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Design of a Free Model Adaptive-Neural Controller for Level and Temperature Control of Liquid Storage Tanks

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Abstract

In this paper, an adaptive-neural free model scheme is proposed to control a widely-used nonlinear multivariable industrial system, a quadruple-tank process (QTP). The system consists of four tanks that are arranged in two upper and two lower formations. The main objective is defined as maintaining the level of the liquid in lower tanks via two pumps. Controlling this system is not an easy task since it has nonlinear dynamics, strong interaction between different channels, and highly interacted input and output variables. In the adaptive part of the proposed controller, the parameters and rules obtained from Lyapunov stability analysis, along with the estimation of nonlinear functions performed with the neural network, constitute the controller design steps. To highlight the controller's abilities, an additional object is defined, which is controlling the temperature of liquid of those two tanks by adding a heater to the QTP system as a modified system. Obviously, the interactions amongst the control loops are multiplied because the modified quadruple tank process (MQTP) system has four inputs and four outputs. One of the main contributions of this paper is the implementation of the closed-loop system. Regarding the importance of such a system in the industry and to test the controller practically, the closed-loop system is implemented in an industrial automation environment with the connection of Process Control System SIMATIC (PCS7) industrial software to MATLAB with Open Platform Communications (OPC) protocol. The effectiveness of the introduced scheme is verified by performing some experimental validation.

Keywords: Four tanks system; model free control; industrial automation; multivariate control system; adaptive-neural control; industrial implementation
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1. Introduction

Acquiring a differential model for the dynamic industrial systems in many cases is not straightforward and economical. On the other hand, the system dynamics may change over time, which dramatically decreases the performance of the designed fixed controller. In these cases, the objective is defined as designing controllers with a remarkable performance that is independent of the system's dynamics. This has attracted the interest of researchers in the industry during the last decades. In [1], an unknown nonlinear single-input single-output (SISO) is put into perspective. Then, an adaptive model-free controller based on the ultra-local model is presented, which gain of the controller is obtained and adjusted by applying an online approach. In [2], a model-free technique based on an adaptive Kalman filter is employed to improve the Continuum robots' operation with structural compliance. The proposed controller has two main advantages: reducing the number of sensors and showing robustness against the system uncertainty and disturbances. In [3], a model-free fractional-order nonsingular fast terminal sliding mode controller based on time-delay estimation is proposed to control a nonlinear system without any profound knowledge about the dynamics of the system, lower-limb in a robot exoskeleton system in the presence of external disturbances. In [4], an optimal adaptive model-free controller based on neural networks is introduced for a class of time-dependent nonlinear systems with completely unknown dynamics. The proposed scheme is applied to a tracking problem. Also, tracking the unknown velocity pattern of drivers by motor torque-speed characteristic for the hybrid vehicles is another problem that has been solved in [5] by proposing a neural network-based PID control. A feed-forward neural network is applied to adjust the PID gains for reducing the tracking error of the closed-loop system. The quadruple-tank process (QTP) includes many industrial specification systems that are widely used. The main challenge in dealing with this system is keeping the level of the liquid exactly at a predefined scale.

Various papers have proposed model-based and model-free controllers. In [6], a model predictive controller (MPC) has been designed to control the modified QT system level. It has been realized by minimization of a defined cost function based on the system's regulation errors. Then, the closed-loop system's performance has been analyzed and compared with two well-known methods, linear quadratic regulator (LQR) and proportional-Integral (PI) controller. For uncertain nonlinearly multi-input-multi-output (MIMO) robotic system in [7], an adaptive neural network control has been proposed to tackle the time-varying delay and unknown backlash-like hysteresis effect of a MIMO system. In [8], the test bed system is a new four-tank system in which the pipe connects the top and bottom tanks. Employing the neural network makes it possible to identify the system, and the predictive controller is used to predict the future of the system’s output in the nonlinear optimization procedure. In [9], the authors have designed centralized, decentralized, and cooperative distributed multi-parametric MPCs for the linearized constrained version of the QTP. Finally, the robustness of the closed-loop system against uncertainties has been investigated. In addition, in [10], the MPC has been designed for the constrained and unconstrained MQTS. Another interesting approach is the adaptive inverse evolutionary neural (AIEN) controller [11]. It has been shown that the AIEN performs significantly better than the classic PID controller does. The system dynamics are identified and controlled first, and then, the robustness characteristics of the closed-loop system are improved by applying the adaptive controller. Researchers have focused on model-free controllers [12-14]. In [12], to control a quadruple tank system, an algorithm for decoupling multivariable systems based on generalized predictive control is suggested, and to handle the nonlinearities, a Takagi–Sugeno Neuro-Fuzzy system is introduced for modeling. Finally, it has been shown that combining features of the adaptive Neuro-Fuzzy model with the GPC principles results in a successful decoupling scheme.

We know that particular input-output selection is a highly significant stage in the design procedure of MIMI systems. Although there is no general procedure for an appropriate selection, in [13], a new on-line estimation for RGA matrix using neural networks is proposed for nonlinear or uncertain linear multivariable plants. In [14], the authors have presented a controller to keep the level in a four-tank system (FTS) model using fuzzy modified model reference adaptive control (MRAC) method. However, there are new approaches in other papers to keep the liquid level in the tanks at the desired values, but fuzzy modified MRAC (FMMRAC) is introduced in [14], and the performance of the closed-loop system is simulated using LabVIEW software.

This paper does not focus on model-based controllers since the system's exact modeling is not straightforward. It is because of its properties, such as being a strongly interacted multivariable system and having complicated nonlinear dynamics. For this purpose, along with a model-free controller's design by employing a neural-adaptive method, the controller is stimulated and implemented on a platform in industrial software, which is similar to a real experiment. The scheme's effectiveness is also evaluated by complicating the controller's objectives via maintaining the fluid level at a specific point and stabilizing the fluid temperature in the tanks at a particular value.

So far, some similar works on real implementation using industrial software have been done in published papers. In [15], authors have used PLC-PCS7 programming software and industrial automation as a laboratory. In addition, they seek to develop an industrial program with a fuzzy-neural system to prevent stoppages due to equipment failure, especially in the furnace area, to detect and produce prognostic news through feedback from industrial software MATLAB. The OPC protocol (which is a standard interface and provides connectivity between different data sets) is employed in [16]. This paper shows that intelligent and online monitoring systems are significantly effective for the Fars Province Gas Pressure Station System, which is based on the PCS7 Distributed Control System. In [17], communication between MATLAB and PLC via OPC, based on the Ethernet network, is performed to control the water tank pressure, and a real-time remote-control system is created. Similarly, in [18], the MPC approach is implemented on a four-tank system to be able to communicate via OPC technology. In [19], an actual test for connection between PLC and MATLAB on the four tanks system through the OPC server has been investigated.

The rest of the paper is organized as follows: In section 2, the famous 4-Tank System and its modified version are introduced. Since the system's mathematical model details are not used in the controller design procedure, the model-free controller is synthesized for the system in section 3. To show the controller's high abilities in the real world, section 4 is related to the implementation of the plant in PCS7 industrial software and describing how to synchronize it to MATLAB software. The simulation results are presented in section 5. Finally, the conclusion is presented in section 6.

