Zaria Journal of Electrical Engineering Technology, Department of Electrical Engineering, Ahmadu Bello University, Zaria – Nigeria. Vol. 9 No. 2, September 2020. ISSN: 0261 – 1570.

INTERNAL MODEL CONTROL PERFORMANCE EVALUATION IN NONLINEAR COUPLED TANK SYSTEM

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Keywords: –
CTS, LM, NNIMC, NARX, Nonlinear Control

Article History: –
Received: July, 2020.
Reviewed: August, 2020
Accepted: September, 2020
Published: September, 2020

ABSTRACT

Most industrial process control systems are associated with non-linearity behaviour. Control of such industrial process system is a challenging task according to the degree of non-linearity of the system. A typical process control that represent part of such complex industrial process is the principle used in Coupled Tank System (CTS) level control. This paper investigated the performance of Neural Network Internal Model Control (NNIMC) and Two Degree of Freedom Internal Model Control (2DOF-IMC) with application to level control in CTS. For the NNIMC, the Neural Network (NN) forward and inverse models of the plant were identified from process input and output sample data generated from laboratory experimental setup. The network architecture for both models is nonlinear autoregressive network with exogenous inputs (NARX) while the training algorithm selected was Levenberg Marquad (LM). The models developed are then used to design NNIMC. Additionally, the 2DOF-IMC was designed with advanced tracking and disturbance rejection filter. Moreover, conventional PI controller was optimized by integrating neural network feedforward control strategy to serve as advanced feedforward PI control strategy. Performance analysis of the investigated controls algorithms were evaluated. Simulation results indicated that both NNIMC and 2DOF-IMC controllers have similar performance and as well outperforms their traditional control techniques counterpart hence could be used to control levels in a CTS effectively.

1. INTRODUCTION

Tracking control has a broad domain of industrial applications such as in petrochemical industries, water treatment plant etc. Coupled Tank System (CTS) is a laboratory set up that typically represent part of complex industrial process systems. Process Engineers (PE), Research and Development (R&D) as well as in the academia concern more on the development of flexible and cost-effective process for high-quality manufacturing products. Basically, in the industrial process scenarios, the liquid is pumped, mixed and manipulated between numbers of storage tanks system while maintaining desired level/volume of liquid. This is for the reason of safety, protection of the equipment and accident prevention in general. Hence, this makes level control in industrial process systems important and challenging task. The level of challenge and control complexity depend on the system's degree of non-linearity [1].

1.1. State of the Art

Level control is one of important area of research in process industries, a lot of control strategies have been developed by researchers to maintained liquid at desired level. The accuracy and efficacy of any control strategy depend on accuracy of the dynamic model of the system [2]. Conventional controllers such as PID family were the majority controllers being used in most industries despite limitations in their performance on non-linear process systems. This is due to the reason of simple structures, ease of tuning parameters. This acceptability attracted many researchers to continuously investigate the algorithm and proposed different ways of improving their performance and meet the standard of the present global industrialization [3].

Among the recently proposed control algorithm are two degree of freedom PID controller where the authors evaluated the performance of PID control strategy and proposed the best tuning methods for first order and second-order process with time delay [4]. Reference [5] uses interacting and non-interacting tank system to evaluate the performance of PI, PD, and PID controllers under various tuning methods. In [6] Model Reference Adaptive Controller (MRAC) was proposed. The authors gave a brief explanation about the control algorithm, optimal tuning methods and how the algorithm uses a reference model to optimally tune the controller gains automatically. Additionally, IMC, IMC-PI, and IMC-PID control strategies were proposed in [3, 7]. The authors discussed the control strategies and evaluated the performance of the control techniques. Moreover, in [3, 8] comparative analysis between IMC-PI, IMC-PID with conventional PI, PID was reported with IMC-PI to outperform the conventional PI and IMC controls techniques.

Requirement to meet recent industrial globalization trend, industries are becoming more complex, the need for precise and accurate control techniques increases and the control algorithm complexity increases for systems under uncertainties rendered most conventional control techniques less efficient.

To overcome the aforementioned conventional control techniques drawbacks and meet the industrial globalization, researchers developed an interest in advanced and Artificial Intelligence (AI) controls methods. Among such investigated advanced control methods are Sliding Mode Control (SMC) reported by [9], Integral Sliding Mode Control (ISMC) reported by [10], Model Predictive Control (MPC) [11], and Linear Quadratic Regulator (LQR) [12]. Other advanced control techniques that were reported in the literature with application to tracking control problems are Linear Quadratic Gaussian (LQG), Dynamic Matrix Control (DMC), Adaptive Control (AC), Model Reference Adaptive Control (MRAC) [6, 13] and finite-time disturbance observer with application to triple tank system control reported by [14].

