ISSN: 2322-3537
Vol-13 Issue-02 Aug 2024

Methods for direct digital management of hybrid dynamic systems using inverse dynamics controllers and artificial neural network state estimators

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ABSTRACT: This research presents an Estimator Based Inverse Dynamics Controller (EBIDC) that uses an ANN based state estimation strategy for nonlinear autonomous hybrid systems that are stochastically exposed to state disturbances and measurement noises. One notable aspect of the suggested scheme is that it provides more accurate state estimates, allowing for more precise control over non-measurable state variables. It achieves this by avoiding the statistical linearisation found in current methods based on derivative free estimation and instead using a nonlinear approach to correct the a priori estimates. When compared to the best existing work based on Unscented Kalman Filter (UKF) and Ensembeled Kalman Filter (EnKF), the simulation results guarantee a significant reduction in the Integral Square Error (ISE) and standard deviation (σ) of error between the controlled variable and set point and control signal computation time. The simulation results are supported by a thorough examination of the experimental results on real plant under various operating conditions, including servo and regulatory operations, initial condition mismatch, and various types of system faults. This evidence confirms the robustness of the proposed approach in these conditions. The suggested controller's key benefit is that it allows for direct plant control by drastically reducing the time required to compute the control signal compared to the process's chosen sampling time.

Keywords: Artificial Neural Network, Hybrid Dynamic Systems, State Estimation, Inverse Dynamics Controller.

1. INTRODUCTION

Hybrid systems modelling and control approaches are necessary for systems that involve inherent process discontinuities, fundamentally discontinuous actuators and sensors, or discrete events that serve as an abstraction for modelling mode switching in the specification and control of essentially continuous processes [1, 2, 3, 4]. Standard state observers use the Kalman filter (KF) [5] or the extended Kalman filter (EKF) [6] to estimate the state.

When dealing with linear systems, the ideal estimates of state may be generated by using the Kalman filter, which models uncertainty in the state and measurement equations as Gaussian white noise processes.

State estimation in nonlinear systems may make use of the Extended Kalman filter (EKF), a logical extension of the linear filter to the nonlinear domain by analytical linearisation. This method obtains the estimated states by expanding the nonlinear state transition operator using a Taylor series. One critical limitation of EKF for complicated nonlinear systems is that it requires analytical calculation of Jacobians at each time step. The state dynamics and output

dynamics must also include smooth and at least once differentiable nonlinear function vectors. However, as a result of discontinuous state value switching, discontinuities are introduced into dynamical models of hybrid systems. Since non-smooth functions cannot have their Jacobians calculated, EKF cannot be implemented in Hybrid systems [7]. Hybrid system estimation using a moving horizon based state estimation technique is described in [8]. However, state estimates are not ideal since the moving horizon estimator formulation uses a fixed arrival cost. As an alternative to EKF, UKF has been suggested by [9] to remove the fundamental shortcoming of EKF when used to highly nonlinear systems. A method for nonlinear hybrid systems that does not include derivatives has been suggested in [10]. With regard to the control component, a robust model predictive control (RMPC) strategy for a category of hybrid algorithm, like the piecewise affine system, to guarantee a quick and easy suboptimal solution to the control issue with

International journal of applied exercise physiology
ISSN: 2322-3537
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less computing time required. For hybrid systems, the UKF technique was also applied in the state estimation phase of the nonlinear model predictive control (NMPC) in [7] and [12], as well as fault tolerant model predictive control in [13]. The state estimation approaches for hybrid systems that have been published in the literature all rely on analytical or statistical linearisation, which means that they cannot be used to systems that need more precise state estimations [14]. It is crystal obvious from the studies mentioned in Error! that ANN significantly increases performance when used for state estimation and control of various systems. The references [16], [17] and [18] could not be located. However, similar to the situation in [15], this study also applies a nonlinear approach to adjust a priori estimations, allowing for more accurate state estimates in hybrid systems. Differentiating the suggested method from others, it employs nonlinear ANN to rectify the a priori estimations, resulting in superior estimates. With enough training on a wide range of input data, including ill-conditioned system data, the ANN-based state estimator can reliably predict the states of a Hybrid system. In order to govern the hybrid system's non-measurable states, an ANN based Controller (ANNC) is created utilising this estimator. In comparison to current schemes, the suggested controller (ANNC) offers superior performance and has the following benefits.

- Apart from analytical and statistical linearization in the correction part of EKF and UKF based controllers respectively, proposed controller uses a nonlinear correction approach using artificial neural network to correct the a priori estimates and hence offers a better state estimates by avoiding the linearization.
- The correction part of ANNC is completely parameter independent, and thereby gives better state estimates even under parameter mismatched condition.
- ANN has built in noise rejection capability which makes the ANNC scheme robust in performance.

