CHAPTER 5

VIRTUAL FEEDBACK CONTROL

5.1 INTRODUCTION

The Limitations of classic cascade control (Stephanopoulos 2005) scheme in CSTR:

- Continuous concentration measurement is not available.
- Temperature is measured to infer about the concentration.
- Cascade control scheme uses more number of transmitters and controllers.
- Measurement inaccuracies are involved in conventional transmitters.

To overcome these addressed problems, Virtual Feedback Control is proposed. It is a type of inferential control. An inferential control system has been defined as a control system that requires an estimated or inferred value of a variable to calculate the value of a manipulated input (Srinivasan 2000). The design of an inferential control system consists of two steps:

i) The synthesis of a controller assuming that all the controlled outputs are measured readily

ii) The design of an estimator to estimate the controlled outputs that are not measured readily
The EKF acts as a soft sensor which is used to estimate concentration (unmeasured) from readily available temperature measurement. The estimated value is given to the feedback controller as process variable and the control will be executed. The block diagram of the proposed virtual feedback controller is shown in Figure 5.1.

![Block Diagram of Virtual Feedback Control](image)

**Figure 5.1 Block Diagram of Virtual Feedback Control**

During the past decades, the process control industries have made great advances. Numerous control methods such as Adaptive Control, Neural Network and Fuzzy Control have been studied. Among them, the best known is the Proportional-Integral-Derivative (PID) controller which has been widely used in the industry because of its simple structure and robust performance under wide range of operating conditions. Unfortunately, it has been quite difficult to tune properly the gains of PID controller because many industrial plants are often burdened with problems such as higher order of the system, time delay and nonlinearities associated with the system. Also, it is hard to determine the optimal or near optimal PID parameters using classical tuning methods. For these reasons, it is highly desirable to increase the capabilities of PID controllers by adding many new features. Many Artificial Intelligence (AI) techniques have been employed to improve the controller
performance for a wide range of plants while retaining their basic characteristics. Artificial Intelligence techniques such as Neural Network, Fuzzy Logic have been widely applied to proper tuning of PID controller parameters.

Particle Swarm Optimization (PSO), first introduced by Kennedy &Eberhart (1995), is one of the modern heuristic algorithms. It can generate high quality solution within short calculation time and show stable convergence characteristics than other stochastic methods. PSO is an excellent optimization methodology and is a promising approach for optimal tuning of PID controller parameters. Here, the PSO approach is done for optimal tuning of PID controller parameters for Continuous Stirred Tank Reactor (CSTR) system.

5. 2  TUNING ALGORITHMS

Tuning of a controller refers to the methods of determining the parameters of a PID controller for the given system. The design methods differ with respect to the knowledge of the process dynamics that is required. A PID controller is described by three parameters like $K_p$, $\tau_i$ and $\tau_d$. There are many different methods to find the suitable parameters of the controller. The methods differ in complexity, flexibility and the amount of process knowledge used. Three tuning algorithms discussed below have been used in this work.

5.2.1  Ziegler Nichols Tuning

In Ziegler and Nichols method describing simple mathematical procedures, for tuning the PID controllers. Both the techniques make a priori assumption on the system model, but do not require the system model to be
specifically known. Ziegler-Nichols formulae for specifying the controllers are based on the plant step response.

a) **Open Loop Response:** The open-loop method is typical for a first-order system with transportation delay. The response is characterized by 2 parameters, $L$ the time-delay and $T$ the time-constant. These are found by drawing a tangent to the step response at its point of inflection and noting its intersections with the time axis and steady-state value.

b) **Closed Loop Response:** The closed-loop method targets plant that can be rendered unstable under proportional control. The technique is designed to result in a closed loop system with 25% overshoot.