2. Physical model and description of the quadruple-tank process

A) QTP system (quadruple-tank process)

QTP system is a quadruple process first proposed by Johnson in 1998. This MIMO system includes four water tanks, two control valves and two pumps. The aim is to control the level of the tanks through the pumps. In this paper, the inputs and outputs of the system are respectively the pump output flow and the tank level height. The linearized model of this process has an adjustable zero and allows the evaluation of multivariate control methods in the minimum phase and non- minimum phase modes. This value can be adjusted by the control valve coefficient. In this paper the focus is on the minimum phase mode. According to the physical laws governing this system [20], Mass balances and Bernoulli's law, yield:

$$\frac{dh_1}{dt} = \frac{-a_1}{A_1}\sqrt{2gh_1} + \frac{a_3}{A_1}\sqrt{2gh_3} + \frac{\gamma_1 k_1}{A_1}v_1 \tag{1}$$

$$\frac{dh_2}{dt} = \frac{-a_2}{A_2}\sqrt{2gh_1} + \frac{a_4}{A_2}\sqrt{2gh_4} + \frac{\gamma_2 k_2}{A_2}v_2 \tag{2}$$

$$\frac{dh_3}{dt} = \frac{-a_3}{A_3}\sqrt{2gh_3} + \frac{(1-\gamma_2)k_2}{A_3}v_2 \tag{3}$$

$$\frac{dh_4}{dt} = \frac{-a_4}{A_4}\sqrt{2gh_4} + \frac{(1-\gamma_1)k_1}{A_4}v_1 \tag{4}$$

Where, A_i indicates cross-section of Tank, a_i cross-section of the outlet hole and h_i water level. The voltage applied to Pump I is v_i and $v_i \times k_i$ is corresponding flow. The parameters γ_1 , γ_2 are determined from how the valves are set prior to an experiment. The flow to Tank 1 is $v_1 \times k_1 \times \gamma_1$ and the flow to Tank 4 is $v_1 \times k_1 \times (1-\gamma_1)$ and similarly for Tank 2 and Tank 3. The acceleration of gravity is denoted g. The measured level signals are $k_c \times h_1$ and $k_c \times h_2$. The parameter values of the laboratory process are given in the Tab. 1.

B) MQTP system (modified quadruple-tank process)

In the modified system, called MQTP, the lower tanks are equipped with a heater system. In this case, in addition to controlling the level of tanks 1 and 2, the temperature control of the two tanks

Table.1.
Parameters of the Plant [20]

Parameter	*Value*	*Parameter*	*Value*
A_1, A_3	$28\ Cm^2$	$h_1{}^0, h_2{}^0$	$\mathbf{(12.4, 12.7)\ cm}$
A_2, A_4	$32\ Cm^2$	$h_3{}^0, h_4{}^0$	$\mathbf{(12.4, 12.7)\ cm}$
a_1, a_3	$0.071\ Cm^2$	k_1 , k_2	$\mathbf{(3.33, 3.35)\ Cm^2 /vs}$
a_2, a_4	$0.057\ Cm^2$	γ_2 , γ_2	(0.7,0.6)
k_c	$0.50\ v/_{cm}$	g	$\mathbf{981\ cm/\ s^2}$

will also be considered and the complexity of the issue is much greater. As shown in Fig. 1(a), the heat required by the tanks 1 and 2 with temperatures of t_1 and t_2 , is supplied by Q_1 and Q_2 control signals respectively through the two heaters. Factors affecting the temperature of the tanks to obtain the dynamic equations include: temperature of the water supply pump of the tanks, the level or height of the tanks, the fluid flow from the upper tanks, the fluid temperature of the upper tanks, the heat generated by the agitator operation, and the amount of energy applied through the actuator. For implement the dynamic relationships governing the MQTP system, PCS7 software is used and simulated according to Fig. 1(b). To see the performance of the controller on another system the dynamic equations of temperature control loop are required as follows. The basic equations of mass and enthalpy equilibrium are written, where the mass changes are equal to the sum of the mass fluxes entered w_i and exited w_o:

$$\frac{d(m)}{dt} = w_o - w_i \equiv w_i = F_i\rho_i \equiv w_o = F_o\rho_o \tag{5}$$

Using (6) and (7) from [21], the mass flow is changed to the volumetric flow and A_1 and h_1 are named the level and height of tank1, respectively. Then for a temperature range up to 100 degrees it can be assumed that ρ_i and ρ_o are equal for water and can be written:

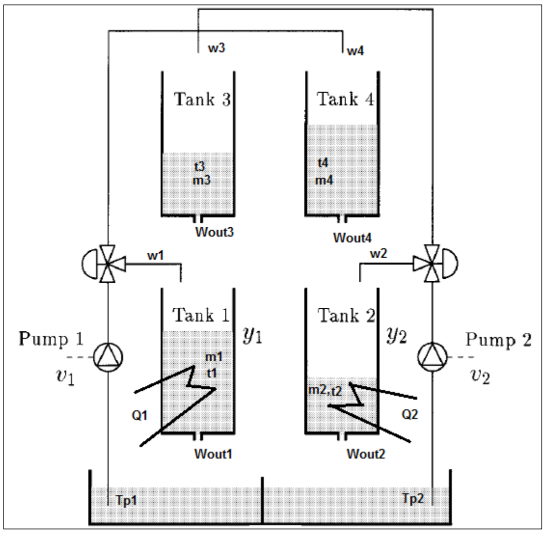
$$m = \rho v = \rho A h \tag{6}$$

$$\frac{d(v_1)}{dt} = \frac{d(A_1 h_1)}{dt} = F_{pump1} + F_{out_{tank\,3}} - F_{out_{tank\,1}} \tag{7}$$

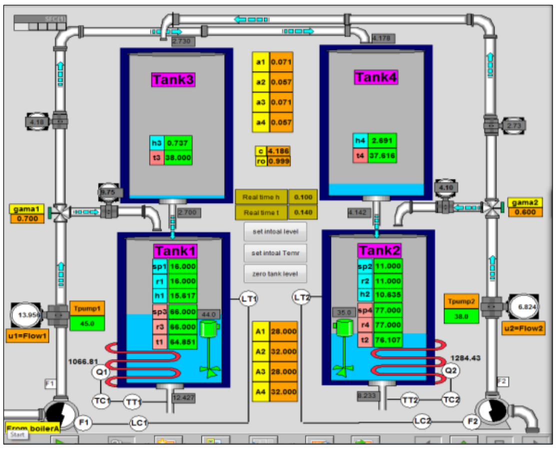
That F_{pump1}, $F_{out_{tank3}}$ and $F_{out_{tank1}}$ are respectively, the volumetric flow part of the pump flow1 into tank1 , drain flow from tank3 to tank1, and the volume flow coming out of tank1. Generally, from this reference and from [22-26], the energy equilibrium relationship of a tank with a heater with heat energy Q (J / S) is as follows:

$$\frac{\rho d(vH)}{dt} = \mathrm{Q} + w_{in1}c\,\Delta T_{in} - w_{out}c_{out}\Delta T_{out} + Q_{Agiator} \tag{8}$$

Where H is the heat of the tank and $Q_{Agiator}$ is the thermal energy generated by the stirrer shaft and the molecular motion. A very low-speed stirrer is mounted to uniform the temperature. This value is usually in calculations, but is considered to be more natural in simulation such a parameter. The height H of the tank is variable so it must follow the chain rules.