Comparative evaluation of the proposed approach with best relating work based on UKF (statistical linearization approach) and EnKF (Particle Filter) is made in terms of ISE and standard deviation in state estimates on the same benchmark model and it reveals the proposed approach is able to reduce the error in state estimation of Hybrid systems. Detailed performance evaluation of proposed approach under servo/ regulatory operations, and plant model parameter mismatch were conducted and comparative evaluation to best existing related work was conducted based on ISE and standard deviation of error between the controlled variables and corresponding Set points and average computation time per iteration. Detailed analysis of the experimental results on real plant under different operating conditions such as servo and regulatory operations, initial condition mismatch, and different types of faults in the system confirms efficacy of proposed approach in these conditions and supports simulation results obtained. Here, an inverse dynamics controller is utilized for controlling the non-measurable states of the system so that the computational burden is very much reduced when compared with the model predictive control scheme implemented in [7], [12] and [13] without compromising the performance. Also the constraints handling capability for this scheme is also achieved with this approach by introducing upper and lower limiting functions at the output of both estimator and controller.

The rest of the paper is organized as follows. In section 2, description of the ANN state estimation algorithm developed for hybrid systems is given. The Section 3 explains the EBIDC scheme. Simulation results and detailed performance analysis of the scheme and comparison to best related work is given in section 4. Experimental results and its analysis are presented in Section 5. Finally, section 6 summarizes the paper.

2. ANN for Hybrid State Estimation

In this scheme, an ANN based correction is developed. As in the case of EKF and UKF, ANN based state estimation is also recursive in nature. Even though it has the same framework of Kalman filter based state estimator, it is designed for eliminating the analytical and statistical linearization [14] used in the case of EKF and UKF. This structure is suggested because recurrent type of ANN is better for the complex dynamic system [18]. The schematic diagram of proposed ANNC is as given in Fig. 1.

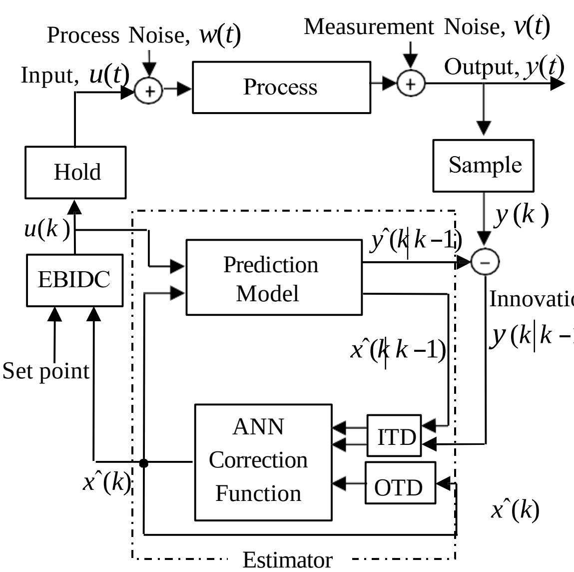

Fig.1. Schematic representation of proposed ANNC

International journal of applied exercise physiology
ISSN: 2322-3537
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The detailed NARX structure used for the considered problem is given in Fig. 2 and the other NARX parameters used for this study are provided in Table 1.

The current output can be predicted as a function of present and past inputs and past outputs as given below, in which Y and X represent the outputs and inputs of the network respectively and K_{NN} is a nonlinear ANN function.

$$Y(k) = K_{NN}\{X(k), X(k-m), Y(k-1) \ldots Y(k-n)\} \quad (1)$$

Table 1
Values of Different ANN Parameters

Parameter	Value
ANN Structure	NARX
No. of hidden layers	1
Hidden Layer neurons	5
Hidden layer activation function	'tan sigmoid'
Output layer activation function	'purelin'
No of epochs	100
No of exogenous inputs	4
No. of delayed inputs	0
No of outputs	3
No. of feedback output delays	2
Training method	Back propagation
Training function	Levenberg–Marquardt
Performance Function	Mean Square Error

A sequence of current and past input vectors (X (k), X (k-1), X (k-m)) are obtained by passing X (k) through an input time delay unit, ITD (0: m). Similarly output time delay unit, OTD (1: n) provides a sequence of past output vectors (Y (k-1), Y (k-n)). For the considered problem, the input and the output are $X(k) = [\hat{h}_1(k|k-1), \hat{h}_2(k|k-1), \hat{h}_3(k|k-1), y(k|k-1)]^T$

$Y(k) = [\hat{h}_1(k), \hat{h}_2(k), \hat{h}_3(k)]^T$ respectively.

Similar to Kalman filter based state estimators and its nonlinear extensions; proper value for the initial state vector is assumed for the prediction model. The input and output measurements are made from the process and the input measurement are presented to the prediction model along with the assumed initial state vector in order to compute the time updated values for states.

$$\hat{x}(k|k-1) = F(\hat{x}(k-1), u(k)) \quad (2)$$

With, $\hat{x}(k-1) = \hat{x}(0) = E[x(0)]$, the assumed initial value of state vector.

