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Conical Tank Process Control by Conventional PI and ANN-PI Controllers

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Abstract - Controlling a conical tank process can be a difficult task because of its changing dynamics. Thus, to overcome this problem, a tank either has to be linearized or some sort of nonlinear control has to be introduced. This research investigates the effectiveness of controlling a conical tank process using conventional Proportional-Integral (PI) controller and Artificial Neural Network based PI controller (ANN-PI), which are implemented in real-time on a PIC18F4550 microcontroller. First, the process is modeled by linearizing it around operating regions so that five transfer functions describing the entire process are obtained. For the control part, a PI controller is designed for each transfer function. The results showed that controlling the process using single PI controller was not effective as it produced excessive overshoot and large settling time. However, when applying ANN-PI controller, it produced less overshoot and smaller settling time compared with PI controller response.

Keywords— Conical tank process, PI control, ANN-PI control

I. Introduction

It is important to maintain tank level in various fields. One of the systems used in industries such as water treatment plants, paper mills, sludge tanks, biofuels, and fertilizer industries is the conical tank process. It is an example of a single input single output (SISO) nonlinear system [1]. Controlling such a process with nonlinear dynamic characteristics is a challenging task [2].

The primary task of any controller is to overcome various disturbances in order to keep a process in a stable condition [3]. Parametric variation may be caused by disturbances or by the system's inherent nonlinearity. The time constant and gain of the chosen process vary as a function of level. Time-varying and nonlinear systems are of great interest to researchers because they exhibit erratic behavior when compared to linear systems.

Control theory is mostly concerned with the design of linear controllers for linear systems. Proportional-Integral-Derivative (PID) controllers have proven to be ideal for simple and linear processes. Nonlinear systems, on the other hand, require continuous adjustment of controller parameters. Artificial neural networks (ANN) can estimate any nonlinear function with at least one hidden layer and enough neurons.

Intelligent controllers were used in [4] to regulate liquid level in a conical tank process. Various controllers were implemented, namely conventional PID controller, Fuzzy Logic controller, Fuzzy PI controller, and ANN controller. When their settling time and peak overshoot were compared, it was determined that the ANN controller performed the best.

In [5], a conical tank process is controlled using Ziegler- Nichols tuned PI controller, internal model control (IMC) controller and particle swarm optimization (PSO) based PI controller. The results demonstrated that the PSO-based PI controller outperformed the others.

Reference [6] implemented Adaptive PID controller on a programmable logic controller (PLC) to control the level of a conical tank. Online estimation of model parameters, i.e., gain and time constant was found to be accurate. By using this model, IMC is used to tune PID controller in order to control the process according to the desired height.

In this project, the model of the tank is obtained by using step test method, where the tank is divided into five regions and a transfer function is obtained for each region.

The remainder of this paper is organized as follows: In section II, the process is described. In section III, process modeling procedure is explained. In section IV, the control system is described. Section V provides results and discussions. Finally, section VI concludes the paper.

II. PROCESS DESCRIPTION

The process being considered here is a conical tank liquid level system, in which water flows into the tank via a pulse width modulation (PWM) controlled pump. As soon as the pump is operated, water level starts to accumulate inside the tank because of the difference in flowrate between inlet flow delivered by the pump and outlet flow discharged from a valve located at the bottom of the tank. This accumulation continues until a state of equilibrium is reached, at which inlet flowrate equals outlet flowrate; meaning that the process is non-integrating or as also referred to as self-regulating.

Even though the process is self-regulating and level in the tank will eventually stop rising, a sort of control system is still required because the desired output level may be higher or lower than the steady-state level. For this process, the control system is implemented on a PIC18F4550 microcontroller, which offers two 10-bit PWM outputs as well as 13 analog to digital converter (ADC) channels with 10-bit resolution.

On the other hand, with regard to data acquisition required for modeling and analyzing process response, a Personal Daq/56 data acquisition device is used, which can read up to 20 analog inputs with ADC resolution up to 22-bit.