(a)



(b)

Fig. 1. (a) schematic diagram of the MQTP , (b) simulation of the MQTP in PCS7 automation software

$$\frac{\rho v\, d(H)}{dt}+\frac{\rho H d(v)}{dt}=\mathrm{Q}+w_{in1}c\,\Delta T_{in}-w_{out}c_{out}\,\Delta T_{out}+Q_{Agiator} \tag{9}$$

$$\frac{d(H)}{dt}=c\,\frac{d(\mathrm{t1})}{dt} \tag{10}$$

$$\rho v\, c\,\frac{d(\mathrm{t1})}{dt}+c\Delta T\,(F_i\rho_i-F_o\rho_{out})=\mathrm{Q}+\rho_i F_{in1}c\,\Delta T_{in}-\rho_{out}F_{out}c_{out}\,\Delta T_{out}+Q_{Agiator} \tag{11}$$

$$H=c(\mathrm{t1}-\mathrm{t_{ref}})=c\Delta T \tag{12}$$

$$\rho v\, c\,\frac{d(\mathrm{t1})}{dt}+c(\mathrm{t}-\mathrm{t_{ref}})(F_i\rho-F_o\rho)=\mathrm{Q}+\rho F_i c\,(\mathrm{t_i}-\mathrm{t_{ref}})-\rho F_o \mathrm{c}(\mathrm{t_o}-\mathrm{t_{ref}})+Q_{Agiator} \tag{13}$$

Assuming the zero origin of the $\mathrm{t_{ref}}$ signal, the relationships can be summarized as follows:

$$\frac{d(\mathrm{t1})}{dt}=F_i(\mathrm{t_i}-\mathrm{t1})+F_o(t-\mathrm{t_o})+\frac{\mathrm{Q}+Q_{Agiator}}{\rho c} \tag{14}$$

Now the above relation for tank1 characteristics is more completely written:

$$\frac{d(\mathrm{t1})}{dt}=\frac{\mathrm{Q1}+Q_{Agiator1}}{\rho V_1 c}+\frac{F_{T3}}{V_1}(t_{T3}-\mathrm{t1})+\frac{F_{p1}}{V_1}(t_{p1}-\mathrm{t1})+\frac{F_{T1}}{V_1}(t_{out1}-\mathrm{t1}) \tag{15}$$

That V_1 is the volume of water in the tank at any given moment. In the above relation the values of t1 and t_{out1} are assumed to be equal. Because with the existence of agitator, the temperature uniformity is created and the water temperature of the tank1 is equal to the outlet fluid temperature of the same tank.

$$\frac{d(\mathrm{t1})}{dt}=\frac{\mathrm{Q1}+Q_{Agiator1}}{\rho V_1 c}+\frac{F_{T3}}{V_1}(t_{T3}-\mathrm{t1})+\frac{F_{p1}}{V_1}(t_{p1}-\mathrm{t1}) \tag{16}$$

Where F_{p1}، t_{p1} ، F_{T3} ،t_{T3} ، t1 ، t1 are the volume flow of the pump1 that pours into tank1, the flow temperature of pump1, outlet flow of tank3, water temperature of tank1.The same is true for tank2.

$$\frac{d(\mathrm{t2})}{dt}=\frac{\mathrm{Q1}+Q_{Agiator1}}{\rho V_2 C}+\frac{F_{T4}}{V_2}(t_{T4}-\mathrm{t2})+\frac{F_{p2}}{V_2}(t_{p2}-\mathrm{t2}) \tag{17}$$

The top tanks are not equipped with heaters and no other tanks on them, so the relationships for this tanks become easier. Therefore, the temperature changes of tanks 1 and 2 are as follows:

$$\frac{d(\mathrm{t3})}{dt}=\frac{F_{p2}}{V_3}(t_{p2}-\mathrm{t3}) \tag{18}$$

$$\frac{d(\mathrm{t4})}{dt}=\frac{F_{p1}}{V_4}(t_{p1}-\mathrm{t4}) \tag{19}$$

3. The Proposed control Scheme

A) Error control signal structure and dynamics

This section first describes the structure of the proposed control scheme using the neural network approach with no need of dynamical model of the system. This controller is designed to achieve optimal performance in order to reduce tracking error. The nonlinear relationships of this system are rewritten as follows:

$$\dot{y}_1=f_1(y_1,h_3)+b_1u_1 \tag{20}$$

$$\dot{y}_2=f_2(y_2,h_4)+b_2u_2 \tag{21}$$

where $y_1=h_1$ and $y_2=h_2$ are the system outputs and $u_1 and\, u_2$ are the control signals. Therefore:

$$f_1(x) = \frac{-a_1}{A_1}\sqrt{2gh_1} + \frac{a_3}{A_3}\sqrt{2gh_3} \tag{22}$$

$$b_1 = \frac{\gamma_1 k_1}{A_1} \tag{23}$$

$$f_1(x) = \frac{-a_2}{A_2}\sqrt{2gh_2} + \frac{a_4}{A_2}\sqrt{2gh_4} \tag{24}$$

$$b_2 = \frac{\gamma_2 k_2}{A_2} \tag{25}$$

Assuming that the nonlinear functions f1 and f2 and the control gain are unknown, the system is estimated as follows:

$$\dot{\hat{y}}_1 = \hat{f}_1(\theta_1 \mid u_{nn1}) + \hat{b}_1 u_1 \tag{26}$$

$$\dot{\hat{y}}_2 = \hat{f}_2(\theta_2 \mid u_{nn2}) + \hat{b}_2 u_2 \tag{27}$$

Where $\hat{f}_1(\theta_1 \mid u_{nn1})$ and $\hat{f}_2(\theta_2 \mid u_{nn2})$ are MLP neural networks that estimate nonlinear functions $f_1$and f_2. θ_1 and θ_2 are neural network parameters. u_{nn1} and u_{nn2} are neural network input vectors defined as:

$$u_{nn1} = \left[y_1(t), y_1(t-1), \ldots y_1(t-n_1+1)\right]^T \tag{28}$$

$$u_{nn2} = \left[y_2(t), y_2(t-1), \ldots y_2(t-n_2+1)\right]^T \tag{29}$$

Where $y_i(t-k_i), k_i = 1,\ldots,n_1-1, \; i = 1,2$ indicates outputs in past samples. To determine the neural network parameters, the network output is written as a vector $\hat{y} = \theta^T \xi$, where θ is a vector of adjustable weights and ξ is its output derivative with respect to θ parameters. To reduce the tracking error, the error is defined as follows:

$$e_1 = y_1 - r_1 \tag{30}$$

$$e_2 = y_2 - r_2 \tag{31}$$

where, y_i and r_i are system output and reference signal. After deriving from the dynamic relationship error and placements of (20) and (21), it yields:

$$\dot{e}_1 = f_1 - \dot{r}_1 + b_1 u_1 \tag{32}$$

$$\dot{e}_2 = f_2 - \dot{r}_2 + b_2 u_2 \tag{33}$$

From the above equation, the control signals are considered as:

$$u_1 = \frac{1}{b_1}(\dot{r}_1 - f_1 - \lambda_1 e_1) \tag{34}$$

$$u_2 = \frac{1}{b_2}(\dot{r}_2 - f_2 - \lambda_2 e_2) \tag{35}$$

here λ_1 and λ_2 are assumed to be positive constant values. Unknown nonlinear functions replaced by neural networks $\hat{f}_1$, $\hat{f}_2$ and the unknown control gains are estimated with $\hat{b}_1$ and $\hat{b}_2$. Consequently, the structure of the desired control signals with the aim of reducing the tracking error is as follows :

$$u_1 = \frac{1}{\hat{b}_1}\left(\dot{r}_1 - \hat{f}_1 - \lambda_1 e_1 + u_{s1}\right) \tag{36}$$

$$u_2 = \frac{1}{\hat{b}_2}\left(\dot{r}_2 - \hat{f}_2 - \lambda_2 e_2 + u_{s2}\right) \tag{37}$$