5.2.2 **Genetic Algorithm (GA)**

Genetic Algorithm is a search technique to determine approximate solutions to optimization and search problems. The problem consists in finding out the solution that fits the best from all the possible solutions. GA handles a population of possible solutions. Each solution is represented through a chromosome, which is just an abstract representation. A set of reproduction operators has to be determined. Reproduction operators are applied directly on the chromosomes, and are used to perform mutations and recombination over solutions of the problem. It can be extremely difficult to find a representation, which respects the structure of the search space and reproduction operators, which are coherent and relevant according to the properties of the problems. Selection is supposed to be able to compare each individual in the population.
Selection is done by using a fitness function (Mohammed El-Said & El-Telbany 2007). Each chromosome has an associated value corresponding to the fitness of the solution it represents. The fitness should correspond to an evaluation of how good the candidate solution is. The optimal solution is the one, which maximizes the fitness function. Genetic Algorithm deals with the problems that maximize the fitness function. But, if the problem consists in minimizing a cost function, the adaptation is quite easy. Either the cost function can be transformed into a fitness function, by inverting it; or the selection can be adapted in such way that they consider individuals with low evaluation functions as better. Once the reproduction and the fitness function have been properly defined, a Genetic Algorithm is evolved according to the same basic structure. It starts by generating an initial population of chromosomes. Generally, the initial population is generated randomly.

5.2.3 Particle Swarm Optimization

Particle swarm optimization (PSO) is a population based stochastic optimization (Kennedy & Eberhart 1995), inspired by social behavior of bird flocking or fish schooling. PSO shares many similarities with evolutionary computation techniques such as Genetic Algorithms (GA). The system is initialized with a population of random solutions and searches for optima by updating generations. However, unlike GA, PSO has no evolution operators such as crossover and mutation. In PSO, the potential solutions called particles, fly through the problem space by following the current optimum particles.

In the past several years, PSO, (Clerc & Kennedy 2002) has been successfully applied in many research and application areas. It is demonstrated that PSO gets better results in a faster, cheaper way compared with other methods. Another reason that PSO is attractive is that there are few parameters to adjust. One version, with slight variations, works well in a wide
variety of applications. Particle swarm optimization has been used for approaches that can be used across a wide range of applications, as well as for specific applications focused on a specific requirement.

**a) Operations in PSO:** In D-dimensional search space (Mohammad Ali Nekoui et al 2010), the position of the \(i^{th}\) particle can be represented by a \(D\)-dimensional vector \(x_i = (x_{i1}, \ldots, x_{id}, \ldots, x_{iD})\). The velocity of the particle can be represented by another \(D\)-dimensional vector \(v_i = (v_{i1}, \ldots, v_{id}, \ldots, v_{iD})\). The best position previously visited by the \(i^{th}\) particle is denoted as \(p_i = (p_{i1}, \ldots, p_{id}, \ldots, p_{iD})\) and \(p_g\) as the index of the particle visited the previous position in the swarm, then \(p_g\) becomes the best solution found so far, and the velocity of the particle and its new position will be determined according to the following two equations with inertia weight \(w\) added to it.

\[
\begin{align*}
v_{id} &= w v_{id} + c_1 r (p_{id} - x_{id}) + c_2 R (p_{gd} - x_{id}) \quad (5.1) \\
x_{id} &= x_{id} + v_{id} \quad (5.2)
\end{align*}
\]

where \(c_1\) and \(c_2\) are positive constants, and \(r\) and \(R\) are two random functions in the range \((0,1)\). \(x_i = (x_{i1}, \ldots, x_{id}, \ldots, x_{iD})\) represents the location of \(i^{th}\) particle and \(p_i = (p_{i1}, \ldots, p_{id}, \ldots, p_{iD})\) represents the previous best position (the position giving the best fitness value) of the \(i^{th}\) particle. The symbol \(g\) represents the index of the best particle among all the particles in the population. \(v_i = (v_{i1}, \ldots, v_{id}, \ldots, v_{iD})\) represents the rate of change of position (velocity) for the \(i^{th}\) particle (Clerc&Kennedy2002). The parameter \(w\) in the equation (5.1) is the inertia weight that increases the overall performance of PSO. Larger value of \(w\) can increase the ability for global search while lower value of \(w\) implies higher ability for local search.
b) **Optimal Tuning of PID controllers using PSO**: The value of fitness function defined by the optimization algorithm would be minimal. Performance characteristic of evaluation function would include over-shoot, rise-time and settling-time. Evaluation function computes the evaluation value of each particle in the swarm according to the control objective. The steps involved in designing PSO algorithm is given below. The block diagram representation of tuning the PID controllers of the CSTR system using PSO is shown in the Figure 5.2. The soft sensor used here is EKF which aids in the virtual feedback control.

