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Adaptive Neural Network based control to counter disturbances for Coupled-Tank Water Level control

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Abstract

This paper addresses the tough issues pertaining to water level control issues in coupled-tank systems, which might be prevalent specifically to Process industries but has also seen widespread nonlinearities in its behaviour being sensitivity to disturbances of any kind. Here we posed a novel Adaptive Neural Network control-based strategy which excellently compensates parameter uncertainties, for machine nonlinearities, and influx disturbances. This control architecture perfectly combines a conventional Proportional-Integral (PI) controller with a single hidden-layer neural network offering online weight adaptation. Here to approximate and cancel unknown nonlinearities Neural Network based compensator accompany radial basis capabilities has been employed, while the adaption law has been devised Lyapunov Stability theory to insure stability of all closed-loop processes. Extensive MATLAB/Simulink simulations show how well the controller performs in a variety of difficult situations, such as setpoint changes, inflow disruptions, and parameter fluctuations. The proposed controller has some added advantage over PID control exhibited in improvement in Settling Time, decrease in Overshoot , and good disturbance rejection. It also has almost zero steady state error. All these advantageous favours it for real world industrial applications where accuracy matters.

Keywords: Coupled-Tank System, Adaptive Control, Neural Networks, Level Control, Lyapunov Stability, Disturbance Rejection.

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Introduction

In any industry like Electricity generation, water treatment, pharmaceutical company , petroleum industry the liquid level control is most import parameter and its has related issues which we can't ignore [16]. As the complexity if the system increases the interaction between different parameters also gets increases which make it more problematic for level control [2].

The system posed in this work has a practical applicability which has also been validated through MATLAB Simulink.

Control challenges in Coupled-tank are quite wide as the complex configuration of this system. Most common is the processes which involves low level operation as there is non linear relation between the water level and output flowrate based on Torricelli's law [14].

The traditional controllers can effectively manage the behaviour of linear systems, but as the case put forward here has extreme non linearity reasoning asymmetric behaviour posed by the parameters involved. Let the case of the valve connecting both the tank in interacting type is completely asymmetric [3]. Additionally, these difficulties becomes more prominent in real time application as there may be imperfections in sensors , volve pening and closing and ambient effect in industries [12].

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The most popularly used controller can not handle these complexity to much extent , however PID controllers still the most usable controller in the industry . The easy to implement and easily controllable is the prime reason of its widespread acceptability, however fixed gain parameters deployed in PID causes poor performance in some of the operating conditions [1]. The gain-scheduled PID [9] and Fuzzy Logic techniques [15] have shown some better performance although one demerit associated to it the parameters have to be adjusted manually only and not necessarily ensures stability. The model based controller has relatively edge over parameter variation . these models are generally based on Linear quadratic Gaussian control but the issue is that due to complex implantation strategy modelling mistake likely to affect the stable operation

An important development in managing system uncertainties and time-varying factors was the introduction of adaptive control algorithms [13]. However, unmodeled dynamics and large nonlinearities frequently cause problems for traditional model reference adaptive controllers. Because of its model-free learning features and universal approximation capabilities, neural network-based control techniques have attracted a lot of attention [10]. Neural networks are especially appealing for applications where precise system identification is difficult or expensive because of their capacity to learn intricate nonlinear mappings without explicit system modelling [5].

The main contribution of this study is the creation of an advanced adaptive neural network controller that combines the potent approximation skills of neural networks with the dependable tracking performance of PI control. A radial basis function network structure that offers effective nonlinear compensation, a Lyapunov-based adaptation law that ensures stability while ensuring effective learning, and a comprehensive framework that requires little system knowledge while delivering robust performance across a range of operating conditions are some of the key innovations in our approach.

The structure of this document is as follows: A thorough analysis of pertinent literature is given in Section II. Section III show the mathematical modelling of the system proposed. The controller designed and The modelling and analysis of the coupled-tank system are stability analysis has been given in section IV. Performance analysis and simulation findings are discussed in Section V. Then there is Conclusion section VI which concludes the findings of this paper . There is still some scope left to carry forward this work, the key future problems has been put forward in section VII.

