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Adaptive and optimal control of a non-linear process using intelligent controllers

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ABSTRACT

A 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 in this work. Time-optimal level control was formulated using dynamic programming algorithm and basic properties of the solutions were analysed. It was found that the control is of bang–bang type and there is only one switching. In this method, a mathematical step-by-step procedure is used to obtain the optimal valve position path with one switching and is trained by neural network, based on the back-propagation algorithm. The dynamic programming procedure allows the set point to be reached as fast as possible without overshoot. An adaptive system is also designed and proved to be useful in adjusting the trained parameter of the dynamic programming based neural network for the process parameter variations. A prototype of conical tank level system has been built and implementation of dynamic programming based neural network control algorithm for set point changes and implementation of adaptive control for process parameter variations are performed. Finally, the performance is compared with conventional control. The results prove the effectiveness of the proposed optimal and adaptive control schemes.

1. Introduction

The control of liquid level in tanks and flow between the tanks is a basic problem in process industries. The process industries require the liquids to be pumped, stored in tanks and then pumped to another tank. Many times the liquid will be processed by chemical or mixing treatment in the tanks, but always the level of the fluid in the tanks must be controlled. Vital industries where liquid level and flow control are essential include petrochemical industries, paper making industries, water treatment industries, etc.

Serious difficulties arise in a system when the liquid level in a chosen process varies. In many processes such as distillation columns, evaporators, reboilers and mixing tanks, the particular level of liquid in the vessel is of great importance in process operation. A level that is too high may upset reaction equilibria, cause damage to equipment, or result in spillage of valuable or hazardous material. If the level is too low, it may have bad consequences for the sequential operations. So control of liquid level is an important and common task in process industries. Conical tanks find wide applications in process industries. They are widely used in hydrometallurgical industries, food process industries and wastewater treatment industries. Their shape contributes to better disposal of solids, while mixing, provides complete drainage, especially for viscous liquids. So control of conical tank presents a challenging problem and also due to its non-linearity and constantly changing cross section. Hence, the conical tank process is taken up for study here.

The majority of the control theory deals with the design of linear controllers with linear systems. PID controllers proved to be a perfect controller for simple and linear processes. When it comes to the control of non-linear and multivariable processes, the controller parameters have to be continuously adjusted.

Conventional controllers are widely used in industries since they are simple, robust and familiar to the field operator. Practical systems are not precisely linear but may be represented as linearized models around a nominal operating point, the controller parameters tuned at that point may not reflect the real-time system characteristics due to variations in the process parameters. Many researchers have done work on the conical tank process and time-optimal control. Anandanatarajan et al. [1] have done work on the conical tank process using two different controllers at two different operating points, globalized local controller and fuzzy logic controller. Lee and Sung [2] have brought out the limitations of PI controllers. Madhubala et al. [3] designed the fuzzy controller

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for conical tank process by tuning the membership functions of the input variables and optimized the peak of the fuzzy sets using genetic algorithm. This method is a trial and error method and time consuming. Bhuvaneswari and Kanagasabapathy [4] proposed a time-optimal control using dynamic programming method for two tank system. They proved that, this method was the best, for the servo problem in the level process. Malmbarg and Eker [5] proposed time-optimal control for a hybrid control of a double tank system. They dealt with non-linear switching curves that are linearized and then implemented. Borrelli et al. [6] proposed dynamic programming time-optimal control method for discrete time hybrid systems where computations are more. Song and Shin [7] used time-optimal control algorithm for Impact angle control of vertical plane engagements in which switching instants with random weighting factors are used. Sakagami and Kawamura [8] proposed time-optimal control for under water robot manipulators. The position error described is not negligible and hence during fast motion the dynamics get change and it needs redesign of the controller. Kulkarni [9] proposed time-optimal control for a swing. The linearized assumptions are made by him, in the formation of state and co-state vectors. Fang and Dissanayake [10] proposed time-optimal feedback control of a non-holonomic vehicle using neural networks. He has taken data as many trajectories from the process and trained using neural networks. If the process parameters vary, the network has to be retrained. Chen et al. [11] proposed optimal control for non-linear reactor problem. Nayeri et al. [12] proposed neural optimal control for spacecraft where optimal data are generated from the cost function evaluation through plant Jacobians. Many researchers have done work on the adaptive control also. Guoping et al. [13] proposed a variable neural network for deriving the adaptive algorithm for a non-linear process and tuned the radial basis function center and width for adaptive control. Hwang et al. [14] proposed reinforcement learning based adaptive control for non-linear systems. Goléa et al. [15] proposed a fuzzy model reference adaptive control for non-linear systems where adaptive law is obtained through PI law. Kothare et al. [16] proposed predictive control for controlling level in the steam generator of a nuclear power plant. Na et al. [17] designed a genetic fuzzy controller for the water level control of steam generator. Munasinghe et al. [18] proposed a neuro-fuzzy controller for water level control in nuclear power plants. For their work, the data were taken from the closed loop system using PI controller and used in neuro-fuzzy design. O'Dwyer and Ringwood [19] have proposed a classification of techniques for the compensation of time delayed processes with parameter optimized controllers. Zervos and Dumont et al. [20] have proposed a deterministic adaptive control based on laguerre series representation. Park et al. [21] have proposed a self-organizing fuzzy controller for dynamic system using auto-regressive moving average (FARMA) model. Kim [22] proposed a neural network based tuning PID controller for the level control of steam generator. Lin et al. [23] have proposed adoptive algorithm for PID controllers based on a theory of adaptive interaction. Jagannathan et al. [24] have dealt with unknown non-linear dynamical system using a discrete time fuzzy controller. Viljamaa and Koivo [25] have developed a fuzzy logic system in PID gain scheduling. Marcelo et al. have proposed a Lyapunov based stabilizing control design method for uncertain non-linear dynamic system using fuzzy model.

