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Design of Control Schemes to Adapt PI Controller for Conical Tank Process

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Abstract

The non-linearity and constantly changing cross section of the conical tank are the immense challenge in process control and it cannot be effectively controlled by the linear PID controllers. Hence, an attempt is made here to adapt the PI controller suitable to control the conical tank by two methods namely an adaptive PI controller and neural network based PI controller, which are designed by choosing level as the scheduling variable. The first method combines the output of multiple linear PI controllers, each describing the process dynamics behavior at a specific level of operation. The global output is insertions of individual PI controller outputs weighted depending on the current value of the measured process variable. In the second method, a neural network is used to calculate the PI controller parameters based on the scheduling variable that corresponds to major shift in process dynamics. The real time implementation of these two control schemes is done in simulink toolbox using VMAT-01 data acquisition module for the conical tank process. The experimental results show that the proposed control schemes have good setpoint tracking and disturbance rejection capability.

Keywords: *Adaptive PI controller, Conical tank, Multiple model adaptive PI, Neural network adaptive PI, Scheduling variable.*

1 Introduction

In process industries, the primary task of the controller is to maintain the process under stable conditions even at different kinds of disturbances. The Proportional

Integral Derivative (PID) controllers are widely used in many industrial control systems for several decades due to their acceptable performance since the invention of the first tuning method by Ziegler and Nichols [1]. The shape of the tank has vital role in the process of designing the controllers, since the availability of the tanks in the process industries are in linear and non-linear shapes like conical, spherical, cylindrical, etc. The shape of the conical tank contributes to better disposal of solids, while mixing, provides complete drainage, especially for viscous liquids in industries such as petrochemical, paper making, wastewater treatment, hydrometallurgical, and food process industries. So that, the controlling of conical tank is the challenging problem due to its non-linearity and constantly changing cross section. The challenge and the demand in the real time applications is the motivation to consider the conical tank process for the research.

Thereafter, a non-linear controller is designed by Anandanatarajan *et al.* [2] on the basis of a variable transformation for the first order non-linear process with dead time, which is tested on a conical tank level process with dead time. The controller is tested by simulation and experimentation, and then compared with the Ziegler Nichols PI controller [3]. The Ziegler Nichols PI controller gives an oscillatory response even at the nominal operating point [2]. On the other hand, the Globally Linearised Controller (GLC) gives an almost oscillation free response because the open loop non-linear system becomes a closed loop linear system and the dead time is moved out of the loop by the Smith predictor. Though, prediction of a future variable of a non-linear system is very difficult, it can be predicted by the Smith predictor since the process variable in the transformed domain is linear [4]. Finally, the simulation and real time experimentation on a hemispherical tank level process are performed for the nominal operating point of 50% and compared with the conventional PI controller.

N.S. Bhuvaneswari *et al.* [5] proposed a neuro based model reference adaptive control for conical tank level process. Furthermore, a dynamic programming algorithm based time-optimal control for set point changes and an adaptive control for process parameter variations using neural network for a non-linear conical tank level process are proposed by Bhuvaneswari *et al.* [6]. While, comparing the servo response of control schemes obtained through real time, the neural network based dynamic programming method outperforms with existing schemes in terms of integral square error and integral time absolute error. Similarly, the adaptive control using neural network performs very well, as it eliminates the steady state error. As an outcome, it is affirmed that the neuro based dynamic programming method is employable for servo operation and the adaptive method using neural network is utilizable for regulatory operations and process parameter variation based operations.

In the field of multi-model controllers, Vinodha et al. [7] designed the multiple-model adaptive PI strategy and the neural network adaptive PI strategy for the control of spherical tank process to show the way to extend the classical linear control design methods to control non-linear process. These control schemes are simple in structure and the effectiveness of these schemes has been demonstrated in the spherical tank process, which exhibits dynamic non-linearity due to the constantly changing cross section. But the work is limited to simulation. A non-linear model predictive controller using the family of local linear state space models is developed by Prakash and Srinivasan [8] to control the continuous stirred tank reactor process, which holds dynamic non-linearity. Further in this paper, non-linear process is built by the combination of local linear models and this forms a strong foundation for multiple model based structures to handle nonlinearities.

Liu Loren [9] has proved that combining artificial neural network with PID control can make PID tolerate to non-linear complex systems with better robustness. Jinzhu Peng, Rickey Dubay [10] have presented an adaptive control approach based on the neural networks to control a DC motor system with dead-zone characteristics (DZC). Here a feedforward neural network is proposed to formulate the traditional PID controller, termed as PID-type neural network (PIDNN), which is then used to control and compensate for the DZC.

Xiaofang Yuan and YaonanWang [11] have proposed a self-learning PID controller where the controller parameters, K_P , K_I , and K_D are treated as neural networks weights and they are adjusted using a neural networks algorithm. The results are verified using computer simulations. Md. Selim hasan et.al., [12] have compared PID and model reference adaptive control for a prototype water level control system.

There are many existing control methods for conical tank level process [4], [6]. In addition, the applications of fuzzy logic, genetic algorithm neural networks and neuro fuzzy in designing the controllers have also been suggested in the literature [13], [14]. Although several methods have been developed, in most of them, either some assumption is made or wide operating is not concerned. Furthermore, the accuracy of the model has a significant effect on the performance of the closed loop system. Hence, the capabilities of the controller will degrade as the operating level moves away from the original design level of operation.

The intention of this paper is to design and compare the performance of two different adaptive schemes namely Multiple Model Adaptive based PI (MMAPI) and Neural Network based Adaptive PI (NNAPI). The proposed schemes are imposed on the conical tank process which is stationary in time, but non-linear with respect to the operating level. Furthermore, the objective of this paper is to develop the adaptive control law in order to adopt the linear PI controller in the wide operating range of the process by scheduling the variable which causes a major shift in the operating point. The paper is organized as follows: In Section 2, the experimental set-up for conical tank process is described. In Section 3, the mathematical model for conical tank process and block box modeling are presented. The design procedure for adaptive controllers namely MMAPI and

NNAPI are discussed in Section 4. The obtained results are analyzed in Section 5. Finally, the conclusion is given in Section 6.

