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Closed Loop Experimental Validation of Linear Parameter Varying Model with Adaptive PI Controller for Conical Tank System

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Abstract: The control of the liquid level in a conical tank system is a complicated task in many process industries, where it is used for drainage of slurries, viscous liquids and solid mixtures. The conical tank system is highly nonlinear due to its variation of the area of cross section, with respect to height of the system. The process identification of this nonlinear system is done, using the linear parameter varying method. Linear Parameter Varying (LPV) modeling is capable of describing the system over its entire operating trajectory. Based on the open loop response of the conical tank, the entire region of the nonlinear process is split into approximate linear regions, and their respective transfer function models are formed. Then the linear parameter varying model is identified, by interpolating the transfer function models. The obtained model is investigated and validated with the real time process data. Further, a conventional PI controller is designed for the control of the liquid level in the conical tank system, using the direct synthesis method. To improve the closed loop performance, the adaptive PI control scheme is designed and implemented for the conical tank system. The single PI controller and Adaptive PI controller are designed for the LPV model, and it is implemented on the conical tank system in real time. From the experimental results, it is proved that the performance of the Linear Parameter Varying model based PI and the Adaptive PI controller is significantly better than that of the other control strategies

Keywords: Time varying process, servo performance, multi-model approach, LPV model, adaptive control.

1. INTRODUCTION

Conical tanks find wide applications in process industries, namely, hydrometallurgical industries, food processing industries, concrete mixing industries, and sewage and wastewater treatment industries. Their shape contributes to the better drainage of solid mixtures, slurries and viscous liquids at the bottom of the tank. So, control of the level in the conical tank is a challenging problem due to its non-linearity and constantly changing cross section. If the level in the tank increases, then the overflow of valuable or hazardous material will occur. On the other hand, the decrease in the level leads to bad consequences for the sequential operations. The primary task of the controller is to maintain the process at the desired operating conditions, and to achieve the optimum performance when facing various types of disturbances. The control of these systems is often found to be challenging due to its nonlinearity. Under changing steady state conditions, the process exhibits nonlinear characteristics, and often requires the use of dedicated nonlinear control approaches. Control design methods like model-based control and optimization strategies are applied. This approach requires accurate dynamic models to obtain satisfactory performance and robustness. First principle models are developed for this reason. The drawbacks of these models are that they suffer from a lack of validation on real-life data and model complexity, in terms of nonlinear relationships, partial differential terms, etc. Therefore, nonlinear process models are obtained from the measured data.

In nonlinear model identification, neural-networks models, Block-oriented nonlinear models such as Hammerstein models and Wiener models are mostly used (Zhu, 2001),. The structure of these models is simpler, but the computation of the model parameters is complex, due to the detailed plant test that is needed in the entire operating region of the process. Thus, instead of a global nonlinear description of the plant, it is sufficient to have a model that can approximately represent the process behaviour in its operating trajectory.By dividing the entire operating trajectory into a linear segment, linear models were developed in each segment. Linear models were interpolated using a scheduling (or) varying parameter of the process. This method is termed as Linear Parameter Varying (LPV) modeling. The framework of the Linear Parameter Varying (LPV) models has been shown to provide a good approximating model for a lot of industrial processes which are non-linear and time varying. The Linear Parameter Varying(LPV) Model is used in identification and control, for the following merits (i)Easy identification of the process (ii)Accurate capturability of the process dynamics along the operating trajectory (iii)Low cost and less time consumption (iv)Suitable for both continuous and batch processes.