There are many existing control methods for conical tank level process [1,2,3]. In addition, the applications of neural networks and fuzzy logic in optimal control have also been suggested in literature [4,9,12]. Although several methods have been developed, in most of them, either some assumptions are made or the non-linear process characteristics and switching curves are linearized and then the controller is designed. In this paper, without any assumptions and linearization for the non-linear characteristics, using neural networks, the optimal and adaptive controller are designed. The method introduced in [4] is used to generate the time-optimal trajectories for servo problems. In order to perform the time-optimal feedback control in on-line, a neural network is used. In particular, the neural network is trained to produce the time-optimal control signal to the valve. The main contribution of this paper is the development of a time-optimal control law using neural network with dynamic programming for controlling the level in the conical tank as well as development of adaptive control law using neural network. Also, the advantage of using such a neural network based time-optimal control method is demonstrated.

The paper is organized as follows. In Section 2, the process and the lab scale experimental hardware set-up are described. In Section 3, simulation studies and real-time conventional control are discussed. In Section 4, time-optimal control, development of dynamic programming algorithm and neurobased dynamic programming (DP) method are discussed. In Section 5, adaptive control through model based neural network is discussed. The operation of the adaptive control is also described in detailed manner. Finally, results and conclusions are discussed.

2. Process description

2.1. Mathematical model

The process considered is the tank, conical in shape in which the level of liquid is desired to maintain at a constant value. This is achieved by controlling the input flow into the tank. The conical tank diagram is shown in Fig. 1.

Using the law of conservation of mass,

$$F_{\text{in}} - F_{\text{out}} = A(h)\frac{\mathrm{d}h}{\mathrm{d}t} \tag{1}$$

where F_{in} is inflow rate of the tank cm^3/s = 125 cm^3/s, F_{out} is the outflow rate of the tank cm^3/s, R is the top radius of the tank

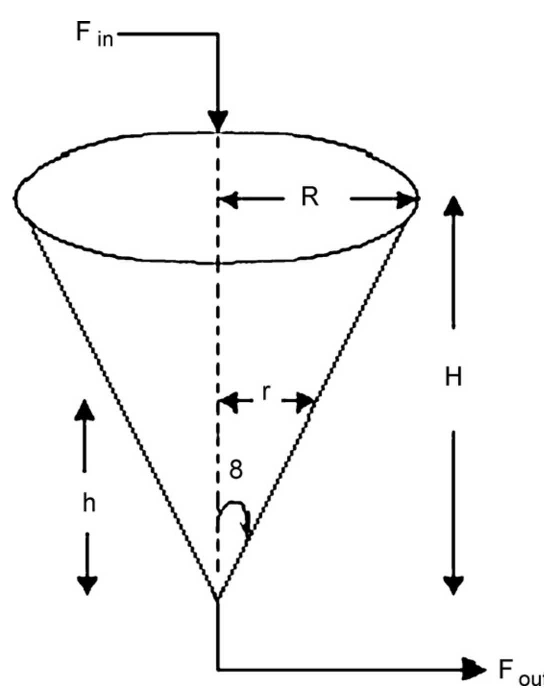

Fig. 1. Conical tank level process.

Fig. 2. Lab scale experimental set-up.

cm = 20 cm, H is the total height of the tank cm = 80 cm, and r is the radius at any height h_i cm.

From Fig. 1,

$$\tan\theta = \frac{R}{H} = \frac{r}{h} \tag{2}$$

Also,

$$F_{out} = b\sqrt{h}, \text{ where } b \text{ is valve constant} = 4.3. \tag{3}$$

Therefore,

$$F_{in} - b\sqrt{h} = A(h)\frac{dh}{dt} \tag{4}$$

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

2.2. Lab scale experimental set-up

The lab scale experimental set-up is shown in Fig. 2. The set-up consists of a conical shaped process tank, submersible pump, level sensor arrangement, overhead sump, inlet and outlet valve, level indicator and interfacing card. The height of the conical tank process tank is 80 cm. The submersible pump is capable of discharging liquid at the rate of 3200 L/h is used. The pump is immersed in the overhead tank and a flexible hosepipe is used to connect the pump and the gate valve. The minimum voltage applied to the pump for discharge is 104 V.

3. Conventional control

Conventional PID controllers are widely used in industry since they are simple, robust provided the system is linear. But the process considered here has non-linear characteristics, is represented as piecewise linearized models around 6 operating points as shown in Fig. 3. Using process reaction curve method, the transfer function model parameters are found for all the regions and controller parameters are tuned using Ziegler Nichole's tuning formula using model parameters are given in Table 1. When the process variable is going through different operating regions, the respective gain values are used. The simulation and experimental results for the step change in set points are shown in Figs. 4 and 5. Optimum performance in the entire range of heights could not be achieved due to non-linear nature of plant. The use of dynamic programming based controller helps to achieve exact time-optimal control action and is discussed in the next section.