This a priori state estimates, $\hat{x}(k|k-1)$ can be given to the output model so that a priori estimates of the output, $\hat{y}(k|k-1)$ can be obtained as

$$\hat{y}(k|k-1) = H_L[\hat{x}(k|k-1)] \quad (3)$$

The innovation between plant output, $y(k)$ and a priori output estimates, $\hat{y}(k|k-1)$ is calculated as

$$\tilde{y}(k|k-1) = y(k) - \hat{y}(k|k-1) \quad (4)$$

In the correction step of the algorithm, the a priori state estimates will be corrected using this innovation with the help of the ANN to obtain a posteriori estimates of states

$$\hat{x}(k) = K_{NN}\{ITD(\hat{x}(k|k-1), \tilde{y}(k|k-1)), OTD(\hat{x}(k))\} \quad (5)$$

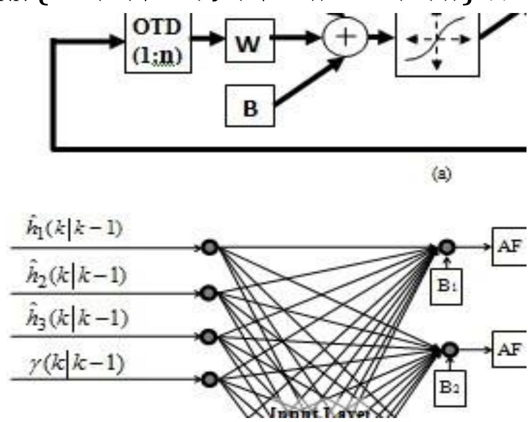

Fig.2. NARX structure for the considered example

These estimated states are fed back to the controller for calculating the new input signal to the plant. For the next iteration, a posteriori estimate of state can be given to the prediction model (instead of assumed initial states as in the first iteration) along with the new input measurement from the plant. This can be continued for the entire process run.

3. Estimator Based Inverse Dynamics Controller (EBIDC)

In hybrid systems, for the controller design, its mode switching property has also to be taken in to account. For such processes, model based control schemes are proposed in the literature ([12], [13], [19], [20], [21] and [22]) for obtaining the satisfactory control of the output variables. In this work a model based controller namely inverse dynamics controller (IDC) is implemented for controlling the non-measurable states of Hybrid System. The objective of this section is to review the non-linear dynamic controller technique that can be applied to develop a non-measurable level control system that is valid over the entire operating region of the hybrid three-tank system described below.

Consider the nonlinear system of the form,

$$\dot{x} = A(x) + B(x)u \quad (6)$$

$$y = Cx \quad (7)$$

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ISSN: 2322-3537
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Where, $A(x) = (n \times 1)$ vector, $B(x) = (n \times m)$ matrix, $C = (m \times 1)$ vector.

The inverse dynamics of (6) and (7) is represented as, $u = F_1(v, x)$

Where, v is the input to the inverse system.

Construction of the inverse dynamics of (6) and (7) is done by repeatedly differentiating the measurement function until the input variable u appears.

Differentiating (7)

$$\dot{y} = C\dot{x} \qquad (8)$$

$$\dot{y} = C[A(x) + B(x).u] \qquad (9)$$

$$\dot{y} = A^*(x) + B^*(x).u \qquad (10)$$

Where, $A^*(x) = C.A(x)$ and $B^*(x) = B.A(x)$

So the control law u can be written as follows [20]

$$u = B^{*-1}(x)[v - A^*(x)] \qquad (11)$$

A sufficient condition for the existence of an inverse system model to (6) and (7) is that B^* in (11) be non-singular. If this is the case, then the inverse system model takes the form,

$$\dot{x} = A(x) + B(x)[-F(x) + G(x)v] \qquad (12)$$

Where, $F(x) = B^{*-1}(x)A^*(x)$ and $G(x) = B^{*-1}(x)$

$$\dot{x} = A(x) + B(x)[-F(x) + G(x)v] \qquad (13)$$

The input to the inverse system is $v = y - y_{ref}$

As the hybrid three-tank system, considered under this study can be directly represented in the form of (6) and (7), applying this procedure will yield the control law as

$$F_{in_1} = A_1C_1\left(h_{1sp} - h_1\right) + Q_1 + Q_3 + Q_5 \qquad (14)$$

$$F_{in_2} = A_2C_2\left(h_{2sp} - h_2\right) + Q_2 + Q_4 + Q_7 \qquad (15)$$

Since h_1, h_2, Q_1, Q_2, Q_3, Q_4, Q_5, and Q_7, are non-measureable for the considered problem, the estimated values can be used so that the controller becomes an estimator based inverse dynamics controller.

$$F_{in_1} = A_1C_1\left(h_{1sp} - \hat{h}_1\right) + \hat{Q}_1 + \hat{Q}_3 + \hat{Q}_5 \qquad (16)$$

$$F_{in_2} = A_2C_2\left(h_{2sp} - \hat{h}_2\right) + \hat{Q}_2 + \hat{Q}_4 + \hat{Q}_7 \qquad (17)$$

Where, C_1 and C_2 are controller tuning parameter, and its values are varied from 0 to 1 on separate runs and the integral square error between the controlled variable and the set point, is noted. The values of C_1 and C_2, which give the minimum ISE, are selected as the tuning parameters. The h_{1sp} and h_{2sp} are the corresponding desired values of water levels.