2 Experimental Conical Tank Process Setup

The experimental setup contains a conical tank, water reservoir, submersible pump, rotameter and Differential Pressure Transmitter (DPT), electro pneumatic converter called as Current to Pressure (I/P) converter, pneumatic control valve, VMAT-01 interfacing module, and a Personal Computer (PC). The VMAT-01 module supports one analog input channel, one analog output channel, and two pulse width modulation inputs. Its sampling time is 0.1 sec and baud rate is 38,400 bytes per sec with 8-bit resolution. It is operating in the voltage range from +5 volts to -5 volts. The block diagram of the conical tank level setup is shown in Fig. 1.

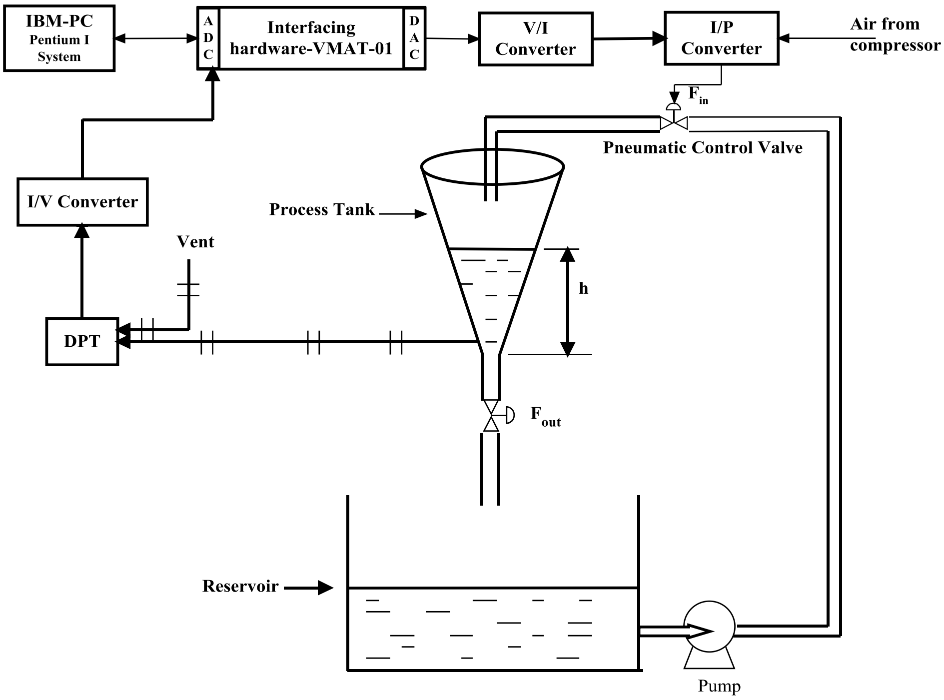


Fig. 1: Experimental setup for liquid level control of a conical tank

The conical tank is made up of stainless steel and is mounted vertically on the stand. The water enters into the tank from the top and leaves to the reservoir, which is placed at the bottom of the tank. The level of the water in the conical tank is quantified by means of the DPT. The quantified level of water in the form of current in the range of (4-20) mA is sent to the Current to Voltage (I/V) converter. The process variable in the form of analog voltage is transmitted to ADC module of the VMAT-01, which converts the analog data to digital data and feed it to the PC. The PC acts as the controller and data logger. The controller considers the process variable as feedback signal and finds the manipulated variable as the output based on the predefined set point. The DAC module of the VMAT-01 converts this manipulated variable to analog form and transmit to the Voltage to Current (V/I) converter, which converts the analog voltage signal in the range of 0-5 volts to 4-20 mA current signal. The I/P converter converts the current signal to pressure in the range of 3 to 15 psi, which regulates the flow of water into the conical tank based on the outflow rate of the tank. The photograph of the experimental setup of the conical tank process is shown in Fig. 2 and its technical specifications are given in Table 1.

Table 1: Technical specifications of experimental setup

Part Name	Details		
	Material	:	Stainless Steel
Conical tank	Diameter	:	32.6 cm
	Volume	:	18 litres
Storage tank	Material	:	Stainless Steel
	Volume	:	76 litres
Differential pressure	Type	:	Capacitance
transmitter	Range	:	2.5-250 mbar
	Span limit	:	0.65-65 kpscal
	Output	:	4-20 mA
	Make	:	ABB
Pump	Centrifugal	:	0.5 HP
Control valve	Size	:	1/4" Pneumatic actuated
	Type	:	Air to open
	Input	:	3-15 psi
Rotameter	Range	:	0-440 lph
Air regulator	Size	:	1/4" BSP
	Range	:	0-2.2 bar
I/P converter	Input	:	4-20 mA
	Output	:	0.2-1 bar
Pressure gauge	Range(G_1)	:	0-150 psi
	Range(G_2)	:	0-30 psi
	Range(G_3)	:	0-30 psi

3 Conical Tank Process Modeling

Usually, most process models can be written in the mathematics or in terms of equations. In such a way, the non-linear conical tank process is expressed in the differential equation model to understand the structure of the process. The real time system identification is helpful in designing a suitable control schematic for a completely unknown system which needs black box model and a partially known system which needs a gray box model. Most industrial processes are black box models, since the actual parameter values within a known model structure are unknown [15]. The rest of this section describes both mathematical modeling and black box modeling of the conical tank process, and the procedure to find tuning parameters using Ziegler and Nichols method [1] from the open loop parameters obtained by black box modeling.

Fig. 2: Photograph of the conical tank setup

3.1 Mathematical modeling

The various dimensions of the conical tank are depicted in Fig. 3. Let H be the maximum height of the tank with R as radius at that height. Let r be the radius at corresponding height h.