(Shamma and Athans ,1991) introduced the terminology of LPV in the study of gain scheduling control. (Rugh and

Shamma, 2000) explained the application of LPV control in an electromechanical system. The LPV identification methods are formulated in discrete-time, commonly assuming a dependence on the scheduling parameter. The LPV model is mainly characterized by the model structure used. (Bamieh and Giarre, 2002) introduced a method of linear parameter varying modeling of a system, using the input and output data of the process. The state space approach was used for the modeling of a multiple input multiple output system, by (Lovera and Mercere, 2007; van Wingerden and Verhaegen , 2009; Verdult and Verhaegen, 2005). (Toth, 2008; Toth et al., 2009) modeled the nonlinear process using the orthonormal basis function. Among the model structures, the input output model structures are widely used, because they can be derived from physical/chemical laws in their continuous form. So, it is usual to express a given physical system through an Input Output form or transfer function modeling.The method of the interpolation of linear models is studied in the paper presented by (Jan De Caigny et al., 2009; Zhu and Ji, 2009). LPV model based on interpolation for MIMO models is discussed in (Jan De Caigny et al., 2008). A method of LPV Model identification for control was discussed by (Zhu and Xu, 2008). (Jiangyin Huang et al., 2010) studied the development of the linear parameter varying model for circulation fluidized bed boilers. LPV modeling, based on first principle modeling, is well explained for SISO CSTR and MIMO polymerisation by (Zuhua Xu, Jun Zhao and Jixin Qian, 2009).LPV model for mechatronic systems are identified with one scheduling variable was explained (Paijmans et al., 2008). The development of a linear parameter varying model for the conical tank system has not been addressed in any literature, so it is considered in this work. In the previous research works, neural network based model, wiener model, linear piece wise models were developed, and controllers were designed.

Normally process industries employ PID controller algorithms as it is simple and provides ease of access. The normal PID controller fails to stabilize the system if the process has non linearity and a time delay was discussed by (Monojmajunath et al., 2011), because non linearity limits the performance of PID. The normal PID controller produces an oscillation when the set point has sudden changes. But non linear adaptive PI provides better control action than ZNPI (Anandanatarajan et al., 2006).

One of the popular methods of nonlinear control design is the gain-scheduling (Rugh et al., 2000; Leith et al., 2000) and it has been used in a wide range of applications including flight control (Nichols et al., 1993; Lee et al., 2001) process control (Qin and Borders, 1994) and wind-turbine control (Leith and Leithead, 1996). (Petre 2005) designed a nonlinear adaptive controller for a fedbatch fermentation process. (Petre, 2013) designed a adaptive and robust Control Strategies for a Class of Fed-Batch Fermentation Processes. (Duka et al., 2007) discussed about model reference adaptive control for inverted pendulum.

(Anandanatarajan et al., 2006) designed a gain scheduled controller for the conical tank process. A Neuro based Model reference Adaptive Control for the conical tank level process is discussed by (Bhuvaneswari et al., 2008). (Bhaba et al., 2007) developed a wiener model based PI controller for the conical tank level process. Although several methods have been developed, in most of them, either some assumptions are made, or the nonlinear process characteristics and switching curves are linearized, and then the controller is designed. In this paper, without any assumptions and linearization of the non-linear characteristics, the adaptive controller was designed, using the gain scheduling technique.
In industrial automation applications, ladder logic, a programming language running on the so-called programmable logic controllers (PLCs) (Erickson, 1996), is usually used for discrete event control. For continuous control, either PID-type controllers are more often employed. The control algorithms are made in two different ways: by Labview Virtual Instruments (VI) on PC, and by ladder-logic program on PLC. Advantages of Labview based controlling over PLCs and other hardware based controllers are listed as follows.

1. In PLC based controllers programming expertise (e.g. ladder logic) is required. Whereas, Labview is more user friendly with drag and drop blocks for which process knowledge would suffice.

2. The complexity of the programs may increase as the parameters of the process increases. The number of hardware components (relays) to be installed also increases.

3. Attending to the basic PID implementation issues like P-kick, D-kick and reset windup is difficult and rarely being done. On the other hand, these issues can be easily solved using the inherent blocks in Labview.

4. In case of changing the controllers between P or PI or PID requires the PLC programs to be modified and is a tedious process, but then its just a matter of few clicks in Labview.

