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DESIGN OF CDM-BASED CONTROLLER FOR INTEGRATING PUMPED TANK PROCESS, ITS COMPARATIVE SETPOINT TRACKING PERFORMANCE, AND DISTURBANCE REJECTION CAPABILITY

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ABSTRACT

Integrating processes are non-self regulating and very difficult to control. The pumped tank process is an example of such processes. In this paper, first of all, first order plus dead time (FOPDT) integrating model of the pumped tank process is obtained by a software called Loop-Pro Trainer. Next, the PI tuning values are computed using the internal model control (IMC) tuning correlations based on truncated (first-order) Taylor series approximation. Subsequently, a controller is designed using the coefficient diagram method (CDM). Eventually, the performances of the PI and CDM controllers are compared. It is concluded that if no overshoot together with a shorter settling time is required, the CDM-controlled system has advantageous performance, although the PI-controlled system yields about 61% faster response as a percentage of the CDM-controlled system.

Keywords: *Integrating pumped tank process, Loop-Pro trainer, FOPDT model, PI-control, CDM-control.*

1. INTRODUCTION

Integrating processes are non-self regulating, and one of the most prevalent categories of systems. Some of the level, temperature, pressure, pH, and other processes have integrating nature. Self regulating processes operating in open-loop naturally struggle for a steady-state operating level if the manipulated and disturbance variables are held constant for a sufficient period of time. Whereas the measured process variable of a stable integrating process does not settle at a new steady-state, but rather, continues to move increasingly in one direction and possibly to dangerous levels as shown in Fig.1-a. Changes in any of the disturbance variables can also cause the process variable to drift. Therefore, the integrating processes are rarely operated in open-loop for a very long time, and are stable in an open-loop configuration only at their balance point. As shown in Fig.1-b, the process variable steadies at a different operating level even if the

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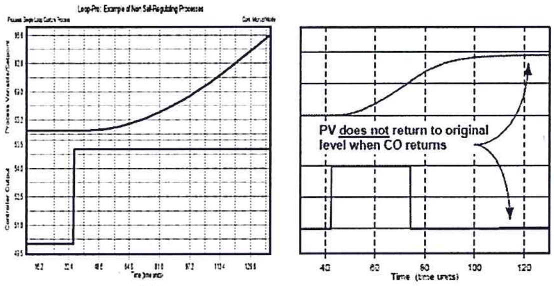
controller output returns to its original value after the step.



(a) (b)

Figure 1. Open-loop behaviour of an integrating process

Integrating processes are very difficult to control. Some of related studies are to be mentioned briefly as follows. Cano and Odloak [1] proposed a method for the control of integrating systems in the presence of model uncertainty. The method overcomes one of the major barriers to the practical implementation of the existing robust model predictive control (MPC) approaches. They [2] also proposed a stable model predictive control approach for systems with stable and integrating poles. The approach eliminates the limitations related to infeasibilities generated by the presence of unknown disturbances and input constraints completely, and the stable MPC is implemented practically as simple as the implementation of conventional MPC.

Chien et al. [3] proposed a simple modified Smith predictor control design for the integrating processes with long dead time. They also developed a simple controller tuning method to obtain the PI tuning parameters in the proposed control method.

In an another study, Svečko et al. [4] presents an adaptive and self-tuning predictive control synthesis on the basis of a nonparametric process model, i.e. process model with integrating behaviour in particular. The result of the synthesis is not a classical parametric controller but a computer algoritm of optimal control.

The PID controller is the most popular controller used in process control, because of its remarkable effectiveness and simplicity of implementation. The technique is sufficient for the control of most industrial processes [5], and used widely. This controller has only three tuning parameters to be optimized which is not simple. Thus, it is desirable to obtain a systematic procedure [6]. Kaya [7] proposed a model-based PI-PD controller design, and presented a modeling method for some integrating processes with or without time delay. The proposed controller is tuned by the ITSE (the integral of time multiplied by the squared error) performance index.