Fig. 1. Experimental setup of the conical tank process

III. PROCESS MODELING:

Designing a good control system requires a mathematical model that represents a system dynamics accurately. Since a conical tank is highly nonlinear, it cannot be described in an accurate manner using linear models such as transfer functions unless the model is extracted around a specific operating point. Thus, in order to obtain reliable system models, the tank is divided into five regions, around which the tank is modeled. The modeling procedure is performed using step test method, where a known input flowrate is given and output level is recorded until the level reaches a steady-state condition. This procedure is repeated five times, and the input-output data collected during the test is used to identify five transfer functions shown in table I, using the MATLAB System Identification Toolbox.

TABLE I IDENTIFIED TRANSFER FUNCTIONS

Region No.	Transfer Function	NRMSE Fit Value (%)
I	$G1(s)=\frac{1.85}{86s+1}$	88.5
II	$G2(s)=\frac{1.08}{245s+1}$	90.01
III	$G3(s)=\frac{0.925}{358s+1}$	95.92
IV	$G4(s)=\frac{0.89}{492s+1}$	96.47
V	$G5(s)=\frac{0.144}{970s+1}$	97.72

According to table I, the bottom region I of the tank with the smallest cross-sectional area has the shortest time constant and the highest process gain values. However, as the cross-sectional area increases, the time constant increases and the process gain decreases. The Normalized Root Mean Square Error (NRMSE) value indicates how well a model matches real data, with higher values indicating better fit.

Fig. 2 illustrates that model V fits the data very well, with a fit value of about 98%.

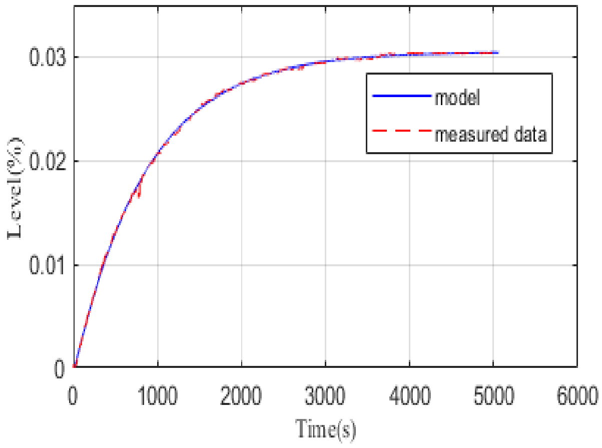

Fig. 2. Model V versus measured data with fit value of 97.72%

IV. CONTROL SYSTEM

Many types of control can be implemented on a conical tank system such as ANN, genetic algorithm and PSO optimization. Since PID control is very widespread in industry due to its simplicity, robustness and successful practical application [3], it can be used in combination with ANN. For this process, PI controller alone cannot be effective in maintaining level at setpoint. Therefore, it needs to be enhanced by ANN intelligent control to overcome the problem of nonlinearity of the tank.

A. PI Control

PI control is the most common form of PID controller[4]. It is based on two terms, namely proportional (P) and integral (I) terms. Proportional term reduces rise time and steady-state error, but it increases overshoot. The integral term, on the other hand, eliminates steady-state error and reduces rise time while increasing overshoot and settling time [5].

For tuning of PI controller, many techniques can be used such as Ziegler-Nichols and Cohen-Coon. In this work, PI controller is tuned by using MATLAB PID autotuning. As a result of the five transfer functions, five PI controllers can be obtained, as shown in table II.

TABLE II P & I PARAMETERS

Region No.	P Term (%/%)	I Term (s^{-1})
I	0.57	0.0198
II	0.98	0.0118
III	1.15	0.0096
IV	1.14	0.0068
V	1.05	0.0037

B. ANNPI Control

In order to address the problem of nonlinearity, ANN is used to tune PI controller online. ANN, first created by McCulloch–Pitt in 1943 [6], is an artificial network intended to function similar to the human brain in acquiring knowledge [7]. As a result, it can handle complex tasks such as pattern recognition, data classification, and system identification [6].

It is composed of basic units called neurons that work together to solve a problem [6]. Neurons are connected in various ways, resulting in a variety of network architectures [6]. Multilayer perceptron feedforward, used in this work, is the most commonly used architecture [8]. It consists of three layers, namely input, hidden and output layers [9] as shown in fig. 3.