![Figure 5.2 Block Diagram of proposed method using PSO](image)

The sequence of steps to study the PSO for the CSTR system is given below:

**STEP 1**: Specify the lower and upper bounds of the three $K_p, K_i, and K_d$. Initialize randomly the particles of the swarm including swarm size,
iteration, acceleration constant, inertia weight factor, the position matrix $x_i$ and the velocity matrix $v_i$ and so on.

**STEP 2**: Calculate the evaluation value of each particle using the evaluation function given.

**STEP 3**: Compare each particle's new fitness value with its personal best position's fitness value, and update the personal best position $p_{best}$.

**STEP 4**: Search for the best position among all particles' personal best position, and denote the best position as $g_{best}$.

**STEP 5**: Update the velocity $v_i$ of each particle according to equation (5.1), and update the particle position matrix according to equation (5.2).

**STEP 6**: Update control parameter.

**STEP 7**: If the number of iterations reaches the maximum, then stop. The latest $g_{best}$ is regarded as the optimal PID controller parameter. Otherwise, go to step 2.

Though PSO algorithm is much advanced and simpler than other artificial intelligence based approach, it has its own short-comings. In this application, PSO algorithm was taken and applied for single set of data ($K_p, K_i$ and $K_d$). Generally this can be seen as a limitation in terms of not being able to analyse multiple sets of data.

### 5.3 STRUCTURE OF ENHANCED PID (EPID)

The inability of a conventional PID controller to optimize set-point response and disturbance response simultaneously has led to a situation to choose one of the next alternatives:
i) To choose one of the Pareto optimal point or

ii) To use the disturbance optimal parameters and impose limitation on the change of the set-point variable (i.e. to use a rate limiter for the set-point r).

Under the process engineering of early days, when the set-point variable was not changed very often, the second alternative was satisfactory enough. Therefore, many of the optimal tuning methods gave only the “disturbance optimal” parameters. However, the situation has changed in the last few decades and the process control systems are required to change the set-point variable frequently nowadays. The EPID controller offers a powerful means to cope with such a situation. So, a controller has to be designed such that both the disturbance and set-point responses can be tuned independently. A general form of the 2 DoF control system is shown in Figure 5.3, where the controller consists of two components $C(s)$ and $C_f(s)$, and the transfer function $P_d(s)$ from the disturbance $d$ to the controlled variable $y$ is assumed to be different from the transfer function $P(s)$ from the manipulated variable $u$ to $y$. $C(s)$ is called the serial (or main) compensator and $C_f(s)$ the feed forward compensator.

![Figure 5.3 Structure of 2DoF PID controller (FF)](image)
The three parameters of $C(s)$ i.e., the proportional gain $K_p$, the Integral time $T_I$, and the Derivative time $T_D$ will be referred to as “basic parameters”, and the two parameters of $C_f(s)$, i.e., $\alpha$ and $\beta$, as “2DoF parameters”. These five parameters will be treated as adjustable parameters. The basic PID tuning parameters is obtained using PSO method. The other two parameters ($\alpha$ & $\beta$) are chosen as 0.5.

5.4 SIMULATION RESULTS AND DISCUSSION

In all the simulation studies, true state variables are computed by solving nonlinear differential equations using ODE solver. These state variables are estimated using EKF algorithm assuming that the plant gets affected by Gaussian noise. The tuning parameters of EKF is given in chapter 4. The optimized PID tuning parameters of the CSTR system is obtained using Ziegler – Nichols Tuning, Genetic Algorithm and Particle Swarm Optimization. The results from all the three tuning techniques are compared on simulated model of CSTR.