4. Simulation Results and Performance Analysis

The same Benchmark model based on three tank system used in [7] is used here with same levels in three tanks (h_1, h_2 and h_3) as continuous states and z_1 and z_2 variables as discrete states for evaluating the performance the controller in comparison to best related work. The schematic representation of hybrid three-tank system is given in Fig.3. Detailed modeling of the hybrid three-tank system is given as appendix. The developed algorithm was simulated in MATLAB.

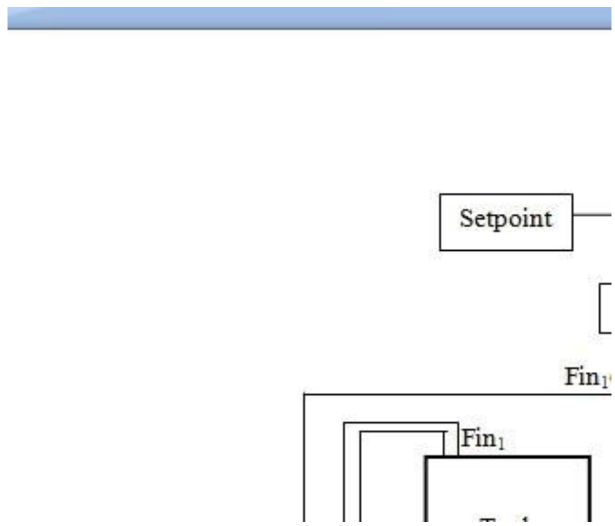

Fig.3. Schematic representation of the benchmark hybrid three tank system

The detailed discussions about the results obtained in simulation are given in the following subsections.

4.1 Performance in Servo Operation

Servo operation of the closed loop system when a change in set point occurs was conducted by introducing a step change with magnitude 0.04 m at 100th sampling instant. The results are given in Fig.4. Comparison with the best existing related work is shown in Table 2. Comparison of proposed approach to UKF based approach based on ISE shows that the new approach is better as ISE reduced from 3.3278 to 0.5533 in level, h_1 and from 3.7203 to 0.4568 in level, h_2. Also, the average computation time per iteration reduced from 60.65 seconds to 0.0777 seconds. Evolution of true and estimated states of hybrid three-tank system with ANNC (Servo operation) is shown in Fig.5.

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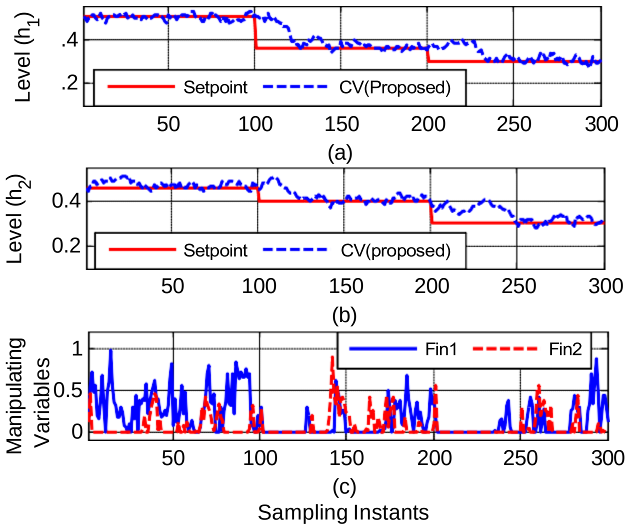

Fig.4. Servo response of hybrid three tank system with ANNC (a) Level in Tank 1, (b) Level in tank 2 (c) Manipulating variables

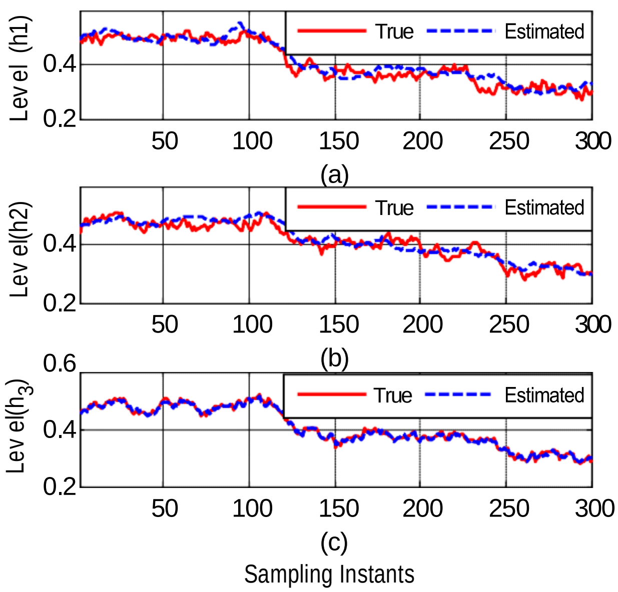

Fig.5. True and estimated states of hybrid three tank system with ANNC (Servo operation) (a) Level in Tank 1, (b) Level in Tank 2, (c) Level in tank 3

Evolution of true and estimated values of discrete variables of hybrid three-tank system with ANNC (Servo Operation) is shown in Fig.6.