Literature Review

Over the period of time, a great efforts have been done to control the water level in industry, by using different controller from simple to the advanced regulatory control. The early work establishes the fundamental application of PID Controller [1]. But it has problem over multivariable control and nonlinearity issues.

Gain scheduling comes into existence to deal with nonlinearities constraint offered by the PID. For the interacting type capacity or tank system , the level has been controlled by this gain scheduling method by Khanduja et. al [9]. Which shows better performance but has disadvantages as it requires much more experimental data. Similarly Chen et. al [4] demonstrated an advanced gain scheduling method for conical tank systems which has employed tough adaptation law and thoroughly demonstrated the computational difficulty in industrial real-time implementation. It still exhibits good performance.

The controlling of interacting capacity is all together a different and tedious concept as it shows nonlinear behaviour. Patel and Joshi (2019) [15] uses fuzzy logic control to showcase better controlling of nolinear system than that of conventional one in Liquid level control. But the barrier associated with Fuzzy level control is its complex implementation, which need expertise acquaintance to controller implementation. Smith et. al (2019) [18] developed a linear quadratic Gaussian (LQG) controller for coupled tank systems, which has good performance under nominal conditions for parameter variations, but it needs efficient model implementation.

Narendra et. al (1989) [13] has given a better approach to deal with uncertainty in the system by introducing adaptive control techniques which further laid down the concept of Model based adaptive control under strict and varying conditions. Still the performance degrades in non-linear systems, but still hold the upper edge over dealing with unknown parameters. Ioannou et. al (2012) [7] has expanded these ideas further and devised robust adaptive control, by better management of model framework.

Neural network become easy to go with choice as it shows effectiveness in approximation [6]. Lewis et. al (1999) [10] established crucial stability guarantees by designing neural network through Lyapunov-based designs in complex problems especially in robotics and mechanical systems. Further Ge et. al [5] created thorough frameworks for future error approximation by still maintaining the stability of the system by advanced Adaptive Neural Network control. It effectively guarantee the effective setpoint tracking.

The above literature has shown the thorough discussion for level control problem but Seborg et. al (2004) has given various controlling technique which are usually practical for interacting capacities [16]. Bequette et. al (2003) has posed mandatory point to be followed for Process industry for set point tracking in different constraints [3]. Although their methods have taken linear systems for study, Skogestad (2007) et. al [17] has provided controller tuning techniques to vary the controller parameters as per need.

In recent study a number of hybrid and intelligent control technique have come into existence. Liu et. al (2018) has taken Sliding mode control which shows strong robustness [11]. Wang et. al (2019) investigated the predictive control for real-time applications [19]. Johnson and Moradi (2018) offered comparative analyses of different control strategies, which establishes the standard for stability [8].

After all these literature survey still some crucial issues are still not being touched. All available controller till date has manual interventions and lacking stability, while some still could not able to track set point. Some control techniques are still not practically implementable .

As per the discussion above to overcome the difficulty can be done by an adaptive based neural network has to be devised in such a way that features the capability of dealing nonlinear systems, which comes with faster settling time, lower overshoot and better decay ratio, should be robust in behaviour while maintain the stability of the system. This method should be capable to deal with real-time application and perfectly deals with parameter variation over wide range.

Coupled-Tank System Modelling

System Description of Coupled Tank

The problem taken in this study is shown in Fig.1 which is coupled tank. The problem of this type can be seen as Multi-capacity system which is made up of two capacities coupled together. This is also a interacting capacity which means level variation in one tank depends on the other also which make the level control problem more stringent quantity to parameter variation .

Maintaining correct water levels in both tanks in spite of external disturbances, parameter uncertainties, and the system's intrinsic nonlinearities is the major control goal. Every tank has level sensors that detect the water's height continuously, and computer-controlled pumps adjust the inflow rates according to the results of the control algorithm. The degree of interaction between the tanks can be changed by adjusting the coupling valve, which makes it possible to examine various coupling scenarios and how they affect control performance.