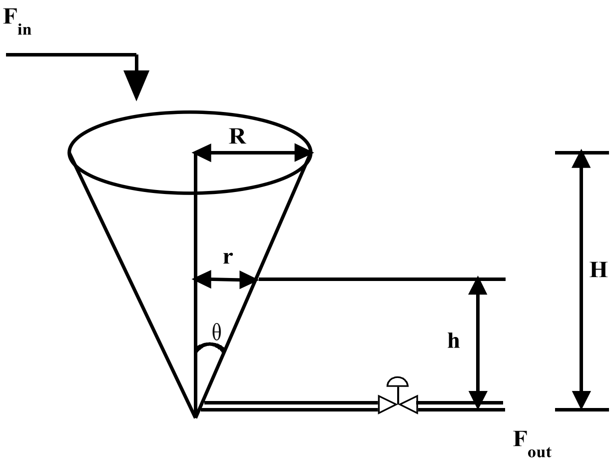


Fig. 3: Conical tank level process

The mass balance of inflow and outflow of the tank is expressed in equation (1).

$$F_{in} - F_{out} = \frac{dV}{dt} \tag{1}$$

where, V is the volume of the liquid in the tank, and F_{in} & F_{out} are the inflow and outflow rate of the tank, respectively. The volume of the tank is computed as in equation (2).

$$V = \frac{1}{3}\pi r^2 h \tag{2}$$

The outflow of the tank F_{out} is assumed to be proportional to the square root of the height h as given in equation (3).

$$F_{out} = c\sqrt{h} \tag{3}$$

where, c is the constant of proportionality. From Fig. 3, tan θ is found as given in equation (4).

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

After substituting equation (4) and the values of V and F_{out} in equation (1), it is modified as given in equation (5).

$$\frac{dh}{dt} = \frac{F_{in} - c\sqrt{h}}{\pi \tan^2\theta h^2} \tag{5}$$

Linearization of the equation (5) around various operating points provides the gain and the time constant in the form of an equation (6).

$$\frac{h(s)}{F_{in}(s)} = \frac{k_p}{\tau_p s + 1} \tag{6}$$

where, $k_p = \frac{2\sqrt{\bar{h}}}{bx}$ and $\tau_p = \frac{2\pi \tan^2\theta}{bx(\bar{h})}\left(-\frac{5}{2}\right)$

3.2 Black box modeling

In the system identification of the conical tank process using black box modeling, the loop is made open and level is maintained constant around a particular operating point [16]. Then, a small step change is given in the PC, which in turn reflects into the DAC module of VMAT-01 interface. The voltage supplied by the DAC module is converted to pressure with the help of V/I converter and I/P converter. The pneumatic input is therefore sensed by the valve and hence the valve opens or closes accordingly. As a result there is a change in level from the operating point, which is observed by DPT and recorded in the PC through ADC module of VMAT-01 with the help of I/V converter.

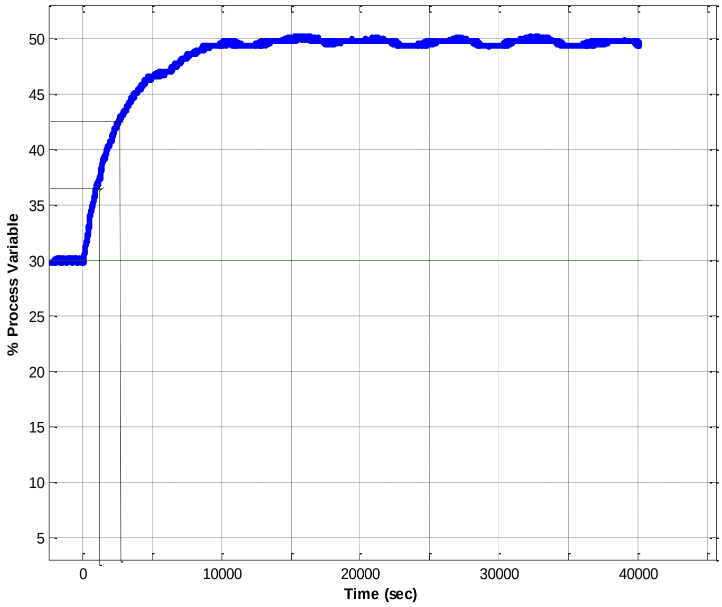


Fig. 4: Open loop response of conical tank process around 30% of the level

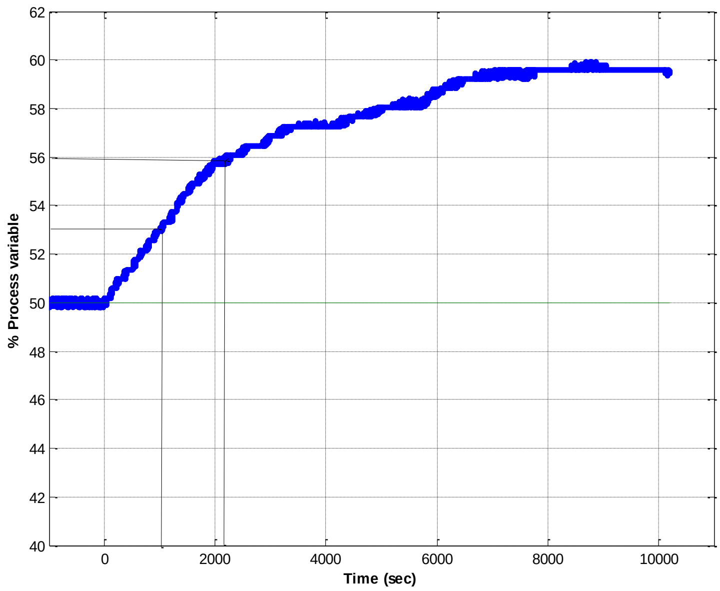


Fig. 5: Open loop response of conical tank process around 50% of the level

Thus for a step increment given in the input flow rate, various readings are recorded till the level in the conical tank reaches a steady value. The open loop responses of the process by changing the manipulated variable from 82% to 84% around 30% of the level, the manipulated variable from 84.6% to 86.6% around the 50% level, and the manipulated variable from 87% to 89% around the 60% level are recoded and the corresponding obtained responses are shown in Fig. 4, Fig. 5, and Fig. 6 respectively. The experimental data are approximated to a First Order Plus Dead Time (FOPDT) model to obtain the open loop parameters of the conical tank process.