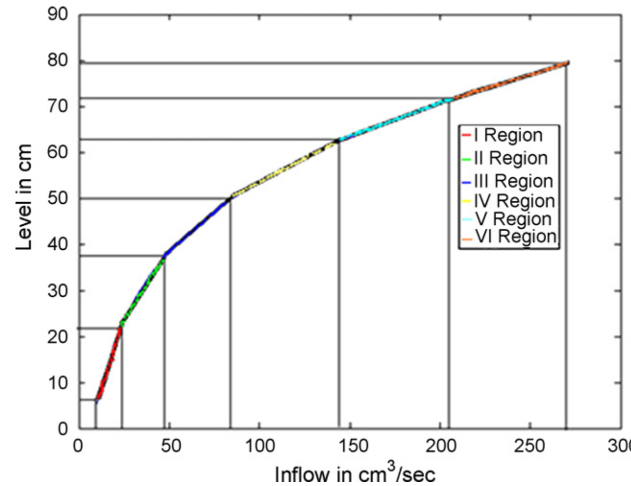

Fig. 3. Process characteristics with operating regions.

4. Time-optimal control

In the conventional approach, it is difficult to tune the controller parameters for different operating regions and could not achieve exact time-optimal control. The conventional control procedures aim at finding an acceptable, but not an optimal control. Thus, a criterion or objective function has to be chosen to arrive at the best system performance. Thus, optimal control law, for the problem considered is formulated as follows.Assuming that, the plant given is $x = f(x,u,t)$, a starting time t_1, starting and end states x_1, x_2 and saturation constraints on u, it is desired to drive the system from x_1 at t_1 to x_2 at t_2 in the least possible time t. For this problem the performance index is,

$$J = \int_{t1}^{t2} dt \tag{6}$$

In the next section, the procedure for effecting time-optimal control using dynamic programming method is discussed.

4.1. Dynamic programming method

In this approach, a step-by-step procedure is used to obtain the optimal valve position. As a first step, time-optimal controller is considered and the procedure for the design of time-optimal controller is discussed and finally trained using neural network.

Table 1
Transfer function model parameters and controller parameters

Inflow range (cm^3/s)	Level range (cm)	K (steady-state gain)	τ, time constant (s)	K_P	T_i (s)	T_d (s)
10–25 (I Region)	7–22	1.46	35	2.0	21.0	2.8
25–48 (II Region)	22–38	1.65	80	4.5	26.4	2.8
48–80 (III Region)	38–50	1.56	146	8.0	29.1	2.8
80–140 (IV Region)	50–64	1.06	245	12.7	30.7	2.8
140–210 (V Region)	64–72	0.9	475	23.0	31.9	2.8
210–275 (VI Region)	72–80	0.8	750	34.5	32.4	2.8

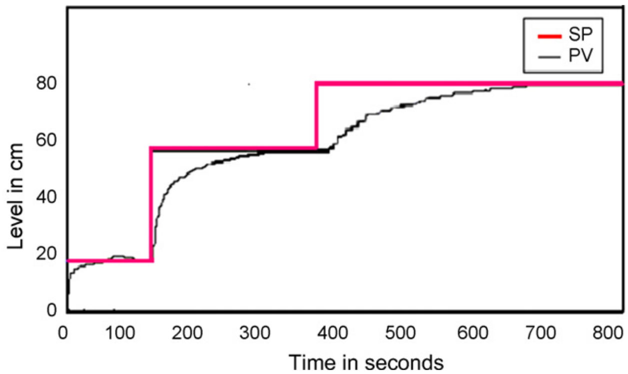

Fig. 4. Simulated response for step changes.

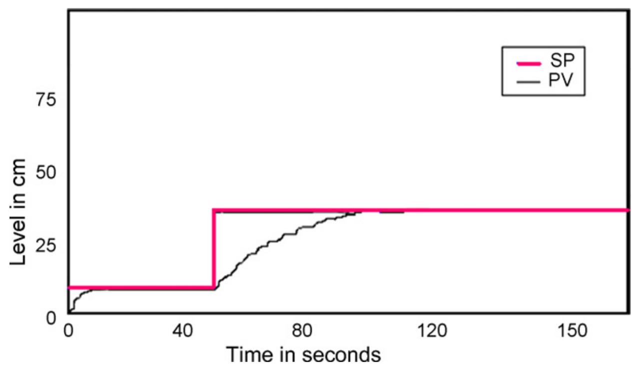

Fig. 5. Real-time response for step changes.

Step 1. The computation of the time-optimal control makes use of mathematical model of the tank described or real-time system. The control objective for the conical tank is to find optimum valve position P_{opt} which allows the set point to be reached as fast as possible without overshoot, i.e. supposing that error ($e = r - c$, where r is set point and c is the present value) is negative, the valve has to be driven in such a way the liquid is released as quickly as possible. The valve has to be opened first and then must be closed at a critical time so that the level does not overshoot.

Step 2. The input variables to the time-optimal controller are those which affect the plant dynamics. For this process, the error 'e' and the level 'h' are taken as inputs to the controller.

Step 3. The time-optimal trajectory can be found, when the number of switching operations for the valve is specified. Here the valve motion is changed only once. The optimal control is thus specified by,

$$U\begin{cases} \text{Close} & \text{for } 0 \le t < t_1 \\ \text{Open} & \text{for } t_1 < t \le t_f \end{cases} \tag{7}$$

where u = close the valve by a step, open the valve by a step, do not change the valve position, and t_1 (time for reaching optimum position) and t_f (final time) are as indicated in Fig. 6. This method of optimal control is simulated and shown in Fig. 7.