Mathematical Modelling

To study the dynamics of Coupled-Tank System the principle of Mass balance equation will apply. For Tank Shown in Fig. 1 the rate of change of water volume will have following equation which implies on the bases of total difference between rate of mass inflow to the rate of mass outflow :

$$\frac{dV_1}{dt} = Q_{in1} - Q_{out1} - Q_{coup} \qquad (1)$$

Where V_1= Ah_1 is water volume in Tank 1, in which A represents area of the cross section and h is water level. Q_{in1} is the inflow rate and Q_{out1} is the outflow rate of Tank1, Q_{coup}

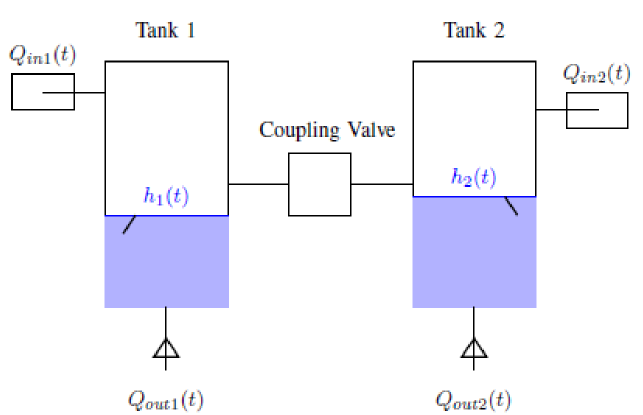

Fig. 1: Schematic diagram of coupled Tank

is the coupling flow rate between the two tanks.
The rate of outflow is based on Torricell's law, which gives the nonlinear relation between water level and velocity of outflow.

$$Q_{out1} = C_{d1}a_1\sqrt{2gh_1} \qquad (2)$$

$$Q_{out2} = C_{d2}a_2\sqrt{2gh_2} \qquad (3)$$

Where C_{d1} and C_{d2} are discharge coefficients to estimate energy loses, outlet orifice areas are a_1 and a_2 and here is the acceleration due to gravity.

The coupling flow depends on the difference in level of both the tank as it is the case of interacting capacities.

$$Q_{coup} = C_c a_c sign(h_1 - h_2)\sqrt{2g|h_1 - h_2|} \qquad (4)$$

Where a_c is the coupled valve area and C_c is the coupling coefficient.

From equations (1) and (4) gives the following equation which perfectly depicts the nonlinear dynamic model of the system behaviour .

$$\frac{dh_1}{dt} = \frac{1}{A}\left(Q_{in1} - C_{d1}a_c\sqrt{2gh_1} - C_c a_c\sqrt{2g|h_1 - h_2|}\right) \qquad (5)$$

$$\frac{dh_2}{dt} = \frac{1}{A}\left(Q_{in2} - C_{d2}a_c\sqrt{2gh_1} - C_c a_c\sqrt{2g|h_1 - h_2|}\right) \qquad (6)$$

Control Challenges

Several difficult traits of the coupled-tank system make control design and execution extremely difficult:

Nonlinear Outflow Characteristics

At low water levels, where little level changes result in comparatively large flow variations, the square root dependency in equations (2) and (3) creates significant nonlinearity.

Strong Coupling Effects

Independent single-input, single-output control methods are essentially useless due to the substantial interaction between tank levels caused by the interconnection term in equation (4).

Actuator Constraints

The controller used must be realistic in tackling the target within the constrains imposed which a real time system could have like finite reaction time , pump saturation, lag in valve operation and measurement of noise.