Rice and Cooper [8] gives a design and tuning recipe for integrating processes. They recommend: 1- To use an FOPDT integrating model form when approximating dynamic model behavior, 2- To note that the closed-loop time constant, τ_c, and sample time, T, are based on model dead time, Θ_p, and 3- To employ PI and PID tuning correlations specific to integrating processes.

Another method is to use a polynomial approach, called the coefficient diagram method, proposed by Manabe [9] for systems with integrating nature. Many studies have been published in relation to the application of CDM in order to obtain a desired performance. It is shown that the CDM design method is good at both of the step response and disturbance rejection, hence an improved performance.

In this paper, a CDM-based control method is applied to the control of an integrating pumped tank process, and its performance compared with that of the PI-controller. The PI-controller parameters and the FOPDT (i.e. First Order Plus Dead Time) integrating model of the process considered for the CDM controller design are obtained from Loop-Pro software. The paper is organized as follows: Loop-Pro Trainer is introduced in Section 2. In Section 3, the FOPDT integrating model is determined for the pumped tank process together with the optimal PI tuning values. In section 4, the coefficient diagram method is presented. In Section 5, a controller is designed using the CDM method for the process. In Section 6, the simulation results are presented. Finally, the concluding remarks are drawn in section 7.

2. LOOP-PRO TRAINER

LOOP-PRO is a special purpose software designed for simulation-based training in process control. The program has advanced graphical analysis tools. These tools enable to dynamically adjust the closed-loop time constant, and then to visualize changes in performance. In real-time, process performance can be interpreted in terms of Set Point Tracking, Robustness/Stability, and other valuable Statistical Measures.

Loop-Pro is divided into three modules: *Case studies, Custom Process and Design Tools*. The *Case Studies* module provides real-world process simulations in modern methods and practices of process control. The simulations are developed using data from actual processes. The basic controllers available include P-Only, PI, PD and PID controllers. Advanced strategies include cascade, feed forward, multivariable decoupling, model predictive (Smith predictor), dynamic matrix control, and discrete sampled data control.

The *Custom Process* module is a block oriented environment that provides for constructing a process and controller architecture with respect to predetermined specifications for a wide range of custom control analyses. The benefits and drawbacks of different control architectures, tuning sensitivities, loop performance capabilites can be investigated.

The *Design Tools* module is used to fit linear models to process data, and to compute PID controller tuning values. The models from *Design Tools* can also be used to construct advanced control strategies which use process models internal to the control architecture. Because the data can be imported from real operating processes, *Design Tools* can solve the difficult proplems for controller design, analysis and tuning [10][11][12][13].

Model fit in the design tools is performed by systematically searching for the model parameters that minimize the sum of squared errors (SSE) between the response contained in the measured data and the response predicted by the model when using the actual manipulated variable process data contained in the file. If the model fit is successful, the model should overlay the processs data on a plot displayed. Sometimes a fit may look good but the model parameters make no sense, such as if the computed time constant is longer than time span used in the experiment for data collection. A judgement is essential to asses, and approve a model fit. In order to obtain a meaningful fit, it is essential to recognize the following limitations:

- The process must be at steady state before collection of dynamic data begins, i.e. a tank liquid level of 4m and a disturbance flow rate of 2.5 L/min.

- The first data point in the file must equal this initial steady-state value.

If these conditions are not met, the model fit will be incorrect, and of little value for tuning model based controller designs in simulation studies. The second feature of *Design Tools* is the controller tuning tool. Using the results of a succesful model fit, tuning values for P-Only, PI and PID controllers are computed. The tuning is performed using a well-known method of internal model control (IMC) correlations.

3. MODELING INTEGRATING (NON-SELF REGULATING) PROCESS

3.1. Pumped Tank

The pumped tank process is a pickle brine surge tank. The measured process variable is liquid brine level. To maintain level, the controller manipulates brine flow rate out of the bottom of the tank by adjusting a throttling valve at the discharge of a constant pressure pump. This approximates the behavior of a centrifugal pump operating at relatively low throughput. The disturbance variable is the flow rate of a secondary feed to the tank (Fig. 2).