Recently, there has been a great resurgence interest in AI. Researchers from various academic and industrial backgrounds have applied AI to solve various problems. This is due to the fact that, AI have been developed as generalizations of mathematical models to represent human cognition [15]. Thus, Artificial Neural Network (ANN) being` one of the AI alternatives to current engineering problems has found a quite number of applications in process control industries such as process modelling, non-linear model predictive control, ANN modelling [16]. NN-IMC with application to stirred tank reported by [17], modelling and control of distillation column proposed by [18]. Other AI techniques that could be found in the literatures are NN wavelet methods and RBF algorithm, NN-PID etc.

1.2. Motivation

Since level control is always associated with lumping lag, non-linearity and control implementation complexity where the accuracy and efficacy of the control are affected by the system dynamics, parameters, control algorithm and tanks number. The main objective in process control application is to maintain the process at the desired Operating Condition (OC) while satisfying environmental and product quality. Generally, in most control system applications, it is very difficult to achieve all the control objectives such as zero Steady State (SS), closed-loop stability, good tracking performance and robustness. This is due to the control objectives have inherent conflicts and trade-off. Hence, the goals must balance between performance and robustness. Since most industrial process control engineers are more familiar with conventional controllers, and it is the most widely applied control algorithm in industries, there is need to investigate simple control techniques that will complement conventional methods but with robust and better performance. AI techniques have demonstrated a very good potential in many real-world applications due to its learning ability of a complex system, easy software and hardware implementation, classification ability, ease of training network using past data, ability to work under noisy condition, fault-tolerant capability among others, it could be an essential step of advancement to investigate a simple control algorithm based on AI techniques that will work under disturbed system such as CTS.

In this research work, artificial techniques based on Neural Network Internal Model Control (NN-IMC) and two degree of freedom IMC (2DOF-IMC) with advanced filter design were investigated and evaluated. This is due to the fact that, 2DOF-IMC with advanced filter design shows a very good performance in some process control system such as CTRS. Moreover, potentialities of NN in process identification and control is expected to have a better performance over conventional control techniques. The NN Forward and inverse models of the coupled tank system were developed using NARX identification from an experimental set of data generated at process control Lab Universiti Teknologi Malaysia (UTM). The performance of the developed model is evaluated with the empirical and mathematical modelling techniques.

Furthermore, 2DOF-IMC and NNIMC were proposed. The NNIMC consists of a forward and inverse model of the plant and a robust tuning filter. Additionally, the 2DOF-IMC consists of set-point tracking and disturbance rejection controllers. The performance of the controllers were evaluated based on ISE, ITAE, IAE overshot and tracking performance against the conventional IMC, PI-IMC, PI-benchmark, and optimized feedforward neural network PI techniques. The paper is organized into the following sections. Section I is on introduction, state of the art and process control problems, section II presents the system description, experimental setup and methodology, section III discusses NARX non-linear system modelling, control objectives and strategies. Section IV presents result and discussion and section v gives concluding remarks.

2. PROCESS DESCRIPTION AND MODELLING

2.1. Process Description

Coupled Tank System (CTS): consist of two tank system mounted one on top of the other as shown in Fig 1. The entire plant consist of pump, water basin, two orifice outlet plates, and two pressure sensors. The two tanks are configured such that, upper tank (tank 1) contents flows through an orifice outlet located at the bottom of the tank into the lower tank (tank 2). The output flow of the lower tank flows into the main water reservoir. The electric pump thrusts water upwards to the orifice "out1" before entering tank 1. The main objective of this set up is to maintain the desired level of water in either of tank 1 or 2, (L1 or L2) by regulating the pump speed through voltage control approach. The CTS configurations parameters are as shown in table 1.