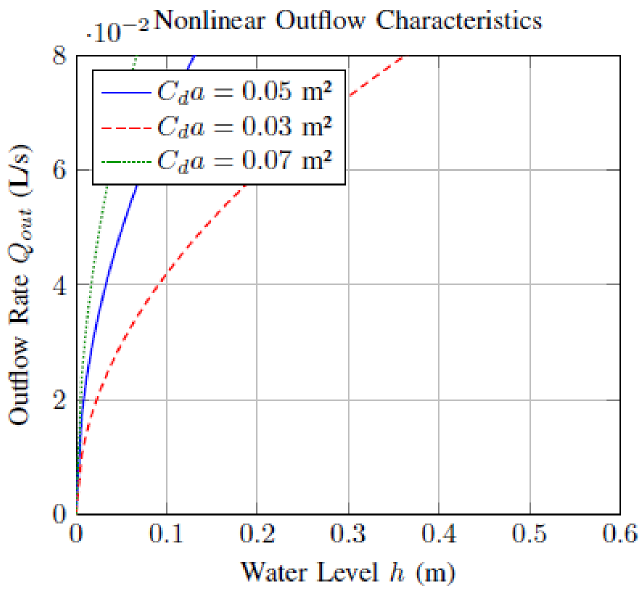

Fig.2 : Relation between water level and outflow rate of valve openings

Parameter Uncertainties

Due to wear, fouling, temperature fluctuations, and other operational parameters that are challenging to precisely define, practical systems display time-varying discharge coefficients.

Asymmetric Dynamics

The controller should be good enough to maintain the dynamic behaviour through out the process like asymmetric between input flow to gravity driven flow and sudden load variation.

The nonlinear relationship between water level and outflow rate is shown in Fig. 2, emphasizing the control issues brought about by the square root dependence. Adaptive control solutions are required for consistent performance throughout the operating range since the fluctuating slope shows that the system gain varies dramatically with operating level.

Controller Design

Adaptive Neural Network Control Architecture

The suggested control architecture is an advanced combination of contemporary computational intelligence methods and traditional control concepts. To effectively address system nonlinearities and uncertainties while maintaining dependable performance, the control system, as shown in Fig. 3, combines a traditional PI controller with a neural network-based compensator.

The overall control signal is on the basis of two controllers decision as shown below, one of the two is $u_{NN}(t)$ denotes the neural network compensation parameter for tackling

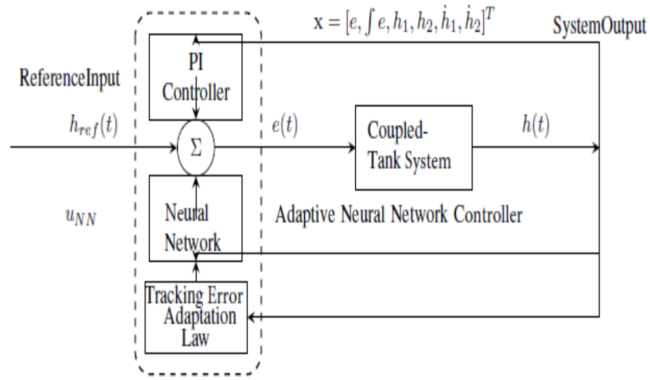

Fig. 3 : Block diagram of proposed Adaptive Neural Network

nonlinearities and uncertainties and the other is to control baseline tracking performance using Proportional Integral control represented by $u_{PI}(t)$. The relation is shown is as below :

$$u(t) = u_{PI}(t) + u_{NN}(t) \tag{7}$$

The PI controller ensures the setpoint tracking . The generalized formula is as below:-

$$u_{PI}(t) = K_p e(t) + K_i \int_0^t e(\tau)d\tau \tag{8}$$

Where e(t) is the difference of reference level $h_{ref}(t)$ and actual level h(t). K_p and K_i is the proportional and integral gain respectively.

Compensator Design using Neural Network

For nonlinear correction, a single-hidden-layer neural network with radial basis function (RBF) activation is used. This architecture's straightforward design and superior approximation skills make it especially well-suited for real-time control applications:

$$u_{NN}(t) = \sum_{i=1}^{N} w_i \varphi_i(x(t)) = W^T \varphi(x(t)) \tag{9}$$

Where $W=[w_1,w_2,.......w_N]^T$ gives the information regarding output layer weight factor and hidden layer activation functions represented by

The Gausian radial basis functions are as follows

$$\varphi_i(x) = exp\left(-\frac{||x-c_i||^2}{2\sigma_i^2}\right), \qquad i=1,2,.......,N \tag{10}$$

Where, is the input vector, ci are the center vectors that determine the locations of the receptive fields, σi are the width parameters that regulate the function spread, and N is the number of hidden neurons.