The pumped tank is not a self-regulating process (does not reach a natural steady state level of operation). Discharge flow rate changes only when the controller output changes. The height of liquid in the tank does not impact the discharge flow rate. Liquid Level in a surge tank seen in Fig. 2 is the process variable. If the flow rate in is not equal to the flow rate out, then the tank is either overflows or completely empties, hence displaying integrating behavior.

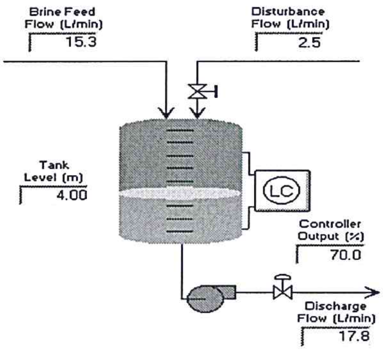


Figure 2. Integrating pumped tank process

This non self-regulating dynamic behavior is associated with integrating processes. The pumped tanks appear almost trivial in its simplicity. Its integrating nature presents a remarkably difficult control challenge.

3.2. Model determination for integrating process

The first step in designing a controller is generating and collecting dynamic data. Using the doublet (two pulse tests amongst the others such as pseudo-random binary sequence, step, pulse, sinusoidal, ramped) test in order to collect the test data in open-loop, the controller output value is changed from 70% up to 75%, then down to 65%, and finally back to 70%. It should be noticed in Fig. 3 that when the controller is returned to its original output of 70%, the process does not return to its initial steady state, at which the tank liquid level was 4m; instead, the level steadies at a new value of 2.59m. The process data is recorded in a file for process modeling and controller tuning studies.

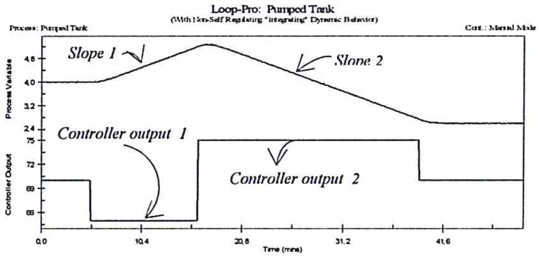


Figure 3. Dynamic process data generation through doublet test

The graphical method of fitting a FOPDT integrating model to process data requires a data set that includes at least two constant values of controller output, u_1 and u_2. Both u_1 and u_2 must be held constant long enough such that the slope (Eqns. 1 & 2) of the measured process variable response trend can be visually identified in the data. The FOPDT integrating model describes the process behavior at each value of constant controller output u_1 and u_2 using Eqn. 3.

$$\left.\frac{dy(t)}{dt}\right|_1 = K_p^* u_1(t-\theta_p) \qquad (1)$$

$$\left.\frac{dy(t)}{dt}\right|_2 = K_p^* u_2(t-\theta_p) \qquad (2)$$

If Eqn. 1 is subtracted from Eqn. 2, the integrating gain is obtained as in Eqn. 3.

$$K_p^* = \frac{\left.\frac{dy(t)}{dt}\right|_2 - \left.\frac{dy(t)}{dt}\right|_1}{u_2 - u_1} \qquad (3)$$

Using Fig. 3, 'the start points' ($y_{start} - t_{start}$) and 'the end points' ($y_{end} - t_{end}$) of each slope segment are determined as shown in Table 1.

Table 1- Start and end points of each slope segment

Controller Output 1, $CO_1 = 65\%$			
$y_{1\ start}$ (m)	$t_{1\ start}$ (mins)	$y_{1\ end}$ (m)	$t_{1\ end}$ (mins)
4.00	5.85	5.28	16.86
Controller Output 2, $CO_2 = 75\%$			
$y_{2\ start}$ (m)	$t_{2\ start}$ (mins)	$y_{2\ end}$ (m)	$t_{2\ end}$ (mins)
5.276	17.7	2.665	39.7

Thus, using the data in Table 1, the integrating gain is calculated as follows:

$$K_p^* = \frac{slope_2 - slope_1}{CO_2 - CO_1} = \text{-}0.0235 \text{ m/\%.min} \qquad (4)$$

The dead time, θ_P, is estimated from Fig. 3 as follows:

$$\theta_P = t_{Ystart} - t_{Ustep} = 5.916 - 5.042 = 0.874 \text{ mins.} \qquad (5)$$

where t_{Ystart} is the time when the measured process variable starts showing a clear initial response to the step change in the controller output, and t_{Ustep} the time at which the step change occurs in the controller output.