Fig.6. Evolution of true and estimated values of discrete variables of hybrid three tank system with ANNC (Servo Operation)

4.2 Performance in Regulatory Operation

The results of the performance of the estimator in regulatory operation are given in Fig.7. Comparison with the best existing related work is shown in Table 3. Comparison of proposed approach to UKF based approach based on standard deviation shows that the new approach is better as standard deviation has reduced from 0.0130 to 0.0127 in level h_2 and from 0.0484 to 0.0065 in level h_3 with very close standard deviation in level h_1. It may be noted that the maximum standard deviation in the case of nonmeasured state variables is 0.0217 in the proposed approach and 0.0484 in the UKF based NMPC(45% reduction with proposed approach).

Table 3: Regulatory Control Problem: Estimator performance Comparison

Controller	$\sigma_E(h_1)$	$\sigma_E(h_2)$	$\sigma_E(h_3)$
Proposed	0.0217	0.0127	0.0065
UKF based NMPC[7]	0.0213	0.0130	0.0484
UKF based NMPC[7]	0.0242	0.0141	0.0488

The results of the performance of the controller in regulatory operation are given in Fig.8 and evolution of true and estimated values of discrete variables of hybrid three tank system with ANNC (Regulatory Operation; Disturbance by varying the valve position of fifth hand valve) in Fig.9. Comparison with the best existing related work is shown in Table 4. Comparison of proposed approach to UKF based approach based on ISE shows that the new approach is better as ISE has reduced from 3.5869 to 0.0587 in level h_1 and from 1.5212 to 0.0366 in level h_2. Also, the average computation time per iteration has reduced from 59.05 seconds to 0.0739 seconds.

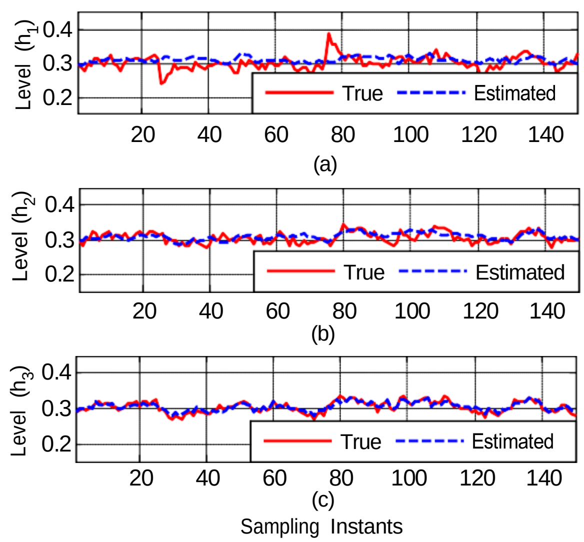

Fig.7. Evolution of true and estimated states of hybrid three tank system with ANNC (a) Level in Tank 1, (b) Level in Tank 2, (c) Level in tank 3

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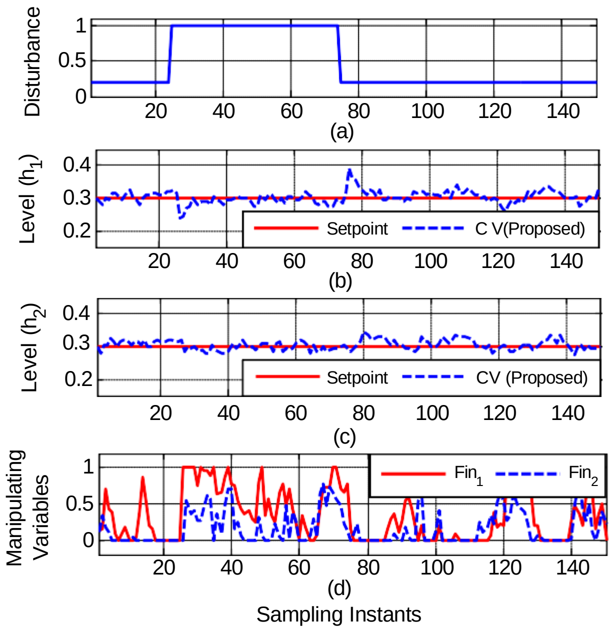

Fig .8. Regulatory response of hybrid three tank system with ANNC (a) disturbance, (b) Level in Tank 1, (c) Level in tank 2 (d) Manipulating variables

Table 4: Regulatory Control Problem: Controller Performance Comparison

Controller	ISE(h_1)	ISE(h_2)	Avg. Computation time per iteration (S)
Proposed	0.0587	0.0366	0.0739
UKF based NMPC[7]	3.5869	1.5212	59.05
EnKF based NMPC[7]	3.3928	1.4011	206.44