Adaptation Law and Stability Analysis

Lyapunov stability theory is used to create the weight adaption mechanism, which ensures both effective learning and closed-loop stability. Examine the following proposed Lyapunov function that takes tracking error and parameter estimate error into account:

$$\dot{V}(t) = \frac{1}{2}e^2(t) + \frac{1}{2}\widetilde{w}^T(t)\Gamma^{-1}\widetilde{w}(t) \tag{11}$$

Where, gives the weight estimation error, gives the ideal weight factor which implies the perfect compensation, and is a +ve definite adaptation gain matrix which determines and control the learning rate.

The time derivative of the Lyapunov function along the system trajectories is :

$$V(t) = e(t)e(\dot{t}) + \dot{\widetilde{w}}^T\Gamma^{-1}\dot{\widehat{w}}^T(t) \tag{12}$$

It is necessary to ensure which implies the stability, so the carefully designed adaptation law is as follows :-

Where k>0 is leakage term that prevents weight drift and ensures boundness of all parameters, by imparting robustness against probable disturbances and errors.

$$\dot{w}(t) = -\Gamma\varphi\big(x(t)\big)e(t) - k\Gamma\big||w(t)|\big| \tag{13}$$

Theorem 1

Using the adaptive neural network controller specified by equations (7) through (13), consider the coupled-tank system represented by equations (5) and (6). The tracking error in the resulting closed-loop system converges exponentially to a compact set around zero, whose size may be made arbitrarily tiny by choosing the right parameters, and all signals are uniformly finally bounded.

Proof

When the adaptation law (13) is substituted into (12) and the system dynamics and standard neural network approximation properties are used, the following results are obtained:

$$\dot{V}(t) \leq -\lambda e^2(t) - k\big||\widetilde{w}(t)|\big|^2 + \epsilon \tag{14}$$

Where λ >0 gives the minimum convergence rate and is positive constant which approximates the errors. This inequality ensures the bounded output of all signals and completes the proof.

Results And Discussion

Simulation Setup

The proposed control system has been modelled and simulated through MATLAB/ Simulink R2019a in which the carefully chosen parameters (noise measurement, parameter variations and estimation etc.) required for this study has been chosen . The carefully chosen parameters for this simulation purpose has been shown in Table 1.

The neural network architecture devised here uses15 hidden neurons with width parameters set to $\sigma_i = 0.5$ and centers in such a way that it is uniformly distributed throughout the anticipated working range to make sure there is enough overlap and smoothness. To achieve balanced learning across all weights, the adaptation gains are chosen as Γ = diag([10, 10,..., 10]), and the leakage coefficient is chosen as K = 0.01 to provide robustness without being overly conservative.

Performance under Setpoint Variation

The system response to a large setpoint variation i.e. taking range from 0.2 m to 0.4 m is shown in Fig. 4, which amply describes the enhanced effectiveness of the adaptive neural network controller purposed. While the fuzzy and MRAC controllers exhibits better but still have performing under constrained, the traditional PID controller shows delayed settling time and have significant overshoot. As seen in the figure smaller overshoots and quick convergence our purposed controller has better response hence proves its merit.