Finally, substituting these model parameters into Eqn. 1 (or Eqn. 2) yields the FOPDT integrating dynamic model as in Eqn. 6 describing the pumped tank process, which presents the model in Laplace domain, too.

$$\frac{dy(t)}{dt} = -0.0235u(t - 0.874)$$
$$\frac{Y(s)}{U(s)} = \frac{-0.0235e^{-0.874s}}{s} \qquad (6)$$

3.3. Computing the PI tuning parameters

Using the IMC-based PI tuning correlations considering first-order Taylor series approximation ($e^{-\theta s} \cong 1 - \theta s$) [14] for integrating processes, the PI controller parameters (K_C, controller gain and τ_I, reset time) are computed for the process. The IMC-based PI tuning relations for integrating processes are given in Eqn. 7 [15].

$$K_C = \frac{1}{K_p^*}\left[\frac{\tau_c + \theta}{(\tau_c + \theta_p)^2}\right] \qquad \tau_I = 2\tau_c + \theta_p \qquad (7)$$

The closed-loop time constant, τ_C, for integrating processes is based on the process dead time, and given by

Standard Tuning :

$$\tau_c = \theta_p\sqrt{10} = 2.764 \qquad (8)$$

Conservative Tuning :

$$\tau_c = 5\theta_p\sqrt{10} = 13.82 \qquad (9)$$

With the information in Eqn. 8 (or, Eqn. 9), one set of the tuning parameters K_C and τ_I can be computed for this integrating process using Eqn. 7.

$$K_c = -20.584 \qquad \tau_I = 6.402 \text{ mins.} \qquad (10)$$

The model parameters and PI controller tuning values computed by hand may be checked using the *Design Tools.*

To this end, the obtained result of fitting is shown in Fig. 4.

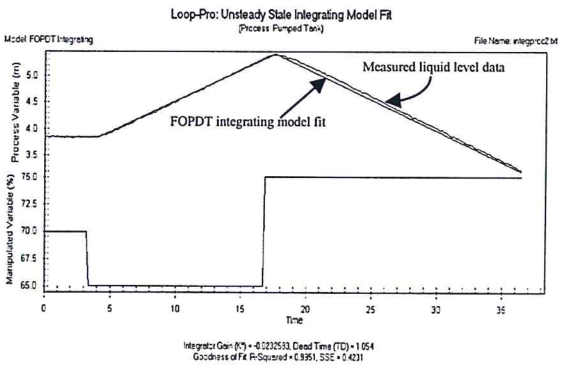


Figure 4. FOPDT integrating model fit to dynamic process data

Both the model parameters and Standard PI tuning parameters suggested by *Design Tools* are given in Table 2.

Table 2. Parameters suggested by the design tools

Model Parameters		PI Tuning Parameters[1]	
K_p^*	θ_p (min)	K_c	τ_I (mins.)
-0.0233	1.05	-15.8	8.64
SSE	Closed-Loop Time Constant (mins.)		
0.167	3.79		

[1] Dependent, Ideal PI Tuning Parameters (IMC tuning correlation)

The suggested PI controller was implemented on the Pumped Tank process, and its performance tested. Fig. 5 shows the step response and disturbance rejection of the controller when the set point is stepped from 4m up to 5m, and after the response is complete, back to 4m.

