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Design and Implementation of Neuro Tuned PI Controller for Non-Linear Conical Tank Level Process

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Abstract: The PID controllers are widely used in industries for nearly a century due to its simplicity, flexibility and efficiency. Recently, the control of non-linear processes in the industries have turned the attention towards the intelligent controllers such as genetic algorithm tuned PI controllers, neural networks based controller, predictive controller, fuzzy logic controller, adaptive controller, etc. This study focuses on the design and implementation of neuro tuned PI controller for the non-linear conical tank level process. A conical tank is a highly non-linear process due to the variation in the area of cross section of the level system with change in shape. In this research, neuro tuned PI controller is designed for the control of non-linear process to ensure the exact level maintenance. The results are obtained by servo, regulatory, servo-regulatory operation for the non-linear conical tank process. For this research, neuro tuned PI controller is compared with Genetic algorithm tuned PI controller. And also, the modeling aspect of the conical tank level process in which the stability analysis of the system is evaluated through the pole zero plot and nyquist stability criteria.

Key words: Non linear conical tank process, genetic algorithm tuned PI controller, neuro tuned PI controller, servo operation, regulatory operation, servo-regulatory operation, performance index values, time domain criteria

INTRODUCTION

In the chemical process industries many challenging control problems arise due to the non-linear dynamic behaviour of the system, uncertain time varying parameters, constraints on the manipulated and controlled variables, interaction between the manipulated and controlled variables, dead time or delay input measurement and unmeasured frequency disturbances. The non-linear conical tank is widely used in hydro-metallurgical industries, cement industries and concrete handling applications, thermal plant's coal handling section, food processing industries and waste water treatment plants. The control of the conical tank is a challenging task due to its non-linearity and constant change in the cross section which depends on the cone inclination angle, height of the cone and radius of the cone.

Literature review: From 1910, onwards the Proportional Integral Derivative (PID) controllers are widely used in process industries due to its simplicity, flexibility and efficiency. A fine tuning concept for closed loop system was developed. The standard methods for tuning of controller includes are: Zeigler-Nichol's ultimate cycling method (Zeigler *et al*., 1942), Open loop tuning method (Cohen and Coon, 1953), the future of PID tuning (Astrom and Hagglund, 2001). A simplified optimum method for PI controller has been introduced (Hwang *et al*., 2003) which produces high performance and widely used for linear self regulating process. The performance between the PID controller and dead time compensating controller based on Integral Average Error (IAE) optimization technique method was developed (ingimundarson and Hagglund, 2002). The tuning concept for fuzzy logic controller for conical tank process was developed (Madubala *et al*., 2004). The real time implementation of wiener model PI controller for conical tank concept was developed (Bhaba and Somasundaram, 2009). The neuro based model reference adaptive control of a conical tank concept was developed (Bhuvaneswari *et al*., 2008). Again the design of intelligent controller for non-linear conical tank process was developed (Nithya *et al*., 2008).

The real time implementation of a new CDM-PI control scheme for a conical tank liquid level maintenance concept was developed (Bhaba *et al*., 2007). Next, the real time application of Ant colony optimizing algorithm was implemented for conical tank process (Ge *et al*., 2002). The design of fuzzy estimator to assist the fault recovery concept was developed (Suresh Manic*et al*., 2009). The objective of this research are:

- To design the neuro tuned PI controller

- And compare the performance of genetic algorithm tuned PI controller for a non-linear conical tank level process and also compare the performance of the controllers

The performance of the controller is evaluated by performance index such as Integral Square Error (ISE), Integral Time multiplied Square Error (ITSE), Integral Absolute Error (IAE), Integral Time multiplied Absolute Error (ITAE) and time domain specifications such as Peak over shoot (M_p), settling Time (T_s) and steady state error (e_{ss}). Since, neuro tuned PI controllers are based on heuristics, they are simple to design and can perform well on ill-defined models. The above designed controllers are operated by servo, regulatory and servo-regulatory operation for the non-linear conical tank level process

MATERIALS AND METHODS

Modeling of non-linear conical tank process: The schematic diagram of the non-linear conical tank process is shown in Fig. 1. The inlet Flow rate (F_{in}) can be modified by the inlet valve and the outlet Flow rate (F_{out}) can be modified by the outlet valve. Under dynamic conditions, the conical tank Height (H) depends on the inlet Flow rate (F_{in}), outlet Flow rate (F_{out}) and Radius (R) of the conical tank. The plant transfer function is obtained in terms of the process characteristics, namely, the process gain (K) and process time constant (τ). Normally, the dead time or delay time (θ_d) cannot be neglected.

The conical tank level process consists of an inflow rate, outflow rate and the change in height with respect to time (Fig. 1). This can be represented by the mass balance equation governing the system dynamics and is given by the Eq. 1-2:

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

Where:

F_{in} = Inlet flow rate of the conical tank ($cm^3\ sec^{-1}$)
F_{out} = Outlet flow rate of the conical tank ($cm^3\ sec^{-1}$)
R = Top radius of the conical tank (cm)
H = Total height of the conical tank (cm)
h = Height of the water in the conical tank (cm)
r = Radius of the water in the conical tank (cm)

Using the trigonometric geometry theory the conical tank tangent angle is obtained as:

$$\text{Tan}\,\theta = \frac{R}{H} = \frac{r}{h} \tag{2}$$

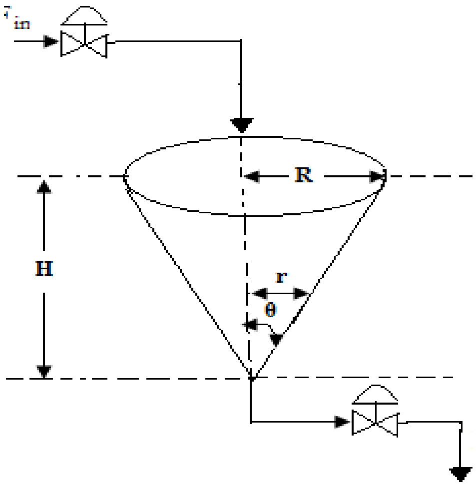

Fig. 1: Geometrical cross-sectional view of the conical tank process

For the conical tank process, the outflow rate is proportional to the square root of level and can be represented as:

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

where, b is the valve constant. The volume of the cone can be written by the mathematical formulae:

$$V = \frac{1}{3}\pi R^2 h \tag{4}$$

From Eq. 1-4, the modified mass balance equation can be written as:

$$\frac{1}{3}\pi\ R^2 \frac{dh}{dt} = F_{in} - b\sqrt{h} \tag{5}$$

$$\frac{A\,dh}{dt} = F_{in} - b\sqrt{h} \tag{6}$$

Where:

$A = \lambda R^2$ = Area of the conical tank process (cm^2)
$\lambda = 1/3\pi$ = Constant or scalar factor between area and radius for conical tank

The conical tank is a highly non-linear process. To convert the non-linear model into a linear approximation model, the taylor series is used for the linearization of the non-linearity of the conical tank. In Eq. 3, a non-linear term ($b\sqrt{h}$) appears which can be linearized using the taylor series expansion. To convert a highly non-linear conical tank process into linear approximation model by applying taylor series, we get:

Table 1: Conical tank process modeling parameters for the different regions and obtaining conventional PI controller parameters

For the conical tank different height locations (cm)	Process parameters			PI controller parameters by Skogestad's tuningrule	
	Process gain (K)	Time constant (τ)	Process delay Time (θ_d) (sec)	Proportional gain (K_p)	Integral gain (K_i)
10	3.160	52.95	4	2.0950	0.0395
20	2.230	149.78	8	4.1979	0.0280
30	1.820	275.18	15	5.0390	0.0183
40	1.580	423.66	22	6.0941	0.0144
50	1.414	592.08	30	7.4773	0.0126

$$A\frac{dh}{dt} = F_{in} - \frac{bh}{2\sqrt{h_s}} \tag{7}$$

$$\frac{2A\sqrt{h_s}}{b}\frac{dh}{dt} + h = \frac{2\sqrt{h_s}\,F_{in}}{b}$$

$$\tau\frac{dh}{dt} + h = K(F_{in}) \tag{8}$$

Where:

h = The transfer function relating the height 'h' and
F_{in} = The inlet Flow rate with the parameters
K = The process gain
τ = The time constant of the conical tank process

$$G(s) = \frac{H_1(s)}{F_{in}(s)} = \frac{K}{(1+s\tau)} \tag{9}$$

$$K = \frac{2h}{U};\tau = \frac{2hA}{U};U = bh^{0.5}$$

For the first order process with delay time, the standard model is given by:

$$G(s) = \frac{Ke^{-\theta}d^{s}}{(1+s\tau)} \tag{10}$$

Where:

K = Process gain
θ_d = Transport lag or delay of the process
τ = Time constant

According to the method proposed by Skogestad's tuning rule for the PI controller is given by:

$$\text{Proportional gain } K_p = \frac{1}{K}\frac{\tau}{(\theta_d + \tau_c)} \tag{11}$$

$$\text{Integral Time Ti} = \tau$$

$$\text{Integral gain} K_i = \frac{K_c}{T_i} \tag{12}$$

Modelling aspects of the conical tank for different heights obtaining the process parameters (K, τ and θ_d) and PI obtaining PI controller parameter such as proportional gain (K_p) and integral gain (K_i) by Skogestad's tuning rule is tabulated in Table 1. For the conical tank process the selected transfer function model:

$$G_p(s) = \frac{1.82e^{-15S}}{(275.18s+1)}$$

This model is considered for the simulation studies of the conical tank process control with different control structures.

Stability analysis of the conical tank process: The stability analysis is necessary to check whether the given system is stable or not. The obtained transfer function of the conical tank process is given by:

$$G(s) = \frac{H_1(s)}{F_{in}(s)} = \frac{K}{(1+s\tau)} \tag{13}$$

Pole-zero stability analysis: The transfer function of the conical tank process can be written as:

$$G(s) = \frac{H_1(s)}{F_{in}(s)} = \frac{K}{(1+s\tau)} = \frac{\frac{K}{\tau}}{\left(\frac{1}{\tau}+s\right)} \tag{14}$$

The pole-zero plot for the conical tank process is shown in Fig. 2. The pole S = -1/τ which lies on the left half side of the s-plane. Hence, the given system is stable.

Nyquist stability criteria: The Nyquist plot is an alternative way to represent the frequency characteristics of the dynamic system. For the obtained transfer function, s = jω and therefore:

$$G(j\omega) = \frac{K}{\tau j\omega + 1}$$

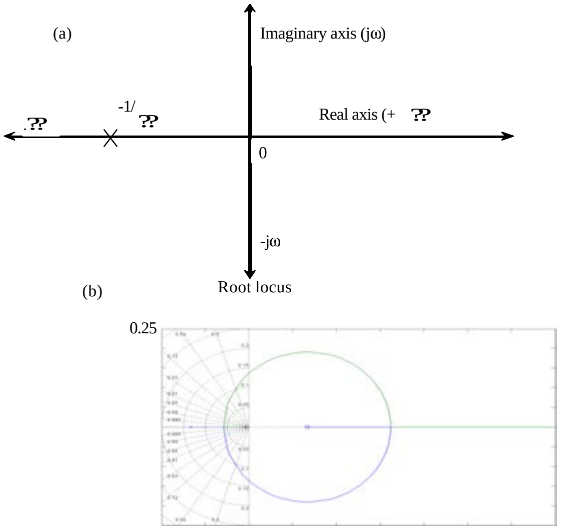

Fig. 2: Pole-zero plot representation for the conical tank process; a) first order process without time delay; b) first order process with delay by Pade's approximation through MATLAB

$$\text{Amplitude Ratio}(\text{AR}) = \left|G(j\omega)\right| = \frac{K}{\sqrt{\tau^2\omega^2+1}}$$

$$\text{Phaseshift} = \varphi = |G(j\omega) = -\tan^{-1}(\tau\omega)$$

In the Nyquist plot, the frequency varies from 0 to ∞, we trace the whole length of the Nyquist plot and find the corresponding values of the amplitude ratio and phase shift. The mirror image of the polar plot is the Nyquist plot.

Case 1: When $\omega = 0$ then $AR = 1$ and $\varphi = 0$. Therefore, the beginning of the Nyquist plot is on the real axis $\varphi = 0$ and at a distance from the origin (0, 0) equal to 1.