2. CONICAL TANK SYSTEM EXPERIMENTAL SETUP

The experimental setup of the Conical Tank System is shown in Fig.1. It consists of a conical tank, water reservoir, pump, rotameter, pressure transmitter, electro pneumatic converter (I/P converter), pneumatic control valve, interfacing module and Personal Computer .The level of liquid in the tank is measured by the EMERSON make (Model: 1151DP SMART) differential pressure transmitter whose output is in the form of a 4-20 mA current signal. The control valve is fitted with the EMERSON make smart valve positioner, which will take 3–15 psi as an input signal. The level transmitter and the control valve are interfaced to a PC, with the help of the National Instruments Educational Laboratory Virtual Instrumentation Suite (NI-ELVIS) N114 Multifunction DAQ board. It has eight analog input channels and two analog output channels.

Fig. 1. Experimental setup of the Conical Tank System.

The current signal from the transmitter is converted into a voltage signal by a current to voltage (I-V) converter, so that it could directly be fed into the interfacing unit. Similarly, the voltage signal from the interfacing unit is converted into a current signal by a voltage to current (V-I) converter, and then to a pressure signal by a current to pressure (I-P) converter, so that it could be fed to the control valve to take corresponding control action.

The level transmitter is connected with the input channel AI-0 of the NI-ELVIS N114 Multifunction DAQ board through the I-V converter. The control signal in the form of a 1-5 V voltage signal is generated from the output channel AO-0 port, and connected to the control valve CV through the V-I converter and I-P converter.

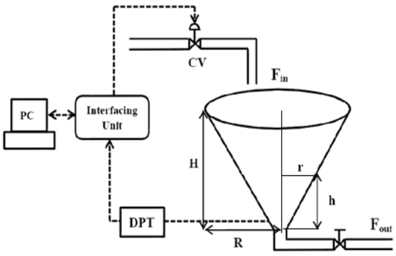


Fig. 2. Schematic of the Conical Tank System.

The schematic diagram of the Conical Tank system is shown in Fig. 2, which is a bench mark problem for a number of research topics. It consists of an inverted conical tank with an inlet flow (F_{in}) at the top, and an outlet flow (F_{out}) at the bottom, a pump that delivers the liquid flow, and a control valve with coefficient (C_v) to manipulate F_{in}. The operating parameters of the Conical Tank system are shown in Table 1.

Table 1. Operating parameters of the Conical Tank System

Parameter	Description	Value
R	Top radius of the conical tank.	0.4m
H	Maximum height of the tank.	0.5 m
F_{in}	Maximum in flow to the tank.	$2.7675e^{-4}$ m^3/sec

The Conical Tank system is a single input single output (SISO) process, in which the tank liquid level h is considered as the measured variable, and the inlet flow F_{in} is considered as the manipulated variable. The radius (r) of the tank is a varying parameter; so it is expressed as the ratio of the maximum radius (R) to the maximum height (H) of the Conical Tank.

The mathematical model of the CTS is given by

According to mass balance equation

Rate of Acculumation = inflow-outflow

$$\frac{d(M(h))}{dt} = \rho_1 F_{in} - \rho_2 F_{out} \tag{1}$$

Where $M(h) = \rho V(h)$

V(h) is the volume of liquid in the tank, ρ is the density of liquid in the tank, ρ_1 is the density of liquid in the inlet stream and ρ_2 is the density of liquid in the outlet stream. Assuming room temperature as constant, density of liquid is same throughout.

$\rho_1 = \rho_2 = \rho$

$$\frac{dV(h)}{dt} = F_{in} - F_{out} \tag{2}$$

$$V(h) = \frac{\pi r^2 h}{3} \tag{3}$$

$$\tan\theta = \frac{R}{H} \tag{4}$$

At any level (h)

$$\tan\theta = \frac{r}{h} \tag{5}$$

Equating (4) and (5)

$$\frac{r}{h} = \frac{R}{H}$$

$$r = \frac{Rh}{H} \tag{6}$$

Substitute (6) in (3)

$$V(h) = \frac{\pi R^2 h^3}{3H^2} \tag{7}$$

Differentiate volume of the tank

$$\frac{dV}{dt} = \frac{\pi R^2 h^2 dh}{H^2 dt} \tag{8}$$

The cross sectional area of the tank at any level

$$A(h) = \pi r^2 \tag{9}$$

Substitute (6) in (9)

