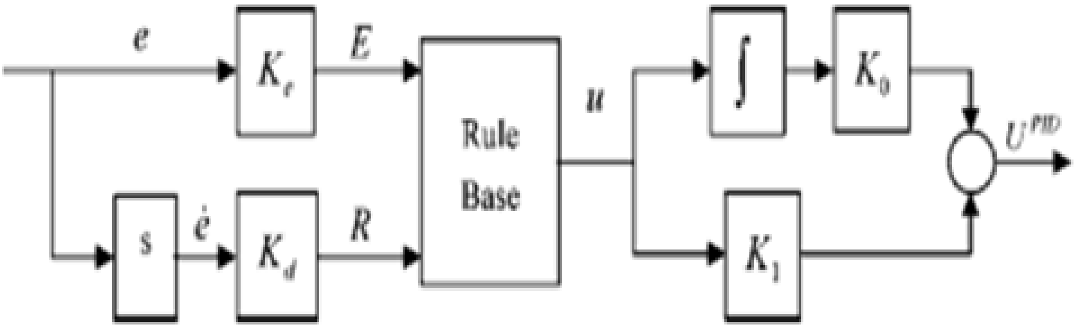

Figure 3.4 : Fuzzy-PID controller structure with $K_d=\alpha K_e$ and $K_I=\beta K_0$

Designing Fuzzy PID controllers by internal model control technique is a recently proposed idea. The Fuzzy PID control actually has two level of gain. The scaling gains (K_0, K_1, K_e and K_d) are at lower level. The contribution of each K_0, K_1, K_e and K_d to different control actions is still no clear, which makes the practical design and turning process rather difficult [9]. K_1 is integral gain and K_d is derivative gain. IMC PID controller scheme and location of scaling gains are shown in Figure 3.3.

While tuning Fuzzy PID controllers based on IMC design, Duan [9] defined K_0, α and β as below;

$$K_e = 1 \quad \textbf{(3.10)}$$

$$K_d = K_e \times \alpha \quad \textbf{(3.11)}$$

$$K_0 = \left(\frac{A}{B}\right) \times \left\{ \frac{1}{\left[K \times K_e \left(t_c + \frac{L}{2} \right) \right]} \right\} \quad \textbf{(3.12)}$$

$$K_1 = K_0 \times \beta \quad \textbf{(3.13)}$$

$$\alpha = T, \beta = L/2 \quad or \quad \alpha = L/2, \beta = T \quad \textbf{(3.14)}$$

A and B are half of the spread of each input and output membership function, so A/B equals one according to our membership functions. L is the distance velocity lag.

3.3 FUZZY LOGIC AND FUZZY PID CONTROL

Traditionally, computers make rigid “yes” or “no” decisions, by means of decision rules based on two valued logic: true /false, yes/no or 1 / 0. An example is an air conditioner with thermostat control that recognizes just two states: above the desired temperature or below the desired temperature. On the other hand, fuzzy logic allows a graduation from “true” to “false”. A fuzzy air conditioner may recognize “warm” and “cold” room temperatures. The rules behind this are less precise [28]. For example;

“If the room temperature is warm and slightly increasing, then increase the cooling.”

Many classes or sets have fuzzy rather than sharp boundaries, and this is the mathematical basis of fuzzy logic. The set of “warm” temperature measurements is one example of a fuzzy set.

The core of a fuzzy controller is a collection of “verbal” or “linguistic” rules of the “if – then” form. The rules can bring the reasoning used by computers closer to that of human beings.

In the example of the fuzzy air conditioner, the controller works on the basis of a temperature measurement. The room temperature is just a number, and more information is necessary to decide whether the room is warm. Therefore; the designer must incorporate a human’s perception of warm room temperatures. A straightforward implementation is to evaluate beforehand all possible temperature measurements. For example; on a scale from “0 to 1”, “warm” corresponds to “1” and “not warm” corresponds to “0” [28].

For a temperature interval from 15 to 27 ºC;

Measurements (ºC)	15	17	19	21	23	25	27
Grade	0	0.1	0.3	0.5	0.7	0.9	1

3.3.1 Fuzzy Sets

Fuzzy logic and fuzzy control begins with the concept of a fuzzy set. A fuzzy set is a set without a crisp, clearly defined boundary. It can contain elements with only a partial degree of membership.

To understand what a fuzzy set is, the example about the days of the week and their contribution to the set of "weekdays" could be given.

According to the thinking based on classical sets, one can say that, the days which can be called as weekdays are Monday, Tuesday, Wednesday, Thursday and Friday while Saturday and Sunday should be named as weekend days. On the other hand, getting fuzzy sets as the basis for classifying these days, one can say that, Friday is a little more likely to be a weekend day compared to Tuesday or Wednesday. So its membership grade to the set of weekend days is some value between 0 and 1 where the grades for Saturday and Sunday are 1. Figure 3.4 shows this difference between the philosophies of classical sets and fuzzy sets [29].

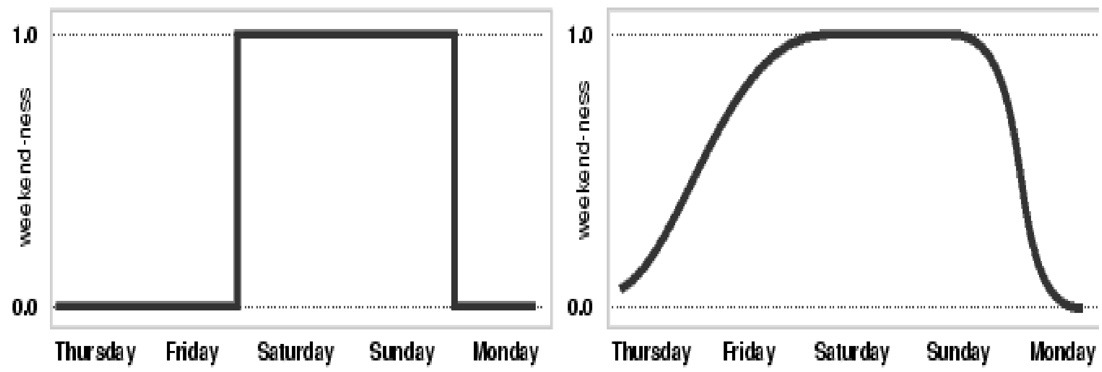

Figure 3.5 : Membership grades of the days for the set of "weekend days" according to classical set and fuzzy set theories [29].

3.3.2 Fuzzy Rules and Rule Bases

Fuzzy rules are the statements that receive the inputs of the controllers, generate the appropriate decision according to them and define the control action to be performed. The most common definition of this process could be demonstrated by giving a rule base table as an example. A rule base that simply takes the measurement error and the rate of change of error as input and decides for the control action is shown in Table3.1. The translations for shortcuts could be done as; NB means negative big, or PS means positive small and Z means zero and so on for the other ones.

For example, according to this table; if the error from the set point is very large positive and it is still increasing rapidly; the rule base takes it as: error is PB and change of error is PB. So, the decision that follows this realization will be PB. In other words for example, if the temperature of the reactor is much larger than the desired value and it is still increasing rapidly, then the cooling water stream rate should be very high. The fuzzy rules work on if then statements such as the prior example.

If error is NS and change of error is PS then control output is Z.

It means that; if the temperature is a little higher than the set point and it is slightly decreasing then there is no need to perform any spectacular control action.

Table 3.1: A rule base table for an error-change of error type fuzzy control strategy [30]

e \ Δe	NB	NM	NS	Z	PS	PM	PB
NB	NB	NB	NB	NM	NM	NS	Z
NM	NB	NB	NM	NM	NS	Z	PS
NS	NB	NB	NS	NS	Z	PS	PM
NO	NB	NM	NS	Z	Z	PM	PB
PO	NB	NM	Z	Z	PS	PM	PB
PS	NM	NS	Z	PS	PS	PB	PB
PM	NS	Z	PS	PM	PM	PB	PB
PB	Z	PS	PM	PM	PB	PB	PB

3.3.3 Fuzzy Membership Functions

A membership function is a curve that defines how each point in the input space is mapped to a membership value between 0 and 1. The input space is sometimes referred to as the universe of discourse [29].

The simplest membership functions are formed using straight lines. Of these, the simplest is the triangular membership function. It is simply defined by three points. Another common type of membership functions is trapezoidal shape membership functions. This type has a flat top that smoothes the membership recognition for the data defined near to the center of the shape. Figure 3.5 shows triangular and trapezoidal type membership function curves.

The work held by membership functions is to classify the input data by partially introducing it to the several definitions. For example, there exists a temperature interval from 150ºC to 250ºC. The input signal is received such that, the measured temperature is 200ºC. The membership of this temperature value for the set of moderate is 1 over 1. On the other hand it also has partial membership in cold and hot temperature sets, for example 0.4 (Some value between 0 and 1).

Another example could be given for set point control cases. For example, if the temperature of a reactor is desired to be kept constant at 170ºC and the reference temperature for the controller is set as 170ºC. During operation, the temperature is measured as 175ºC. The error will be +5ºC. This corresponds to positive error. It also has some membership values for PB, PM, PS, Z, NS, NM, NB sets. The membership of +5ºC error for PM is 0.8 while its membership for PB is 0.1, for PS 0.3, for Z 0.1 while for NS, NM and NB it is 0. This means that controller accepts this error as positive medium as a general definition but it also does not ignore its contribution to the other relevant neighbor fuzzy sets. On the other hand, for the same controller -45ºC error would be accepted as totally NB error and coupled with 1 over 1 membership grade for that set while its membership for other sets would be defined as 0.