Case 2: When $\omega = \infty$ then $AR = 0$ and $\varphi = -90°$. The end of the Nyquist plot is at the origin and at a distance from the origin (0, 0) equal to 0. The intermediate frequency is $0 < AR < 1$ and $-90° < \varphi < 0$. The Nyquist plot will be inside a unit circle and will not leave the first quadrant. The Nyquist plot stability analysis for the conical tank process is shown in Fig. 3. For the condition of the stability analysis for the Nyquist plot:

$$N = P - Z$$

Where:

P = Number of poles on the RHS of the s-plane
N = Number of encirclements of (-1+j0)
Z = Number of zeros on the RHS of the s-plane

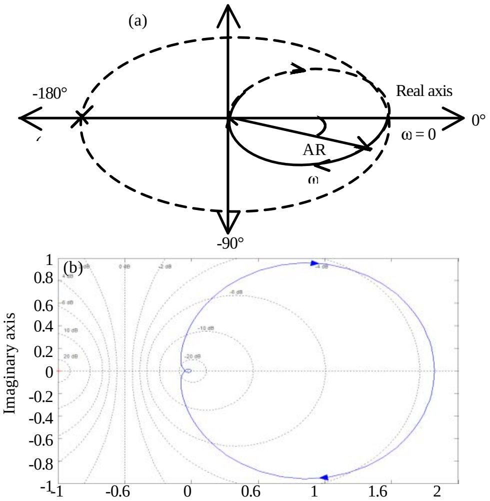

Fig. 3: Nyquist plot stability analysis for the conical tank process; a) first order process without time delay; b) first order process with delay by Pade's approximation through matlab

$N = p-z$; $0 = 0-0 = 0$; hence, the given system is stable. For this research, the inflow rate is considered as the input variable for the conical tank level process and the height is considered as the output variable.

The conical tank or first order process is controlled by the proportional integral controller which forms a closed loop system and is considered as a second order process. In the second order process, the oscillation may be of:

- Undamped system
- Critically damped system
- Over-damped system and
- Under-damped system

To improve the system's performance the important factor is the oscillatory response. For this research, the oscillatory response can be analyzed properly for the conical tank dynamics. For this research, the Skogestad's tuning rule is used.

Control of conical tank process: A conical tank is a highly non-linear process due to the variation in the area of cross section of the level system with change in shape. A conical tank is a highly non-linear process, due to its non-linearity and constant change in the cross section which depends on the cone inclination angle, height of the cone and radius of the cone. The control action of the conical tank can be obtained by servo, regulatory and servo-regulatory operation. In servo operation, the set point is variable and the process or load variable is constant. In regulatory operation, the set point is constant and the process or load variable is variable. In servo-regulatory operation, the set point is variable and the process or load variable is also variable.

For the given system, the error is defined as the difference between the set point value and the measured value. The formula for error is given by:

$$e(t) = r(t) - c(t) \tag{15}$$

Where:

$e(t)$ = Error signal at time t
$r(t)$ = Reference input signal may be step input
$c(t)$ = Output signal produced by the process

For the above four performance index value as time reaches infinity and the error reaches to zero:

$$\lim_{t\to\infty} e(t) = 0 \tag{16}$$

The performance of the controller is evaluated in terms of the following performance indices are:

$$\text{Integral Square Error}\left(\text{ISE}\right) = \int_0^\infty e^2(t)dt \tag{17}$$

$$\text{Intagral Time multipied Square Error}\left(\text{ITSE}\right) = \int_0^\infty te^2(t)dt \tag{18}$$

$$\text{Intagral Absolute Error}\left(\text{IAE}\right) = \int_0^\infty |e(t)|dt \tag{19}$$

$$\text{Intagral Time multipied Square Error}\left(\text{ITSE}\right) = \int_0^\infty t|e(t)|\,dt \tag{20}$$

The PI controllers are generally used to control the conical tank. Tuning of PI controller is very much essential for the satisfactory operation of the system. Zeigler *et al*. (1942)'s method and Cohen and Coon (1953) method are generally preferred for PID controller tuning. For conical tank process, the above mentioned controller performance index values such as Integral Square Error (ISE), Integral Time multiplied Square Error (ITSE), Integral Absolute Error (IAE), Integral Time multiplied Absolute Error (ITAE) and also through time domain specifications as well as graphical approach.

Review of the Genetic algorithm: The Genetic algorithm was first introduced by John Holland in 1975. The Genetic Algorithm (GA) is a random search technique which imitates Darwin's theory of the natural evolution and the survival of the fittest approach. This technique was inspired by the mechanism of natural selection, a biological process in which stronger individuals are likely to be winners in a competitive environment. The Genetic algorithm is related to biology, computer science, image processing, pattern recognition, physical science, social science and neural networks.

The genetic algorithm has been used for different problems such as the filter design technique, machine learning technique, system identification and process control applications successfully. Teng *et al*. (2003) used the genetic algorithm and its direct analogy of such natural evolution to do global optimization, to solve highly complex problems. To solve non-linear system parameters, the genetic algorithm uses the direct analogy of such natural evaluation with the global optimal approach. The non-linear parameters are regarded as the genes of a chromosome and can be structured by a string of concentrated values. The variables are represented in the form of binary real numbers or other forms. The genetic algorithm is governed by three operations namely selection, cross-over and mutation.

Selection: Selection is a stochastic method for the selection of individuals from a population, according to their fitness to produce successive generations and plays an important role in the Genetic algorithm. An individual with the highest fitness has more chance to be selected for the next generation. For this research, the tournament selection method is used.

Cross-over operation: If the selection or reproduction is over, it is again applied for the crossover operation. In the crossover operation, the information is exchanged among the strings for the mating pool, due to which a new string is formed. Similarly, the crossover operation is mainly responsible for the global search property of the genetic algorithm. Crossover basically combines the substructures of two parent chromosomes to produce new features with a specified probability.

Mutation: The final Genetic algorithm operation is mutation, even though the mutation operation is scarcely used, it is valuable in preventing the involuntary loss of good genetic material. Mutation involves the alternation of information at a random selected bit position. The value of the chromosome at this position is changed (1 or 0 or vice versa). Normally, the mutation rate is selected with a very low value and may be 0.075 for this research.