$$A(h) = \frac{\pi R^2 h^2}{H^2} \tag{10}$$

Substitute (10) in (8)

$$\frac{dV(h)}{dt} = A(h)\frac{dh}{dt} \tag{11}$$

Substitute (11) in (2)

$$A(h)\frac{dh}{dt} = F_{in} - F_{out} \tag{12}$$

$$F_{out} = C_V\sqrt{2gh} \tag{13}$$

Substitute (10) and (13) in (12) to get

$$\frac{dh}{dt} = \frac{F_{in} - C_V\sqrt{2gh}}{\pi\left(\frac{R}{H}\right)^2 h^2} \tag{14}$$

where h is the liquid level in the conical tank in m, R is the top radius of the tank in m, H is the maximum height of the tank in m, C_V is the valve coefficient, F_{in} is the liquid inlet flow rate in m^3/sec, θ is the half cone angle of the conical tank, and g is the acceleration due to gravity in m/sec.

3. MODEL IDENTIFICATION

The model identification of the conical tank system is done by conducting open loop tests in the experimental setup. The input, inlet flow F_{in}, is varied in steps and the corresponding changes in the liquid level of the tank are observed. The obtained liquid level of the tank is termed as the real time data. For the given first step input the system attains the steady state at 0.1152m. The same procedure is repeated at different operating regions in the conical tank system. It is necessary to maintain the liquid level in the tank within the maximum selected height of 0.45m. Fig.3 shows the liquid level response of the system at various step changes in the input flow. From the response, the non-linear process can be split into four linear regions, using the input-output data. The linear regions are represented in the transfer function form as in (15). The process parameters K and τ_s are computed and listed in Table 2 for the four operating regions.

$$G(s) = \frac{K}{\tau_S S + 1} \tag{15}$$

Where K is the Process gain and τ_s is the Process time constant.

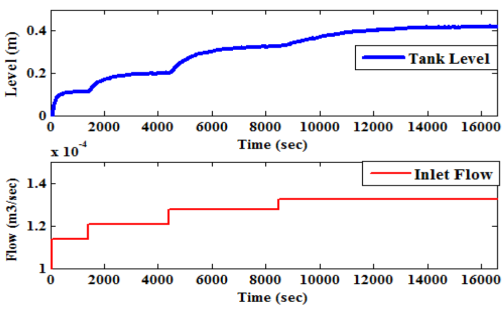
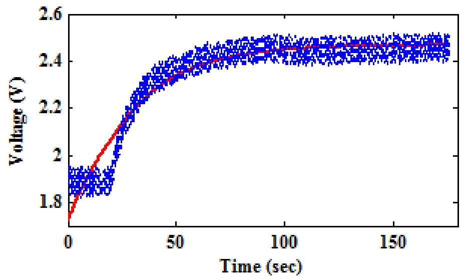


Fig. 3. Open loop response of the Conical Tank System for step change in the input flow

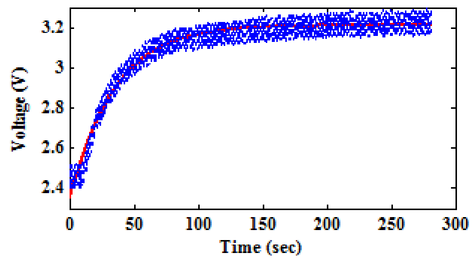
Table 2. Linear models of the Conical Tank System

Operating regions	Process gain (k)	Timeconstant (τ_s)
Region 1	0.8814	27.2208
Region 2	1.1071	33.5472
Region 3	1.2001	62.0102
Region 4	1.381	79.5361

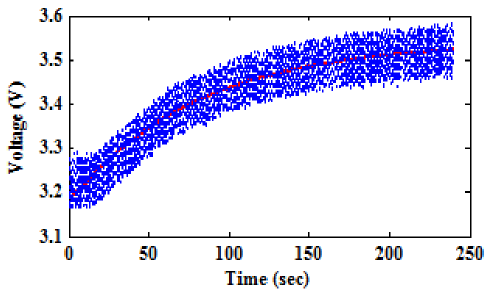
Fig. 4 shows the model output data that tracks the real time data accurately in all the four regions. The four linear transfer function models formed are validated with the real time open loop data of the Conical Tank system. In all the figures red line represent the model output and blue line represent the real time data.