5.4.1 Standard Operating Conditions

The standard operating conditions were considered for all the iterations as they have offered improved repeatability. The parameters of a PSO algorithm and Genetic Algorithm (GA) are given below. It is to be noted that for obtaining optimum PID parameters, the swarm iteration alone is varied.

\[
C(s) = K_p\left\{1 + \frac{1}{T_I s} + T_D D(s)\right\}
\]

\[
C_f(s) = -K_p\left\{\alpha + \beta T_D D(s)\right\}
\]
PSO specifications:

Weight / Inertia of the system – 0.5.

Acceleration constants, $c_1$ and $c_2$ – 1.5.

Swarm population – 100.

Dimension of the search-space – $3(K_p, K_i, K_d)$.

GA Specification:

No.of generation: 100

Type of Scale: Normal geometric

Type of cross over: arithmetic

Type of mutation: non uniform

5.4.2 Robustness of PSO Algorithm

Since varying the swarm iteration is considered as the only tuning factor, compare the results of PID controller for various iterations in PSO and conclude which among these gives the best fitness function. Iterations considered are 50, 100, 150 and 200.

From Figure 5.4, it is seen that the tuning parameters obtained for 200 iterations shows far better results than the others. The optimized PID parameters are listed in the Table 5.1.
Figure 5.4 Plot of PSO response for different iterations

Table 5.1 Optimized PID tuning parameters of PSO for different iterations

<table>
<thead>
<tr>
<th>No of Iterations</th>
<th>$K_p$</th>
<th>$K_i$</th>
<th>$K_d$</th>
</tr>
</thead>
<tbody>
<tr>
<td>50</td>
<td>0.2896</td>
<td>0.01177</td>
<td>0.6638</td>
</tr>
<tr>
<td>100</td>
<td>0.3260</td>
<td>0.02488</td>
<td>0.7497</td>
</tr>
<tr>
<td>150</td>
<td>0.3297</td>
<td>0.02548</td>
<td>0.7936</td>
</tr>
<tr>
<td>200</td>
<td>0.4140</td>
<td>0.02714</td>
<td>0.8487</td>
</tr>
</tbody>
</table>

5.4.3 Calculation of Fitness Function

A particular point in the search-space is the best point for which the fitness function attains an optimum value. In this case, four components are taken to define the fitness function. The fitness function is a function of steady-state error, peak overshoot, rise time and settling time. However, the contribution of these component functions towards the original fitness function is determined by a scaling factor. Scaling factor ($\beta$) is chosen as 1 in this application. The chosen fitness function is expressed as
\[ F = (1 - \exp(\beta))(M_P + E_{SS}) + (\exp(-\beta))(T_s - T_r) \]  

(5.5)

where,

- \( F \) - Fitness Function
- \( M_P \) - Peak Overshoot
- \( E_{SS} \) - Steady State Error
- \( T_s \) - Settling Time
- \( T_r \) - Rise Time
- \( \beta \) - Scaling Factor

The fitness function calculated for different values of iteration are shown below in Table 5.2. Table 5.2 show minimum fitness function value is obtained when number of iteration is chosen as 200. So the system exhibited best performance index to 200 iterations.

**Table 5.2 Fitness function calculated for different iterations**

<table>
<thead>
<tr>
<th>No of Iteration</th>
<th>Fitness Function</th>
</tr>
</thead>
<tbody>
<tr>
<td>50</td>
<td>7.1221</td>
</tr>
<tr>
<td>100</td>
<td>5.7467</td>
</tr>
<tr>
<td>150</td>
<td>5.2415</td>
</tr>
<tr>
<td>200</td>
<td>4.9916</td>
</tr>
</tbody>
</table>

5.4.4 **Performance Index**

Performance Index is a quantitative measure of the performance of the system. A system is considered as an optimal system when its parameters are adjusted so that the index reaches an extreme value, commonly a
minimum value. A suitable performance index is the Integral Square Error (ISE), which is defined as

\[ ISE = \int_{0}^{T} e(t)^2 \, dt \] (5.6)

ISE is more suitable to minimize large amount of errors. The squared error is mathematically more convenient for analytical and computational purposes.