The block diagram representation of the conical tank process controlled by the genetic algorithm tuned PI controller is shown in Fig. 4. The main parts are: the conical tank level process and the genetic algorithm to find the PI parameters such as proportional gain (K_p) and

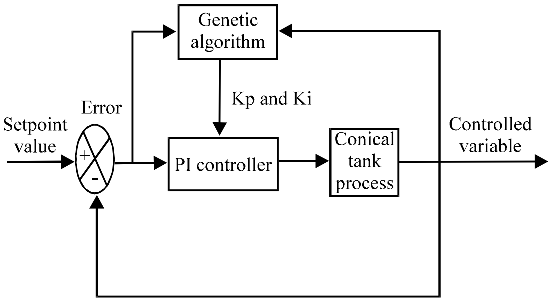

Fig. 4: Block diagram representation of the genetic algorithm tuned PI controller for the conical tank process

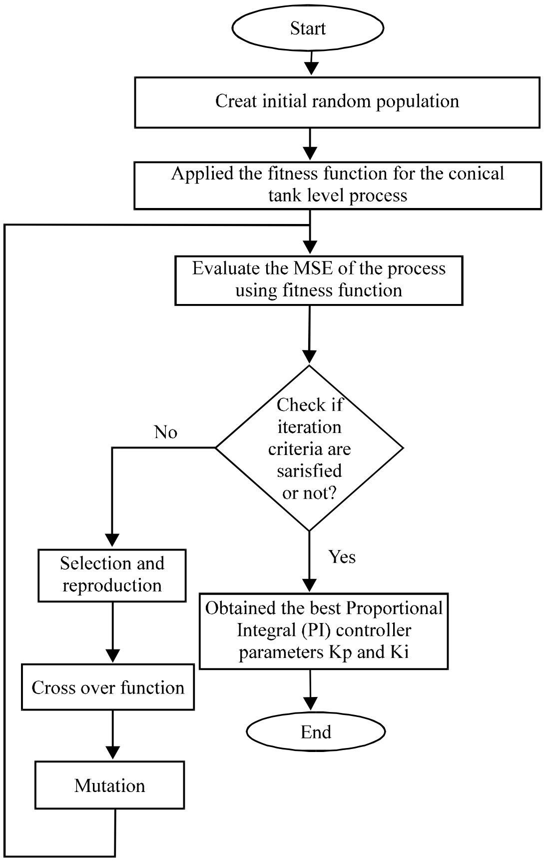

Fig. 5: Flow chart of the genetic algorithm tuned PI controller for the conical tank process

integral gain (K_i). The process output is a controlled variable which is again applied as an input to the set point value. The value of error is obtained as the difference between the set point value and measured value. The conical tank process for the servo, regulatory and servo-regulatory operations with the genetic algorithm tuned PI controller. The flow chart representation of the genetic algorithm tuned PI controller for the conical tank process is shown in Fig. 5. The Genetic algorithm tuned PI controller, consists of the following steps:

Step1: Initial setting of the Genetic Algorithm (GA) parameters and generating an initial random population interval.

Step 2: Evaluate the fitness function for each chromosome.

Step 3: Check whether if the iteration criterion is satisfied or not.

Step 4: If satisfied, generate the PI controller parameters such as proportional gain (K_p) and integral gain (K_i).

Step 5: If not satisfied, apply the genetic operations such as selection, crossover and mutation.

Design of neuro tuned PI controller: Neural networks are normally preferred for control applications due to their learning capability, fault and uncertainty tolerance, robustness, non-linearity, optimization and real time implementation, etc. A well trained neural network with the minimum Mean Square Error (MSE) technique can minimize the error and be used to tune the PI controller. In this research, the neuro tuned PI controller, based on the back propagation algorithm is developed for the non-linear conical tank process and its performance compared with that of the genetic algorithm tuned PI controller. The simulation results are obtained by the servo, regulatory and servo-regulatory operations for the above mentioned controllers in the conical tank level process.

RESULTS AND DISCUSSION

Block diagram representation of neurotuned PI controller for the conical tank process: The block diagram of the back propagation neural network based PI controller for the conical tank process is shown in Fig. 6. The controller consists of two parts, namely, the conventional PI controller and the neural network, in which the conventional PI directly controls the controlled object with a closed loop and its control parameters, viz, the proportional gain (K_p) and integral gain (K_i) are in an online adjustment mode. The neural network is used to adjust the parameters of the PI controller, based on the operational status of the system to achieve the parameters of the PI controller. In the neuro controller, the error (e) and rate of change of error (de) are applied as an input.

A well defined neural network provides the online tuning of PI controller with appropriate gains, according

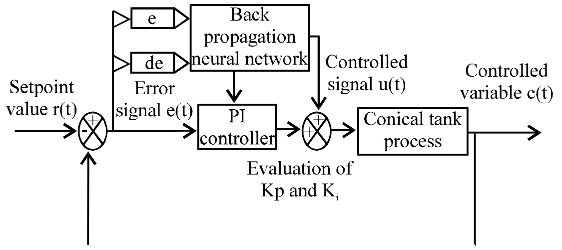

Fig. 6: Block diagram representation of the neuro tuned PI controller for the conical tank process

to the changes in the operating conditions. The aim is to study the capability of the approach to design a well trained neural network with minimum Mean Square Error (MSE) which tunes a PI controller. In order to train this neural network, input patterns that contain the above mentioned parameters under different conditions are used and the output patterns that contain the optimal values of gain are collected over several iterations of simulation. These patterns are used to train the neural network and the output of the neural network will be the optimal values of the proportional gain (K_p) and integral gain (K_i).

Review of the neural network: Neural networks are simplified models of the biological nervous system and their motivation is similar to that of the human brain. The artificial neural network has major characteristics such as speed of operation, processing, size and complexity, fault tolerance and control mechanism. Neural networks are applicable in areas such as image processing, data compressing to forecast the behaviour of complex systems for optimization, quality control, voice recognition and process control applications.