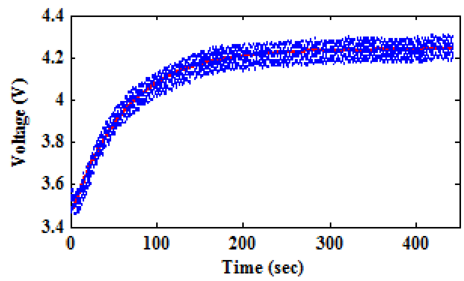
(a) First region



(b) Second region



(c) Third region



(d) Fourth region

Fig. 4. Validation of Transfer function model at four regions with real time data.

4. LINEAR PARAMETER VARYING MODEL FORMULATION

The linear parameter varying model is used to represent the nonlinear process in the entire operating trajectory. The LPV model is the interpolation of the transfer function (or) linear models using weighting functions . The LPV model denoted in (16) is formed, based on the weights which are computed, based on the variation of the liquid level in the conical tank system.

In general the LPV model is given by,

$$y(t) = w_1(h)y^1(t) + w_2(h)y^2(t) + w_3(h)y^3(t) + w_4(h)y^4(t) \qquad (16)$$

where $y^1(t)$, $y^2(t)$, $y^3(t)$ and $y^4(t)$ are the respective Linear model outputs for the four operating regions, w_1 (h), w_2 (h), w_3 (h) and w_4 (h) are the weights, which are the function of the scheduling parameter, and the liquid level in the conical tank system, *h*.

These weights can be determined using the Triangular Weighting function, represented in (Zhu and Ji, 2009).

$$y(t)=\begin{cases} y^1(t) & h(t)\le w_1 \\ \dfrac{w_2-h(t)}{w_2-w_1}y^1(t)+\dfrac{h(t)-w_1}{w_2-w_1}y^2(t) & w_1<h(t)\le w_2 \\ \dfrac{w_3-h(t)}{w_3-w_2}y^2(t)+\dfrac{h(t)-w_2}{w_3-w_2}y^3(t) & w_2<h(t)<w_3 \\ \dfrac{w_4-h(t)}{w_4-w_3}y^3(t)+\dfrac{h(t)-w_3}{w_4-w_3}y^4(t) & w_3<h(t)<w_4 \\ y^4(t) & w^4\le h(t) \end{cases}$$

where h(t) is the scheduling parameter and w_1, w_2, w_3 and w_4 are the nominal values of the scheduling parameter in each operating region. The variation of the weights with respect to time is shown in Fig.5. In Fig.5, weights 1, 2, 3 and weight 4 represent the weights as the function of the scheduling variable (liquid level of the tank) associated with transfer function output of the first, second, third and fourth regions respectively.

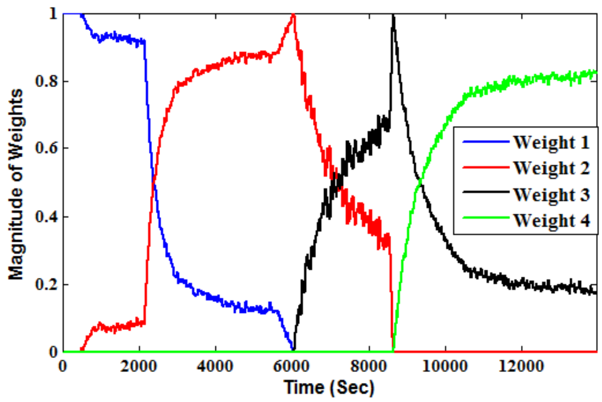


Fig. 5. Variation of weights in the formation of LPV model.