Other performance criteria include evaluation of rise-time, settling-time and peak overshoot are given in Table 5.3. Rise time is the time taken for the response to rise from 0 to 100% for the first time. Settling time is defined as the time taken by the response to reach and stay within specified error limit. Peak Overshoot is the ratio of maximum peak value measured from maximum value to the final value.

**Table 5.3 Comparison of performance indices**

<table>
<thead>
<tr>
<th>Performance Index</th>
<th>ZNT</th>
<th>GA</th>
<th>PSO</th>
</tr>
</thead>
<tbody>
<tr>
<td>ISE</td>
<td>2.844</td>
<td>2.011</td>
<td>1.706</td>
</tr>
<tr>
<td>Rise Time (s)</td>
<td>20.06</td>
<td>28.56</td>
<td>50.47</td>
</tr>
<tr>
<td>Settling Time (s)</td>
<td>164.32</td>
<td>89.34</td>
<td>79.38</td>
</tr>
<tr>
<td>Peak Overshoot (%)</td>
<td>28.20</td>
<td>12.58</td>
<td>2.74</td>
</tr>
</tbody>
</table>

**5.4.5 Comparative results of GA, ZNT and PSO**

A single loop PID tuning of a CSTR system is done using three standard tuning techniques like Ziegler-Nichols Tuning, Genetic Algorithm and Particle Swarm Optimization. The closed loop response of the three discussed methods is shown in Figure 5.5. The set point is given as 0.08235 mol/lit.
The desired PID tuning parameters from these three methods are given in Table 5.4.

**Table 5.4 Tuning parameters obtained for GA, ZNT and PSO**

<table>
<thead>
<tr>
<th>Tuning Algorithm</th>
<th>$K_p$</th>
<th>$K_i$</th>
<th>$K_d$</th>
</tr>
</thead>
<tbody>
<tr>
<td>ZNT</td>
<td>0.9903</td>
<td>0.0877</td>
<td>0.4288</td>
</tr>
<tr>
<td>GA</td>
<td>0.8861</td>
<td>0.0587</td>
<td>0.6271</td>
</tr>
<tr>
<td>PSO</td>
<td>0.4140</td>
<td>0.02714</td>
<td>0.8487</td>
</tr>
</tbody>
</table>

By comparing all the three methods using performance indices are given in Table 5.3. It is found that PSO algorithm has minimum ISE value, Settling time and peak overshot than ZNT and GA method. So PID controller parameters obtained from PSO algorithm gives smooth response and better performance than the other two methods.
5.4.6 Closed loop control of Enhanced PID (EPID)

The closed loop analysis of CSTR is performed with virtual feedback control using EPID (2 DoF). The closed loop servo and regulatory response of 2 DoF PID is compared with conventional PID (1 DoF) in simulation mode. The comparative results obtained is shown in following Figures.

Case 1: Servo Response (Normal operating conditions)

Figure 5.6 Servo response of concentration with virtual feedback control

Figure 5.6 shows the closed loop servo response of the concentration for a set point change of 0.08 to 0.06 mol/l. The variation in the control input (coolant flow rate) is shown in the Figure 5.7.
Case 2: Regulatory response:

Figure 5.8 shows the regulatory response of concentration. A change in inlet feed temperature has been introduced at an instant of 130 Sec from 350K to 340K as disturbance and the variation in the coolant flow rate is as shown in the Figure 5.9. At the instant of disturbance, a deviation is observed. The concentration settles with an offset in 1 DoF. In 2 DoF it settles with desired set point after some short time instance.

Figure 5.8  Regulatory response of concentration with virtual feedback control( feed temperature variation)

Figure 5.9  Variation in coolant flow rate in regulatory operation (expanded view)

Figure 5.10 shows the regulatory response of concentration, when the inlet coolant temperature introduced as a disturbance. A change in inlet
coolant temperature has been varied at an instant of 130 Sec from 350K to 340K. The variation in the coolant flow rate is shown in the Figure 5.11. At the instant of disturbance, an overshoot in response is observed. Both the controllers settles in desired set point after some time. So coolant temperature variation has been less impact on controlled variable of CSTR process.