This type of control called bang–bang control because the control has a switchover (discontinuity) at time $t = t_1$ and the control valve either keeps closing or opening. If the number of switching operations is more, it is found that the settling time increases.where $h(t)$ is the actual level curve, P_i is the initial valve position, P_f is the final valve position, P_{opt} is the optimum valve position, and $r(t)$ is the reference level.

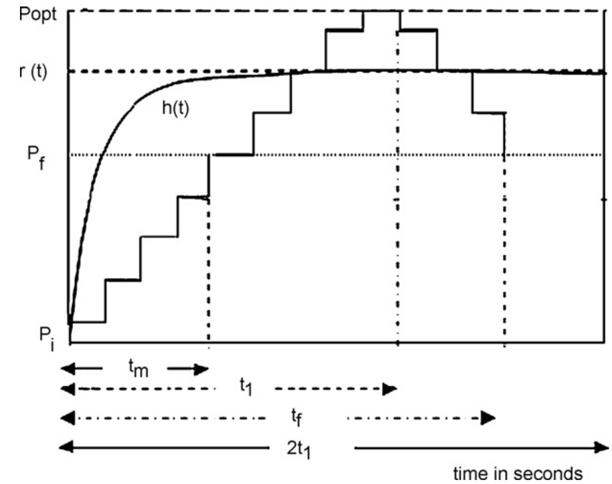

Fig. 6. Time-optimal control on positive step change in reference height.

Step 4. Thus, the control law for the above system can be stated as: if $P(t) < P_{opt}$, then close the valve by a step, if $P(t) > P_{opt}$, then open the valve by a step, and if $P(t) = P_{opt}$, then do not change the valve position.

The time-optimal control involves the computation of optimum position of the control valve each time during the operation of system so that t_f is minimum.

4.1.1. Computation of P_{opt}

The computation of P_{opt} is very difficult with the available optimization technique owing to the non-linearity of the process. Hence, an iterative procedure as given below is adopted to find out P_{opt}.

(i) Let us assume that initially the level in the tank is at steady state, i.e. outflow is equal to inflow. $q_{out} = q_{in}$ at steady state.
(ii) The corresponding valve position can be easily calculated using Eq. (5) in steady-state mode and is presented in Table 2 for many initial levels.
(iii) When a set point change is given, level should reach the new set point, that is $h = r_{new}$ at time $t = t_f$.
(iv) Now depending on the regulation error, the valve has to be either closed or opened up to t_1 as shown in Fig. 7,

$$\begin{aligned} &\text{i.e. if } Z = 1\begin{cases} \text{valve opens for} & 0 \le t \le t_1 \text{ and} \\ \text{valve closes for} & t_1 < t \le t_f \end{cases} \\ &\text{if } Z = -1\begin{cases} \text{valve closes for} & 0 \le t \le t_1 \text{ and} \\ \text{valve opens for} & t_1 < t \le t_f \end{cases} \end{aligned} \tag{8}$$

where Z is the control command.

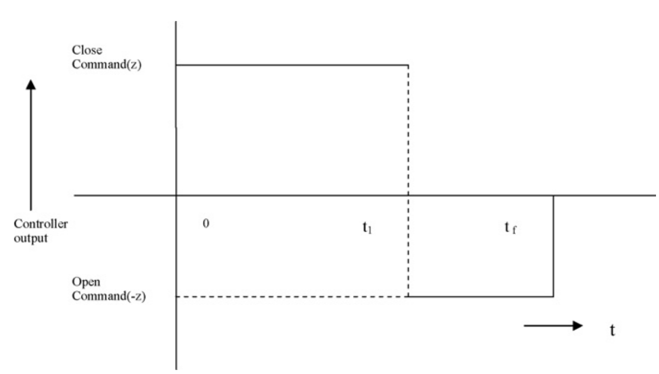

Fig. 7. Time-optimal control.

Table 2
Process steady-state input–output data

S. no.	Steady-state level (cm)	Valve position (%)
1.	10	13.6
2.	20	19.25
3.	30	23.6
4.	40	27.2
5.	50	30.4
6.	60	33.4
7.	70	36.1
8.	80	38.8
9.	90	41.6

The control command Z is decided upon whether P_f is greater than P_i or not.

$$Z = 1 \quad \text{if } P_i > P_f$$
$$Z = -1 \quad \text{if } P_i < P_f$$

The valve has to be kept open or closed for a minimum time t_m so that the valve position reaches P_f quickly. Again t_m is given as

$$t_m = \begin{cases} P_i - P_f & \text{if } P_i > P_f \\ P_f - P_i & \text{if } P_i < P_f \end{cases} \tag{9}$$

It may be noted that the valve moves at a speed of 10% movement for 10 s. t_f is computed by means of formula

$$t_f = 2t_1 + P_f Z - ZP_i \tag{10}$$

(v) Depending on the regulation error, starting t_1 at t_m, t_1 is varied iteratively until error is zero, which means at $t = t_f$, $h = h_f = r_{new}$.

Then the optimum valve position is given by

$$P_{opt} = P_i - Zt_1 \tag{11}$$

Using this procedure the optimum valve position is calculated for the particular set point and error values. This is repeated for many such values and few are presented in Table 3.