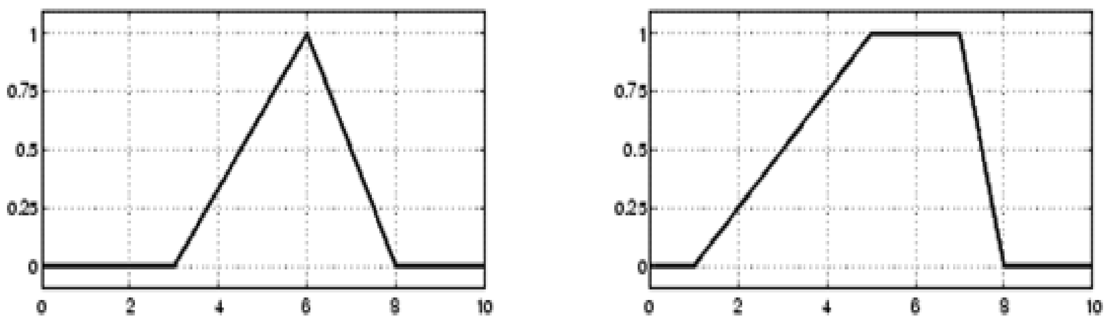

Figure 3.6 : Triangular and trapezoidal membership function curves [29]

3.3.4 Input and Output Scalings

Input and output scaling is a very important feature for fuzzy controller mechanism since it determines the quality of input feed to the inference mechanism and correct reading of the output. Input and output scaling factors of a fuzzy controller could be demonstrated as gain blocks placed before and after the inference core of the fuzzy controller. Figure 3.6 shows the general placement of the scaling blocks in a control scheme that determines the output control signal by means of evaluating error and change of error input signals.

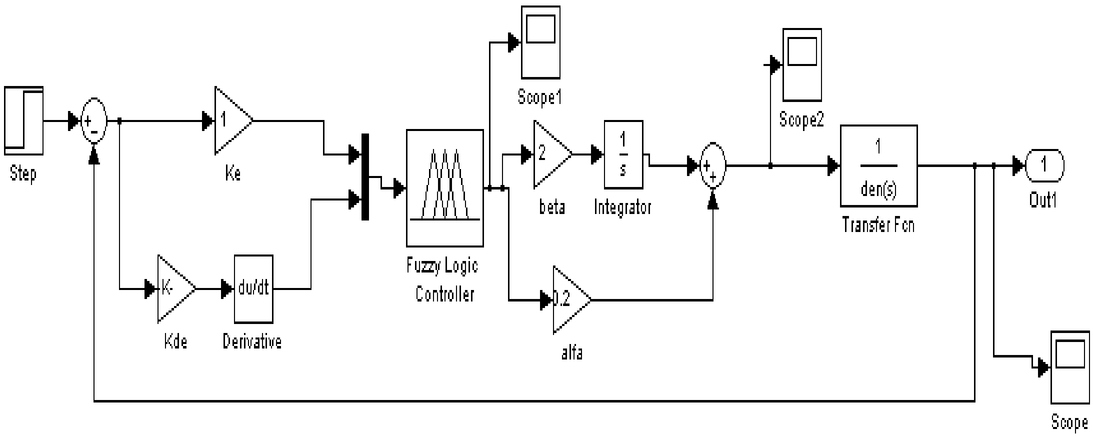

Figure 3.7 : Placement of scaling factors in fuzzy control scheme: a simple fuzzy PID control scheme

In the control scheme in Figure 3.6, a three term fuzzy controller is used. Three term fuzzy controller means for a fuzzy controller to include proportional, derivative and integral actions of a conventional controller. For example, a fuzzy PI or fuzzy PD controller could also be named as two-term fuzzy controllers. In this scheme, K_e is proportional error input scaling factor the output of which is $e*K_e=E$, where E is the scaled error input. Kde is change of error scaling factor. Since its output is fed to a differential block element, it could easily be recognized as the derivative gain such as the one observed in conventional controllers. The integral action of the fuzzy controllers in literature examples are generally placed after the inference mechanism. Placing it on to output control signal, the integration of all observed control signals can be evaluated. So; beta gain factor here is becoming the integral gain element the output of which is directly fed to integrator. Finally, alpha is the regular proportional output scaling factor. Fuzzy controller gain parameters for specific control systems are generally determined by means of first defining the parameters of a conventional controller which successfully manages the desired control action for the same system. Once the parameter of the conventional controller is determined, stochastic assignment of fuzzy controller scaling (gain) factors can be done by using heuristic tables.

4. MODELLING AND CONTROLLER DESIGN

4.1 Process Modeling

Modeling studies began with generation and testing of a first order model with time delay and comparison of responses that belong to the model and the real process. On this path, the studies are firstly conducted by taking vapor phase as the basis. The time where the system response reached 63% of its largest value is noted. The magnitude of the response at this time is also imported from graph. These values are 26.25 minutes and 89.67^{0}C, respectively. After that two values are substituted into Equation 4.1 in order to calculate time constant that represents the system. In this equation, t is time, y(t) is open loop system response, K is ultimate output gain (133.33^{0}C), τ is time constant and L is the delay time which was formerly determined to be 2 minutes. [33]

$$y(t) = K\left(1 - e^{-(t-L)/\tau}\right) \qquad \textbf{(4.1)}$$

As the result of calculations, first order time constant (τ) of process has been found to be 21.72 minutes. With the given (K) of 0.187^{0}C.minute/kcal, which was previously found in recent studies, the first order transfer function with dead time (FOPDT) is created as shown in Equation 4.2. [33]

$$G_{P1}(s) = \frac{0.187}{(21.72s + 1)} e^{-2s} \qquad \textbf{(4.2)}$$

Step response of FOPDT model is shown in Figure 4.1. Comparison between the model and the process yield that, first order model does not actually represent this system. Its response is by too far from the actual curve. [33]

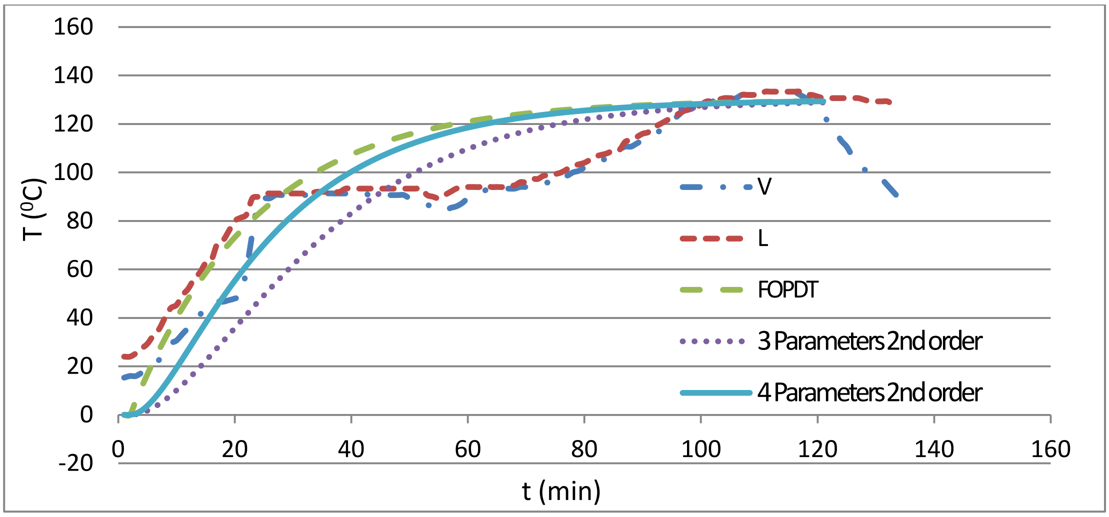

Figure 4.1 : Comparison of process model curve and three different model curves

After FOPDT model, the next model to be generated and investigated is three term second order with dead time process model. The time period to be selected as basis for calculating time constant are selected properly in order to represent the system curve at its most critical points. In other words, classical 63% of response rule has not been used in this particular study. So, system response at t=43 minutes is imported from graph and it is 90.67°C. These two values are substituted in to Equation 3.

$$y(t) = K\{1 - [1 + (t - L)/\tau]\}e^{-(t-L)/\tau} \quad \textbf{(4.3)}$$

From Equation 4.3, the time constant of second order transfer function is determined to be 17.46 minutes. Transfer function of three-term second order model with dead time is given in Equation 4.4.

$$G_{P2}(s) = \frac{0.187}{(17.46s + 1)^2}e^{-2s} \quad \textbf{(4.4)}$$

From Figure 4.1, it is obvious that second order model gives better result and represents the system curve much more realistic compared to the first order model.

The third step of modeling studies is creating a four parameter second order model for the process and investigating its representation abilities. In order to determine two different time constants for the second order transfer function, the times where the step response of the process reaches 33% and 67% of its maximum value are noted. The magnitudes of the response at these times are also read from the graphic. These are; t_1=23 min., t_2=85 min., $y(t_1)$=74.67°C, $y(t_2)$=106.67°C, respectively. These values are substituted in to Equation 4.5 in appropriate order.

$$y(t) = K\{1 + [(\tau_2 e^{-(t-L)/\tau_2} - \tau_1 e^{-(t-L)/\tau_1})/(\tau_1 - \tau_2)]\} \quad \textbf{(4.5)}$$

In Equation 4.5, $y(t_1)$ is solved for t_1 and $y(t_2)$ is for t_2. τ_1 and τ_2 values that prove both equations true are determined to be the time constants of four parameter model. Approximate results of the calculations show that time constants of the model could be selected as: τ_1=6 and τ_2=21. Transfer function of four parameter second order model is given in Equation 4.6.

$$G_{P3}(s) = \frac{0.187}{(6s+1)(21s+1)} e^{-2s} \quad \textbf{(4.6)}$$

Step response of four parameter model can be seen in Figure 2. Its performance is observed to be better than FOPDT model but not as successful as three parameter second order model. Therefore, three-term second order model is chosen for this study.[33]

4.2 Fuzzy IMC PID Controller Design

Design calculations are conducted according to [9] by taking first order model of the process as basis. First Order Pade Approximation is applied to our second order transfer function;

$$e^{-2s} = \frac{(1-s)}{(1+s)} \quad \textbf{(4.7)}$$

$$P(s) = P_-(s)P_+(s) \quad \textbf{(4.8)}$$

$$P_+(s) = \frac{1-S}{1+S} \qquad P_-(s) = \frac{0.187}{21.72s+1} \quad \textbf{(4.9)}$$

Filter transfer function can be calculated by,

$$G_f(s) = \frac{1}{(t_f + s)^n} \quad \textbf{(4.10)}$$

Filter time constant is taken as the half of the process time constant (10.86 min) and n=1 [23]. The transfer function of the IMC based PID controller is calculated by [25];

$$C_{IMC}(s) = \frac{(21.72s^2 + 21.72s + 1)}{(2.03s^2 + 2.40s)} \quad \textbf{(4.11)}$$

The scaling factors for our first order transfer function are calculated according to above equations. When the step response applied as 95^0C, the response of none controlled process, classical IMC PID controller and fuzzy IMC PID controller for different alpha and beta given in Figure 4.2. It can be concluded from the graph that the small value of α gives wide bandwidth and fast response otherwise it gives low bandwidth and sluggish response.