The outcome of Fig. 4 has been summarized in Table II which clearly shows how much better our purposed controller is performing. This

adaptive neural network method, improves the settling time by 63% compared than that of regular PID control. The other aspect visible in this Table II is that the overshoot come down by 76% and it also shows the improvement in the

Table I : System Parameters for Simulation

Parameters	*Value*	*Unit*	*Description*
Tank Diameter	0.14	m	Circular Tank diameter
Tank Cross-sectional area (A)	0.0154	m^2	Area of the tanks
Maximum water level	0.6	m^2	Operational Limit
Sampling Time	0.1	s	Discrete Implementation
Pump maximum flow rate	0.1	L/s	Actuator constraints
Outlet area (a1,a2)	$5x10^{-5}$	m^2	Orifice Size
Discharge Coefficient (Cd1,Cd2)	0.8	-	Outflow characteristics
Coupling valve are (ac)	$3x10^{-5}$	m^2	Coupling Flow rate
Coupling Coefficient (Cc)	0.7	-	Interaction Strength

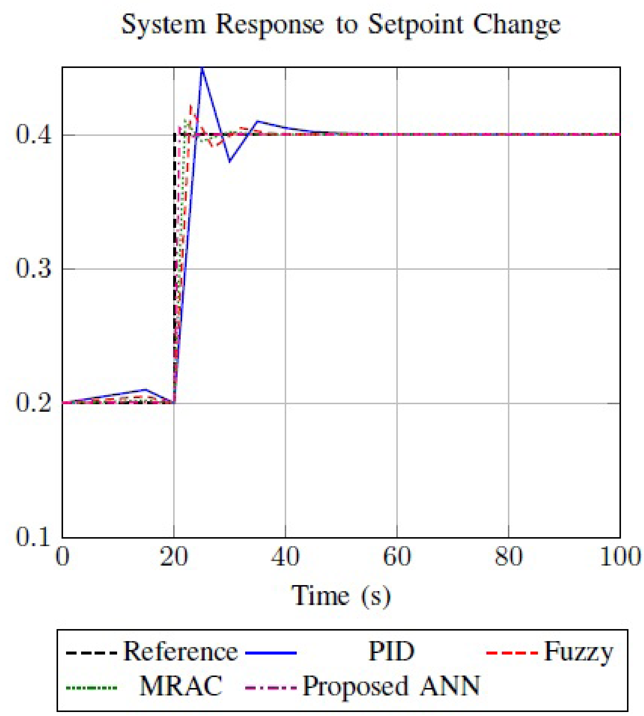

Fig. 4: Performance of different controller as setpoint variation from 0.2m to 0.4m in water level.

integral absolute error (IAE) which is by 74%. Most important parameter is its set point tracking as the steady-state error is almost equivalent to zero

Disturbance Rejection

A crucial performance indicator for realistic control systems is the disturbance rejection capability. The system is put through a difficult 25% inflow rate reduction at t=30 s while keeping the level setpoint at 0.4 m, as illustrated in Fig. 5.

With little level deviation and quick recovery to the intended setpoint, the suggested controller exhibits remarkable disturbance rejection capabilities.

The significant benefits of the suggested strategy are demonstrated by the quantitative disturbance rejection metrics shown in Table III. When compared to traditional PID control, the adaptive neural network controller provides

TABLE : 2. Performance comparison of controller under Setpoint variation

Controller	Settling Time (s)	Overshoot (%)	IAE	Steady-state Error
MRAC	32.1	7.2	5.1	0.4
PID	45.2	12.8	8.9	0.8
FUZZY	38.7	9.3	6.4	0.6
Proposed ANN	16.8	3.1	2.3	0.1

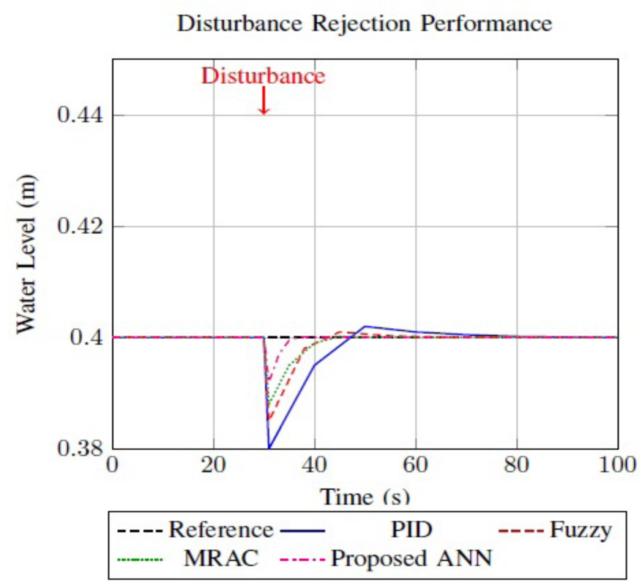

Fig. 5: Performance of different controller on the basis of disturbance rejection.