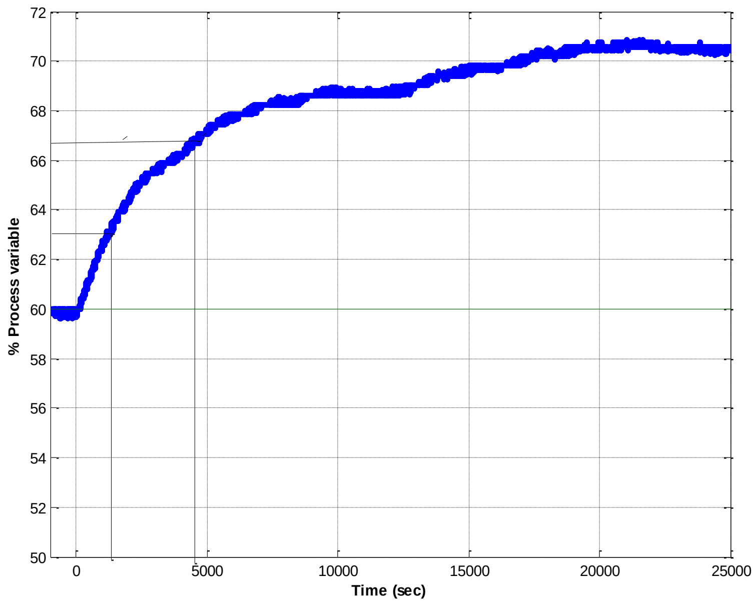


Fig. 6: Open loop response of conical tank process around 60% of the level

There are several disadvantages in the existing methods [1], [17] in finding the FOPDT process model, which are the accuracy in the point of inflection and the difficulty in locating the point of inflection in practice. To overcome this difficulty, the method proposed by Sundaresan and Krishnaswamy [18] is used to obtain the parameters of the transfer function of the FOPDT model by letting the response of the actual system and that of the model to meet at two points, which describe the two parameters τ and θ. The proposed times, t_1 and t_2, are estimated from a step response curve on the 28.3% and 63.2% response times respectively.

Based on the values of t_1 and t_2, the time constant τ is calculated as given in equation (7), and time delay θ is calculated as given in equation (8). Another important parameter of the process model, the process gain K_p is calculated as given in equation (9).

$$\tau = 1.5(t_2 - t_1) \tag{7}$$

$$\theta = t_2 - \tau \tag{8}$$

$$K_p = \frac{\text{Change in process output}}{\text{Change in process input}} \tag{9}$$

From the open loop parameters, the controller parameters namely proportional gain K_c and Integral gain K_I are calculated by using Ziegler and Nichols [1] tuning rules and listed in Table 2.

Table 2: Process model and PI controller parameters at different operating points of conical tank process

Process Model	Level *h*	Transfer Function Model	Controller Gain K_c	Integral Gain K_I
Model 1	30%	$G(s) = \frac{10e^{-156s}}{2344s+1}$	1.35	0.00019
Model 2	50%	$G(s) = \frac{4.8e^{-530s}}{1652s+1}$	0.58	0.000057
Model 3	60%	$G(s) = \frac{5.5e^{-469s}}{3749s+1}$	1.30	0.00064

4 Design Procedure for Adaptive Controllers

The design of proposed controllers is discussed in this section. The controller output is determined using the adaptive PI control law as given in equation (10).

$$u(k) = K_c(h)\left[\left(e(k) - e(k-1)\right) + \frac{T}{T_I(h)}e(k)\right] + u(k-1) \tag{10}$$

where, T is the sampling instant. $K_c(h)$ and $T_I(h)$ are adaptable proportional gain and integral time to be obtained for each sample based on the scheduling variable h, by the two proposed methods. The first method (MMAPI) uses a combination of 3 models taken at three different operating points to determine $K_c(h)$ and $T_I(h)$ at each instant. The second method (NNAPI) uses trained information of K_c and T_I to determine them instant by instant, based on the value of scheduling variable h.

4.1 Design of multiple-model based adaptive PI controller

Modeling and control of nonlinear dynamic systems are one of the most challenging areas in system theory. Linear controllers are conventionally used in the control of such systems for the past decades. But the lack of robustness of the conventional linear controllers under varying operating conditions leads to the motivation behind adopting an adaptive strategy for the control of nonlinear systems [19].

For control applications, PID controller tuned at one operating point does not work for any other operating points. In such situations, we can implement multiple model PID control algorithm. The linear models at different operating points of PI controller are done separately and combined to form a global controller output in [7]. The design of PI controller is done on the basis of local linear models. To design the controller based on MMAPI concept, the conical tank process has been linearised at three different operating points. The corresponding transfer function models are derived and listed in Table 2. The three different operating points are chosen at a height of h_1 = 30%, h_2 = 50% and h_3 = 60%, so as to cover the entire height of the conical tank. At each sampling instant, the scheduler will assign weights for each controller and the weighted sum of this output will be applied as input to the plant as shown in Fig. 7.