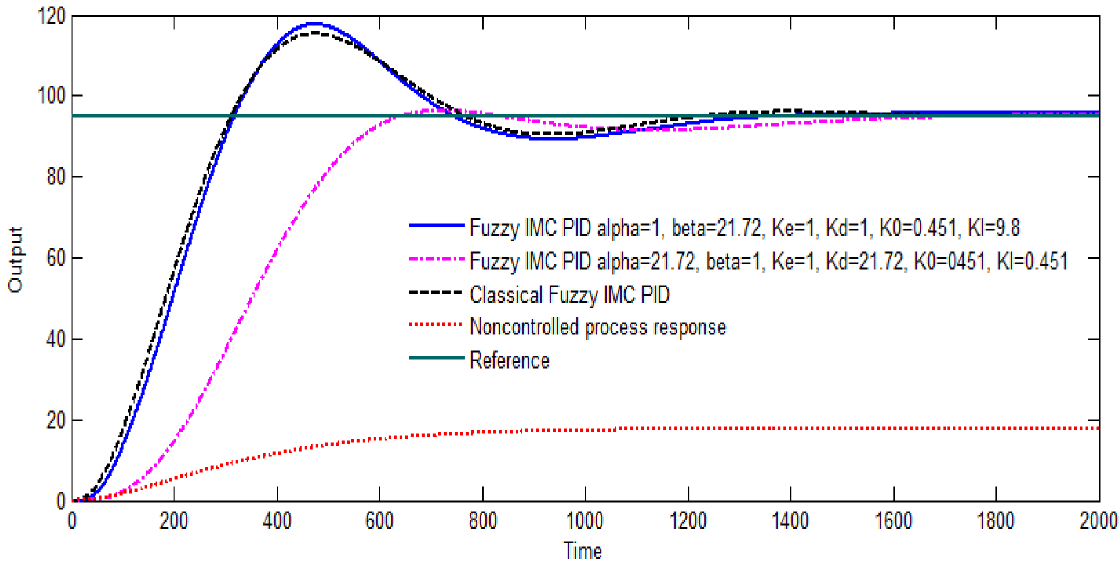

Figure 4.2 : Comparison of the process controlled with Classical IMC PID and Fuzzy IMC PID for the process $G_{P1}(s) = [0.187/ (21.72s+1)^2]*e^{-2s}$

4.3 Analysis of Design Parameters of Fuzzy IMC PID Controller

As it is seen in previous section, smaller α and larger β section makes the system response faster but causes some overshoot while larger α and smaller β provides more sluggish response but smaller settling time with much less overshoot. In order to achieve the best possible result, a serious of trials all of that concerns to different α-β combinations are conducted for the process under investigation. According to Duan [9], α and β will be between L/2 (1) and τ (21.72). The results are given in Table 4.1.

According to Table 4.1, when α is increased gradually and β is kept constant, system response is getting slower at the beginning but it shows less overshoot and a better settling. On the other hand, when β is increased gradually and α is kept constant, the transient part of the response keeps in unity.

It is important to mention that the increments or decreasing α value affects the rise time in great proportions and slightly affects the overshoot behavior. On the other hand, the changes in β causes nearly zero effect for rise time though it very strongly manipulates overshoot amplitudes.

It is seen that, for the transient part, the best choice is $\alpha=1$ and $\beta=21.72$ system because it has the smallest rise time and for the steady state performance the system with $\alpha=10$ and $\beta=21.72$ gives the smallest settling time and the smallest overshoot. On the other hand, error indexes show that the configuration with $\alpha=5$ and $\beta=21.72$ gives the most appropriate results according to ISE, ITSE, and ITAE calculations. Although ITAE result is smallest for $\alpha=15$ and $\beta=10$, overall examination of all three indexes shows $\alpha=5$ and $\beta=21.72$ is the most successful one.

The transient part of $\alpha=1$ and $\beta=21.72$ system and steady state performance of $\alpha=10$ or 5 and $\beta=21.72$ system is planned to be combined to make system response rise fast and settle well. As it is seen β should be constant at 21.72 but α should be selected a value between 1 and 10.

Table 4.1 : Error Indices, Rise Time, Settling Time, Overshoot and Offset Results for Control Systems with Various α and β Combinations

Alpha (α)	Beta (β)	ISE (105)	ITSE (104)	ITAE (104)	TR	TS	Overshoot	Offset
1	21.72	1.423	6.733	10.155	19.5	120	22.6	0.70
5	21.72	1.421	6.906	10.978	24.5	86	10.6	-1.20
10	21.72	1.498	7.072	11.646	32.3	54	1.60	1.40
15	21.72	1.599	7.175	15.863	24.5	110	0.00	-1.80
18	21.72	1.689	7.261	16.482	52.2	146	0.00	-1.70
21.72	21.72	1.828	7.428	18.209	62.7	122	0.00	-1.70
1	10	2.210	9.133	28.774	24.3	268	24.8	0.10
5	10	1.945	9.049	18.366	27.0	222	38.0	0.70
10	10	1.905	9.268	16.777	32.3	110	11.5	-1.70
15	10	1.923	9.408	6.8535	36.7	112	4.10	-0.03
18	10	1.965	9.470	11.108	41.0	66	0.00	0.95
21.72	10	2.049	9.558	9.9383	49.5	89	0.00	0.50
10	1	2.611	12.64	29.343	29.9	215	27.4	0.24
10	5	2.199	10.87	19.945	31.7	153	18.4	1.33
10	10	1.905	9.268	16.777	32.3	100	11.5	-1.68
10	15	1.696	8.141	7.4355	32.6	93	7.00	-0.22
10	18	1.598	7.614	8.8815	32.7	46	4.40	0.66
10	21.72	1.498	7.072	11.646	32.6	47	1.66	1.38
1	1	6.113	44.72	17.274	25.3	>600	67.5	-
5	1	3.572	17.95	83.158	26.7	403	48.8	-0.5
10	1	2.611	12.65	29.343	29.4	215	27.4	0.38
15	1	2.435	12.74	17.534	31.1	144	16.4	0.83
18	1	2.403	12.78	14.245	32.6	88	9.75	1.11
21.72	1	2.418	12.84	11.045	36.0	57	1.18	0.66

4.4 Double Step Adjustment of Alpha

It is can be concluded from the previous section that as α value gets bigger gradually, rise time increases, so response slows down too early but overshoot decreases. Because of the system response needs to be kept fast until a specified ratio of ultimate response is achieved, EIR (Error Input Ratio) is defined and α is kept minimum until the specified ratio, after the specified ratio α begins to increase gradually. This allows system response stay fast as long as possible and begin to slow down when it is about to reach the set point.

$$EIR = \frac{Error(e)}{Input(u)} \quad \textbf{(4.12)}$$

In order to create global rules that will be true for various processes with different parameters such as time constant and delay time, the selection of boundaries between different control equations and parameters of these equations must be generalized based on system parameters. The strategy for this section is defined with following rules. EIR;

If	EIR > 0.37	Then	α=min(τ,L/2)
Else if	EIR > 0.01	Then	α=0.5*max(τ,L/2)
Else		Then	α=max(τ,L/2)

Limiting EIR values 0.37 and 0.01 are still arbitrary but selection of α is based on system parameters. For the main process, according to the previous section, α should be between 1 and 10, and β should be constant at 21.72. Therefore, a generalization can be made by giving α; min(τ,L/2) and 0.5 of the max(τ,L/2). Step response graphics of proposed double step self tuning control scheme for our process is given in Figures 4.3.

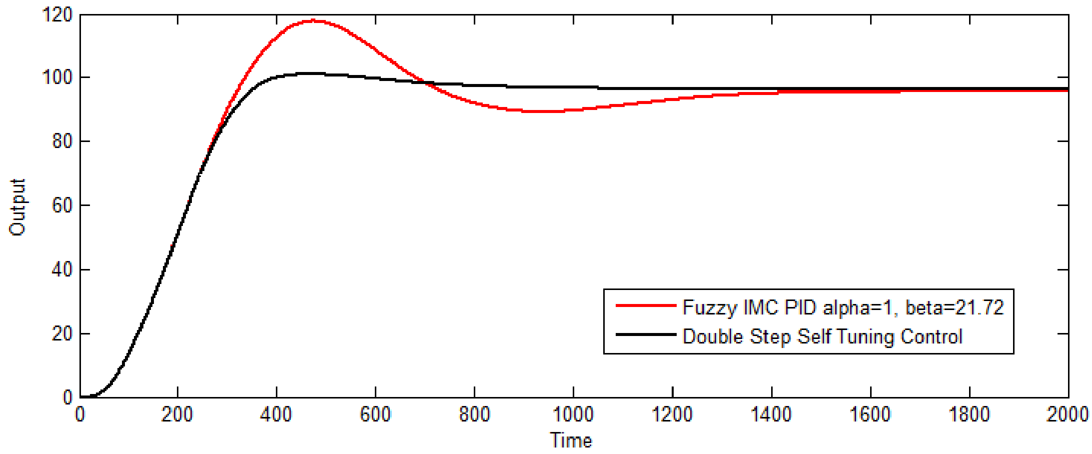

Figure 4.3 : Comparison of step responses for Fuzzy IMC PID alpha=1, beta=21.72 and Double Step self-tuning control for $G_{P1}(s)=[0.187/(21.72s+1)^2]xe^{-2s}$

As it is seen in Figure 4.3, double step self tuning Fuzzy IMC PID controller gives better results compared to its non-self tuning type but these results cannot be generalized for all kinds of processes.

Table 4.2 : Limiting EIR values for "Else If" case

EIR (Else If)	Overshoot	Offset	TR	TS
0.01	5.80	1.10	20.0	56.5
0.05	4.90	1.05	20.0	49.3
0.10	3.90	0.95	20.0	31.3
0.15	2.30	1.00	20.0	29.3
0.20	1.30	0.60	20.4	29.4
0.25	0.63	-0.04	20.7	32.8
0.30	0.06	-0.40	21.1	34.1

Table 4.3 : Limiting EIR values for "If" case

EIR (If)	Overshoot	Offset	TR	TS
0.05	13.0	1.8	20.07	75.2
0.37	6.0	1.3	20.77	62
0.50	4.6	1.2	22.07	32.25
0.80	2.5	1.0	27.47	40.25

Different EIR values are shown in Table 4.2 and 4.3. According to these analyses, it can be concluded that for "If" case, 0.37 or 0.50 can be chosen because of those parameters; overshoot, offset, rise time and settling time. For "Else If" case 0.25 seems the appropriate one between the others.