4.1.2. Neural network with dynamic programming

If DP method is used in on-line, P_{opt} computations take more time. Instead, the data generated from the DP method is trained using neural network. If a neural network is trained, the network is able to generalize for untrained input also. So computation time decreases. The data are trained by using popular back-propagation algorithm. The set point level and error in level are taken as inputs and the initial, optimal and final valve positions are taken as output data. The architecture used for the training is given in Fig. 8. For slightly non-linear problem, it is sufficient to use single hidden layer in the architecture. Because the conical tank level process has only slightly non-linear characteristics, it is sufficient to use single hidden layer in the architecture and hence single hidden layer is selected. The number of hidden nodes in that layer is changed from 2 to 6 during training. For 5 hidden nodes the error was found to be minimum as shown in Table 4 and it is used in training the network.

Table 3
Few optimal data used for training the neural net

S. no.	Set point (cm)	Error (cm)	P_i (%)	P_f (%)	P_{opt} (%)
1.	20	10	13.6	16.8	19.25
2.	30	20	13.6	18.8	23.6
3.	50	40	13.6	22	30.4
4	60	20	27.2	30.4	33.4
5.	40	40	38.8	23.5	27.2

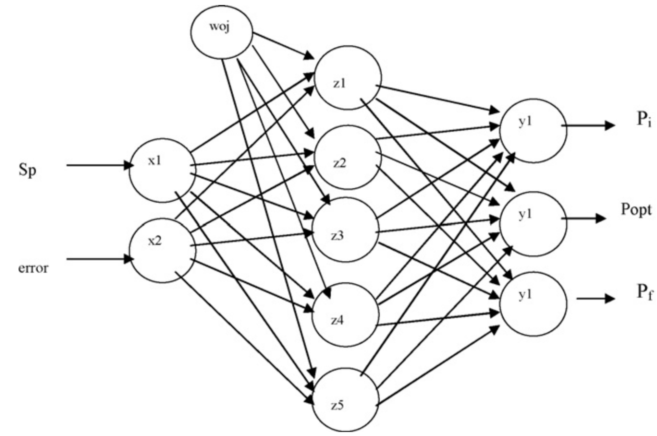

Fig. 8. Neural based DP network architecture.

Table 4
Selection of number of nodes in hidden layer

No. of hidden nodes	RMSE after 6000 epochs
2	5.6
3	3.2
4	1.7
5	0.15
6	0.83

The stopping criterion was specified to be 0.25, Root Mean Square Error (RMSE), i.e. the training was stopped when the Root Mean Square Error between the network outputs and the targets was lesser than or equal to 0.25. The learning rate was fixed at 0.5. The number of training epochs was fixed uniformly at 6000. Some of the patterns were also used to test the network in order to prevent over fitting of the training data. Finally, the values of the weights obtained after training was obtained and was used for the feed forward implementation. The results are shown in Figs. 9 and 10 for neurobased DP method.

5. Adaptive control

The control of dynamical systems in the presence of large uncertainties is of great interest at the present time. Such problems arise when there are large parameter variations due to failures in the system, or due to the presence of large external disturbances. In such cases, controller parameters are adjusted on the basis of plant parameter estimates. However, if conventional adaptive control is used, experience indicates that the presence of large parameter errors will generally result in slow convergence, with large transient errors. An alternative approach which has gained a large

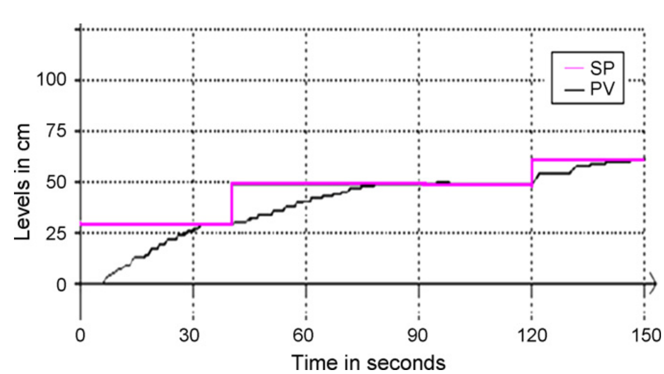

Fig. 9. Real-time response with neurobased DP method for positive step change.

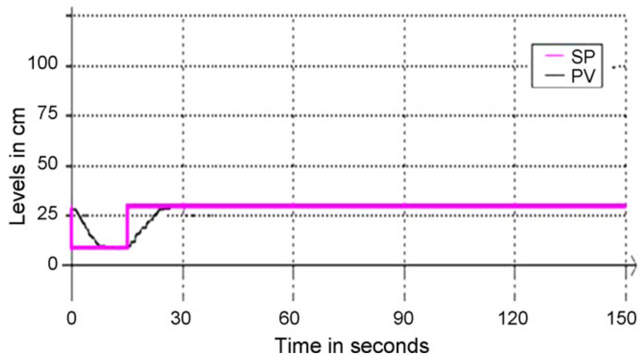

Fig. 10. Real-time response with neurobased DP method for negative step change.