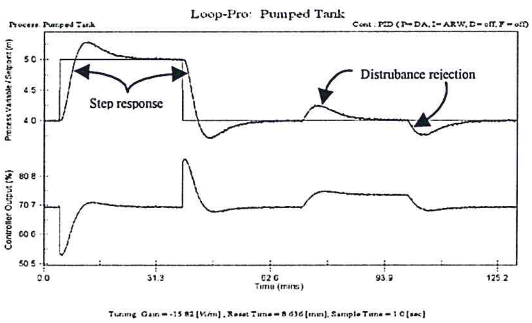


Figure 5. Step response and disturbance rejection of PI-controlled pumped tank process

The controller's disturbance rejection capability is also seen in Fig. 5. It is tested through stepping the disturbance flow rate from 2.5 L/min to 3.5 L/min, and after the response is complete, back down to 2.5 L/min. If the controller tuning values that are best for the set point tracking does not appear to be the best for the disturbance rejection, trial and error method may be used to determine the best values for disturbance rejection. Eventually, the resultant tuning parameters satisfying both the set point and disturbance rejection requirements obtained by trial and error method may be averaged in order to get the "best" tuning values, i.e. K_C and τ_I.

The response characteristics of the controller provided by the program is given in Table 3. Again, this performance may be improved by use of trial and error in order to determine the "best" values for K_C and τ_I for set point tracking.

Table 3. The response characteristics of PI-controller

Stability Factor	Settling Time (min)	Percent Overshoot	CO Travel (%CO/hr)
1.89	21.4	25.3	41.5
IAE		ITAE	
4.80		46.0	

4. COEFFICIENT DIAGRAM METHOD

4.1. Introduction

When the dominator and nominator polynomials of a tranfer function describing the input-output relationship of a linear time invariant (LTI) dynamic system are determined independently according to stability and response requirements, the design of controller transfer function is not difficult except for the robustness issue. But this is also addressed by the coefficent diagram method as well as the others [9].

The CDM is an algebraic approach which simplifies the controller design process using the given characteristic polynomial, and gives sufficient information with respect to stability, response, and robustness in a single diagram. The CDM has three theoretical features: 1- The coefficient diagram, 2- The improved Kessler's standard from, and 3- The Lipatov's sufficient condition for stability.

When the plant dynamics and the performance specifications are given, one can find the controller under some practical limitations together with the closed-loop transfer function satisfactorily. As a first step, the CDM approach specifies partially the closed-loop transfer function and the controller simultaneously, and then decides on the rest of parameters by design. The parameters are stability index γ_i, equivalent time constant τ, and stability limit γ_i^* which represent the desired performance.

4.2. Mathematical relations

In CDM, the characteristic polynomial is represented as in Eqn. 11. This is also called as the target characteristic polynomial.

$$P(s) = a_n s^n + \cdots + a_1 s + a_0 = \sum_{i=0}^{n} a_i s^i \qquad (11)$$

The stability index γ_i, the equivalent time constant τ, and the stability limit γ_i^* are defined in Eqn. 12.

$$\begin{aligned}
&\gamma_i = a_i^2 / (a_{i+1} a_{i-1}), \qquad i = 1 \sim n-1 \\
&\tau = a_1 / a_0 \\
&\gamma_i^* = 1/\gamma_{i+1} + 1/\gamma_{i-1}, \qquad \gamma_n = \gamma_0 = \infty
\end{aligned} \qquad (12)$$

The coefficients in Eqn. 11 are derived from Eqn. 12 by the relations given in Eqn. 13.

$$\begin{aligned}
&a_{i-1}/a_i = (a_j/a_{j-1}) / (\gamma_i \gamma_{i-1} \cdots \gamma_{i+1} \gamma_j) \qquad i \geq j \\
&a_i = a_0 \tau^i / (\gamma_{i-1} \gamma_{i-2}^2 \cdots \gamma_2^{i-2} \gamma_1^{i-1}) = a_0 \tau^i / \prod_{j=1}^{i-1} \gamma_{i-j}^j
\end{aligned} \qquad (13)$$

Then Eqn 11 can be expressed in terms of a_0, τ, and γ_i by Eqn. 14.

$$P_{target}(s) = a_0 \left[\left\{ \sum_{i=2}^{n} \left(\prod_{j=1}^{i-1} 1/\gamma_{i-j}^j \right) (\tau s)^i \right\} + \tau s + 1 \right] \qquad (14)$$

The equivalent time constant of the i-th order τ_i and the stability index of the j-th order γ_{ij} are defined by Eqn. 15.

$$\begin{aligned}
&\tau_i = a_{i+1}/a_i = \tau / (\gamma_i \cdots \gamma_2 \gamma_1) \\
&\gamma_{ij} = a_i^2 / (a_{i+j} a_{i-j}) = \left[\prod_{k=1}^{j-1} (\gamma_{i+j-k} \gamma_{i-j+k})^k \right] \gamma_i^j
\end{aligned} \qquad (15)$$

τ is considered to be the equivalent time constant of the 0-th order, γ_1 to be the stability index of the 1-st order.