Table 4.4 : Comparison of overshoot, offset, rise time and settling time parameters for some intervals of If and Else If cases

	Overshoot	Offset	Rise Time	Settling Time
If EIR > 0.37 Else if EIR > 0.01	6.0	1.3	21.4	61.0
If EIR > 0.50 Else if EIR > 0.25	0	-0.4	23.0	36.0
If EIR > 0.50 Else if EIR > 0.15	1.0	0.3	22.0	33.5
If EIR > 0.37 Else if EIR > 0.15	3.1	0.85	20.5	31.5

According to Table 4.4, it can be concluded that limiting EIR values 0.37 and 0.15 can give best controller action between the others.

4.5 Overshoot-Input Ratio Based Self Tuning Fuzzy IMC PID

In this strategy, control action is divided into 2 steps. On the first step, the step response of the process controlled by non-self-tuning controller is examined and first overshoot peak value is observed. By dividing this value with input value, a new ratio parameter is defined as OSR (Overshoot-Input Ratio);

$$OSR = \frac{Overshoot}{Input} \tag{4.13}$$

On the second step, OSR is used to produce self tuning rules and boundaries as follows:

If	u> $\sqrt{OSR}$	Then	α=min(τ,L/2)
Else if	u> OSR^2	Then	α= $\sqrt{OSR}$ *max(τ,L/2)
Else		Then	α=max(τ,L/2)

This is done to generalize the limiting EIR values in previous part because they were arbitrary and not able to be applied to all processes. However, with OSR value, they can be used for the other processes. Limiting OSR values are now based on system response and input. Boundaries are defined based on OSR value because when it is analyzed, upper and lower limiting values which were found in previous part, are close to each other and even output responses are improved. Therefore, they can be generalized.

Simulation 4.1: $G_P(S) = [0.187 / (17.46S + 1)^2] \times e^{-2S}$ (Primary process model)

Step response of non self tuning controller for this process was given in Figure 4.2. It is seen from that graph that, OSR for this loop can be calculated as:

$$OSR = (118-95) / 95 \quad OSR=0.242$$

$$\sqrt{OSR}=0.492 \quad (OSR)^2 = 0.0586$$

The step response graphic of proposed self tuning controller is given in Figure 4.4.

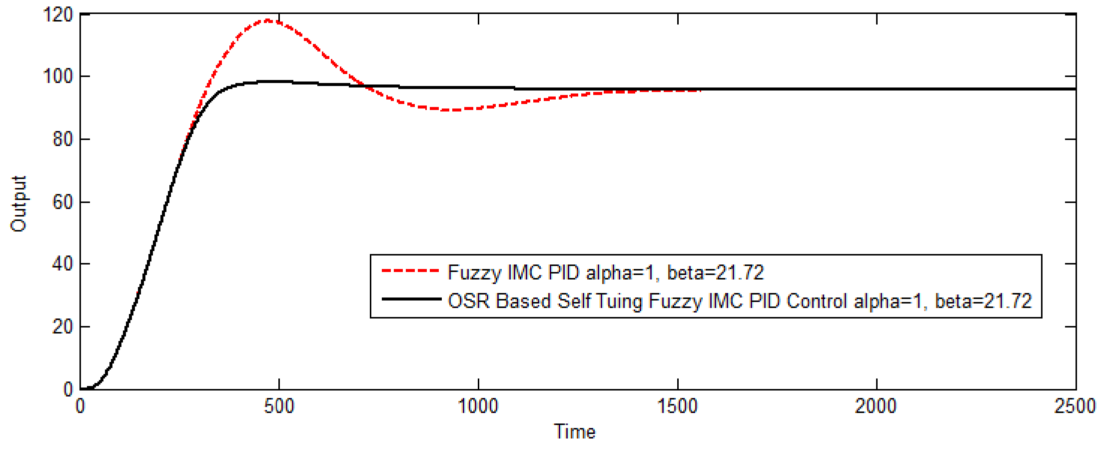

Figure 4.4 : Step Responses of Non self tuning and OSR Based self tuning control for $G_{P1}(s)=[0.187/(21.72s+1)^2]xe^{-2s}$

Figure 4.5 shows block diagram of overshoot based double step self regulating control scheme for primary process model.

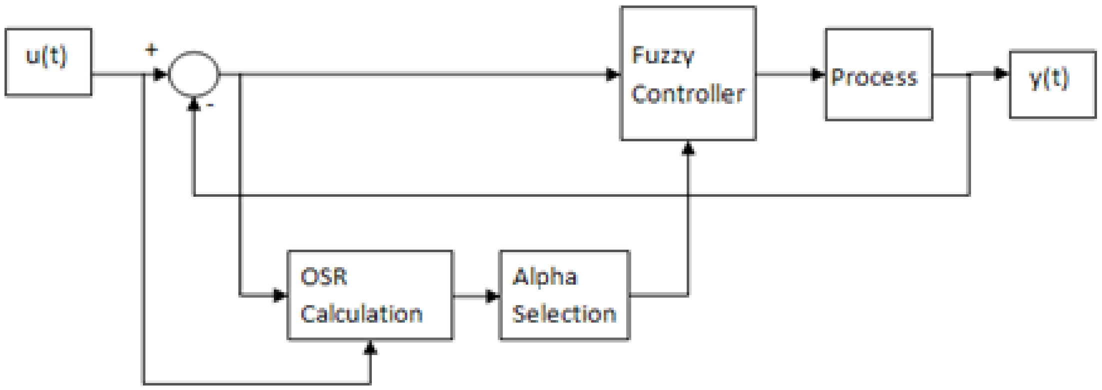

Figure 4.5 : Double step self tuning scheme for primary process model.

OSR based self tuning control scheme performs well as the previous methods but for some processes, it is seen that the proposed strategy shows negative effect on control performance. Therefore, the limiting case for this strategy is;

$$R = \left[\frac{L}{(L+\tau)}\right] < 0.33$$

If the R ratio goes beyond the mentioned boundary 0.33, then the advantage introduced by OSR based self tuning controller gets weaker gradually and as R goes beyond 0.5~0.6, self tuning controller begins to show unacceptable effect and corrupts overall system performance as it can be understand from Table 4.5. It is seen that as R ratio increases, settling time increases. Therefore, it can be understood that as R>0.333, increasing of settling time shows oscillations starts to increase.

Table 4.5 : Overshoot, offset, rise time and settling time parameters for different transfer functions and R values

Transfer Function	R	Overshoot	Offset	T_R	T_S
$G_{P1} = \frac{0.187}{(17.46s+1)^2} e^{-2s}$	0.0843	0.80	0	22.5	34.27
$G_{P2} = \frac{3}{(2s+1)^2} e^{-0.1s}$	0.0332	0.01	-0.016	2.45	3.84
$G_{P3} = \frac{3}{(5s+1)^2} e^{-2s}$	0.20	0.03	-0.013	6.75	11.4
$G_{P4} = \frac{1}{(25s+1)^2} e^{-19s}$	0.333	0.15	0.002	35	207
$G_{P5} = \frac{1}{(25s+1)^2} e^{-25s}$	0.396	0.20	0.006	35.5	524

5. MULTI-REGION SELF TUNING FUZZY IMC PID CONTROLLERS

5.1 Hybridized Three Region Self Tuning Fuzzy IMC PID Control

The control strategy proposed in Overshoot-Input Ratio Based Self Tuning Method takes overshoot data of non-self tuning controller as basis and conducts calculations and decision makings according to the ratio of overshoot to input value. So it requires reading of non-self regulating controller data, it is somehow dependent to another control scheme from its very foundation. This naturally makes this strategy be regarded as a half-manual / half automatic one because it still needs the observation and decision making of control operator.

In order to maintain some more improvement, it will be necessary to make the whole procedure independent of any other control scheme operation and resulting data. Thus, another strategy will be proposed in this section. This strategy is about reading directly the parameters of the process that will be controlled rather than overshoot data of non-self regulating control data.

This strategy is about reading time constant (τ) and delay time (L) values with relevant process and calculating the characteristic ratio of $R=L/(L+\tau)$. After this step the procedure includes deciding in to which range the value of R corresponds to and use specific functions that are already set up for each individual range. The important point here is, all of these functions have a common property of having $R=L/(L+\tau)$ data as the only independent parameter. The procedure of this control strategy is given in the following;

1. Read process data,
2. Learn about the values of τ:time constant and L:delay time,
3. Calculate the ratio $R=L/(L+\tau)$,
4. Learn the range to which R corresponds,
5. Use matching functions and decision boundaries for self tuning of α.

The idea based on which the algorithm of this strategy developed is same with that of the previous method based on overshoot data. Since "R" value gets bigger gradually by dominance of time delay over time constant, it is fair to mention that, as the time constant "τ" loses its effectiveness over system, "R" gets larger. So, tuning alpha in closer ranges to the set point will be more reasonable since it will avoid over damping without causing overshoot also. The list of ranges and corresponding functions, boundaries together with relating control rules are given in Table 5.1.

As the R ratio goes up to higher values, the ability of control techniques is becoming inadequate because the increasing R means increasing effectiveness of time delay L over time constant τ. These kinds of systems are called delay dominant systems and their successful control is much more difficult compared to the time dominant systems that introduce relatively small "R" ratios.

In order to solve the control problem of delay dominant systems, diminishing of integral gain coefficient of fuzzy controller is suggested. The simplified sectioning of R and proposed rules for newly formed sections including the ones for highly delay dominant systems $R>0.67$ are given in Table 5.1.

"Case a" rules are designed according to the following idea: When the system response is far from steady state, the controller action speed should be kept very fast. So value of alpha coefficient should be at minimum in order to prevent sluggish response. As the response approaches to steady state gradually, value of alpha is increased to an intermediate value and kept there until response gets very close to steady state. Finally, when error gets very small and response almost reaches the steady state, alpha is increased to its possible maximum.