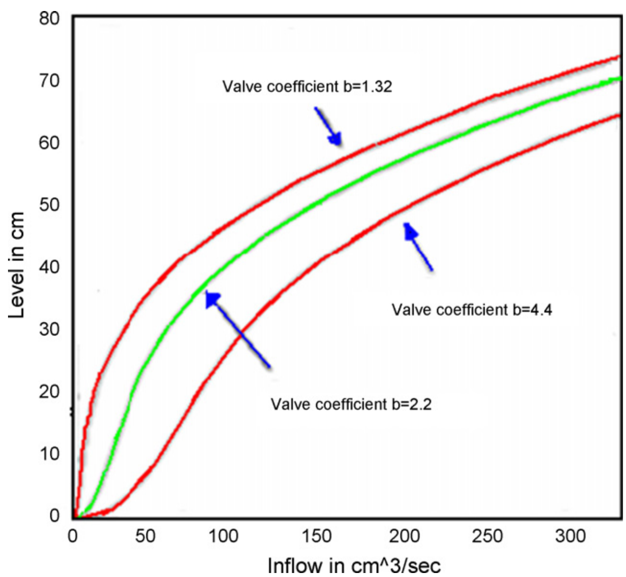

Fig. 11. Change in plant characteristics when plant parameters vary.

following in recent years involves the use of neural networks to identify the unknown plant and can be considered as higher level adaptive control. Hence, neural network based adaptive control is proposed in this work.

When the process parameter changes, the original characteristics get changed. Fig. 11 shows the change in plant characteristics when the valve co-efficient (resistance of the process) changes from 2.2 (normal value) to 1.32 and 4.4. Whenever the plant characteristics change, the exact time-optimal DP method which is designed for original plant parameters generates steady-state error. In order to avoid the error, a model based approach using neural network is proposed.

The block diagram of the proposed scheme is shown in Fig. 12. It consists of four neural networks. (i) The first network, DP based neural network (NN1) which is trained for giving exact time-optimal control and used as a controller. (ii) The second network, forward model neural network (NN2) which is trained for the forward plant identification and used as a model of the original process. (iii) The third network, critic element neural network (NN3) is used to criticize the error about the magnitude and polarity. (iv) The fourth neural network, adaptive neural network (NN4) that is trained for adjusting the weight in the DP based neural network for removing the error created. For all the four neural networks (NN1, NN2, NN3, NN4), the popular back-propagation algorithm is used for training the data.

5.1. Neuro-model (NN2)

When the dynamic programming based controller is used and when there is a process parameter variation, steady-state error is produced. This steady-state error is measured by the error detector element, which finds the difference between the present plant steady-state output and the neuro-model output trained for giving original plant output. The neural network for identifier is designed as a three layer neural network. It has an input layer, a hidden layer and an output layer. The number of neurons in the hidden layers can be chosen depending upon the training result. The neural network identifier models are trained to learn the forward dynamics of the plant. Three inputs and one output are selected as the identifier model for the system. These three inputs are the control signal $u(t)$ and the previous output signals $y(t-j), j = 1,2$. A set of input–output training patterns is selected from the open loop response and the last two steps of the output of the system. The control input signal is directly given to system input and system output signal is reflected with the actual water level. In training the neural network, the algorithm used is the back-propagation algorithm. The architecture used for the training is given in Fig. 13. The response of plant and model outputs is shown in Fig. 14.

5.2. Critic element neural network (NN3)

The function of this element is to predict steady-state output. For this purpose, a neural network is used which is already trained for giving the steady-state output from the transient data input.

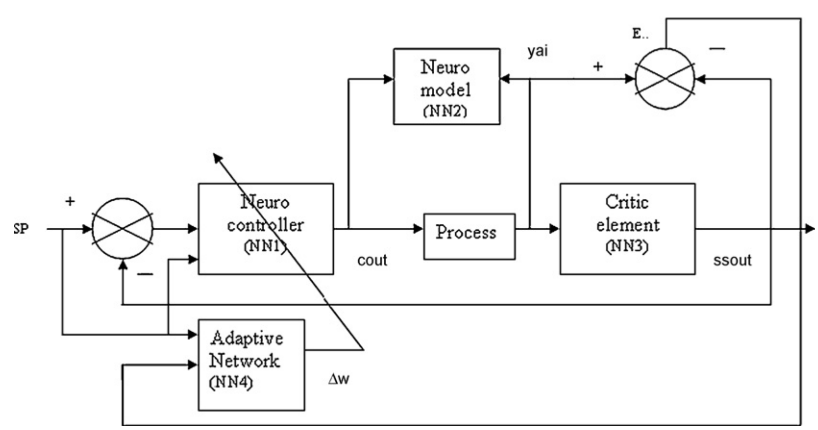

Fig. 12. Adaptive control block diagram.

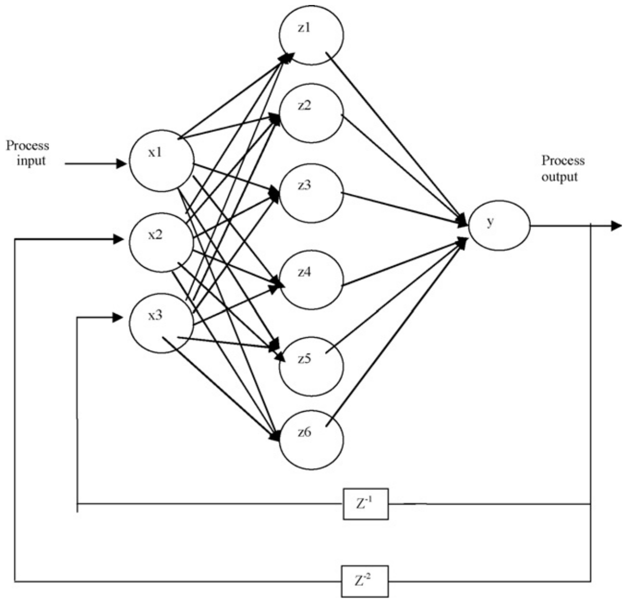

Fig. 13. Architecture of neuro-model network.