Artificial neural networks can be viewed as parallel and distributed processing systems which consist of a large number of simple and massively connected processors. There are a number of architectures proposed to solve different pattern recognition problems. A multilayer feed forward network trained by back propagation is the most popular and versatile form of a neural network for pattern mapping or the function approximation problem. The structure of a multilayer feed forward network is shown in Fig. 7. The input vector representing the pattern is presented to the input layer and distributed to the subsequent hidden layers and finally to the output layer via weight connections. Each neuron in the network operates by taking the sum of its weighted inputs and passing the result through a non-linear activation function. This can be mathematically represented as follows:

$$\text{Out}_i = f(\text{net\_i}) = f\left(\sum_{j=1}^{n} W_{ij}\,\text{Out}_j + b_i\right) \tag{21}$$

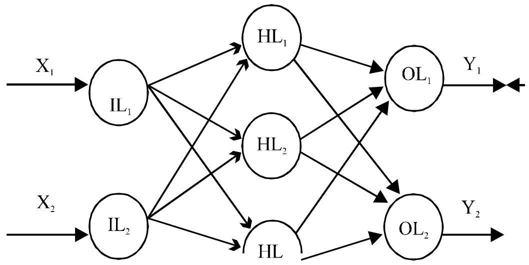

Fig. 7: Architecture of a feed forward neural network

Where:

Out_i = Output of the ith neuron in the layer

Out_j = Output of the jth neuron in the preceding layer

W_{ij} = Connection weights between the ith and jth input

b_i = Constant value or bias

The most commonly used activation function for a neural network is sigmoidal and can be mathematically represented as follows:

$$f(\text{net\_i}) = \frac{1}{1-\exp(\alpha.\text{net\_i})} \tag{22}$$

Where: α represents activation gain which controls the sigmoid function. The back propagation learning is the most commonly used algorithm for training a multilayer pattern. The gradient descent method minimizes the mean square error between the actual and the target output of a multilayer preceptron. Normally, the training of this network is based on the minimization of an energy function representing the instantaneous error. In other words, we desire to minimize a function that can be defined as:

$$E(m) = \frac{1}{2}\sum_{q=1}^{q}\left[d_q - y_q\right]^2 \tag{23}$$

Where

d_q = Desired network output for the qth input pattern

y_q = Actual output of the neural network

Each weight is changed according to the rule:

$$\Delta W_{ij} = -\eta\frac{dE}{dW_{ij}} \tag{24}$$

Where

η = Learning rate

E = Error function

Δw_{ij} = Change in weight connection between neurons j and i

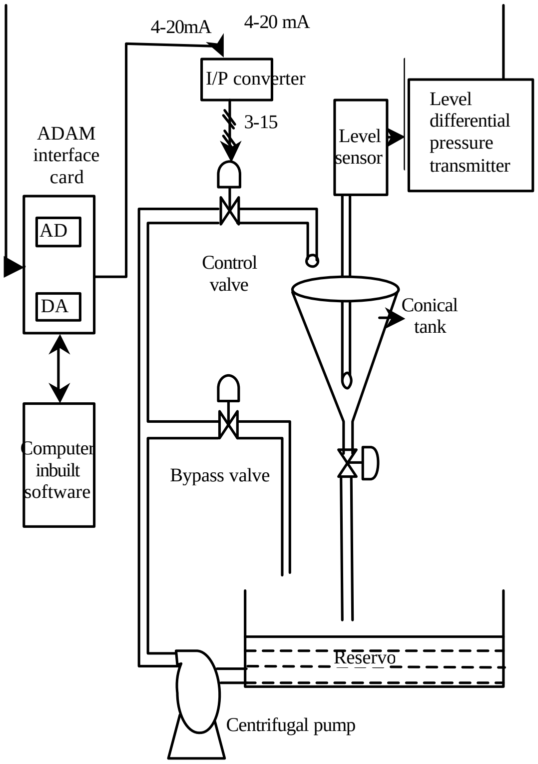

Fig. 8: Piping instrumentation diagram of conical tank level process

The weight adjustment process is repeated, until the difference between the node output and actual output is within some acceptable limit. The training of the back propagation algorithm results in a non-linear mapping between the input and output variables.

Weight update equations: The weight updating of the hidden to the output layer is represented by Eq. 25:

$$W_{jh}^{K+1} = W_{jh}^{K} + ?\,W_{jh}^{K} = W_{jh}^{K} + \eta\delta_{j}^{K}\,Z_{h}^{K} \quad (25)$$

Similarly, the weight updating of the input to the hidden layer is represented by equation:

$$W_{hi}^{K+1} = W_{hi}^{K} + ?\,W_{hi}^{K} = W_{hi}^{K} + ?\,d_{hi}^{K}\,x_{i} \quad (26)$$

The phases 1 and 2 are repeated, until the performance of the network is good enough.

Piping and instrumentation diagram for conical tank setup for level control process: The Piping and Instrumentation Diagram (P & ID) for conical tank process is shown in Fig. 8. The Piping and Instrumentation Diagram (P&ID) which consist of a conical tank, Level Differential Pressure Transmitter (LDPT), ADAM Interface card module, a personal computer, current to pressure converter, compressor, reservoir and pump which feed water forms a closed loop system. The level in the conical tank process is measured by the Level Differential Pressure Transmitter (LDPT) which produces current in the range of 4-20 mA. The 4-20 mA current is applied as an input to the computer or controller through the ADAM interface card input slot.

Fig. 9: Real time experimental set up for conical tank level process

The computer which acts as a controller through the software or algorithm and produces the output in the range of 4-20 mA as the output of ADAM card slot. The ADAM card output slot is connected with the current to pressure converter. The current to pressure converter produces the pressure in the range of 3-15 PSI which operates the control valve due to which inlet flow rate of the conical tank is controlled. The current to pressure produces the pressure in the range of 3-15 PSI which operates the control valve due to which inlet flow rate of the conical tank is controlled.

The real time experimental set up for the conical tank process is shown in Fig. 9. The main elements are of the conical tank process consists of: conical tank, level transmitter, interface card, computer or controller, control valve. The tabulation for real time conical tank set up specification is as shown in Table 2.