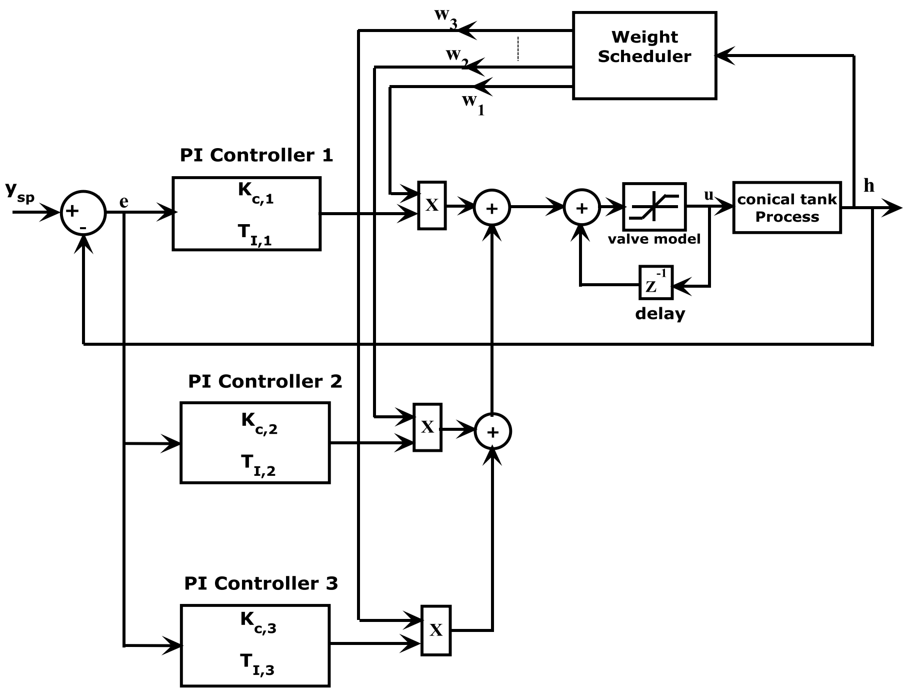


Fig. 7: Block diagram for MMAPI strategy of conical tank process

The tuning parameters of each PID controller have been determined using the IMC tuning rules [1], [20] which yield the IMC based PID controller parameters are given in equation (11).

$$K_{c,i} = \frac{0.9\tau_i}{k_i.\theta_i}; \quad T_{I,i} = 3.33\tau_i; \quad \forall \quad i = 1:3 \tag{11}$$

The controller parameters $K_c(h)$ and $T_I(h)$ are calculated using the equation (12) and equation (13) respectively and these computed values are used in the control law stated in equation (10).

$$K_c(h) = \sum_{i=1}^{3} w_i(h) * K_{c,i} \tag{12}$$

$$T_I(h) = \sum_{i=1}^{3} w_i(h) * T_{I,i} \tag{13}$$

The process gain and process time constant are functions of liquid level (h) which is chosen as the scheduling variable. In equation (11), $w_i(h)$ is a weighting factor which determines the weights w_1, w_2 *and* w_3 assigned to three controllers based on the scheduling variable h. The weights are in the range of 0 to 1. The weight calculation algorithm followed in this work is shown in Fig. 8.

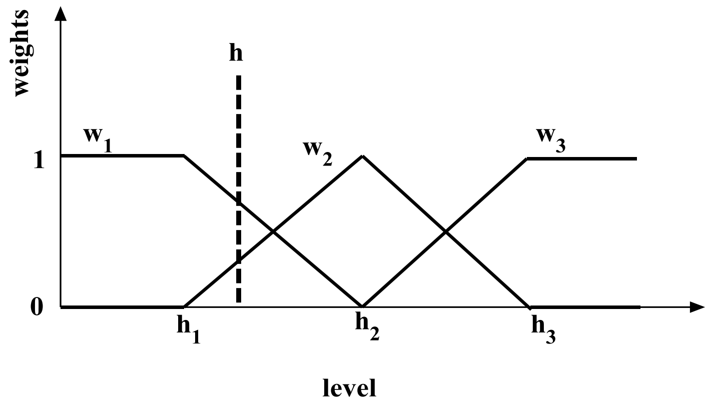


Fig. 8: Calculation of weights based on scheduling variable

4.2 Design of neural network adaptive PI controller

Neural networks are capable of learning and reconstructing complex nonlinear mapping with all its parameters being adaptable. In this work, the PI controller parameters are adapted by using a simplified neural adaptive structure. The neural structure has been proposed with one input neuron and two output neurons. The input neuron represents the scheduling variable, which is the liquid level of the conical tank process. The output neurons are the PI controller parameters namely controller gain K_C and integral time T_I. The network is trained with K_C & T_I values for a wide range of height in the conical tank using a simple back propagation algorithm. The architecture used for the training is given in Fig. 9. For nonlinear conical tank process, it is sufficient to use single hidden layer in the architecture. The structure of back propagation neural network and its training parameters are shown in Table 3.

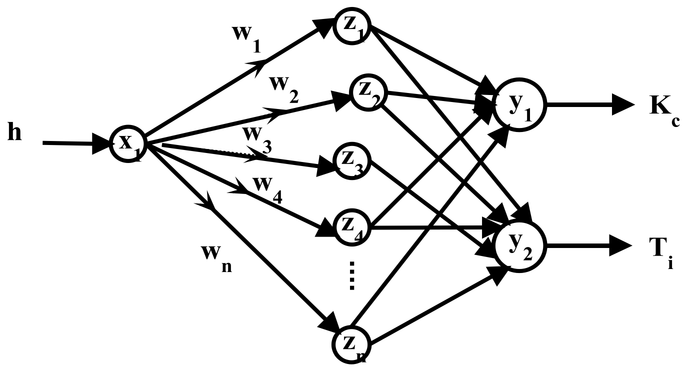


Fig. 9: Neural based adaptive-PI network architecture

Table 3: Training parameters for NNAPI controller

Neural Network Training Parameter	Specification
Training algorithm	Levenberg-Marquardt optimization algorithm
Activation function	Hidden Layer: Tansigmoidal Output Layer: Pure linear
Initial weight selection	Nguyen-Widrow criterion
Number of neurons in the input layer	1 (Scheduling variable liquid level (h))
Number of neurons in the output layer	2 (Controller gain K_c and Controller lntegral Time T_I)
Number of neurons in the hidden layer	10
Objective function	Mean square error: 1.24258e-007 Number of epoch:500

The training of the back propagation neural network has been implemented using the commands available in the neural network toolbox of MATLAB. The block diagram of the NNAPI control scheme is shown in Fig. 10. The neural structure takes up the scheduling variable (h) as input and determines the controller parameters namely controller gain $K_c(h)$ and integral time $T_I(h)$ at every instant based on the scheduling variable (h). These controller parameters $K_c(h)$ and $T_I(h)$ are utilized in the PI control law given in equation (10), which in turn keeps the level of the conical tank at the desired setpoint.