4.3. Stability condition

The sufficient condition for stability is given in Eqn. 16.

$$\begin{aligned}
&a_i > 1.12 \left[\left(a_{i-1} / a_{i+1} \right) a_{i+2} + \left(a_{i+1} / a_{i-1} \right) a_{i-2} \right] \\
&\gamma_i > 1.12 \gamma_i^*, \qquad for \text{ all } i = 2 \sim n-2
\end{aligned} \qquad (16)$$

The sufficient condition for instability is given in Eqn. 17

$$\begin{aligned}
&a_{i+1} a_i \leq a_{i+2} a_{i-1} \\
&\gamma_{i+1} \gamma_i \leq 1, \qquad for \text{ some } i = 1 \sim n-2
\end{aligned} \qquad (17)$$

4.4. Standard Manabe form

The recomended standard Manabe form of the stability index for an nth-order system is expressed in Eqn. 18.

$$\gamma_{n-1} \sim \gamma_2 = 2, \qquad \gamma_1 = 2.5 \qquad (18)$$

This provides no overshoot in response to a step input for type-1 system, but some overshoots for higher-type systems.

The standard form yields the shortest settling time for the same value of τ for all types of systems, which is about $2.5 \sim 3\ \tau$.

4.5. Robustness consideration

The robustness concerns how fast the poles move to imaginary axis for the variation of parameters, and is only specified after the open-loop structure is specified. The robustness can be integrated into the characteristic polynomial with a small loss of stability and response. The condition may then be given as in Eqn. 19.

$$\gamma_i > 1.5\,\gamma_i^* \tag{19}$$

4.6. CDM design

The standard block diagram of Fig. 6 is used in the CDM design process.

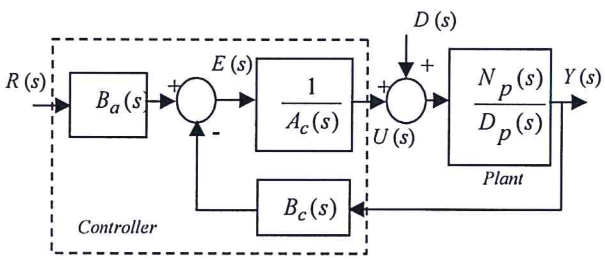


Figure 6. 2-DOF configuration

The system output is given by Eqn. 20.

$$Y(s) = \frac{N_p(s)B_a(s)}{P(s)}R(s) + \frac{A_c(s)N_p(s)}{P(s)}D(s) \tag{20}$$

where $P(s)$ is the characteristic polynomial of the closed-loop system, and is defined by Eqn. 21.

$$P(s) = A_c(s)D_p(s) + B_c(s)N_p(s) = \sum_{i=0}^{n} a_i s^i \tag{21}$$

When the performance specifications are given, they must be modified to the design specifications. In CDM, the design procedure is given in the following:

1. Define the plant in the right polynomial form.
2. Analyze the performance specifications and derive design specifications for CDM, i.e. τ, γ_i, γ_i^*.
3. Assume the controller polynomials in the simplest possible form. Express it in the left polynomial form.
4. Derive the Diophantine equation, convert it to Sylvester Form,

$$[C]_{nxn}\begin{bmatrix} l_i \\ k_i \end{bmatrix}_{nx1} = [a_i]_{nx1} \tag{22}$$

and solve for unknown variables .

Obtain the coefficient diagram of the closed-loop system and make some adjustments to satisfy the performance specifications if necessary.