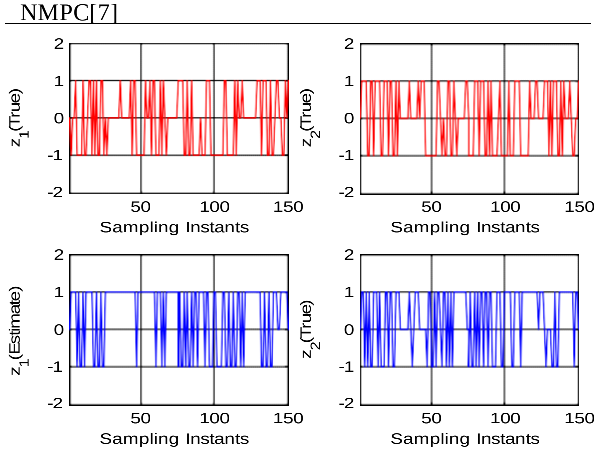

Fig.9. Evolution of true and estimated values of discrete variables of hybrid three tank system with ANNC (Regulatory Operation)

In order to obtain better insight of the ability of the proposed controller to achieve decoupling and offset-free control action, hypothetical situation, in which state and measurement noise are not present, is simulated. Response given in Fig. 10 reveals that the effect in level of tank 2, due to the disturbance in tank 1 is very much less compared with that given in [7]. As in the case of UKF based NMPC in [7], proposed method also giving a slight offset.

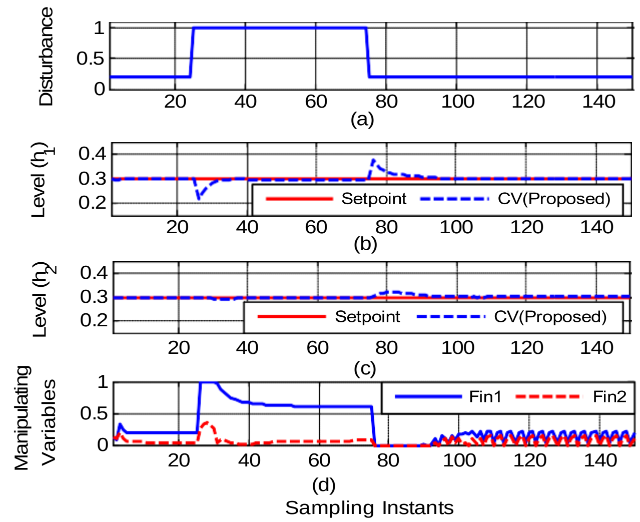

Fig .10. Regulatory response of hybrid three tank system with ANNC (without state and measurement noise) (a) disturbance, (b) Level in Tank 1, (c) Level in tank 2 (d) Manipulating variables

4.3 Plant Model Parameter Mismatch

The performance of the controller in case of plant model parameter mismatch is considered and the performance is given in Fig. 11. From Table.5, it can be seen that the ISE is improved to 0.0276 from 0.9231 for level h_1 and to 0.0228 from 1.0579 for level h_2 when compared to best existing related work based on UKF.

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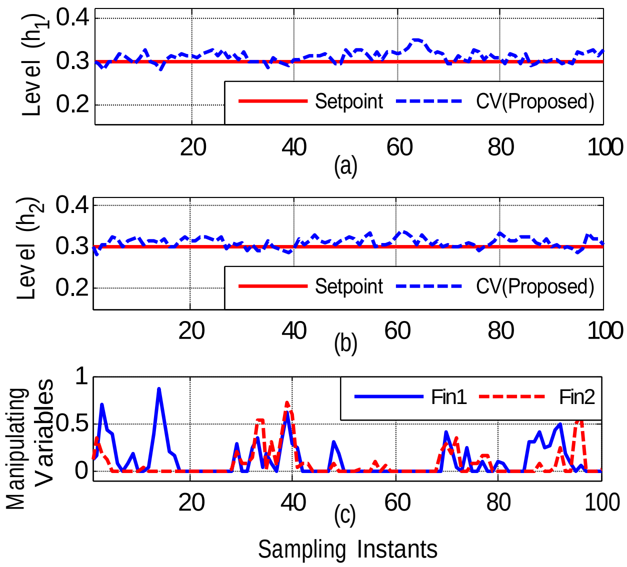

Fig.11. Response of hybrid three tank system with ANNC (Plant-Model mismatch) (a) Level in Tank 1, (b) Level in Tank 2, (c) Level in tank 3

Table 5: Plant Model Parameter Mismatch: Controller Performance Comparison

Controller	ISE(h_1)	ISE(h_2)
Proposed	0.0276	0.0228
UKF based NMPC [7]	0.9231	1.0579
EnKF based NMPC[7]	0.8647	0.9688

5. Experimental Results and Performance Analysis

Real-time experimental validations were carried out on the experimental setup. In addition to the experimental setup, other tools used, which were for the real time implementation are the software Lab VIEW and the NI DAQ pad (USB6251). In the real system, the performance of the controller in regulatory operation and servo operation based on ISE and average computation time per iteration is shown in Fig. 12, Table 6, Fig. 13, and Table 7. In Table 8 and Fig. 14 response of the system in initial condition mismatch is shown. The response of the system in +10% and -10% plant model parameter mismatch is given in Tables 9 and 10 and Figures 15 and 16 respectively. Results of hand valve faults which can occur in real time application are given in Table 11, Fig. 17, Table 12 and Fig. 18. The real time experimental results support the simulation results on performance.