In which, u_{s1} and u_{s2} are the compensators designed to compensate for the estimation error effects. Considering the optimal control signal relationship, the block diagram of the proposed control system is shown in Fig. 2, where the optimal control signal relationship is calculated in C1 and C2 sub-blocks. These blocks need the derivatives of the reference signal, the neural network output and the tracking error. Into control loops of Fig. 2. , the outputs y1, y2 are controlled by the Controller1, Controller2 with U1, U2 control signals, respectively. NN1 and NN2 neural networks with subsystems C1 and C2 are designed according to Lyapunov's law. In fact, within the controller box, Lyapunov stability rules are implemented to reduce the tracking error.

$$\dot{e}_1 = -\lambda_1 e_1 + f_1 - \hat{f}_1 + \left(b_1 - \hat{b}_1\right)u_1 + u_{s1} \tag{38}$$

$$\dot{e}_2 = -\lambda_2 e_2 + f_2 - \hat{f}_2 + \left(b_2 - \hat{b}_2\right)u_2 + u_{s2} \tag{39}$$

Functions $\hat{f}_1^*(\theta_1^* | u_{nn1})$ and $\hat{f}_2^*(\theta_2^* | u_{nn2})$ as neural networks with optimal parameters θ_1^*، θ_2^* and b_1^*, b_2^* as optimal control gains values, are added and subtracted from the above equation, the result becomes

$$\dot{e}_1 = -\lambda_1 e_1 + \hat{f}_1^* - \hat{f}_1 + \hat{b}_1^* u_1 - \hat{b}_1 u_1 + f_1 - \hat{f}_1^* + \left(b_1 - \hat{b}_1^*\right)u_1 + u_{s1} \tag{40}$$

$$\dot{e}_2 = -\lambda_2 e_2 + \hat{f}_2^* - \hat{f}_2 + \hat{b}_2^* u_2 - \hat{b}_2 u_2 + f_2 - \hat{f}_2^* + \left(b_2 - \hat{b}_2^*\right)u_2 + u_{s2} \tag{41}$$

By defining the estimation errors as

$$\varepsilon_1 = f_1 - \hat{f}_1^* + \left(b_1 - \hat{b}_1^*\right)u_1 \tag{42}$$

$$\varepsilon_2 = f_2 - \hat{f}_2^* + \left(b_2 - \hat{b}_2^*\right)u_2 \tag{43}$$

And the parameter estimation errors as:

$$\tilde{\theta}_1 = \hat{\theta}_1^* - \hat{\theta}_1 \tag{44}$$

$$\tilde{\theta}_2 = \hat{\theta}_2^* - \hat{\theta}_2 \tag{45}$$

$$\tilde{b}_1 = \hat{b}_1^* - \hat{b}_1 \tag{46}$$

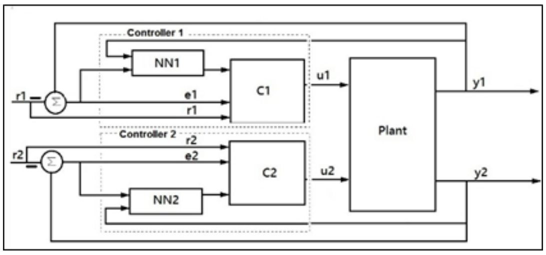


Fig. 2. Block diagram for the proposed controller

$$\tilde{b}_2 = \hat{b}_2^* - \hat{b}_2 \tag{47}$$

The (40-41) can be rewritten by

$$\dot{e}_1 = -\lambda_1 e_1 + \hat{f}_1^* - \hat{f}_1 - \tilde{b}_1 u_1 + \varepsilon_1 + u_{s1} \tag{48}$$

$$\dot{e}_2 = -\lambda_2 e_2 + \hat{f}_2^* - \hat{f}_2 - \tilde{b}_2 u_2 + \varepsilon_2 + u_{s2} \tag{49}$$

Now, consider $\hat{y} = \theta^T \xi$ in which θ is a vector of adjustable weights and ξ is a derivative of neural network output with respect to θ parameters. As a result, the error dynamics are:

$$\dot{e}_1 = -\lambda_1 e_1 + \tilde{\theta}_1^T \xi_1 + \tilde{b}_1 u_1 + \varepsilon_1 + u_{s1} \tag{50}$$

$$\dot{e}_2 = -\lambda_2 e_2 + \tilde{\theta}_2^T \xi_2 + \tilde{b}_2 u_2 + \varepsilon_2 + u_{s2} \tag{51}$$

B) Lyapunov stability analysis to derive adaptive rules

Consider the following candidate Lyapunov function:

$$\mathrm{v} = \frac{1}{2}e_1^2 + \frac{1}{2}e_2^2 + \frac{1}{2\gamma}\tilde{\theta}_1^T \tilde{\theta}_1 + \frac{1}{2\gamma}\tilde{\theta}_2^T \tilde{\theta}_2 + \frac{1}{2\gamma}\tilde{b}_1^2 + \frac{1}{2\gamma}\tilde{b}_2^2 \tag{52}$$

Where γ is the weight coefficient. The derivative of v becomes

$$\dot{V} = e_1\dot{e}_1 + e_2\dot{e}_2 - \frac{1}{\gamma}\tilde{\theta}_1^T \dot{\hat{\theta}}_1 - \frac{1}{\gamma}\tilde{\theta}_2^T \dot{\hat{\theta}}_2 - \frac{1}{\gamma}\tilde{b}_1 \dot{\hat{b}}_1 - \frac{1}{\gamma}\tilde{b}_2 \dot{\hat{b}}_2 \tag{53}$$

Use (50) and (51) to obtain

$$\begin{aligned}\dot{\mathrm{v}} &= e_1\left[-\lambda_1 e_1 + \tilde{\theta}_1^T \zeta_1 + \tilde{b}_1 u_1 + \varepsilon_1 + u_{s1}\right] + e_2\left[-\lambda_2 e_2 + \tilde{\theta}_2^T \zeta_2 + \tilde{b}_2 u_2 + \varepsilon_2 + u_{s2}\right] \\ &- \frac{1}{\gamma}\tilde{\theta}_1^T \dot{\hat{\theta}}_1 - \frac{1}{\gamma}\tilde{\theta}_2^T \dot{\hat{\theta}}_2 - \frac{1}{\gamma}\tilde{b}_1 \dot{\hat{b}}_1 - \frac{1}{\gamma}\tilde{b}_2 \dot{\hat{b}}_2\end{aligned} \tag{54}$$