65% faster recovery and a 60% reduction in the maximum level deviation. Significantly improved overall disturbance handling capability is indicated by a 71% reduction in the integrated absolute error during the disturbance period.

Robustness Analysis under Parameter Variations

Another essential prerequisite for useful control systems is robustness to parameter fluctuations. The controller performance under difficult ±30% fluctuations in important system parameters, such as discharge coefficients and tank size, is shown in Fig. 6.

As depicted in above figure the controller shows the robustness over parameter variations and preforms quite well. The visible advantage shown in robustness analysis.

Adaptation Efficacy

The learning capacity

TABLE : 3. Performance comparison of controller under disturbance rejection

Controller	Recovery Time (s)	Max. deviation (m)	IAE during disturbance
MRAC	18.7	18.7	0.31
PID	28.5	0.020	0.42
FUZZY	22.3	0.015	0.31
Proposed ANN	9.8	0.008	0.12

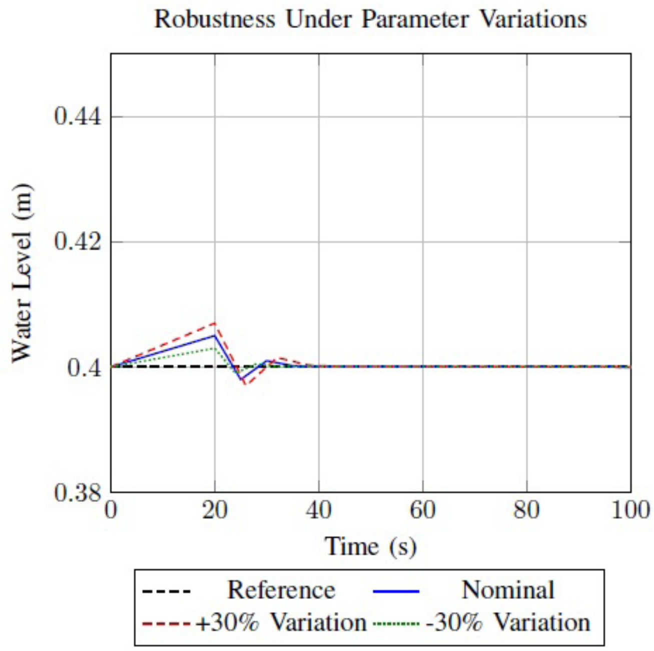

Fig. 6: Robustness analysis of proposed controller in comparison to other controller under parameter variation.

to neural network compensator successfully estimates the future error and compensates the effect of parameter variations.

Practically Viable

This controller can be applied to real-life problems as it has precise parameter knowledge as the situation varies , which make it practically useful and deployable at any situation.

Performance Conservancy

Despite parameters variations and external disturbance the system does well in all condition, by not disturbing the stability of the system. So this controller keeps assure the performance of system.

Conclusion

This paper perfectly implemented the Advanced neural network framework on multi-capacity system of interacting type of second order. The proposed system is having faster settling time by 63% , 74% better disturbances and 76% reduced overshoot. The Lyapunov-based adaption law has better control over parameter variation in the range of -30% to 30%. The comparison Table I & II establishes the versatility of proposed controller.

Future Scope

The future work can be carried out by using two more interacting capacities which makes the level control even more difficult parameter to control. For the controller point of view the performance of Model predictive control, sliding mode control can also be checked. In this study only level control has been studied, this study can be put forward for temperature and pressure control which varies on the disturbance rejection.

Acknowledgment

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