Table 6: Regulatory Control Problem: Controller Performance Comparison

Controller	ISE(h_1)	ISE(h_2)	Avg. Computation time per iteration (S)
Proposed	0.0200	0.0193	0.1038

Table 7: Servo Control Problem: Controller Performance Comparison

Controller	ISE(h_1)	ISE(h_2)	Avg. Computation time per iteration (S)
Proposed	0.0172	0.0144	0.1152

Table 8: Initial Condition Mismatch: Controller Performance Comparison

Controller	ISE(h_1)	ISE(h_2)	Avg. Computation time per iteration (S)
Proposed	0.0214	0.0592	0.1017

Table 9: Plant Model Parameter Mismatch (+10%): Controller Performance Comparison

Controller	ISE(h_1)	ISE(h_2)	Avg. Computation time per iteration (S)
Proposed	0.0045	0.0069	0.2112

Table 10: Plant Model Parameter Mismatch (-10%): Controller Performance Comparison

Controller	ISE(h_1)	ISE(h_2)	Avg. Computation time per iteration (S)
Proposed	0.0122	0.0131	0.1037

Table 11: Hand Valve Faults -Leakage: Controller Performance Comparison

Controller	ISE(h_1)	ISE(h_2)	Avg. Computation time per iteration (S)
Proposed	0.0600	0.0077	0.0768

Table 12: Hand Valve Faults -Clogging: Controller Performance Comparison

Controller	ISE(h_1)	ISE(h_2)	Avg. Computation time per iteration (S)
Proposed	0.0082	0.0078	0.0943

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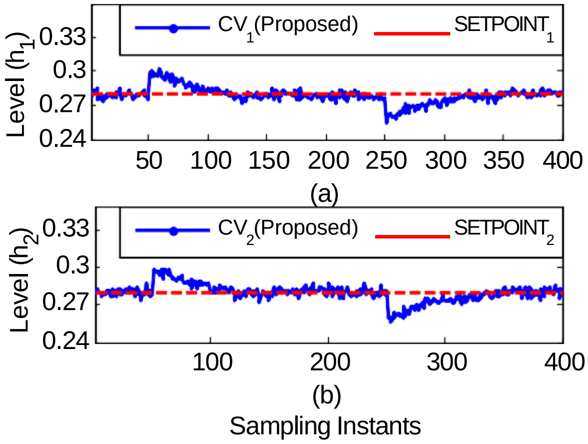

Fig.12. Regulatory response of hybrid three tank system with ANNC (a) Level in Tank 1, (b) Level in tank 2

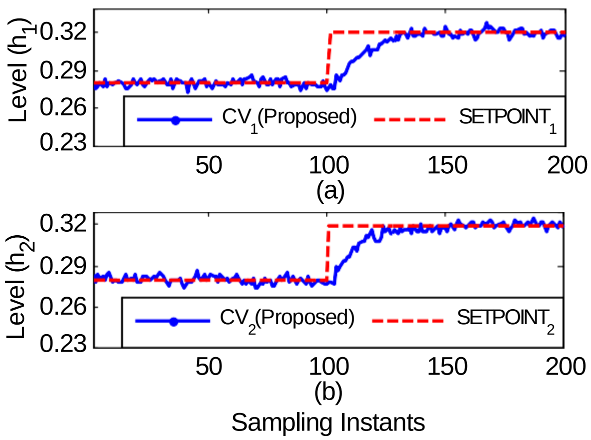

Fig.13. Servo response of hybrid three tank system with ANNC (a) Level in Tank 1, (b) Level in tank 2

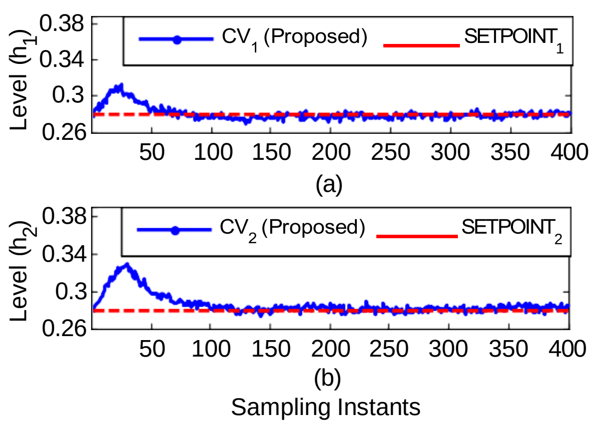

Fig.14. Closed response of hybrid three tank system with ANNC (Initial Condition Mismatch) (a) Level in Tank 1, (b) Level in Tank 2