After some more calculations we ends up with

$$\begin{aligned}\dot{\mathrm{v}} &= -\lambda_1 e_1^2 - \lambda_2 e_2^2 + \tilde{\theta}_1^T\left[-\frac{1}{\gamma}\dot{\hat{\theta}}_1 + e_1\zeta_1\right] + \tilde{\theta}_2^T\left[-\frac{1}{\gamma}\dot{\hat{\theta}}_2 + e_2\zeta_2\right] + \tilde{b}_1\left[-\frac{1}{\gamma}\dot{\hat{b}}_1 + e_1 u_1\right] \\ &+ e_1\left(\varepsilon_1 + u_{s1}\right) + e_2\left(\varepsilon_2 + u_{s2}\right)\end{aligned} \tag{55}$$

Finally, the adaptive rules are derived as:

$$\dot{\hat{\theta}}_1 = \gamma_1 e_1 \zeta_1 \tag{56}$$

$$\dot{\hat{\theta}}_2 = \gamma_2 e_2 \zeta_2 \tag{57}$$

$$\dot{\hat{b}}_1 = \gamma_1 e_1 u_1 \tag{58}$$

$$\dot{\hat{b}}_2 = \gamma_2 e_2 u_2 \tag{59}$$

This leads to

$$\dot{\mathrm{v}} = -\lambda_1 e_1^2 - \lambda_2 e_2^2 + e_1\left(\varepsilon_1 + u_{s1}\right) + e_2\left(\varepsilon_2 + u_{s2}\right) \tag{60}$$

To compensate for the effects of the estimation errors ε_1 and ε_2, the compensators are considered as follows:

$$u_{s1} = -\bar{\varepsilon}_1 e_1\, sign\left(e_1\right) \tag{61}$$

$$u_{s2} = -\bar{\varepsilon}_2 e_2\, sign\left(e_2\right) \tag{62}$$

where $\bar{\varepsilon}_i$ is the upper bound of ε_i. By inserting (61) and (62) in (60) we will have

$$\dot{\mathrm{v}} \le -\lambda_1 e_1^2 - \lambda_2 e_2^2 + \left|\varepsilon_1 e_1\right| + \left|e_2\varepsilon_2\right| - \bar{\varepsilon}_1 e_1\, sign\left(e_1\right) - \bar{\varepsilon}_2 e_2\, sign\left(e_2\right) \tag{63}$$

Knowing the fact $e_i\, sign(e_i) = |e_i|$, the above inequality becomes

$$\dot{\mathrm{v}} \le -\lambda_1 e_1^2 - \lambda_2 e_2^2 + \left|e_1\right|\left(\left|\varepsilon_1\right| - \bar{\varepsilon}_1\right) + \left|e_2\right|\left(\left|\varepsilon_2\right| - \bar{\varepsilon}_2\right) \tag{64}$$

Since $|\varepsilon_i| \le \bar{\varepsilon}_i$ and the second-order derivative of the error is finite, the asymptotic stability is guaranteed. The smooth Tanh function in compensators (61) and (62) will be used to prevent control signals from fluctuation.

4. Connection between Industrial Automation Environment and MATLAB

Fig. 3 illustrates how the system components and software windows of different environments communicate as an industrial connection and the only difference is that in the real test, there are analog input and output cards in plc. For this reason in this article PLCSIM simulator software has been used. To do this, we first create tags in the interface software called KEPSERVER (as OPC server), between MATLAB and SIMATIC NET from the DCS_ PCS7 software subset. In addition, for commands sent from MATLAB software and feedback signals from PCS7 to MATLAB, tags of the same type are defined on both sides and information is exchanged.

5. Simulation

In this section first, the controller is examined on the level control loop, and the control system is implemented in MATLAB. To ensure the performance of the controller designed in this paper, in the next section, the level and temperature control loops are simulated with the same controller. The difference is that, this time the plant is implemented in the industrial automation environment. Finally, the sample of the industrial unit is designed by integrating the topics of the previous sections and its simulation results will be depicted.

A) Simulation when both the controller and the plant are implemented in the MATLAB environment

Only for this experiment, the new dynamic equations are changed according to the parameters table of this paper. According to Fig. 5(a), from the two inputs F4 and F3 it is possible to disturb the upper tanks. To control the level of the tanks, in the first part, both plant and relevant controller are implemented and tested in MATLAB environment. With the same conditions, in the second and third experiments the results of the controller robustness test and the disturbance reject effect test will be observed. As shown in Fig. 4(a), in the control loop of the tank level 1 and 2, the optimal response to the sine and step reference signals is shown, along with the appropriate control signal. In this study, as a free model, the controller must respond appropriately to systems with similar dynamic, and should be robust against changes in model. Suppose that without changing the main structure of the controller, it is necessary to increase the production capacity by changing the dimensions of the system. For this purpose, another system from the paper [27] is selected to test this controller. In that article, tanks' cross section, have been changed to A1 = 58, A2 = 58, A3 = 62, and A4 = 62, respectively). According to in Fig. 4(b), the desired result of the second experiment is shown along with the corresponding control signals. In the simulation, r1 and r2 are the reference signals of the tanks 1 and 2, respectively, and u1 and u2 are the command signals for the h1 and h2 tank respectively.

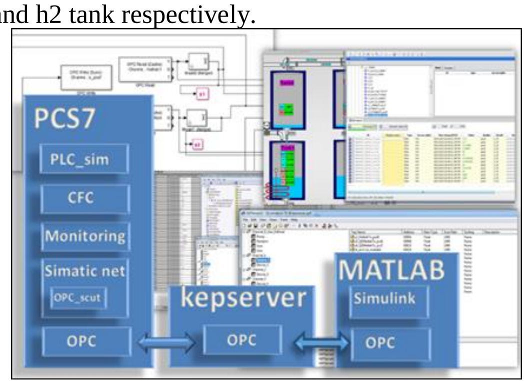
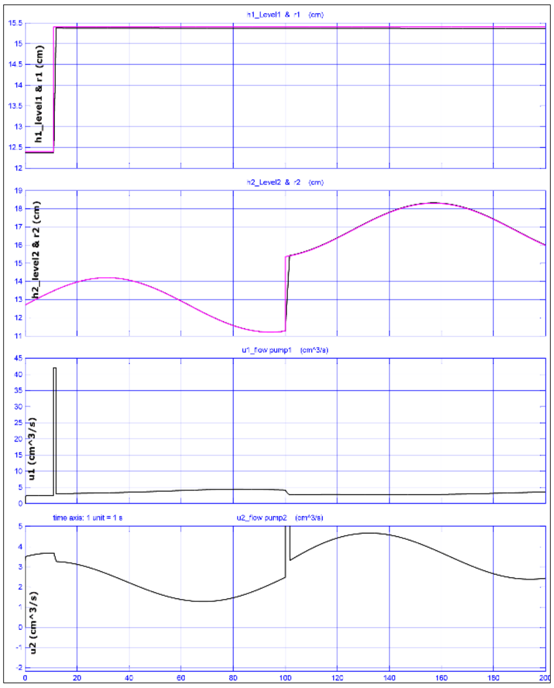
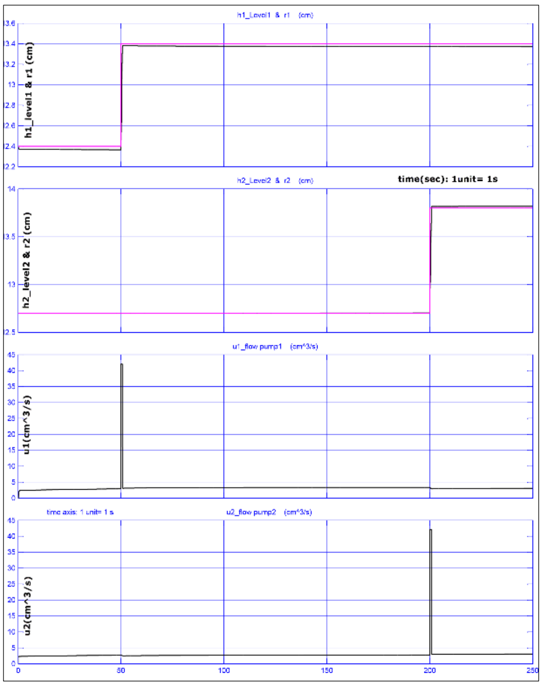