Table 5.1 : Scaling ranges and concerning control rules for three hybridized region self tuning Fuzzy IMC PID control

Case a	0 < R < 0.33	If EIR > $\sqrt{R}$ Else if EIR > 0.0001 Else	Then $\alpha = \min(L/2, \tau)$ Then $\alpha = \sqrt{R} \times \max(L/2, \tau)$ Then $\alpha = \max(L/2, \tau)$
Case b	0.33 < R < 0.67 $t = 1 - R$	If EIR > $\sqrt{0.63}$ Else	Then $\alpha = \max(L/2, \tau) / \sqrt{t}$ Then $\alpha = \min(L/2, \tau) \times \sqrt{t}$
Case c	0.67 < R < 1		$\alpha = \beta = \min(L/2, \tau)$

"Case b" processes needed to be controlled with much larger alpha values far from the steady state and alpha should be decreased rapidly as system response approaches to set point. So alpha is first kept at values higher than the maximum of range limited by min-max of (L/2, τ) by dividing the max(L/2, τ) by √(1-R). Then the second rule that deals with steady state is defined to produce a much smaller alpha value because processes in Case b (0.67R>0.33) gave very oscillatory responses to control attempts with high alpha values near steady state.

In "Case c" calculation of "integral scaling gain K_0" according to the Equation 3.12 is corrected by replacing "variable L" with " "Lx1.67" and calculating K_0 according to 67% excess of original time delay L value. This correction maintains achieving a rather smaller K_0 value which also leads to a smaller K_1 gain with β factor held constant. So as a result, diminishing integral scaling gains enforces the controller performance for processes with very large time delay.

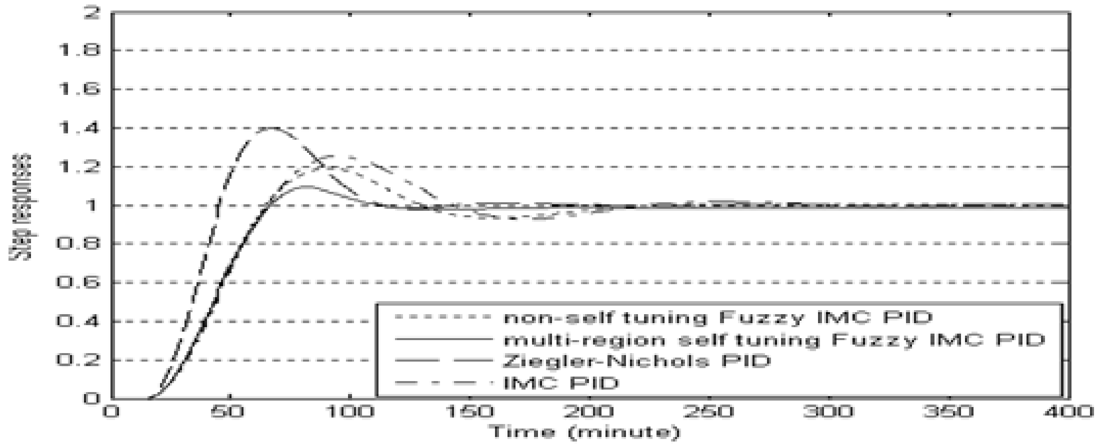

Figure 5.1 : Comparison of the step responses for the process;
$G_P(S) = [1 / (25S + 1)^2] \times e^{-14s}$ τ =38, R=0.269

As it can be inferred from Figure 5.1, fuzzy tuned self-tuning fuzzy controller strategy improves control performance for primary process model derived from the concerning reboiler by minimizing overshoot while also keeping pace high at transient zone.

5.2 Self Tuning IMC PID Control Based on Fuzzified Controllability Ratio

At this stage of the study, the main concern of this section is providing the current control strategy with a level further fuzziness. In fact, by being based on a fuzzy logic controller that is self tuned by if-then rules according to error value and in addition, determining the necessary rules by fuzzy (hybrid) transitions between rule bases, current level of control scheme is already contains a few layers of fuzziness. Next layer of fuzziness that is thought to be added to these is about fuzzifying if-then rules that determine the value of alpha. Although the rules that were finally mentioned in previous section gave a simple overview of process behaviors and provided improvement in control performances of Fuzzy IMC PID controller, their boundaries such as "if u>0.63 clause" may go under further simplification in order to give possibility to much easier design of controllers.

In fuzzifying the concerning rules and replacing strict rule bases by fuzzy decision making mechanisms, there are some important key issues which can be described briefly like following:

i. Take three section partitioning of R range as basis and divide in same manner as cases a, b and c.

ii. Since all these rules are based on minimum and maximum values of (L/2, τ) couple, they are process based and change with the process. So calculate the concerning minimum and maximum limits and store them for rules base design.

iii. For each cases (a, b and c) create a fuzzy rule base that work on one input and one output variable.

Each of the fuzzy input and output ranges shall contain five membership functions those shall be named as: very small, small, medium, large and very large. Five membership functions provide required distinction of minimum and maximum values in fuzzy understanding scheme. Input ranges shall be set between 0 and 1 since the minimum and maximum values of input u=error/input are 0 and 1 respectively. Output ranges shall be carefully set according to minimum and maximum values of alpha that could be inferred by coupling the process data and rules given in previous a, b, c case based algorithm. Once all steps mentioned above are satisfied, self tuning mechanisms based on strict if-then rules can now be replaced by relational fuzzy logic tuners.

For each three cases, a separate characteristic fuzzy rule base is defined and these rule bases are given in following:

Case a - Rule Base (u=error / input):

i. If u is very large, then alpha is very small.

ii. If u is large, then alpha is very small.

iii. If u is medium, then alpha is very small.

iv. If u is small, then alpha is small.

v. If u is very small, then alpha is very large.

These rules can be better understood if one observes the numerical rules that were generated for case a in previous section. According to both for case a, when the system response is very far from the set point, alpha scaling factor is kept at minimum level in order to provide fast response. This manner is kept constant until the system response penetrates in to a range close to steady state. When error gets small enough, alpha is slightly increased to degree “small” and when response reaches set point, output alpha is set to very large immediately in order to provide robustness around set point and avoid overshoot.

Case b – Rule Base:

i. If u is very large, then alpha is very large.

ii. If u is large, then alpha is very large.

iii. If u is medium, then alpha is very small.

iv. If u is small, then alpha is very small.

v. If u is very small, then alpha is very small.

Taking in to account the behavior of processes that are classified in case b, rule base for this case is inevitably different from that for case a. The successful control of these processes could be made by setting alpha to high values for large error zones and decreasing it immediately as response approaches set point. Experimental step response studies showed that, processes of this class returned undamped oscillatory behavior for large alpha values near steady state. Minimum and maximum boundaries of output membership functions for this case are out of boundaries determined by min $(L/2, \tau)$ – max $(L/2, \tau)$ range which was the base for case a rules. Detailed understanding of these boundaries can be obtained from the rules given in previous part about simple three section self tuning of alpha with a hybridization device.

Case c – Rule Base

i. If u is very large, then alpha is very small.

ii. If u is large, then alpha is very small.

iii. If u is medium, then alpha is very small.

iv. If u is small, then alpha is very small.

v. If u is very small, then alpha is very small.

Rule base for this case is simply based on keeping alpha at its minimum level independent of any variable. As a result, output action is kept constant at "very small" degree in each case. Besides α and β scaling factor, which conducts the relationship between K_0 and K_1 gain factors, is also kept at min (L/2, τ) value only for this case. In cases a and b, beta factor is always set to be equal to max (L/2, τ) as default.

Calculation of K_1 gain is also made by taking 67% excess of time delay (L) as basis for it was also made the same way for case c in previous three cases based study. Figure 5.2 and 5.3 show comparative graphical representation of step responses generated by both the non-self tuning and the fuzzy tuned IMC PID controllers.

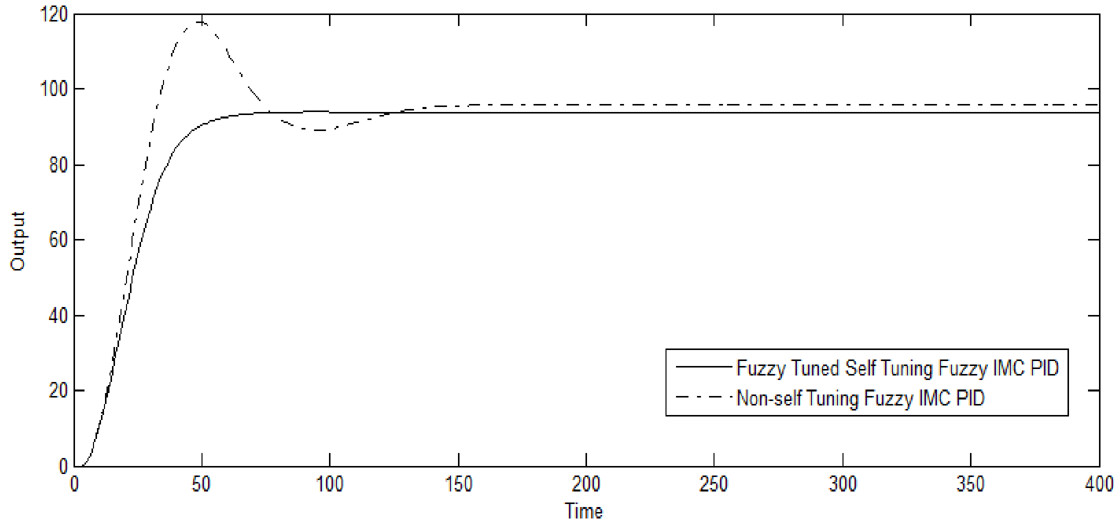

Figure 5.2 : Comparison of the step responses for the process;
$G_{P1}(s)=[0.187/(21.72s+1)^2] \times e^{-2s}$