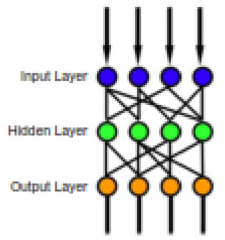

Fig. 2. Multilayer perceptron [10]

In this type of network, information moves in a single direction, beginning at the input layer and progressing through the hidden and output layers respectively [10]. A neuron's inputs are multiplied by weight coefficients, summed, and then subjected to an activation function to generate an output, which is then delivered to the next layer [6].

First, weights are initially generated randomly, but are then modified through the training process so that a particular input produces a particular output. This kind of training is known as supervised learning, and it involves providing known input and target data to the network, which is then trained to bring the network's actual output as close to the given target data as possible.

The following steps are taken in this work to design and implement the ANN:

- A loop is simulated in MATLAB Simulink using the identified transfer functions and corresponding PI controllers so that error, process value, controller output and setpoint signals are generated.

- These values are then introduced as inputs to the MATLAB ANN toolbox, while the obtained P and I terms are introduced as target data.
- The network is trained, generated in Simulink and a C code is obtained using Simulink Coder.
- The ANN code is integrated with a PI algorithm and deployed to the microcontroller.

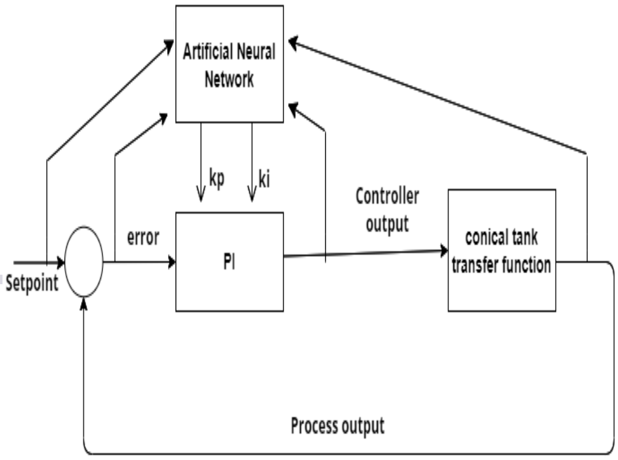

Fig. 3. Block diagram of the system

V. Results and Discusions

In order to compare the results of PI and ANN-PI controllers, the PI controller designed for region I and the ANNPI controller were implemented in real-time to maintain water level in the tank at different operating regions.

Because the PI controller is originally designed for region I, it is noted that response I shown in fig. 5 has acceptable properties. Table III displays the values for overshoot, settling time and rise time.

TABLE III Response properties of conventional PI controller

Region No.	Rise Time (s)	Peak Value	Overshoot (%)	Settling Time (s)
I	95.5	12.8	19.7	552.5
II	175	16.8	38.38	1090
III	218	21.55	44.31	2232
IV	247	23.8	57.5	2654
V	301	unknown due to sensor dead zone		3720

However, PI controller response degrades when moving away from operating region I, as shown in fig. 5 and as indicated by the large increase of PI output in fig. 6(a). The response becomes faster, but at the cost of increased overshoot and settling time.