Fig. 3. How to connect PCS7 to MATLAB via OPC

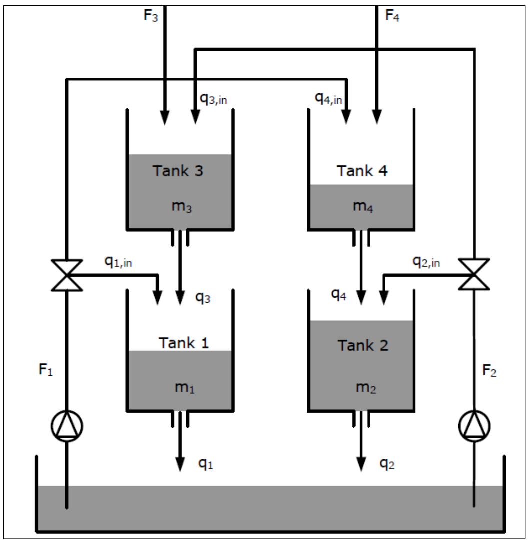


(a)

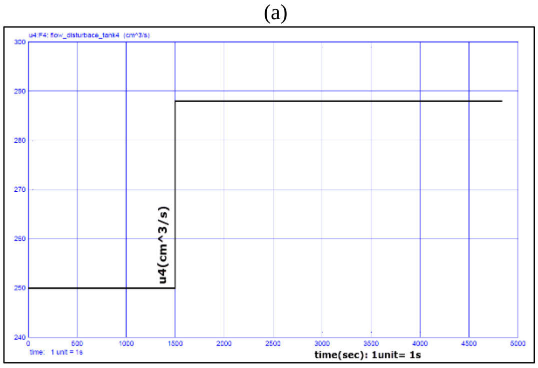


(b)

Fig. 4. (a) respond to a situation where the reference signal is incremental and sinusoidal, (b) response of Free Model Control Method after resizing Tanks (robust Model test)



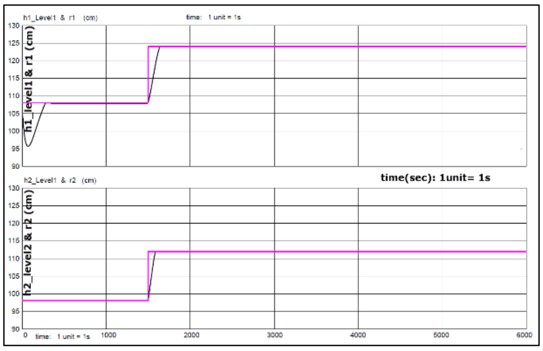
(a)



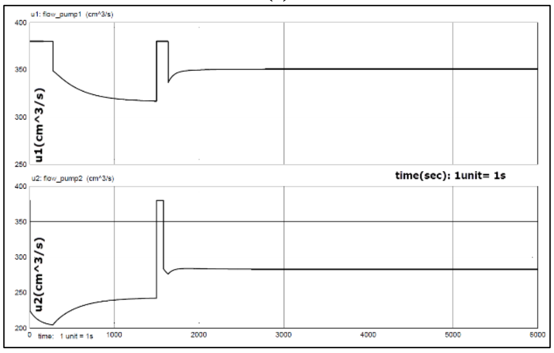
(b)

Fig. 5. (a) schematic diagram of the modified quadruple tank process with disturbance in the upper tanks [10], (b) the change of disturbance signal of the incoming fluid to tanks 3 and 4

In the third experiment of this section, the performance of the controller on another modified system from [10] is examined in relation to the addition of disturbances to the level of the upper tanks. These two disturbance signals assumed in Fig. 5(b), and unlike flow signals of pumps 1 and 2 (F1, F2) cannot be controlled. First, the step response of the proposed control scheme without considering effect of disturbances are depicted in Fig. 6(a) to Fig. 7(a) and then response to external disturbances is shown in Fig. 7(b) and 8(a). Fig. 7(a) shows the result of the previous simulation with more magnification. In this simulation, with 15% step input change in reference signal after 25 minutes applied to the system. Steady state response error is an acceptable value, therefore, the controller performs well. The step response of the proposed neural-adaptive control scheme by considering effect of disturbances is depicted in Fig. 7(b). By comparing the control signals before and after the disturbance changes, it can be seen that the controller is able to eliminate the effect of unwanted



(a)



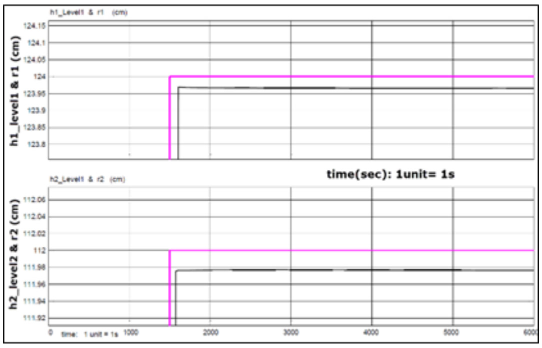
(b)

Fig. 6. (a) System response to the reference signal, without any disturbance changes, (b) Step response control signal without any disturbance changes

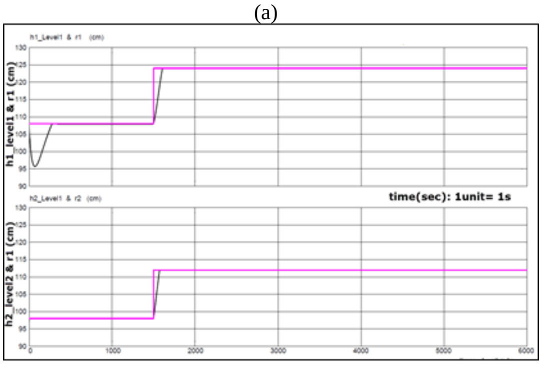
changes with a proper command. Fig. 8(a), is a look at changes in the levels of upper tanks that are not under control and it can be seen that their variations are in limited and desirable range and the overflow will not occur in the tanks.