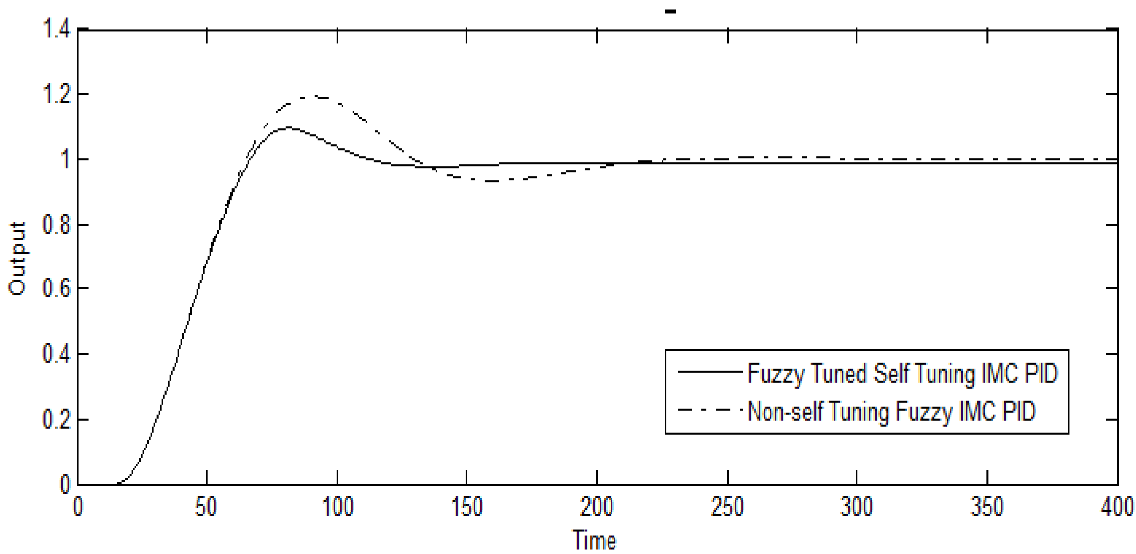

Figure 5.3 : Comparison of the step responses for the process;
$G_P(s)=[1/(25s+1)^2] \times e^{-14s}$

As it can obviously be inferred from graphics above, fuzzy tuned self tuning fuzzy controller strategy improves control performance for primary process model derived from the concerning reboiler by minimizing overshoot while also keeping pace high at transient zone. This provides the system with a much shorter settling time and taking energy input into account which is the case in real systems, proposed scheme promises much cheaper operating conditions.

Table 5.2 : Comparative rise time and maximum overshoot results of non-self tuning and multi-region self tuning Fuzzy IMC PID controllers for various processes

Process Transfer Function	Rise Time (Unit Time Period)		Maximum Peak (OS)	
	Non-Self Tuning	Multi-Region Self	Non-Self Tuning	Multi-Region Self
$\left[1/(25s+1)^2\right]\times e^{-25s}$	78.2	113	23.0%	1.5%
$\left[6/(15s+1)^2\right]\times e^{-44s}$	88.6	95.6	48.0%	25.0%
$\left[1/(25s+1)^2\right]\times e^{-14s}$	64.0	65.7	19.0%	9.5%
$\left[5/(10s+1)^2\right]\times e^{-20s}$	45.1	45.4	40.0%	19.7%
$\left[5/(3s+1)^2\right]\times e^{-75s}$	89.0	148	141.5%	47.6%

Table 5.2 and 5.3 show the advantage of fuzzy rule based self tuning Fuzzy IMC PID controllers. According to rise time, overshoot, settling time and ITSE index, the proposed method show better performance.

Table 5.3 : Comparative settling time and ITSE results of Non-Self Tuning and Fuzzy Rule Based Self Tuning Fuzzy IMC PID controllers for various processes.

Process Transfer Function	Settling Time (Unit Time Period)		ITSE (Integrated Time Square of Error)	
	Non-Self Tuning	Fuzzy Rule Based Self Tuning	Non-Self Tuning	Fuzzy Rule Based Self Tuning
$\left[1/(25s+1)^2\right]\times e^{-25s}$	325	234	1514	1251
$\left[6/(15s+1)^2\right]\times e^{-44s}$	1934	471	39670	3091
$\left[1/(25s+1)^2\right]\times e^{-14s}$	256	184	784	680
$\left[5/(10s+1)^2\right]\times e^{-20s}$	337	269	1126	681
$\left[5/(3s+1)^2\right]\times e^{-75s}$	No settling	860	9.8x105	1.2x104

6. MODEL BASED PREDICTIVE PEAK OBSERVER

There exist various heuristic and non-heuristic tuning strategies for the adaptation of scaling factors of fuzzy controllers. The peak observer idea given in [31] proposes a simple tuning structure that needs no additional designer parameter. It basically keeps watching on the system's output and transmits a signal at each peak time to adjust the input scaling factor corresponding to the derivative coefficient and the output scaling factor corresponding to the integral coefficient of the PID type fuzzy logic controller [32]. The block diagram of the proposed method is shown in Figure 6.1.

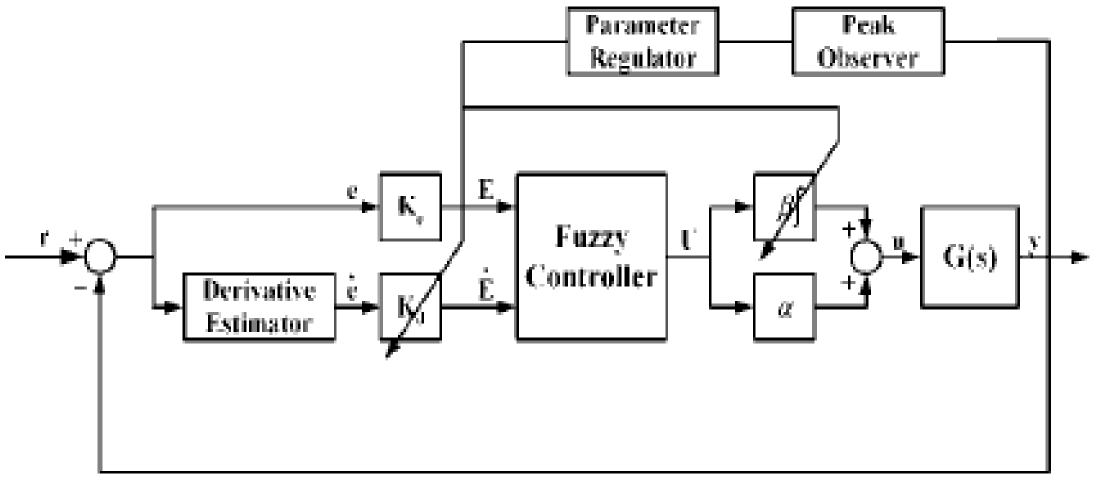

Figure 6.1 : The closed-loop control structure for parameter adaptive PID type fuzzy logic controller via peak observer

The algorithm for tuning these parameters is as follows:

$$K_d = \frac{K_{ds}}{\delta_k} \qquad\qquad \beta = \delta_k \beta_s \tag{6.1}$$

where K_{ds} and β_s are the initial values of K_d, β and δ_k values are the peak values as it is shown from the typical step response of a second order system in Figure 6.2. It can be easily deduced that if in the meanwhile of decreasing β, K_d is increased in the same rate as β is decreased, the equivalent proportional control strength will remain unchanged. Then, the system can always keep quick reaction against the error under this condition. This is achieved by updating the integral coefficient as the reciprocal of the derivative coefficient.

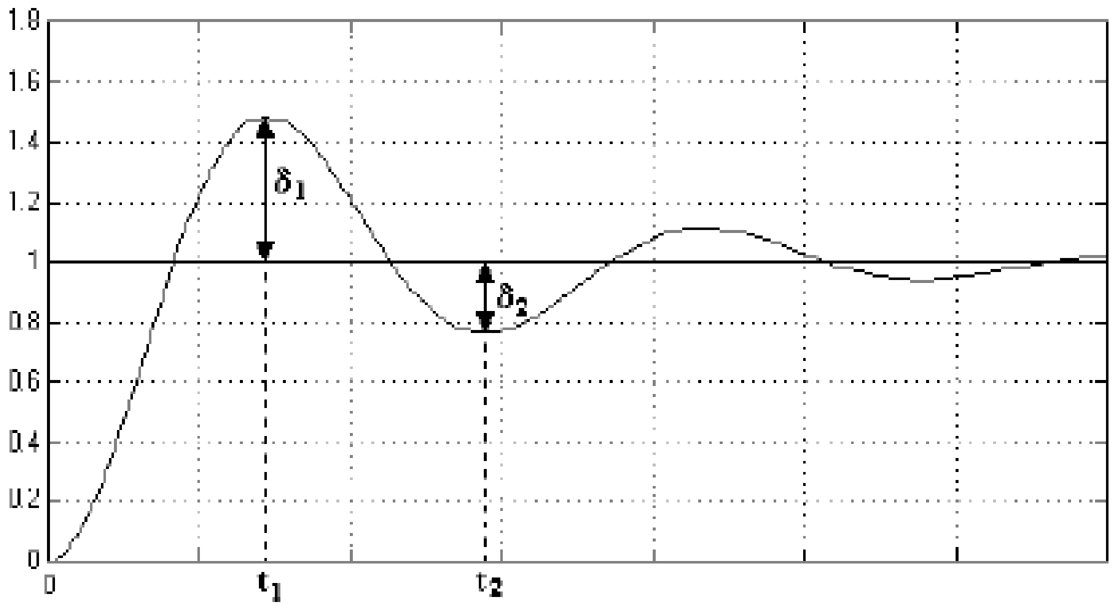

Figure 6.2 : Different phases of the step response of a control system

6.1 Fuzzy IMC PID Peak Observer Controllers

In the peak observer method, it is proposed to replace the parameters of PID with the factors related to error in the points which the output of the controlled system have the peak. This idea is first come out in the fuzzy type PID controller [31].

In this study, model based predictive peak observer method is adapted to a Fuzzy PID based on IMC. When the process responses of Multi-Region Self Tuning Fuzzy IMC PID controllers are observed, it is seen that those systems have some overshoot and oscillations. This proposed model based peak observer method can prevent oscillations in the systems with overshoot.

In this first step, a reference is applied to the system and the system is observed. In this method, the overshoot, which is obtained by adjusting the control parameters before the system reaches the peak point, will be lessening with respect to the first peak obtained by the system. In order to decrease the overshoot, it is aimed to adjust the control parameters after the system passes the reference value. Obtaining a formula which can be applied to all the systems was attempted. However, this will be the future work. But in this study, the scaling factors of PID parameters are obtained by trial and error method.

The proposed method takes the output of the system with IMC based Fuzzy PID controller basis and the PID parameters are adjusted according to the error and so before it reaches to first peak, the overshoot can be decreased by adjusting the controller parameters. Figure 6.3 shows the block diagram of the Model Based Peak Observer Fuzzy IMC PID controller.