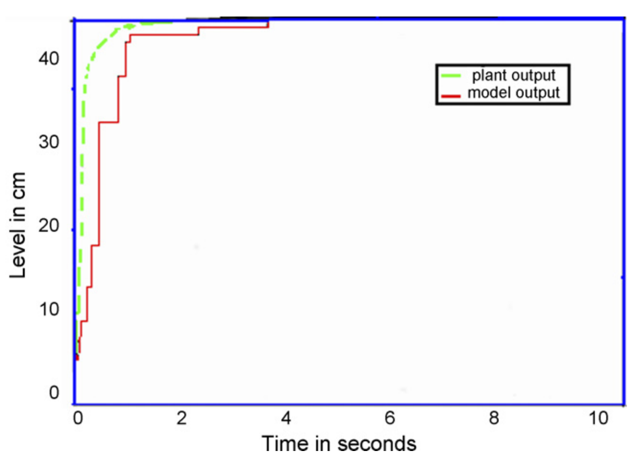

Fig. 14. Response of model and plant output.

Few training and test data set are presented in Table 5. The architecture used for the training is shown in Fig. 15. After the training, the network is able to generate the steady-state value during the transient period itself.

5.3. Adaptive neural network design (NN4)

When the dynamic programming based controller is used and there are process parameter variations, steady-state error is produced. The critic network gives the present plant steady-state output from the transient data. The neuro-model gives the original plant output. The error which is the difference between the critic output and the model output is now found by the error detector element. For removing this error, the weight in the DP based controller is adjusted by this neural network called as adaptive network. Hence, the adaptive neural network is initiated automatically whenever steady-state error is noticed as given by error detector element.

Table 5
Few critic network data

Data type	Transient input (cm)	Steady-state output (cm)
Training data	0.13, 0.93, 3.4, 13.9, 30, 61	80
	0.1, 0.2, .88, 2.8, 7.2, 9.5	10
	0.1, 0.2, 0.92, 3.3, 12.6, 32.7	50
Testing data	0.1, 0.2, .92, 3.3, 13.6, 37.9	70
	0.1, 0.2, 0.91, 3.3, 11.1, 24.8	30

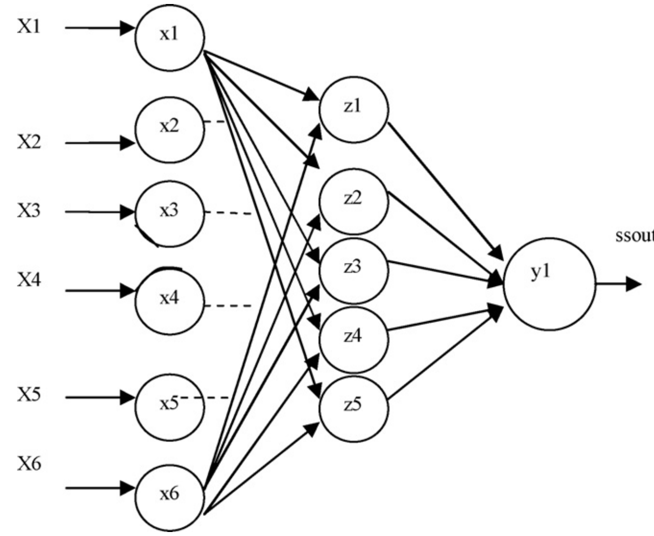

Fig. 15. Architecture of critic network.

The valve constant is changed from 1.32 to 4.4 insteps of 0.5 by changing the valve position and for many process inputs for every valve position, the steady-state error is measured by the error detector element. The weight from the bias node to the output node in the trained network is adjusted until the errors are zero. These are taken as input, output data and trained using the architecture shown in Fig. 16. Few data are given in Table 6. Once the network is trained, it adjusts the correct amount of weights in the DP based neural network whenever steady-state error is noticed automatically. The responses for change in process parameters are shown in Figs. 17 and 18.

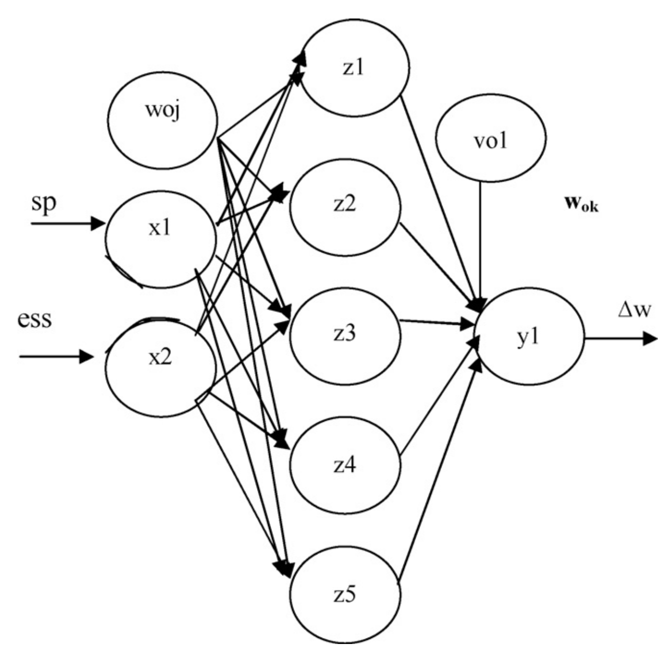

Fig. 16. Adaptive neural network architecture.