Figure 5.10  Regulatory response of concentration with virtual feedback control (coolant temperature variation)

Figure 5.11  Variation in coolant flow rate in regulatory operation (coolant temperature variation)
Table 5.5 Comparative Performance Analysis of virtual feedback control

<table>
<thead>
<tr>
<th></th>
<th>Conventional PID( 1 DoF)</th>
<th>EPID (2 DoF)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Performance index</td>
<td>ISE</td>
<td>ISE</td>
</tr>
<tr>
<td>Servo operation</td>
<td>0.03304</td>
<td>0.03396</td>
</tr>
<tr>
<td>Regulatory operation (Feed Temperature variation)</td>
<td>0.0607</td>
<td>0.0367</td>
</tr>
<tr>
<td>Regulatory operation (Coolant Temperature variation)</td>
<td>0.0535</td>
<td>0.0399</td>
</tr>
</tbody>
</table>

Figure 5.12 Comparative performance analysis of 1 DoF and 2 DoF PID

The Integral Square Error (ISE) of servo and regulatory response of concentration control of the CSTR process is given in Table 5.5 and ISE bar graph shown in Figure 5.12. An EKF is placed in the feedback path instead of the physical hardware sensor. It leads to virtual feedback control. Then, virtual feedback control has implemented for direct concentration control using both 1 DoF and 2 DoF PID structure. The simulation results confirm that the proposed method can able to control the reactor concentration directly with the help of virtual sensor (EKF). Table 5.5 shows the proposed method using EPID and it gives a minimum ISE value than conventional 1 DoF PID.
for both servo and different cases of regulatory operation. It can be concluded that Enhanced version PID (EPID) controller with proper tuning method is more suitable for real time process control applications.

5.5 EXPERIMENTAL RESULTS AND DISCUSSION

The efficacy of this proposed method is demonstrated in real time. The liquid level process is considered to implement the soft sensing technique using EKF. The same process is taken to implement the virtual feedback control using 1 DoF PID and 2 DoF PID structure in real time using LabVIEW Compact RIO. In Chapter 2, the mathematical model of CSTR liquid level process is obtained using system Identification. That state space model is used to implement the soft sensing technique (EKF) to estimate the liquid level of the process. The estimated value is given as feedback to the PID controller.

5.5.1 Servo response of 1 DoF PID Controller

The set-point and the sampling time are set by the user, and the tank level in mm is displayed by a numerical indicator and a ‘tank’ display. Online monitoring of the process is done to get instantaneous value of the output. The parameters ‘ISE’, ‘IAE’ and ‘ITAE’ describe the performance of the system. The tuning parameters considered are $K_p = 28; T_i = 205.15$ s; $T_d = 50$ s. Improved relay feedback auto tuning method is used to obtain the online tuning parameters of PID.(Thyagarajan & Cheng Ching Yu 2003)
Figure 5.13 Servo response of 1DoF PID controller (Conventional feedback)

Figure 5.13 shows the servo response of 1DoF PID controller for the CSTR liquid level process without an EKF. Since the set-point is varied, keeping the intentional disturbance as zero, it is called as servo response. A set-point of 250 mm is given at the zeroth instant and after the system settles, the set-point is varied to 350 mm (at the sampling instance of 4500). It is found that the process, when controlled by 1DoF PID controller, settles, but with an offset of more than 10 mm. Since the actual process output is considered for feedback, it contains the noise components.

Figure 5.14 Virtual feedback Servo response of 1DoF PID controller
Figure 5.14 shows the virtual feedback servo response of 1DoF PID controller for the CSTR liquid level process. Instead of actual process output, the estimated output from EKF is given as feedback to the PID controller. It is clearly seen that the EKF acts like a digital filter. So the noise components are completely removed. Hence real time implementation of state estimation of process variable is proved.

5.5.2 Regulatory response of 1DoF PID

The regulatory response of the 1DoF PID controller for a CSTR liquid level system without employing filter is shown in the Figure 5.15. Since the disturbance is varied for the system for a constant set-point, it is known as regulatory response. The set-point of the system is set to 250 mm, and after the system settles, a disturbance is applied by varying the outflow of the tank from 50% (initial value) to 70% (final value) (here at the instant of 4000 samples). The process output is found to deviate from the set-point, and takes a longer time to settle.