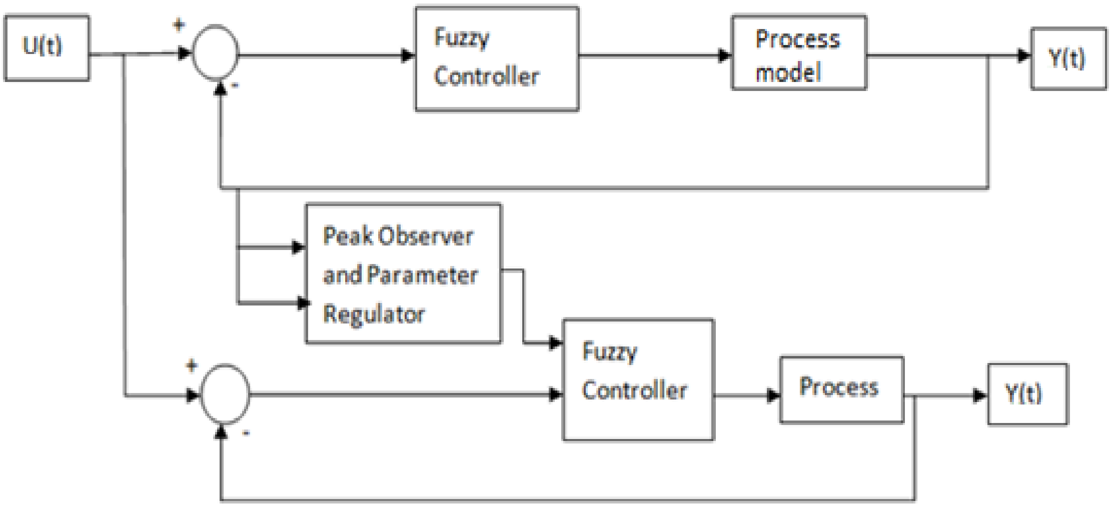

Figure 6.3 : Fuzzy IMC PID Peak Observer Controller

When this method is applied to the process in Simulation 3.1, the response of the system is shown in Figure 6.4. PID scaling factors are found as k_1=0.17, k_2=0.0018, k_3=0.1 by trial and error. It is seen that the proposed peak observer method gives smaller rise time and settling time than the others.

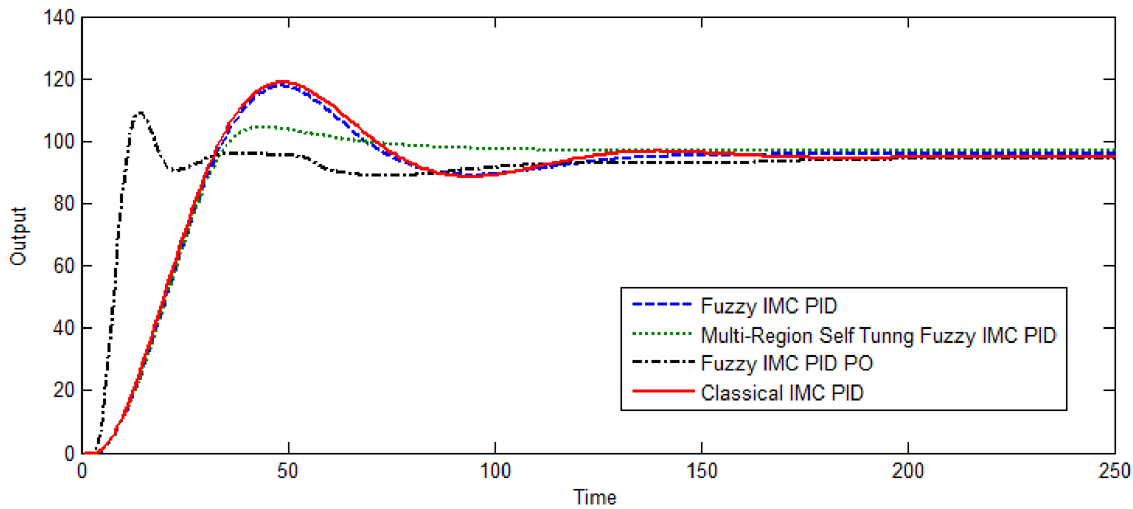

Figure 6.4 : Comparison of the step response of Simulation 3.1

In Figure 6.5, the scaling factors of PID parameters are found as k_1=3.2, k_2=0.21 and k_3=1.2 by trial and error. One can say that peak observer method gives smaller rise time, settling time and less overshoot when it is compared to the other methods.

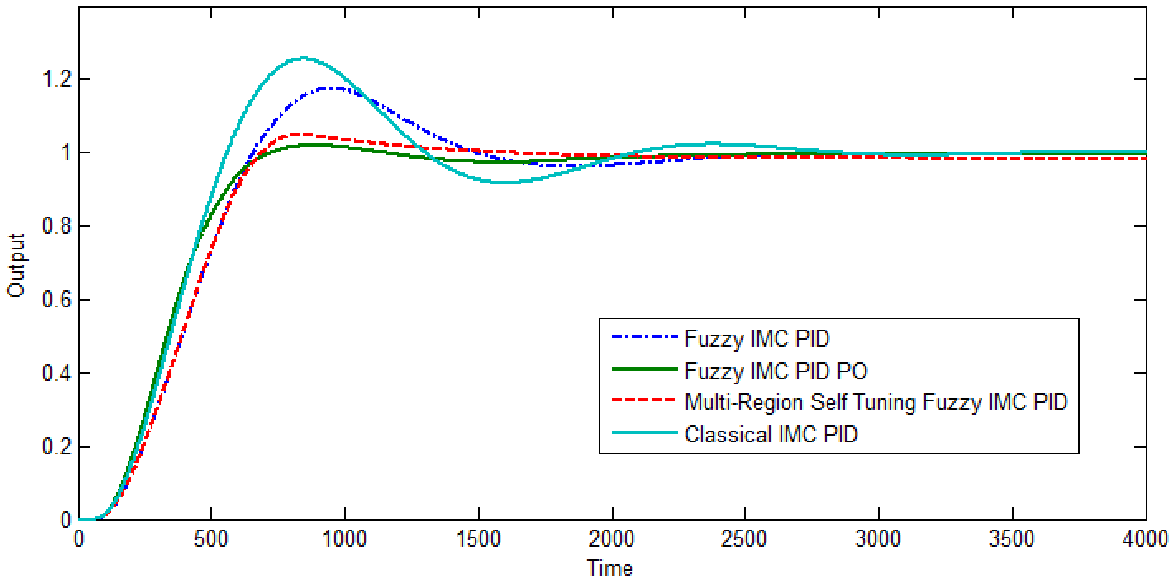

Figure 6.5 : Comparison of the step responses of $G_P(s)=[0.0708/(120s+1)^2]*e^{-18s}$

In Figure 6.6, scaling factors are obtained as k_1=8.5, k_2=0.8 and k_3=4 by trial and error method. The figure clearly depicts that the overshoot decreases considerably, and it settles in a shorter time.

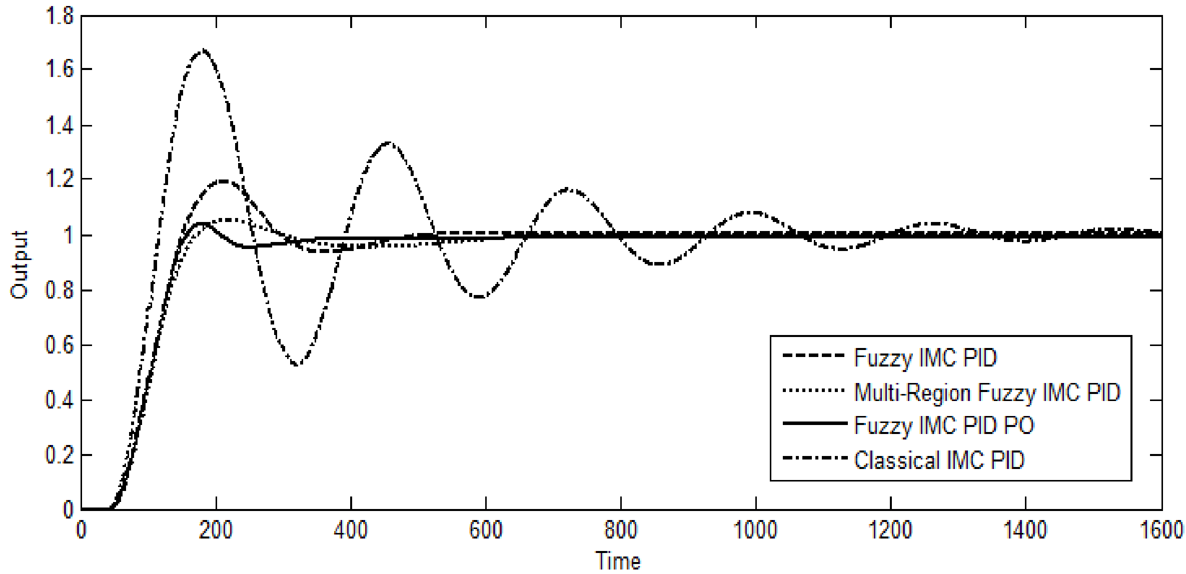

Figure 6.6 : Comparison of the step responses of $G_P(s)=[3/(2s+1)^2]*e^{-0.1s}$

In Figure 6.7, k_1=1.3, k_2=4 and k_3=0.82 are obtained by trial and error method. Again, less overshoot is obtained by peak observer method and also settling time and performance indexes which are shown in Table 6.2 indicate the advantages of this method.