Table 1:CTS Plant Parameter

Parameters	Values
Inside Diameter of Tank 1& 2 D_{t1}, D_{t2}	4.445 (cm)
Pump Flow Constant K_p	3.3 $cm^3/s/V$
Area of tank 1&2 outlet hole A_{o1}, A_{o2}	0.1781 cm^2
Cross sectional area of tank 1&2 A_{t1}, A_{t2}	15.5179 cm^2
Gravitational Constant (g)	981 cm/s^2

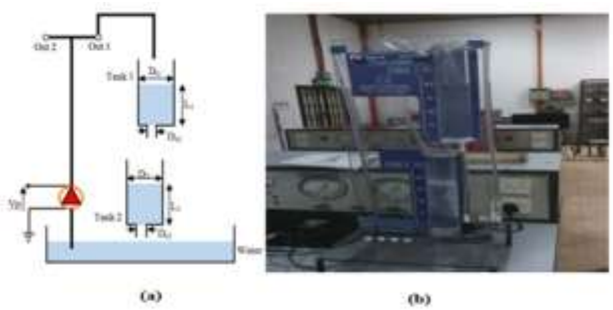

Figure 2.1.: (a) CTS Schematic Description (b) CTS Experimental Setup

2.2. Plant Modelling

The dynamic model of the system under consideration can be obtained through either of the following techniques: Mathematical model, Empirical Modelling (PRC) and non-linear system identification techniques (NARX).

The dynamic model of the CTS can be adopted from the work of [8, 11] and can be presented by equations (1-3). Thus, equation (1) and (2) represent the Differential Equation (DE) for levels in tank 1&2 and equation (3) is the voltage dynamics. Linearizing the non-linear terms in equation (1) & (2) and apply Laplace transformation, the system transfer function can be obtained.

$$\frac{dL_1}{dt} = \frac{K_p}{A_{t1}} V_p - \frac{A_{01}}{A_{t1}} \sqrt{2gL_1} \tag{1}$$

$$\frac{dL_2}{dt} = \frac{A_{02}}{A_{t2}}\sqrt{2gL_2} \;+\; \frac{A_{01}}{A_{t1}}\sqrt{2gL_1} \qquad (2)$$

$$V_{Pss} = \frac{A_{01}}{K_p}\sqrt{2gl_1} \qquad (3)$$

2.3. Non Linear System Identification

A lot of NN architecture and learning algorithm are in existence however, NARX architecture and LM learning algorithm are among the most acceptable for non-linear system identification.

The Neuron Model

A model of a neuron is presented as in Fig 2. The main task of the neuron is to accept an input $\boldsymbol{N = (I_1 \ldots I_N)}$ from j-1 layer associated with weight function given by $\boldsymbol{(W_{i1}^{j} \ldots W_{iN}^{j})}$ and computed the weighted sum of the N-input. The output of the neuron can be computed as in equation (4).

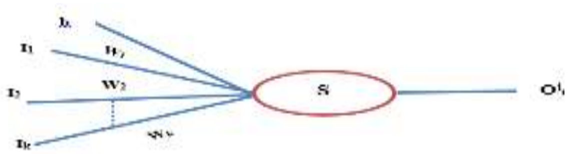

Figure 2.2. Neuron Model

$$S_i^j = \sum W_{iK}^j I_k + b_i^j \qquad (4)$$

Where *'b'* is a bias, '*w'* is the weighting function and '*I'* is the input to the neuron model. The output of the neuron in the output layer can be computed as in equation (5).

$$O_i^j = f(S_i^j) \qquad (5)$$

Where '*f* 'is the activation function (AF). The AF chosen for this research work is sigmoidal function given by equation (6).

$$f = \frac{1}{1+e^{-x}} \qquad (6)$$

Hence, combining equation (4-6), the output of the network 'y_N' can be computed as in equation (7).

$$y_N = \sum_{i=1} W_{ik}^j \left[\frac{1}{1+e^{\left(\sum W_{ik}^j + b_j\right)}} \right] \qquad (7)$$

Now, the error is the difference between targeted output and the computed output given by equation (8):

$$e_N = d_N - y_N \qquad (8)$$

Where d_N = targeted output and y_N = computed output. While the mean square error can be computed as in equation (9).

$$E = \frac{1}{2}\sum_{i=1}^{N} e_N^2 \qquad (9)$$

Model Selection

Selecting a family of model architecture suitable for describing the system under study is an important aspect of neural network identification process. In this research, non-linear autoregressive with external (exogenous) input (NARX) has been selected to be the model architecture due to its effectiveness in learning, well suited for non-linear modelling and control [2].NARX is a subset of recurrent neural network architecture having a feedback structure consisting of layers of the network. The model of NARX was derived according to linear auto regression with external input. A typical NARX structure shown in Fig 3 has an input applied to a delay units' memory, the output is fed back to the input line through another tapped delay memory. Furthermore, the model-output is always one level ahead of the input (prediction features). The past data input to the network given by equation (10) represent the exogenous inputs generated outside the network.