![Figure 5.15 Virtual feedback Regulatory response of 1DoF PID controller](image-url)
5.5.3 Servo Response of 2 DoF PID CONTROLLER

Figure 5.16 shows the front panel view of the 2 DoF PID controller for a CSTR liquid level process. The set-point and the sampling time are set by the user, and the tank level in mm is displayed by a numerical indicator and a ‘tank’ display. Online monitoring of the process is done to get instantaneous value of the output. The parameters ‘ISE’, ‘IAE’ and ‘ITAE’ describe the performance of the system. The tuning parameters considered are $K_p = 28; T_i = 205.15\text{ s} ; T_d = 50\text{ s} ; \alpha = 0.5; \beta = 0.5$

Figure 5.17 shows the servo response of the 2 DoF PID controller without employing a filter for a CSTR liquid level process. Since the set-point is varied, keeping the disturbance as zero, it is called as servo response. A set-point of 250 mm is given at the zeroth instant and after the system settles, the set-point is varied to 350 mm (here at the sampling instance, of 4500). It is found that the process, when controlled by 2DoF PID controller, settles without ant offset.
5.5.4 Regulatory response of 2 DoF PID

Figure 5.18 shows the regulatory response of 2DoF PID controller without employing a filter for a CSTR liquid level process. Since the disturbance is varied for the system for a constant set-point, it is known as regulatory response. The set-point of the system is set to 250 mm, and after the system settles, a disturbance is applied by varying the outflow of the tank from 50% (initial value) to 70% (final value) (here at the instant of 4000 samples). The process output is found to stay much closer to the set-point, and settles much faster.
5.5.5 Comparative Performance analysis

The following performance index parameters are obtained for 1DoF and 2DoF PID controllers:

**Table 5.6 Performance index parameters for 1DoF and 2DoF PID**

<table>
<thead>
<tr>
<th></th>
<th>1DoF PID CONTROLLER</th>
<th>2DoF PID CONTROLLER</th>
</tr>
</thead>
<tbody>
<tr>
<td>SERVO RESPONSE</td>
<td>REGULATORY RESPONSE</td>
<td>SERVO RESPONSE</td>
</tr>
<tr>
<td>ITAE</td>
<td>1.46727E+8</td>
<td>5.79748E+8</td>
</tr>
<tr>
<td>IAE</td>
<td>1.11205E+6</td>
<td>1.68736E+6</td>
</tr>
<tr>
<td>ISE</td>
<td>2.48544E+8</td>
<td>3.00434E+8</td>
</tr>
<tr>
<td>REGULATOR RESPONSE</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>469616</td>
</tr>
<tr>
<td></td>
<td></td>
<td>8.42166E+7</td>
</tr>
</tbody>
</table>

From the performance index parameters shown in Table 5.6, it is seen that the performance index parameters are minimum for 2DoF PID controller than that for 1DoF PID controllers for both servo and regulatory response. Since 2DoF PID controllers give minimum performance index parameter values like IAE, ISE and ITAE, they are found to be much better than the conventional 1DoF PID controllers in their performance.

From the real-time simulation results the following observations are made:

The real time implementation of soft sensing technique can be done with the help of proper mathematical model of the system considered. EKF acts like a model based filter. It is not only used as an estimate to the unmeasured process variables but also it can be used to filter the noise components present in the observed measurement signals through entire range of frequency.
• The servo response of a 1DoF PID controller is found to have a considerable amount of offset but in the case of 2DoF PID controller the process output is obtained without any offset.

• From Figure 5.15 it is found that once the disturbance is given to the 1DoF PID controller by varying the outflow of the CSTR liquid level process, the process variable deviates much from the set-point and settles down after large amount of time.

• From Figure 5.18 it is found that once the disturbance is given to the 2DoF PID controller by varying the outflow of CSTR liquid level process, the process variable settles down with a very slight deviation from the set-point.

Thus, it is observed that a two-degree-of-freedom PID controller with optimal tuning parameters serves both servo and regulatory response with a minimised error simultaneously in real time.