B) Simulation when the controller is in the MATLAB environment and the plant is implemented in the industrial automation environment

In this experiment, similarly with a slight change in the parameters of the same controller, two level and temperature control loops having the same dynamic model form the MQTP plant are implemented in the industrial environment. Nevertheless, the real meaning of free model control is felt, because the controller does not have the dynamic information of the system. The optimal control signal is sent via OPC from the MATLAB environment to the plant in pcs7 and the output of the process returns to MATLAB as a feedback to the controller, to update the adaptive parameters. In the tank level control loop1, the sine signal is traced (Fig. 10(a)).

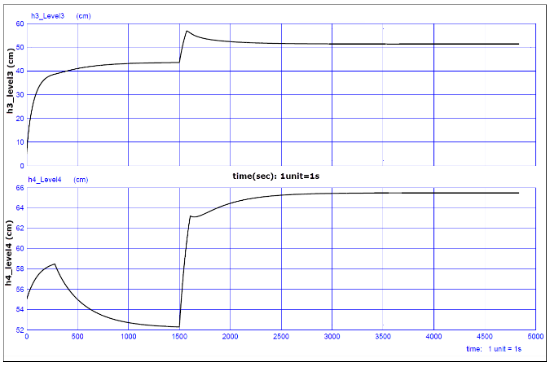


(a)

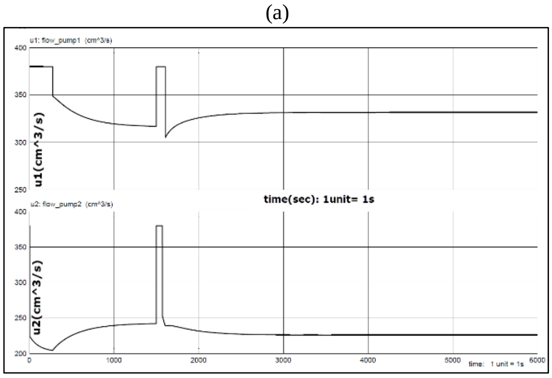


(b)

Fig. 7. (a) shows the result of the previous simulation with more magnification, (b) The step response of the system to the reference signal by applying disturbance changes

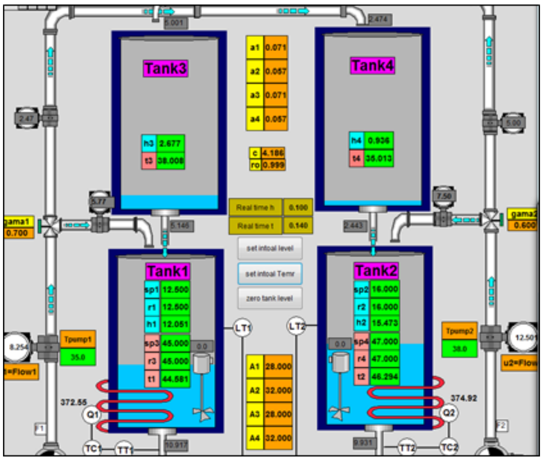


(a)

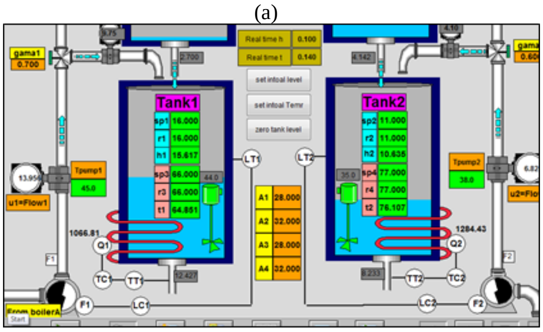


(b)

Fig. 8. (a) changes in levels of tanks 3 and 4 in response to disturbance changes and step response, (b) control signal, for step response of the system to the reference signal by applying disturbance changes.



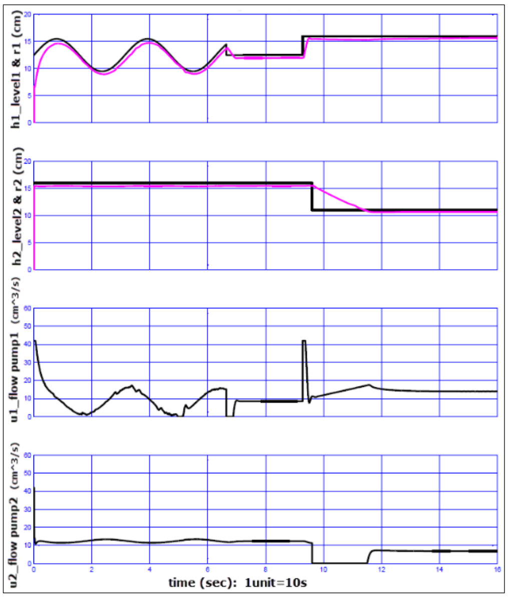
(a)



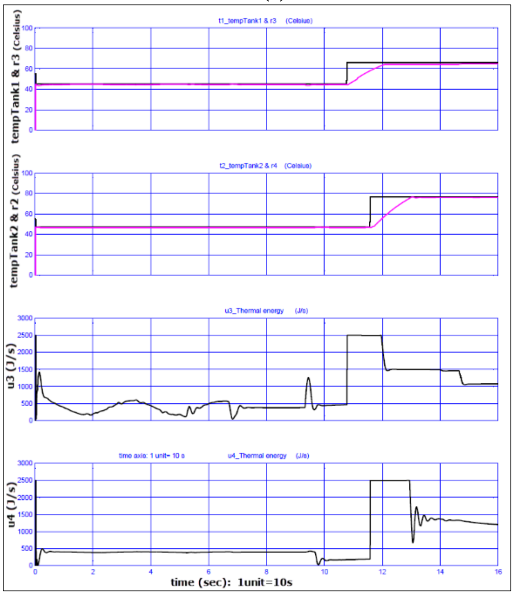
(b)

Fig. 9. (a) Shows the values of the parameters and initial conditions of the four tanks equipped with the heating system, (b) Monitoring the values of temperature and level control loop parameters after applying set points

In this case, the control signals of the other loops are calculated to track their reference signal. In Fig. 10 (a), it is observed that the system is under control, u3 changing so that the temperature of tank 1 (t1) does not change. At 65 seconds, the sinusoidal signal is removed from the r1 reference signal and after a few seconds, the stability is restore. At 95 and 97 seconds, the incremental and descending step response is applied to the level of tanks 1 and 2, respectively. Simultaneously with the level loops being tracked, the control signal of the two temperature loops changes to inhibit the level change disturbance effect on the temperature loops. Fig. 9(a) shows the 4-tank monitoring system equipped with the heater, in which parameters, signal values and initial conditions are considered for the beginning of the experiment. Fig. 9(b) shows the values and parameters after running the equipment and applying the new set points.