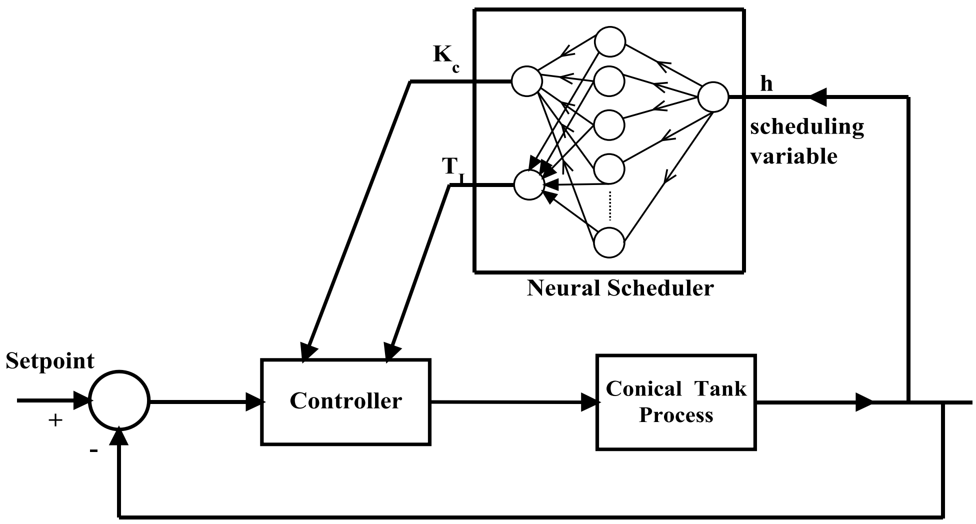


Fig. 10: Block diagram of neural based adaptive PI controller

5 Results and Discussion

The servo response of the conical tank process using MMAPI and NNAPI control strategies for setpoint variations are shown in Fig. 11(a) and (b). In order to assess the tracking capability of the proposed controller, setpoint variation has been introduced as shown in Fig. 11(a). First 20000 sampling instants are used for maintaining the level at a setpoint of 30%. At 20001th sampling instant, the setpoint is moved from 30% to 60%. From the response it can be inferred that, the proposed controllers, namely MMAPI and NNAPI are capable of maintaining the tank level at the desired setpoint in various operating regions. The variations in the controller output for the corresponding setpoint variations are presented in Fig. 11(b). From the Table 4, it is observed that NNAPI performs better when compared with MMAPI controller in terms of ISE values and settling time.

Table 4: ISE Values – Servo response

Sampling Intervals (sec)	MMAPI	NNAPI
1:20000	7.2414×10^6	1.3267×10^6
20001:50000	3.5603×10^6	3.3292×10^6

Fig. 12 gives the weight assignment pattern in MMAPI controller based on the operating level (h) for setpoint variation shown in Fig. 11(a). The distribution of K_c and T_I based on the operating level (h) in NNAPI controller is shown in Fig. 13 for setpoint variation shown in Fig. 11(a).