The formulated LPV model is validated with the real time data of the Conical Tank system. The validation of the LPV model with the open loop data of the Conical Tank system is shown in Fig.6. It is clear that the LPV model is able to track the response of the Conical Tank system in all the regions. The single LPV model is enough to capture the non-linearity of the conical tank process, unlike the multi-model scheme, which had four linear transfer function models.

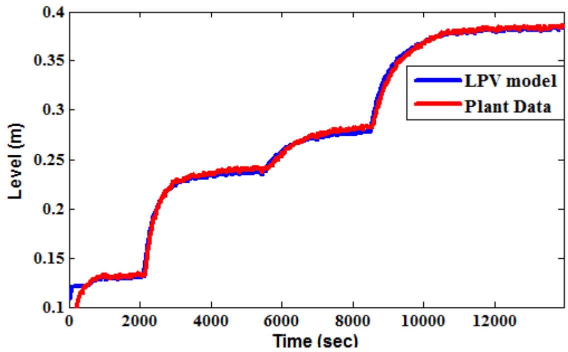


Fig. 6. Validation of the LPV model with real time data of the conical tank system.

5. IMPLEMENTATION AND ANALYSIS OF VARIOUS CONTROL SCHEMES

5.1 Conventional pi control scheme

Conventional PI controllers are widely used in industries, as they are simple and robust, provided the system is linear. There are a number of techniques for tuning the parameters of the PID controllers. Among them, the most effectively used tuning method is the Direct Synthesis method. The controller settings (K_c, proportional constant; τ_I, integral constant) can be calculated using the tuning rules. The direct synthesis method is applied for minimum phase systems, which do not have time delays and right half plane zeroes. The PI settings for the first order process (k, process gain and τ_s, time constant) based on Direct Synthesis are given as

$$K_c = \frac{\tau_p}{k\lambda}, \qquad \tau_i = \tau_s \qquad (17)$$

where λ is the user defined closed-loop time constant, and can be chosen as equal to the process time constant. The process time constant is in seconds. The λ value is very small, which gives a faster closed loop response. In this method, the only parameter to tune is the proportional constant, since the integral constant is equal to the time constant of the process. Tuning a single controller parameter is easier than tuning two or three. Here, the non-linear process is split into four linear regions, and a single PI controller is designed, using the direct synthesis method for the first region. The first region controller setting is used in all the four operating regions. The performance of the controller is not satisfactory in all regions, except the first region for which it is designed. Due to gain mismatch, oscillations occur, and set point tracking is not satisfactory. Hence, to improve the performance of the controller over the entire process, a different control scheme has to be chosen. Instead of a single PI controller, the multi-model control scheme utilizes four tuned PI controllers for the four operating regions. The PI controller parameters for each operating region are calculated using the direct synthesis method mentioned in (17). The controller parameters for their respective regions are shown in Table 3.

Table 3. Controller settings for various operating regions of the Conical Tank System

Operating Regions	Controller Gain (K_c)	Integral Time τ_i (min)
Region 1	1.1345	0.45368
Region 2	0.903	0.55912
Region 3	0.8332	1.0335
Region 4	0.7241	1.3257

As the process variable goes through various operating regions, the respective controller parameters are switched. The servo response is checked in all the regions while the regulatory response is also checked in Region 2. For a better performance and to reduce the number of controllers, the adaptive PI controller strategy is chosen.

5.2 Adaptive pi control scheme

In the conventional approach, it is difficult to tune the controller parameters for different operating conditions; hence, an alternative approach, using the adaptive control scheme is proposed in this work. This scheme can be viewed as having two loops. There is an inner loop composed of the process and the PI controller, and an outer loop that adjusts the controller parameters based on the operating conditions. The scheduling variable used in the conical tank is the level of liquid in the tank, h. When the scheduling variable has been determined at each operating condition, the controller parameters are calculated at each operating condition, by using some suitable set of polynomial equations, which relate the process parameters and controller parameters. The controller is thus tuned for each operating condition. The model parameters (K and τ_s) for the regions along with their respective steady state operating point height (h) are known. Using this, the polynomials for K and τ_s in terms of h are formed separately using least square curve fitting method, and are given in (18) and (19).

$$K(h) = 0.0010h^3 - 0.0183h^2 + 0.4008h + 0.0261 \tag{18}$$

$$\tau_S(h) = 664h^3 - 6394h^2 + 2070h - 21799 \tag{19}$$

The two polynomials give the model parameters for every instance, which are then converted into controller settings for every operating point of the process correspondingly, through the direct synthesis method. The PI controller adapts its parameters with a change in the setpoint. A single PI controller with an adaptive mechanism takes care of both the servo and regulatory performance throughout every operating point of the process.