5. CDM CONTROLLER DESIGN FOR PUMPED TANK

First Order Plus Dead Time (FOPDT) integrating model is given for the pumped tank process in Eqn. 23 using the suggested parameters given in Table 2.

$$G_p(s) = \frac{Y(s)}{U(s)} = \frac{-0.0233e^{-1.05s}}{s} = \frac{N_p(s)}{D_p(s)} \tag{23}$$

Using a simple 1/1 Padé approximation for dead time in the Laplace domain, $e^{-\theta s} = \frac{2-\theta s}{2+\theta s}$, Eqn. 23 becomes

$$G_p(s) = \frac{Y(s)}{U(s)} = \frac{24.46*10^{-3}s - 0.0466}{1.05s^2 + 2s} = \frac{N_p(s)}{D_p(s)} \tag{24}$$

It is considered that there is a step disturbance affecting the system. Thus, let the structure of the controller be chosen with l_0 =0 as follows:

$$G_c(s) = \frac{B_c(s)}{A_c(s)} = \frac{k_2 s^2 + k_1 s + k_0}{l_2 s^2 + l_1 s} \quad (25)$$

where l_2, l_1, k_2, k_1, and k_0 are controller design parameters. Then, the closed-loop characteristic polynomial in terms of the controller design parameters (Eqn. 21) is

$$\begin{aligned} P(s) &= 1.05 l_2 s^4 + (2 l_2 + 1.05 l_1 + 24.46 * 10^{-3} k_2) s^3 \\ &+ (2 l_1 - 0.0466 k_2 + 24.46 * 10^{-3} k_1) s^2 \\ &+ (-0.0466 k_1 + 24.46 * 10^{-3} k_0) s \\ &- 0.0466 k_0 \end{aligned} \quad (26)$$

From the standard form of CDM; the stability indices, and stability limits are chosen to be $\gamma_i = [2, 2, 2.5]$, $\gamma_0 = \gamma_4 = \infty$, and $\gamma_i^* = [0.5, 0.9, 0.5]$, respectively. Substituting them in Eqn. 14 yields

$$P_{target}(s) = 20.68 s^4 + 29 s^3 + 20.34 s^2 + 7.13 s + 1 \quad (27)$$

Thus, setting Eqns. 26 and 27 (the target polynomial) equal yields Sylvester form in five unknowns. Then, $l_i = [19.69,\ 1.15]$, and $k_i = [-473.52, -164.42, -21.74]$ are obtained for a settling time, t_s, of 21.4 mins. (Table 3), i.e. τ =21.4/3 =7.13 mins. $B_a(s)$ is obtained using the following expression in order to eliminate possible steady-state error in the response of the closed-loop system.

$$B_a(s) = \left. \frac{P(s)}{N_p(s)} \right|_{s=0} = k_0 \quad (28)$$

The coefficient diagram is depicted in Fig. 7.

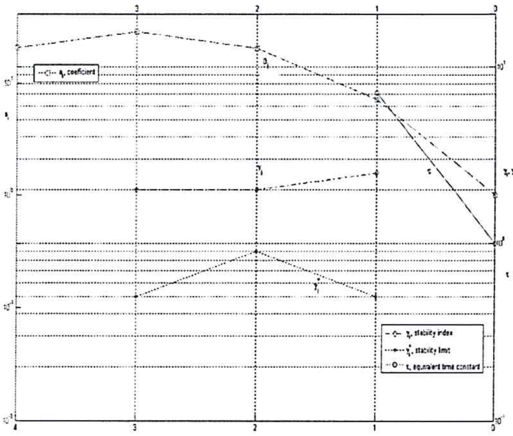


Figure 7. Coefficient diagram for CDM controller

6. SIMULATION RESULTS

In order to evaluate the performance of the two controllers, they were applied to the same process. The step response performance, the disturbance rejection capability, and the root-locus diagram of the CDM-controlled system are seen in Figs. 8 -10, respectively.