Table 6
Few adaptive NN data

Sp	60	60	65	65	70	70	55	55	50	50	45	35	30	20	20
Ess	−4.5	6.83	−3.4	6.82	−3.9	5	−4.71	8.39	−5	10	−6	16.8	−9.17	0	15.1
Δw	−25	40	−22	40	−25	41	−21	37	−20	26	−20	28	−16	0	24.5

6. Results and discussion

To achieve fast response, at first, the time-optimal control method is suggested. This intelligent controller is designed for controlling conical tank level using neural network with dynamic programming approach. The dynamic programming procedure allows the set point to be reached as fast as possible without overshoot. Simulation studies are carried out using MATLAB to find the optimum path for set point changes and trained using neural network. This optimal path is used in real time. The real-time servo responses show that the response is very much fast and superior to other types of control schemes discussed. The performance criteria ISE, ITAE are also reduced by 40% than the conventional scheme.

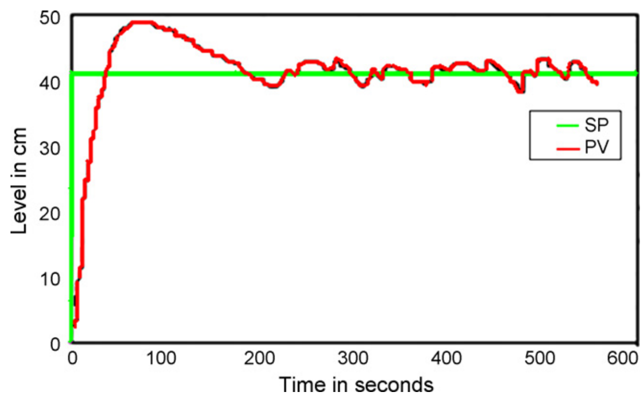

Fig. 17. Real-time response for a step increase in SP from 0 to 40 cm and for a process parameter change from b = 2.2 to 1.4, tries to settle at a higher level, but the designed adaptive network takes action and brings the level to the set point.

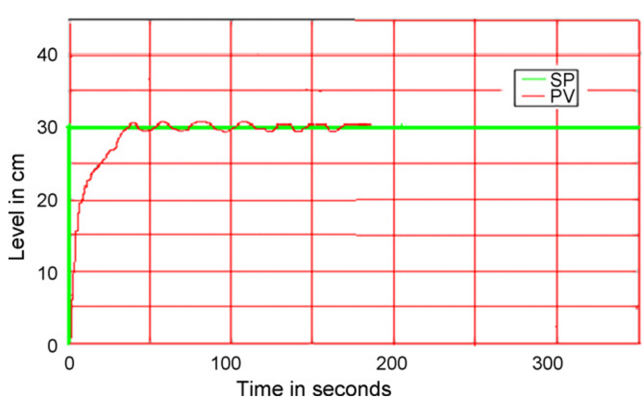

Fig. 18. Real-time response for a step increase in SP from 0 to 30 cm and for a process parameter change from b = 2.2 to 4, tries to settle at a lower level, but NN takes action and brings the level to the SP.

Table 7
Comparison of performance index

Control scheme	SP change	ITAE	ISE	Settling time
PID	0–50	398.95	2960.456	100
	30–50	348.177	2765.767	92
	0–25	156.84	1046.964	36
Adaptive control	0–40	350.75	1986.987	80
	0–60	450.98	2376.55	90
Time-optimal controller	0–50	125.678	564.7324	58
	30–50	134.358	625.359	62
	0–25	92.3846	523.374	20

In adaptive control, simulation studies are carried out using MATLAB for finding the controller parameter changes for process parameter variations. Then these controller parameter changes for the process parameter variations are used in real time. Because the controller parameters are updated, the steady-state error which comes due to process parameter variation is completely eliminated here and the response becomes optimal.

The response for the process parameter variation is fast, without any steady-state error. By predicting the steady-state error and hence updating controller parameter leads to a better transient and steady-state response. Process parameters are varied by varying the outlet valve position from nearly fully closed condition to fully opened condition. For both the direction of the valve movement, the controller parameters are updated in the correct direction and optimal results are obtained. Table 7 shows the comparison of performance measures for the schemes discussed.

7. Conclusion

Comparing the servo response of control schemes obtained through real time, the neural network based DP method outperforms all. For a 25% increase and 50% increase in the set change at any operating point, the proposed DP method gives minimum ISE and ITAE than all other control schemes. Comparing the performance of responses for process parameter variations, the adaptive control using NN performs very well as it eliminates the steady-state error. The performance indices ISE and ITAE are also minimum in this case.

The following are the conclusion for selecting the appropriate controller. For servo operation, neurobased DP method can be employed. For regulatory operations and process parameter variations operations, the adaptive method using neural network can be employed.

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