Simulation results of servo operation for neuro tuned PI controller with Genetic algorithm tuned PI controller: In the servo operation, the process with the load variable is set to be a constant and the set point value is a variable. With the variation of the set point value, the closed loop servo response for the non-linear conical tank process using the neuro tuned PI controller parameters such as the proportional gain (K_p) and integral gain (K_i) is obtained. The simulation diagram of the neuro tuned PI controller with the height of 20 cm from 0-500 sec and further the height is increased 10 cm from 500-1000 sec is

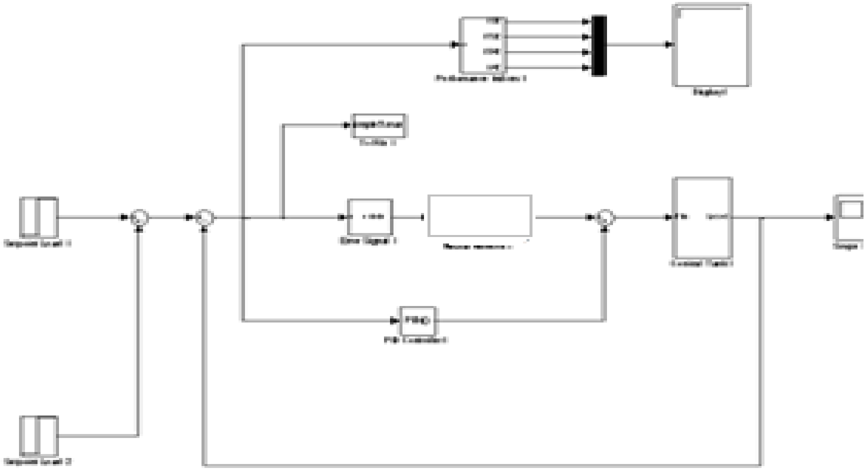

Fig. 10: Simulation diagram of the neuro tuned PI controller for the conical tank process in the servo operation

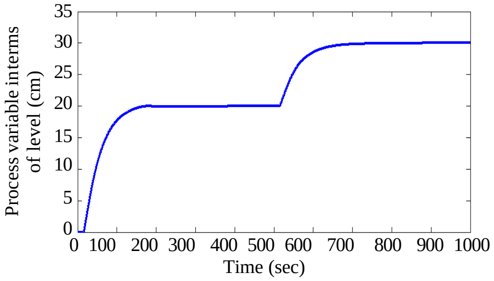

Fig. 11: Process variable versus time graph for the servo operation of the neuro tuned PI controller for the conical tank process with the height of 20 cm and further the height is increased 10 cm

Table 2: Real time conical tank set up specifications

Name of particular apparatus	Details
Conical tank	Stainless steel body, height of the tank 50 cm, top diameter-30.74 cm, bottom diameter-0.7 cm, output 4-20 mA
Level Differential Pressure	Size 1/4" pneumatic actuated, type:
Transmitter (LDPT) control valve	air to open, input 3-15 PSI
Pump type I/P converter	Centrifugal 0.5 HP, Input 4-20 mA, output 3-15 PSI
Compressor generated pressure	50 PSI
Pressure gauge range	0-30 PSI

Simulation results of servo, regulatory and servo-regulatory operation for neuro tuned PI controller with genetic algorithm tuned PI controller for conical tank level process

shown in Fig. 10. The error (e) and rate of change of error (de) are the inputs of the neural network and control signal is the output. The input 1 represents the error (e) and rate of change of error (de) or error signal. The data generation for the neural network can be obtained from the conventional PI controller. The neural network structure and training details are as follows:

- Structure of neural network: back propagation neural network
- Number of samples: 1000 Epochs
- Performance evaluation: mean square error
- Learning rate: 0.01
- Goal: $1\text{-}e^{-5}$

The simulated output graph for level versus time is shown in Fig. 11. The saturation of oscillations in the control signal has been rectified by gain adjustment. Similarly, the simulation diagram and simulated graph for level versus time for genetic algorithm tuned PI controller are as shown in Fig. 12-13. For the above controllers the servo operation, performance index values ISE, ITAE, IAE, ITAE and the time domain specifications are obtained for the above controller and tabulated in Table 3.

Simulation results of regulatory operation for neuro tuned PI controller with conventional PI controller: In the regulatory operation, the set point value needs to be a constant and the process with the load variable is a variable. The closed loop regulatory response for the nonlinear conical tank process, using the neuro tuned PI controller is obtained. The values of the proportional gain (K_p) and integral gain (K)$_i$are tuned and obtained as shown in Table 1. The simulation diagram of the Neuro tuned PI controller for the height of 30 cm from 0-1000 Seconds with+10% load changes after 800 sec through the step signal, is shown in Fig. 14. The response level versus time is shown in Fig. 15. The sustained oscillations in the control signal have been suppressed through gain adjustment. Similarly, the simulation diagram and simulated graph for level versus time for genetic algorithm tuned PI controller for regulatory operation are as shown in Fig. 16 and 17. For the regulatory operation, the performance index values such as ISE, ITSE, IAE, ITAE and the time domain specifications are obtained and tabulated in Table 3.

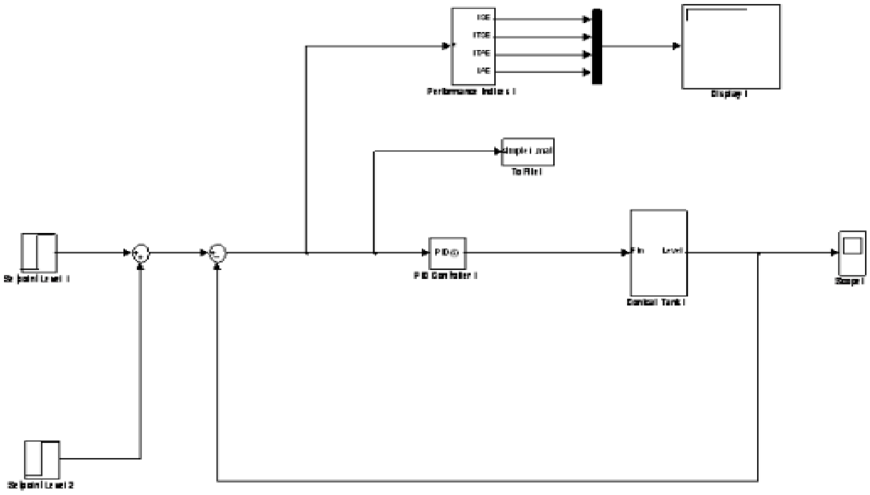

Fig. 12: Simulation diagram of the Genetic algorithm tuned PI controller for the conical tank process in servo operation