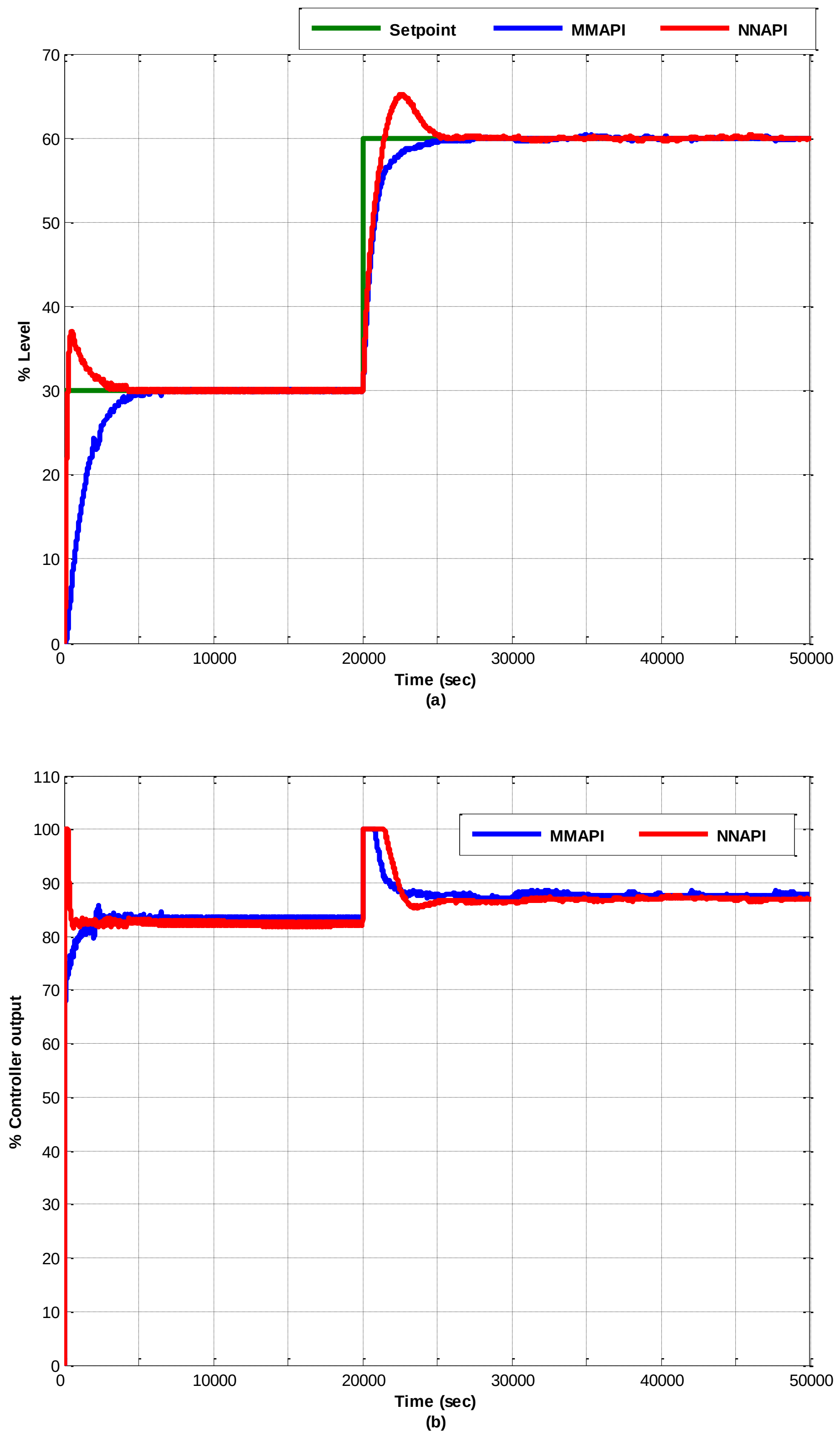


Fig. 11: Servo response of the conical tank process

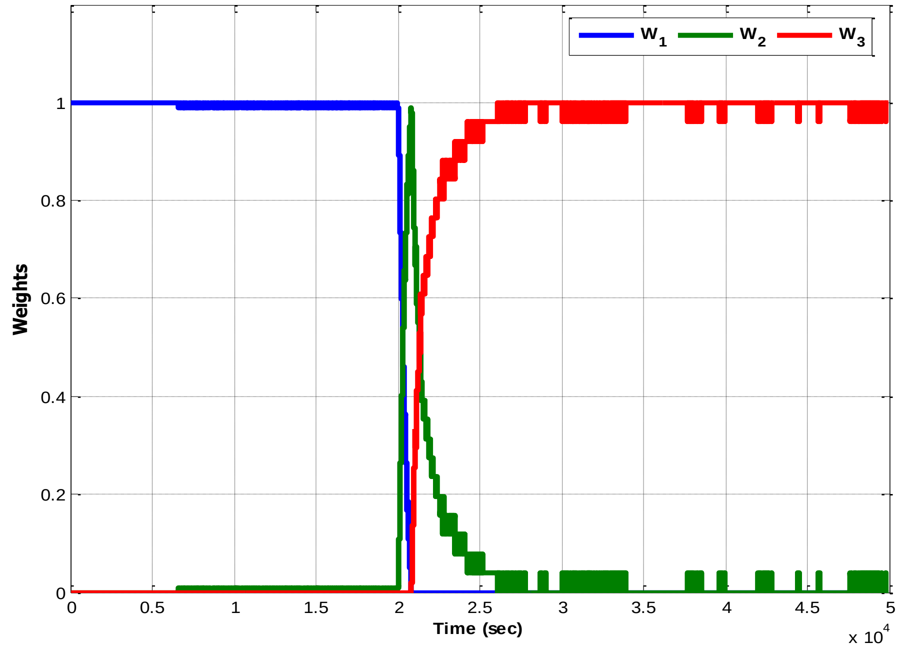


Fig. 12: Weight assignments in MMAPI for setpoint variation in Fig. 11(a)