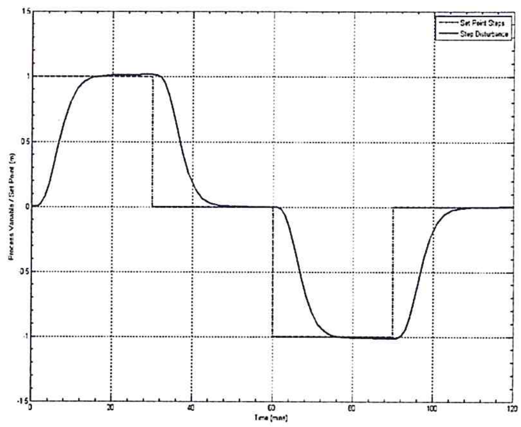


Figure 8. Step response of CDM-controlled pumped tank process

The results in terms of the standard performance measures are summerized in Table 4.

Table 4. Time-domain performance characteristics

Pumped Tank Process			
Controller \ Criteria	T_{r1} (mins)	T_r (mins)	T_p (mins)
PI (1)	2.72	4.26	5.3
CDM	7	-	-
Controller \ Criteria	T_s (mins)	P.O. (%)	e_{ss} (m)
PI (1)	24.5	30.4	0
CDM	14	0	0

(1) Determined from Figure 5

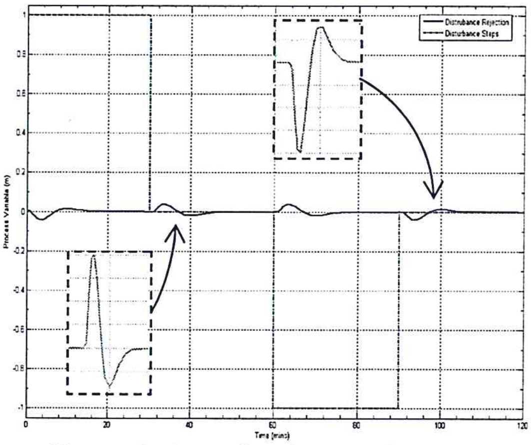


Figure 9. Step disturbance rejection of CDM-controlled pumped tank process

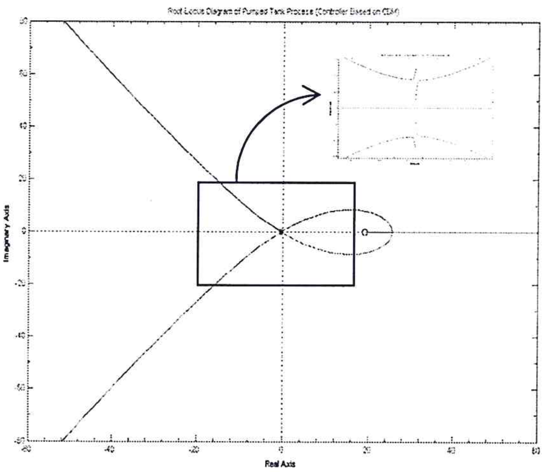


Figure 10. Root-locus diagram of CDM-controlled pumped tank process

The standard performance measures used in Table 4 are 10-90% rise-time, T_{r1}, 0-100% rise time, T_r, peak time, T_p, settling time, T_s, percent overshoot, P.O., and steady-state error, e_{ss}. As it is expected the system is overdamped (no overshoot) in the case of CDM controller. Therefore, the peak time is not defined, and 0-100% rise time is not used. Thus, the controller performances should be evaluated with respect to T_{r1}, T_s, and e_{ss}. The PI-controlled system exhibits faster response than that of the CDM controller. On the other hand, the CDM controller has shorter settling time. Both controllers have zero steady-state error.

7. CONCLUSION

In this paper, the performances of two controllers - namely, the PI-controller and the CDM controller - were investigated on the pumped tank process which has integrating nature. It is seen that if no overshoot together with the shorter settling time is required out of the integrating pumped tank system, the CDM based controller is favorable at a sacrifice of about 61% (i.e. as the percentage of the CDM controller's rise time) faster response in comparison with the PI-controller. Besides, the CDM-controlled system has better quality measure in rejecting a step disturbance compared with that of the PI-controller. Although the excursion times, τ_D, are identical, the peak magnitude of the disturbance error in case of the CDM is less by an amount of about 89% as the percentage of the PI-controller's disturbance error.

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