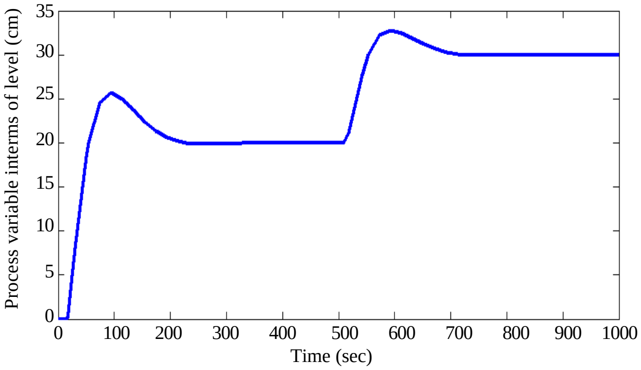

Fig. 13: Process variable versus time graph for the servo operation of the Genetic algorithm tuned PI controller for the conical tank process with the height of 20 cm and further the height is increased 10 cm

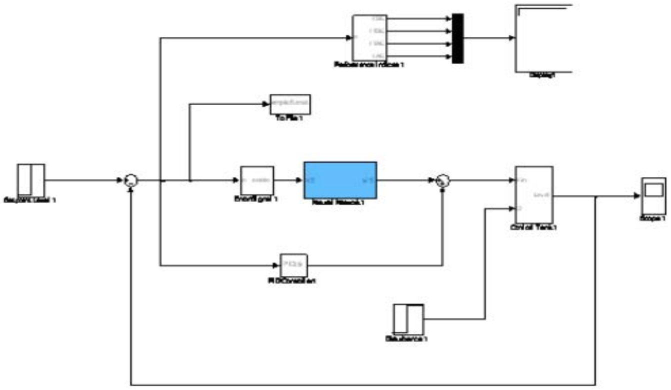

Fig. 14: Simulation diagram of the neuro tuned PI controller for the conical tank process in the regulatory operation

Simulation results of servo-regulatory operation for neuro tuned PI controller with Genetic algorithm tuned PI controller: In the servo-regulatory operation, the set point is variable and the process with load variable is also a variable. With the variation of the set point value and load variable changes, we obtain the closed loop servo-regulatory response for the non-linear conical tank process with the neuro tuned PI controller parameters such as the proportional gain (K_p), integral gain (K_i). The simulation diagram of the neuro tuned PI controller for the

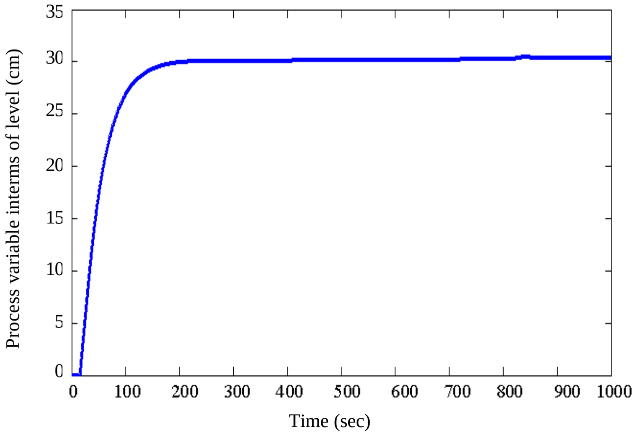

Fig. 15: Process variable versus time graph for the regulatory operation of the neuro tuned PI controller for the conical tank process with the height of 30 cm with+10% load changes after 800 sec

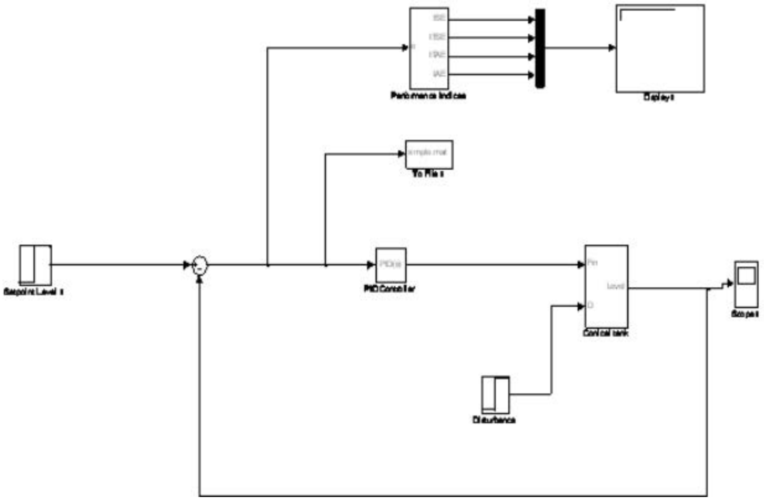

Fig. 16: Simulation block diagram of genetic algorithm tuned PI controller for regulatory operation

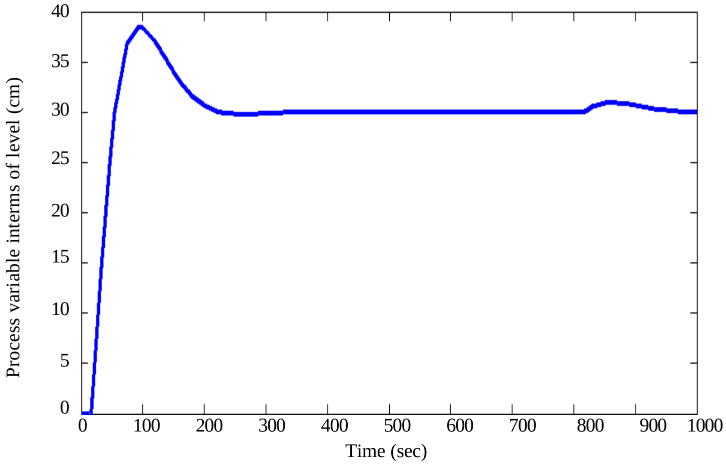

Fig. 17: Process variable versus time graph for the regulatory operation of the genetic algorithm tuned PI controller for the conical tank process with the height 30 cm with+10% load changes after 800 sec