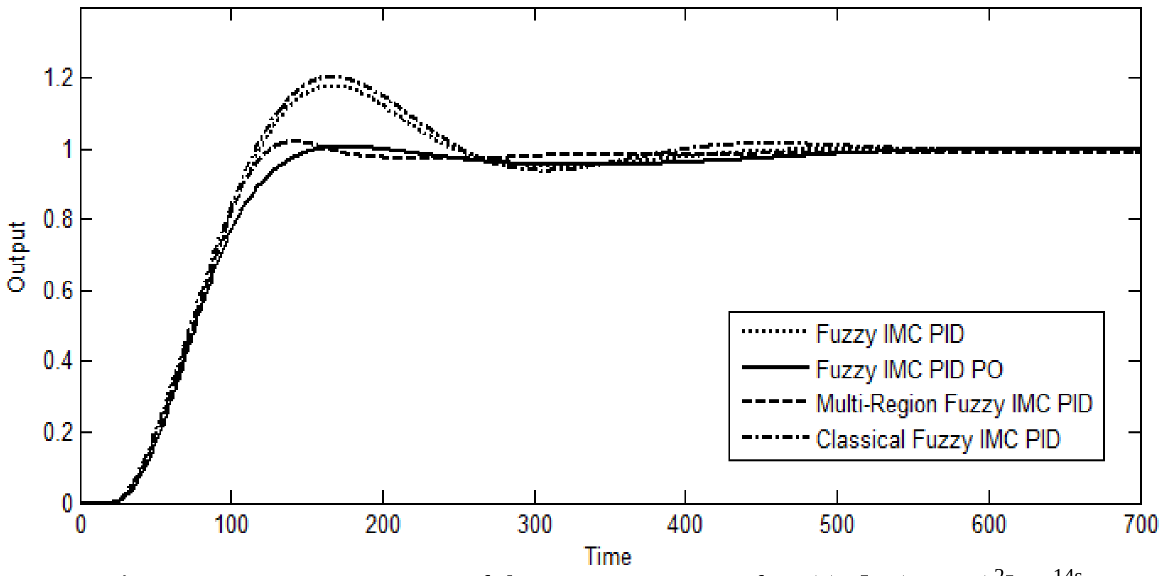

Figure 6.7 : Comparison of the step responses of $G_P(s)=[1/(25s+1)^2]*e^{-14s}$

In Figure 6.8, trial and error method gives the following parameters for PID as k_1=1.6, k_2=1.9 and k_3=0.8. Similar to the previous ones, smaller overshoot, better settling time and rise time are the important features of peak observer method.

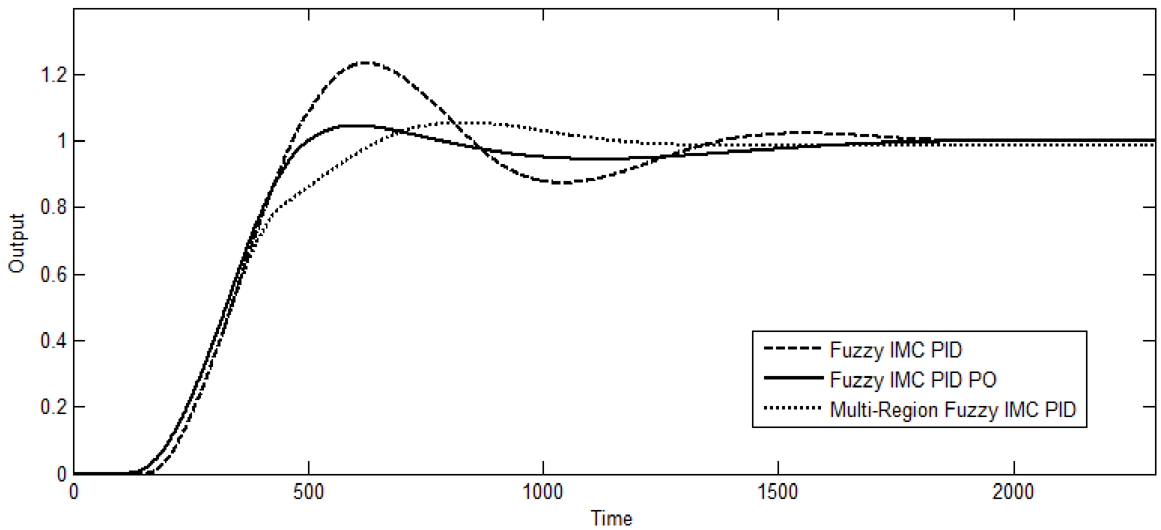

Figure 6.8 : Comparison of the step responses of $G_P(s)=[3/(5s+1)^2]*e^{-2s}$

Table 6.1 : Comparison of non self-tuning control with peak observer based control according to rise time, settling time, overshoot and steady-state error

Processes	Rise Time		Settling Time		Overshoot		Steady-state Error	
	Non P.O*	With P.O*	Non P.O*	With P.O*	Non P.O*	With P.O*	Non P.O*	With P.O*
$\frac{0.187}{(17.46s+1)^2}e^{-2s}$	20.1	5.22	104.2	87.8	22.7	14.5	+0.7	-0.7
$\frac{0.0708}{(120s+1)^2}e^{-18s}$	147.9	145.4	480	230	0.175	0.04	-0.004	+0.015
$\frac{3}{(2s+1)^2}e^{-0.1s}$	2.425	1.27	7.7	7.6	0.16	0.035	-0.007	-0.002
$\frac{1}{(25s+1)^2}e^{-14s}$	33.8	39	180	70	0.195	0.025	+0.0015	+0.001
$\frac{3}{(5s+1)^2}e^{-2s}$	6.68	7.1	22.4	12.3	0.18	0.034	-0.004	+0.0002
$\frac{1}{(25s+1)^2}e^{-25s}$	36	43.5	212.4	83	0.235	0.01	-0.002	-0.0007

Non P.O.* : non self-tuning fuzzy IMC PID process response

With P.O.* : model based predictive peak observer fuzzy IMC PID process response

In Table 6.1, the differences between non self-tuning fuzzy IMC PID control and model predictive peak observer control can be obviously seen. Peak observer based control method shows smaller rise time, settling time, overshoot and also steady state error. Oscillations also decrease with this method.

6.2 Comparison Between Peak Observer and Multi-Region Self Tuning Methods

The advantages of model predictive peak observer based control over multi-region self tuning control can be easily seen in Table 6.2. Performance indexes ITAE and ITSE show that peak observer based control gives relatively less error. Also it can be concluded that this proposed method is the best choice according to overshoot, rise time, settling time and steady-state error parameters.

Table 6.2 : Comparison of multi-region self-tuning control with peak observer based control according to ITAE, ITSE, rise time, settling time, overshoot and steady-state error

		$\frac{0.187}{(17.46s+1)^2}e^{-2s}$	$\frac{0.0708}{(120s+1)^2}e^{-18s}$	$\frac{3}{(2s+1)^2}e^{-0.1s}$	$\frac{1}{(25s+1)^2}e^{-14s}$	$\frac{3}{(5s+1)^2}e^{-2s}$
ITSE	M.R*	1.35x106	6955	1.547	740.2	22.59
	P.O*	0.3x106	5234	0.5195	687.1	20.32
ITAE	M.R*	9.075x104	2.694x104	9.059	4092	74.13
	P.O*	5.374x104	1.654x104	6.722	2615	66.36
Rise Time	M.R*	20.2	149.5	2.47	37	7.6
	P.O*	5.6	142	1.25	34.5	6.6
Settling Time	M.R*	68	227	3.5	99	13.2
	P.O*	87	220	1.85	62	11.4
Overshoot	M.R*	9.5	0.5	0.073	0.053	0.017
	P.O*	4.7	0.2	0.03	0.037	0.005
Steady State Error	M.R*	2	0.016	0.003	0.002	0.001
	P.O*	1	0.002	0.002	0.008	0.012

M.R* : Multi-region self tuning fuzzy IMC PID control based system response

P.O.* : Model based predictive peak observer fuzzy IMC PID control based system response

7. CONCLUSIONS AND RECOMMENDATIONS

In this study, multi-region self tuning method and model based peak observer method for Fuzzy IMC PID controllers are proposed.

After modeling studies of reboiler process transfer function, classical and fuzzy IMC PID controllers were designed for any given process. Reboiler process transfer function and controller design calculations made for this process and were demonstrated as primary model example. According to the results of the primary process model and a few different processes with varying transfer functions, Fuzzy IMC PID controller has advantages over classical controllers but for highly delay dominant systems, it has certain drawbacks.

Therefore, some self tuning strategies were developed for fuzzy IMC PID controller. From the analysis of design parameters of fuzzy IMC PID controller, smaller α and larger β section makes the system response faster but causes some overshoot while larger α and smaller β provides more sluggish response but smaller settling time with much less overshoot. In order to achieve the best possible result, a serious of trials all of that concerns to different α-β combinations were conducted for the process under investigation. The transient part of $\alpha=1$ and $\beta=21.72$ system and steady state performance of $\alpha=10$ or 5 and $\beta=21.72$ system is planned to be combined to make system response rise fast and settle well. As it is seen β should be constant at 21.72 but α should be selected a value between 1 and 10. It can be concluded as α value gets bigger gradually, rise time increases, so response slows down too early but overshoot decreases. Because of the system response needs to be kept fast until a specified ratio of ultimate response is achieved, EIR (Error Input Ratio) is defined and α is kept minimum until the specified ratio, after the specified ratio α begins to increase gradually. This allows system response stay fast as long as possible and begin to slow down when it is about to reach the set point. double step self tuning Fuzzy IMC PID controller gives better results compared to its non-self tuning type but these results cannot be generalized for all kinds of processes. Therefore, the step response of the process controlled by non-self-tuning controller is examined and first overshoot peak value is observed. By dividing this value with input value, a new ratio parameter is defined as OSR. The results of processes with this OSR based self tuning Fuzzy IMC PID controllers are quite well when they are compared to ones with non-self tuning Fuzzy IMC PID controllers. But It is seen that as R ratio increases, settling time increases and for the processes with controllability ratio greater than 0.33, oscillations starts to increase.

The first proposed strategy is Multi-Region Self Tuning Fuzzy IMC PID controllers. Self tuning rule base table was obtained by partitioning the controllability ratio R in to three portions which means 0.33 for each in partitioning of 0-1 range. After that, rules in each three sections were replaced with fuzzy “if – then” rules in order to soften the transient zone behaviors along rule boundaries and also along partitioned portion boundaries. The final results showed that proposed multi region self tuning rules improved step response performance of Fuzzy IMC PID controller by providing it with the proper self tuning strategies for each kind of process behavior.

Another proposed strategy is Model Based Predictive Peak Observer method for Fuzzy IMC PID controllers. In this method, it is treated before the system reaches its peak point based on its process model. The adjustments of PID controller parameters are found by trial and error method. The results of the primary process and the other kinds of processes a comparison was made based on the performance indexes such ITAE and ITSE, rise time, settling time, overshoot and steady state error. It can be easily said that the proposed peak observer method improved the response performance of fuzzy IMC PID controller.

For future work, instead of using trial and error method for adjusting PID parameters, they should be found from process parameters so it can be generalized for all kinds of processes. Also, detailed investigation is needed for disturbance effects and responses.

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