Since the Linear Parameter Varying model is the interpolation of the linear models, multi-model based PI controllers are not necessary; so the PI controller is tuned in a single loop fashion, using the LPV model. A single LPV model based adaptive PI controller satisfies the servo and regulatory responses of the process. Its performance is also better, compared to the other control schemes. The closed loop response of the conical tank system with the LPV model based PI controller and adaptive PI controller, were implemented.

6. EXPERIMENTAL RESULTS

The linear models in the four operating regions of the conical tank system are framed using the experiment data obtained from the experimental setup. The height of the liquid level in tank is taken as the scheduling parameter. The LPV model is identified by interpolating the linear models developed in the four operating regions, using the weights which are the functions of the scheduling point variable. The combined results of the experimental data and LPV model outputs are illustrated in the Fig.6. From the graph, it is inferred that the LPV model is tracking the nonlinearities of the experimental data in an accurate way.

The real time responses to the conventional PI control scheme and adaptive control scheme for the conical tank system were tested, for the linear models and linear parameter varying model. The real time implementation in conical tank system was done with LabVIEW. First, the non linear response of the conical tank system was linearised into four regions, and the optimum PI controller parameters for the first region were estimated, using the direct synthesis method, and the real time responses were obtained for multi step inputs, as shown in Fig.7.It is inferred that the performance of the controller is not satisfactory in all regions, except the first for which it is designed. Due to gain mismatch, oscillations occur, and set point tracking is not satisfactory. In order to improve the controller performance over the entire process, the PI controller is designed for all the four regions, using the direct synthesis method and implemented in real time. Fig.8. shows the servo and regulatory performance of the controller. In each region, the set point is tracked and the disturbance caused is also rejected. When the process parameter changes the control of the level in the conical tank system process is difficult due to its increasing non-linearity and interaction. Hence, the multi PI controller does not provide a satisfactory response. In order to reduce the number of controllers, an adaptive Controller is proposed. From Fig .9. it is understood that the overshoot has been eliminated in the Adaptive PI control scheme, when compared to the conventional PI control scheme. The Coventional PI controller and Adaptive controller schemes were implemented for the linear parameter varying model. The closed loop response of the conical tank system with the LPV model based PI controller and the adaptive PI controller is shown in Figs.10 and 11 respectively. The efficiency of the LPV model based PI and adaptive PI controllers are compared with the other control strategies, using the time domain specifications, and are listed in Table 4. In the LPV model based Adaptive PI control scheme, even though the settling time and rise time are comparatively larger than those of the conventional PI control scheme, the overshoot has been completely eliminated.

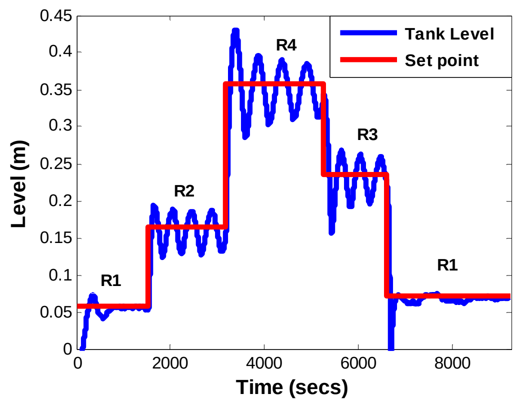


Fig . 7. Closed loop response of the conical tank system with the single PI controller acting for the entire region.