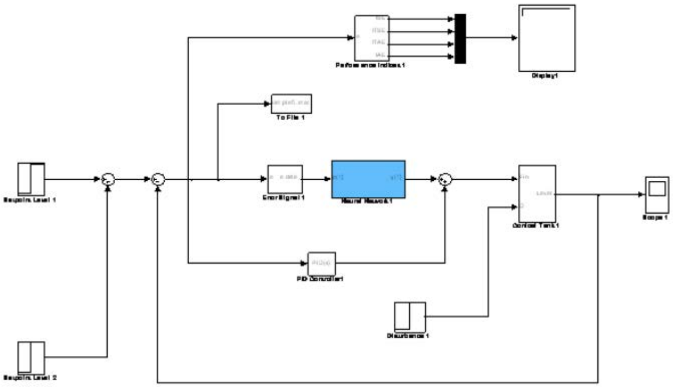

Fig. 18: Simulation diagram of the neuro tuned PI controller for the conical tank process in the servo-regulatory operation

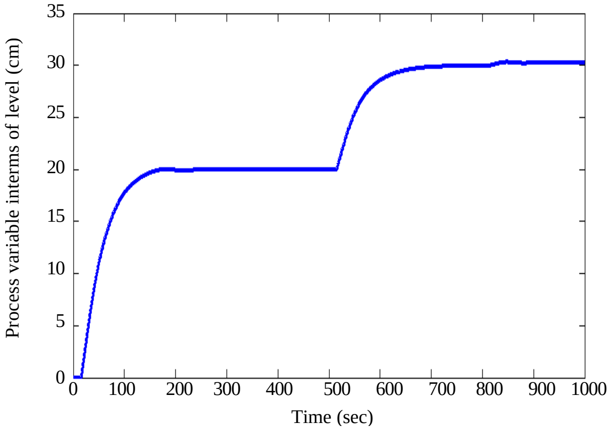

Fig. 19: Process variable versus time graph for the servo regulatory operation of the neuro tuned PI controller for the conical tank process with the height of 20 cm and further the height is increased 10 cm with+10% load changes after 800 sec

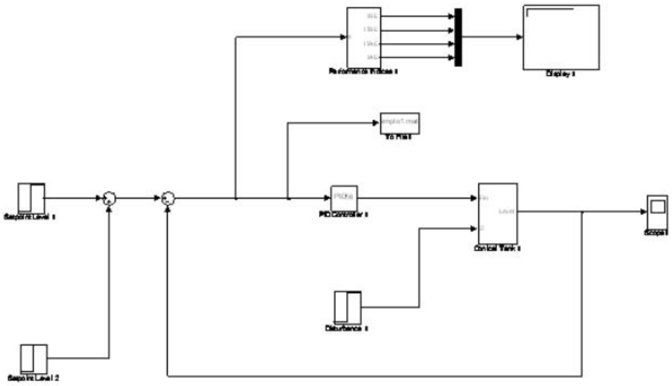

Fig. 20: Simulation diagram of the genetic algorithm tuned PI controller for the conical tank process in the servo-regulatory operation

height of 20 cm from 0-500 sec and further the height is increased 10 cm from 500-1000 sec with load changes of +10% after 800 sec is shown in Fig. 18.

The simulated output graphs for level versus time are shown in Fig. 19. Similarly, the simulation diagram and simulated graph for level versus time for Genetic algorithm tuned PI controller for regulatory operation are as shown in Fig. 20 and 21.

For the servo-regulatory operation, the performance index values such as ISE, ITSE, IAE, ITAE and the time

Table 3: Compaision of neuro tuned controler with genetic algorithm tuned PI controller for performance index values and time domain specifications

	Neuro tuned PI controller			Genetic algorithm tuned PI controller		
Performance index values, time domain specifications and optimal values of PI tuning parameters	Servo operation	Regulatory operation	Servo-regulatory operation	Servo operation	Regulatory operation	Servoregulatory operation
ISE	2160.00	1965.00	2062.00	4652.000	4172.000	4362.000
ITSE	18715.00	17632.00	17958.00	65340.000	51512.000	58352.000
ITAE	6238.30	5877.30	5982.50	20419.000	18615.000	19152.000
IAE	352.50	332.30	340.20	712.800	672.500	693.300
Peak overshoot (M_p)	0.23	0.21	0.20	6.200	5.800	7.900
Settling time (T_{sc})	188.50	185.00	195.80	218.000	215.000	223.000
Steady state error (e_{ss})	0.14	0.13	0.11	0.172	0.156	0.142

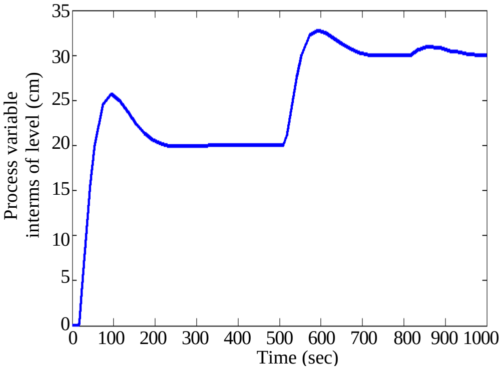

Fig. 21: Process variable versus time graph for the servo-regulatory operation of the genetic algorithm tuned PI controller for the conical tank process with the height of 20 cm and further the height is increased 10 cm with+10% load changes after 800 sec

domain specifications are obtained and tabulated in Table 3. From Table 3, it is concluded that the neuro tuned PI controller which produces minimized performance index error and excellent time domain specifications compare with genetic algorithm tuned PI controller and the simulation results are obtained by servo, regulatory and servo-regulatory operation.

CONCLUSION

This study proposes the design and implementation of neuro tuned PI controller for non-linear conical tank level process and compare the performance with genetic algorithm tuned PI controller. The simulation results are obtained for the above mentioned controllers by adjusting set point and load changes and set point with load changes. The controller performance are evaluated by performance index such as Integral Square Error (ISE), Integral Time multiplied Square Error (ITSE), Integral Absolute Error (IAE), Integral Time multiplied Absolute Error (ITAE) and time domain specifications such as peak over shoot, settling time and steady state error. From the system response, it is observed that the neuro tuned PI controller tracks the set point with smooth transition and with less oscillations compared with Genetic algorithm tuned PI controller. From the simulation results, it is observed that the performance of neuro tuned PI controller are better, smooth response and less oscillations compare with the Genetic algorithm tuned PI controller for the non-linear conical tank process.

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