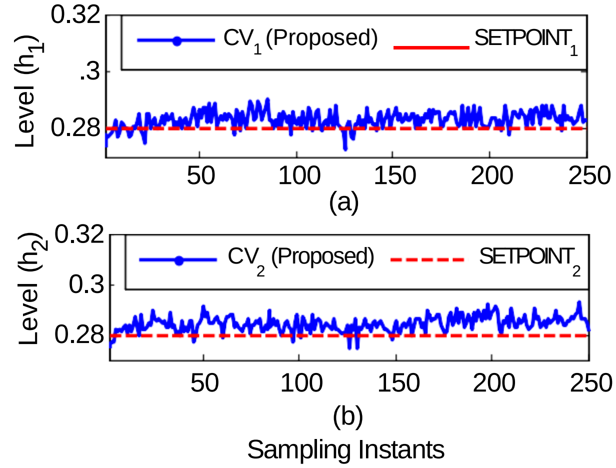

Fig.15. Closed response of hybrid three tank system with ANNC (Plant-Model mismatch +10%) (a) Level in Tank 1, (b) Level in Tank 2

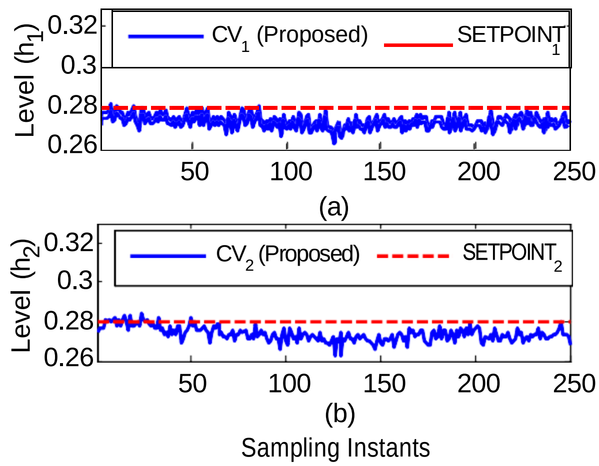

Fig.16. Closed response of hybrid three tank system with ANNC (Plant-Model mismatch -10%) (a) Level in Tank 1, (b) Level in Tank 2

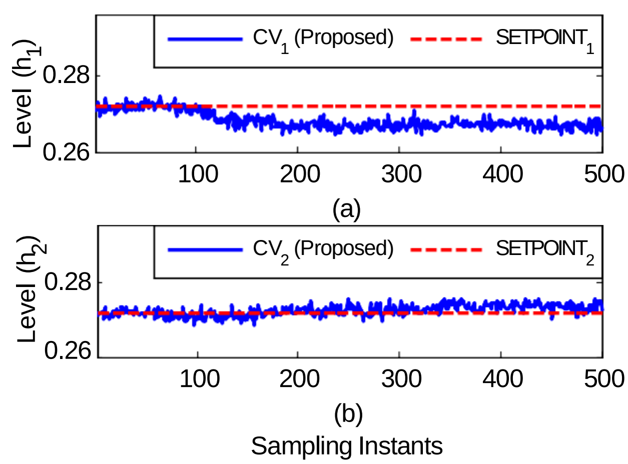

Fig.17. Closed response of hybrid three tank system with ANNC (Handvalve fault-Leakage) (a) Level in Tank 1, (b) Level in Tank 2

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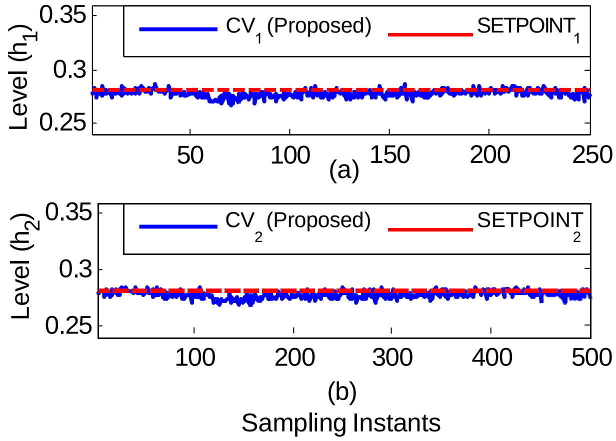

Fig.18. Closed response of hybrid three tank system with ANNC (Handvalve fault-Clogging) (a) Level in Tank 1, (b) Level in Tank 2

6. Conclusion

By eliminating the statistical linearisation inherent in derivative-free estimation, a non-linear strategy is suggested for correcting the a priori estimations, leading to improved control, in an ANN-estimation based control system. When compared to previous research that relies on statistical linearisation, the following results were achieved: a 45% decrease in the standard deviation (σ) of the error between the actual and estimated values of non-measurable states for regulatory control operations, an 85% reduction in the Integral Square Error (ISE) between the controlled variable and the set point for servo operations, and a 97% reduction for regulatory and plant model parameter mismatch operations, respectively. Not only does the proposed method improve performance, but it also guarantees online implementation as a direct control algorithm because the time required to compute control signals is significantly less than the process sampling time. Research on a real-world plant shows that the suggested controller works well to improve online control of hybrid dynamic systems while running in real-time.

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International journal of applied exercise physiology

ISSN: 2322-3537
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