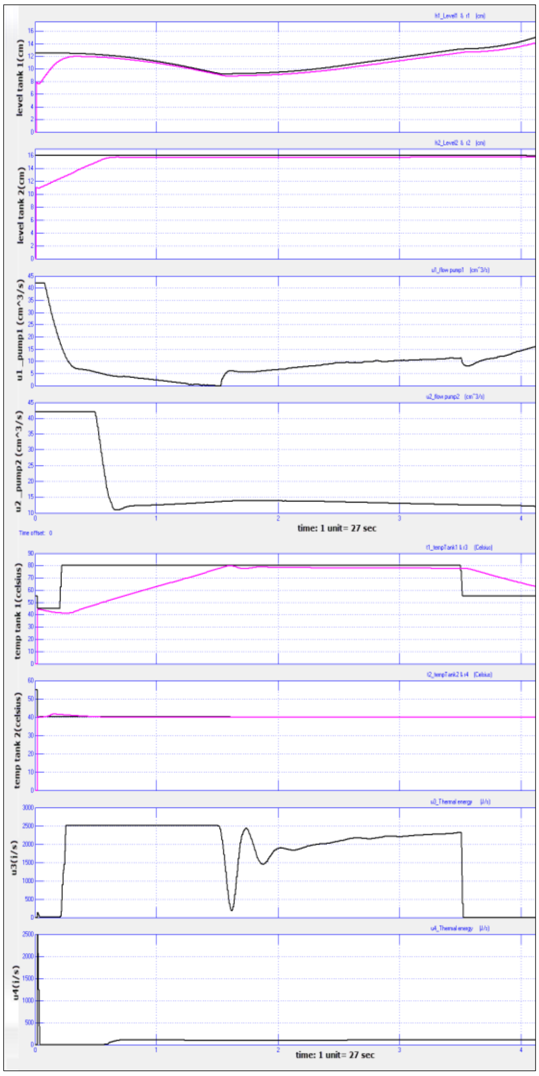
(a)



(b)

Fig. 10. (a) Step response and sinusoidal reference signal for level control loop, (b) Response of temperature control loops to: level changes, temperature changes of pumps and mixer starters, etc.

Comparing the monitoring parameters in Fig. 9(a) and 9(b), the system's response to these changes is shown in Fig. 10(a) and 10(b), where at 108 and 116 seconds, the step response is applied to tank temperatures 1, 2 and their response will be steady at 130 seconds. It was while, the level was constant and only temperature control signals had to compensate for the corresponding step changes to track the reference signal.



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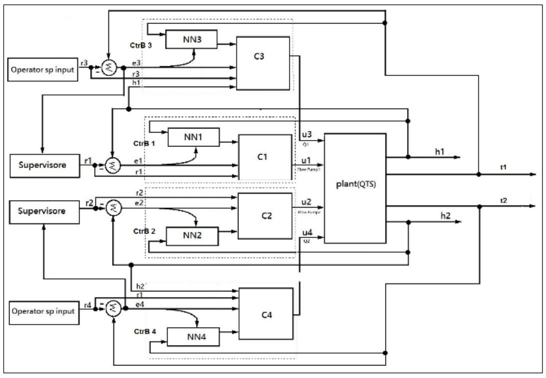

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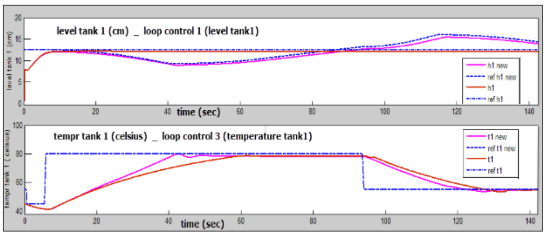

(c)

Fig. 11. (a) Response of control loops to change in temperature of tank 1 while tank volume 1 is variable, along with other control signals, (b) Block diagram for MIMO system, level and temperature control of liquid storage tanks, (b) response comparison of control loop 3 (tank temperature 1) proportional to tank level 1, in fixed level modes and new variable level modes

C) Proposed structure of a control system similar to that of an industrial automation system

The following block diagram is the structure of the final control system of this paper. The design steps are described in previous sections and the desired results were tested for each loop. All study of the preceding sections are seen as an industrial control structure in Fig. 12(b), in which the outputs of the four control loops is: tank level 1, tank level 2, tank temperature 1 and tank temperature 2, are called h1, h2, t1, t2, respectively. They belong to the control blocks of CtrB1, CtrB2, CtrB3 and CtrB4 that generate the control signals, U1, U2, U3, U4, respectively.

Actually, inside the controller box (the dotted box) the stabilizing rules are implemented. Supervisor blocks determine set points for accelerated temperature loop control. That is if the temperature tracking error is large, the level of the tank changes gradually so that, volume of water changes as an aim of faster temperature control. In this case, the level control system should be able to follow a variable reference signal because , the reference signal r is set by the supervisor block and again returns to the SP value that the user specifies in the monitoring fields. When the water volume of the tank1 is variable, the response to the temperature change is shown in Fig. 11(a). Now as a test, the SP of temperature of the tank1 is changed to 80 ° C in 5.4 seconds and then returns to 55 degrees in 86.4 seconds. The result of the simulation is observed for the case where the volume of water changes proportionally. The comparison of this result with the case of constant volume is plotted in Fig. 11(c). In the first step response, it can be seen that only by changing about 30% of the level of tank 1, the temperature control loop is 25% faster. It should be noted for the safety of the equipment, Interference with SP requests and minimum and maximum SP, overflow tanks and other system safety requirements should apply as other management plans. That is, for example, the minimum reference signal from the management plan is limited to the extent that the heating element is covered. The piping and feeding pumps in the 4-tank system are designed to challenge the controllers. In addition, here, all new parts of these simulations were designed to show that the adaptive-neural controller of this paper is able to effectively detect a variable reference signal on such systems and that is industry's need to control the complex systems while their models are not available. This paper has partially tackled these challenges. In this research, it is enough to connect the actual sensors and actuators with the PLC modules to pcs7 software. In this case, it is expected with a bit of controller parameter settings in MATLAB, it is ready for operation on a real system.

6. Summary and Conclusion

In the industry world, the system model is usually unavailable or changing over time. Accordingly, in this paper's approach, the model-free method with adaptive-neural controller utilizes Lyapunov's stability and classical feedback control principle to generate the desired control signal. Industrial systems are highly prone to unwanted external disturbances. Here, the designed controller observes these changes in the form of a new nonlinear signal. In this case, this controller will be applicable to some similar systems. On the other hand, to implement a near-reality model-free experiment, only the plant input-output knowledge is used, which is simulated in an industrial software environment rather than MATLAB. To reassess the performance of this controller, a similar industrial unit with a multivariable nonlinear system with much more challenges was proposed by adding heaters to the four tanks; besides testing the performance of the controller, the aim of accelerating the temperature control is achieved by changing the volume of the water of the tanks along with the heater control. The simulation results show that under the same conditions but without applying the idea (when the volume of the tank content is constant) to the system's response in a situation where the tank level changes by about 30%, the response rate decreases by about 25%. With similar conditions in two simulations of new papers, simulation for disturbance and uncertainty in the model was tested. The results showed that the controller is capable of repelling these changes (without disruption to other loops) with appropriate response speed and acceptable steady-state error. Of course, this answer is advantageous over other papers; that controller has no knowledge of system dynamics. In the end, for a real connection to the Practical system, only the sensors and actuator with

PLC modules need to be connected to pcs7 software. In this case, this project on a similar system (with a few control parameter settings) is able to track normal variable reference signals.

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