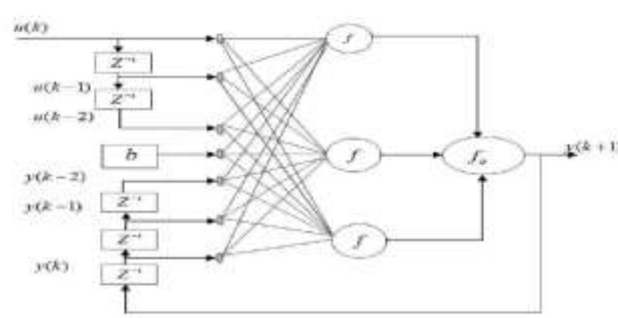

Figure2.3 :NARX Model Structure

$$u(k), u(k-1), \ldots (u(k-r+1) \qquad (10)$$

The general equation for NARX architecture is given by equation (11)

$$y(k+1) = f\{y(k-1), y(k-2), \ldots y(k-r), \ldots u(k-2), u(k-r)\} \quad (11)$$

NARX Model Architecture

The architecture for the ANN selected to be used as discussed in preceding subsection *'C'* of non-linear system identification has three layers, input, hidden and output layers as shown in Fig 4. The layers consist of bias 'b_i' and weight term 'W_i'. The weights are generally initialized randomly. The input to the network is the pump voltage 'V_p', used for thrusting water vertically to plant, while the outputs y_1 (t), y_2 (t) represents the heights in the two tanks. Since our target is to control the level in tank two hence the network output is y_2 (t).

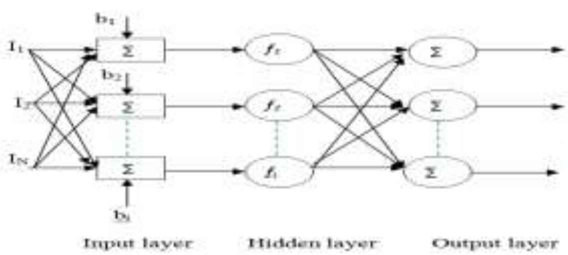

Figure 2. 1: NARX Model Layers Description

Training Process

The forward and inverse model of the system were identified off-line using a set of input-output data generated from the process experimental setup. The structure of the forward and inverse model is as shown in Fig 5. The inverse model is trained by utilizing target data from the forward model as the input to the inverse model while the input to the forward model was the target data to the inverse model. To obtain excellent dynamic model, of the plant, closed-loop system identification technique has been considered. Therefore, a system model was identified using data generated from an experiment carried out with PRBS random signal perturbed into the system.

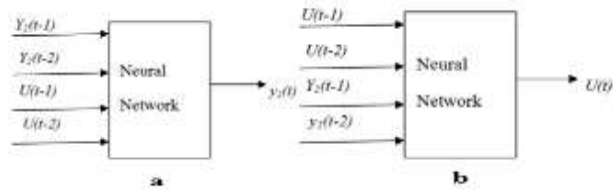

Figure 2.5: *:(a) Forward Model Training Process (b) Inverse Model Training Process*

3. CONTROLLER DESIGN

3.1. NNIMC

The NNIMC structure consists of a process plant model and its corresponding inverse model. The NNIMC controller can be design by cascading the forward NN model of the plant with the inverse NN model of the plant as shown in Fig 6. If a very good dynamic model of the plant is obtained then a very good performance of the closed-loop system, robustness, and stability of the control system could be attain. The NN-IMC, as shown in Fig 6, employed the use of filter for improving set-point tracking performance and disturbance rejection of the controller.

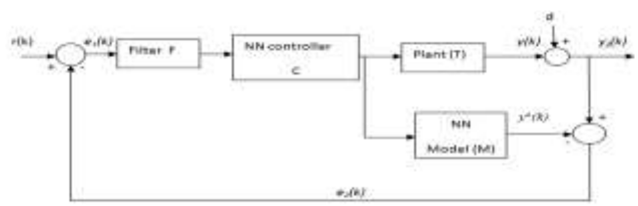

Figure 3.1: NNIMC Control Strategy

Let F, C, T and M be the transfer function of the individual blocks, as shown in Fig 6, the transfer function of the NNIMC can be computed as in equation (12).

$$y_2(t) = \frac{FCT}{1+FC(T-M)} r(t) + \frac{1-FCM}{1+FC(T-M)} d(t) \quad (12)$$