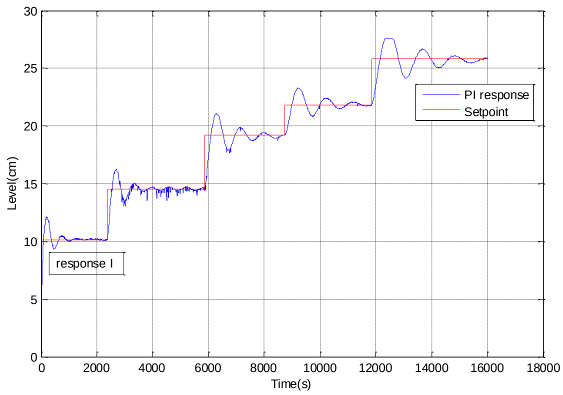

Fig. 4. Conventional PI controller response to step changes

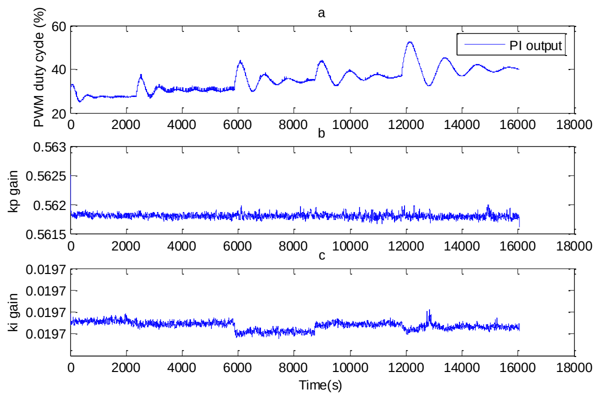

Fig. 5. Conventional PI controller output and gains

When the ANN-PI controller is used, however, the response improves noticeably even though the system is operated in different regions. This is due to the ability of ANN to adapt to changes in process dynamics, so that when switching from one region to another, the PI controller parameters are automatically updated in real-time in accordance with the obtained parameters for each transfer function.

When compared to the results obtained with the conventional PI controller, the response has acceptable properties. In all cases, the ANN-PI controller produces conservative response with less overshoot and settling time than the corresponding PI controller as shown in tables IV.

TABLE IV RESPONSE PROPERTIES OF ANN-PI CONTROLLER

Region No.	Rise time (s)	Peak value	Overshoot (%)	settling time (s)
I	106	14	22.84	600.5
II	243	16.8	24.6	1014
III	309	21.2	27	1410.5
IV	337.5	24.1	31.86	1636.5
V	354.5	27.8	21.36	1148.5

Fig. 7 depicts the ANN-PI controller response to setpoint changes, with P and I parameters changing immediately as the setpoint is changed.

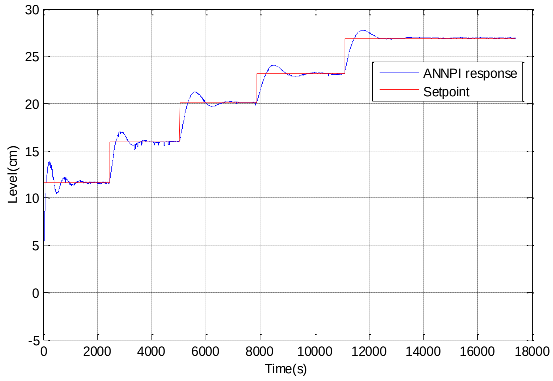

Fig. 6. ANN-PI controller response to step changes

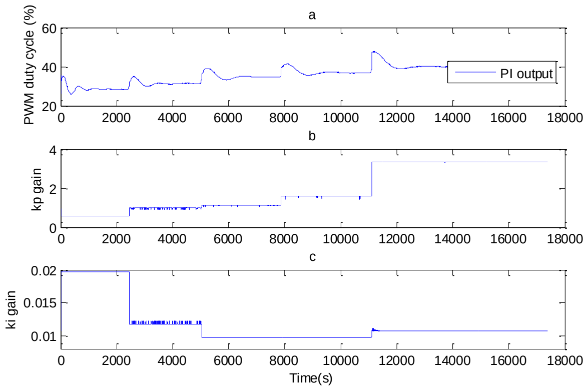

Fig. 7. ANN- PI controller output and gains adapt to changes in the process

VI. Conclusion

The purpose of this paper was to investigate how to control a conical tank by conventional PI and ANN-PI controllers. Controlling a conical tank with conventional methods can be difficult due to its nonlinear nature. The tank was divided into five regions and five transfer functions were identified as a result. Based on the transfer functions, five PI controllers were obtained. When only one PI controller was used to control the tank, the results were not satisfactory because the response showed much oscillation. However, when the ANN-PI controller was used, the performance improved significantly.

This work demonstrated that designing an ANN-PI controller was not complicated. As a result, it can replace conventional PI controllers in industry to address common problems that PI controllers cannot handle, such as nonlinearities.

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