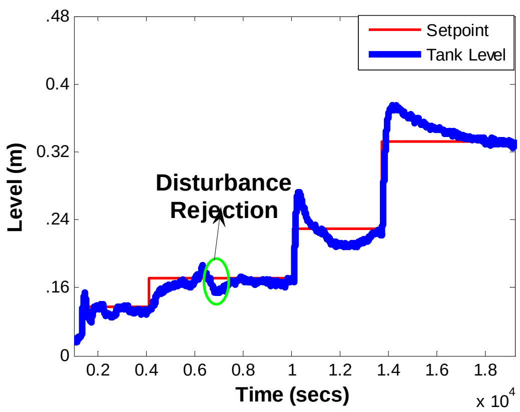


Fig. 8. Closed loop response of the conical tank system with the multi-model control scheme.

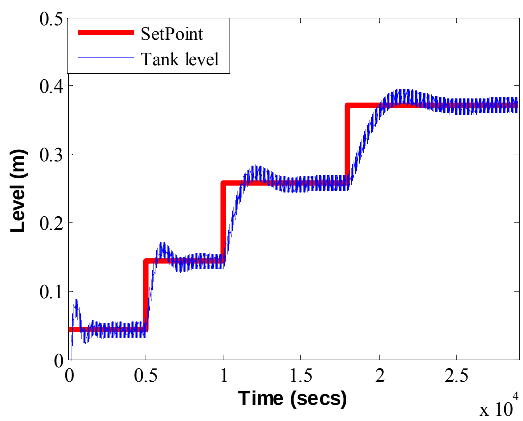


Fig. 9. Closed loop response of the conical tank system with the Adaptive PI controller.

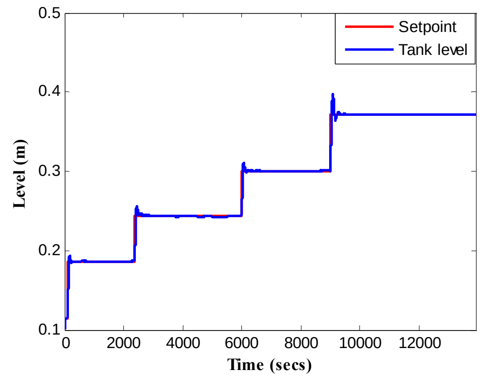


Fig. 10. Closed loop response of the conical tank system with the LPV model based PI controller.

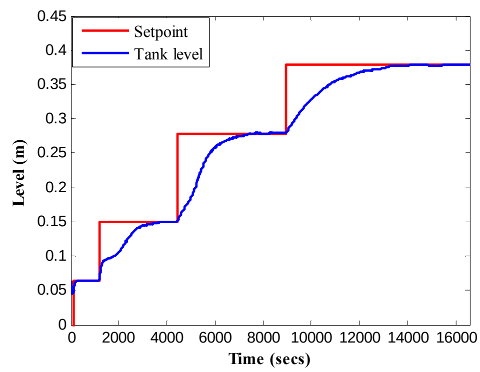


Fig. 11. Closed loop response of the conical tank system with the LPV model based Adaptive PI controller.

Table 4. Comparison of time domain specifications of the implemented control schemes

Timedomain specifications	Rise time(sec)	Settling time(sec)	Overshoot
Single PI controller in all the Regions	450	620	0.4511
Multimodel PI controller	300	455	0.3224
Adaptive PI controller	338	475	0.058
LPV model based PI controller	200	332	0.1687
LPV model based Adaptive PI controller	440	522	0

From the responses it is clear that the performances of the LPV model based controllers are superior to those of the single PI controller and multi-model based control schemes.

7. CONCLUSION

The Linear Parameter Varying model was developed for a conical tank system, which is nonlinear in nature. And the following conclusions are drawn. Among the various types of modelling for a nonlinear system, linear parameter varying modelling proves to be efficient and also simple in structure.

In the Conical Tank system, the conventional PI controller schemes (single PI controller, multi-model based controller and Adaptive PI controller) and the LPV model based control schemes have been implemented at the four operating regions of the system. The single PI controller, multi-model based PI controller and Adaptive PI controller schemes are not able to provide satisfactory performance in terms of overshoot and hence the LPV model is required.

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