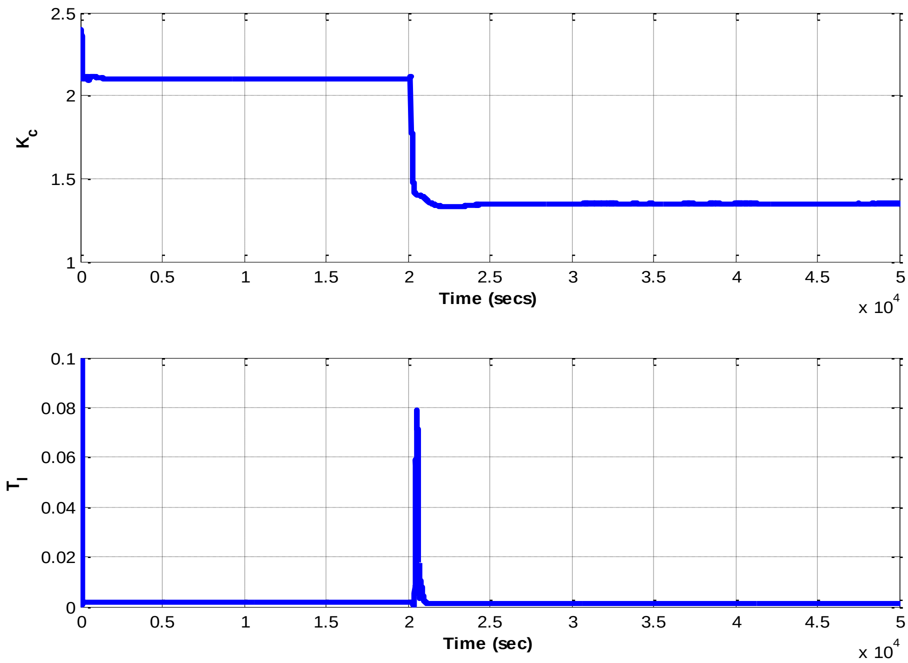
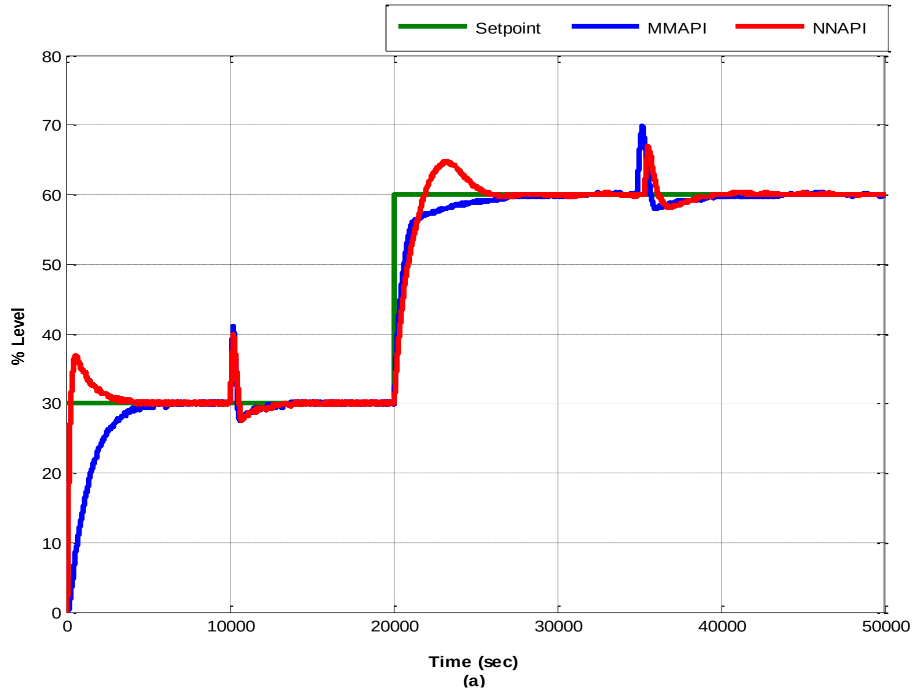


Fig. 13: Distribution of K_c and T_I in MMAPI controller for setpoint variation in Fig.11(a)

The servo regulatory response of onical tank process is presented in Fig. 14(a) and the respective controller output variation is given in Fig. 14(b).



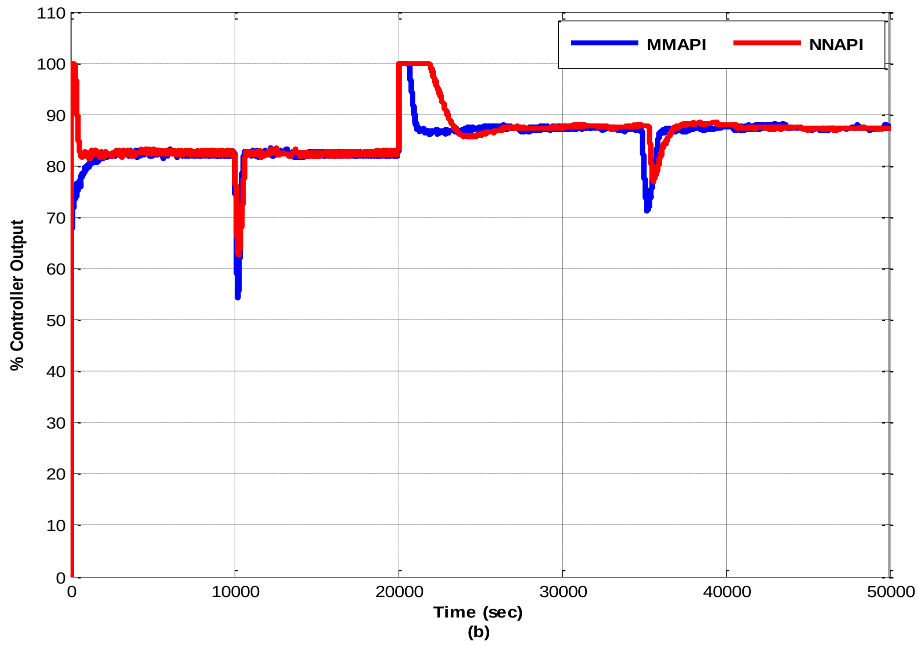


Fig. 14: Servo regulatory response of the conical tank process

To give load disturbance, 700ml of water is added to the inlet of the tank, when the setpoint is maintained at 30% and 60% of the level. The disturbance is given at 10000th second and at 35000th second and maintained for about 60 seconds, uniformly both in MMAPI and NNAPI. From Fig. 14(a) and (b), we infer that when water is added as a disturbance in the inlet, the flow rate at the outlet is decreased to maintain the level.

From Fig. 14(a), it is inferred that both the controllers are capable of rejecting the disturbance and bring the level back to the setpoint. Further, Fig. 14(b) is the evidence that the manipulated variable variations are tackled by both the controllers. The tabulated values of performance indices are listed in Table 5. It has been seen that ISE values and the settling time are less for NNAPI, when compared with MMAPI controller.

Table 5: ISE Values – Servo regulatory response

Sampling Intervals (sec)	MMAPI	NNAPI
1:20000	7.4142×10^{6}	1.6631×10^{6}
20001:50000	3.3490×10^{6}	3.0286×10^{6}

6 Conclusion

In the present work the authors have submitted two control schemes to control the liquid level. Their performances are tested in real time by using the VMAT-01 module for a conical tank process. The proposed controllers use the same control law and differ only in the adaptation of controller parameters. The real time results reveal that proposed controllers have good set point tracking and disturbance rejection at different operating points. The authors conclude that the NNAPI controller shows better performance when compared with the MMAPI control strategy. This is because, mapping between scheduling variable and controller parameters is non-linear using tan sigmoidal activation function in NNAPI, whereas it is linear in MMAPI.

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