Let the NN model predicted output be as in equation (13);

$$y(k+1) = f\left[y(k), \ldots y(k-n+1), , , v(k-\theta), \ldots v(k-\theta-n+1)\right]$$
(13)

According to Henson in [3], the NNIMC controller should be selected to be the right inverse of the neural network model. Therefore since the NN model uses the previous knowledge to predict the feature output of the plant, then the above equation can be written in prediction form as in equation (14).

$$y(k+\theta+1) = f\left[\ y(k+\theta)..........y(k+\theta-n+1),, v(k),....v(k-n+1)\ \right] \quad (14)$$

Let the filter *'F'* output be given by *F (k). T*hen the output of the filter will be equal to the input to the controller *'C'* such that, the controller C is the inverse model of the plant for which its input was the predicted output of the forward model hence.

$$F(k) = y(k+\theta+1) \quad (15)$$

According to reference [4], the filter may be chosen to be a pulse transfer function in the form of first-order filter. By simplification, the filter transfer function can be obtained as in equation (16).

$$F(k) = \frac{1-\lambda}{1-\lambda z^{-1}}\left[r(z) - e_1(z)\right] \quad (16)$$

Where $e_1(k) = y(k) - y^n(k)$ and *'λ'* is a filter tuning parameter selected in the range $0 \leq \lambda < 1$.

Note: The filter tuning values near zero produces vigorous response while values very close to one produces sluggish response [3].

3.2. 2-DOF-IMC

To improved disturbance rejection and tracking performance, a set point tracking and disturbance rejection controllers can be implemented concurrently. The 2DOF-IMC block in Fig 7 consist of set-point tracking and disturbance rejection controllers. Using improved filter design as proposed by [5] for disturbance rejection controller and first-order low pass filter for the set-point controller would result in improved disturbance rejection and tracking performance.

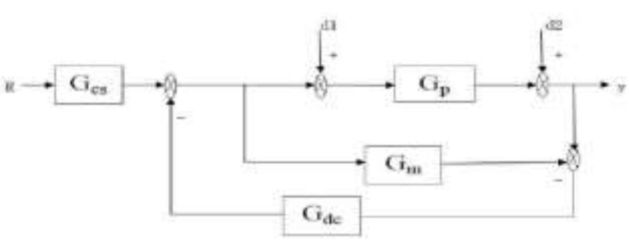

Figure 3.2.: 2DOF-IMC Block

3.3. PI + NN Feedforward

Most controllers used by industries are of conventional PID type. This has been used regardless of the system linearity or non-linearity nature and despite the limitations in conventional control performance. Process engineers, operators with years of experience are well familiar with the conventional controllers and thus might be reluctant to replace the existing conventional controllers with advanced and complex controllers. Therefore, having existed the PI control techniques base on different tuning methods, we can optimize the performance of the PI controllers by improving the reference tracking with neural network feedforward. The structure of the PI controller with the neural network feedforward is as shown in Fig7.

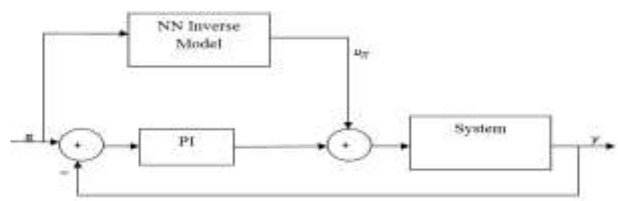

Figure 3.3. : PI plus NN Feedforward

4. RESULT AND DİSCUSSİON

4.1. Training Performance

The performance plot and regression plot for the training process are as shown in Fig 9-10. From Fig 9, it can be observed that the measure of performance set for training which is MSE has approached a value very close to zero as desired. Furthermore, a regression plot Fig 10 has been presented to shows the degree of correlation between input and target data set. A value very close to unity indicates good correlation. It can be observe from the plot of Fig 10 that the regression plot for both training, testing and validation has approached a value very close to unity; hence a perfect model correlation was established.

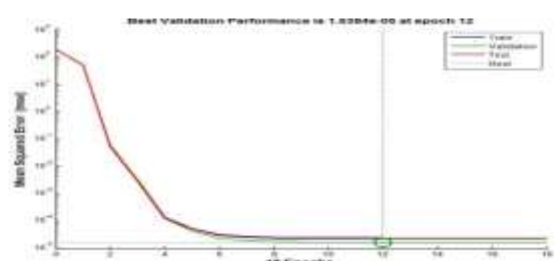

Figure 4.1. *Model Training Performance Plot*

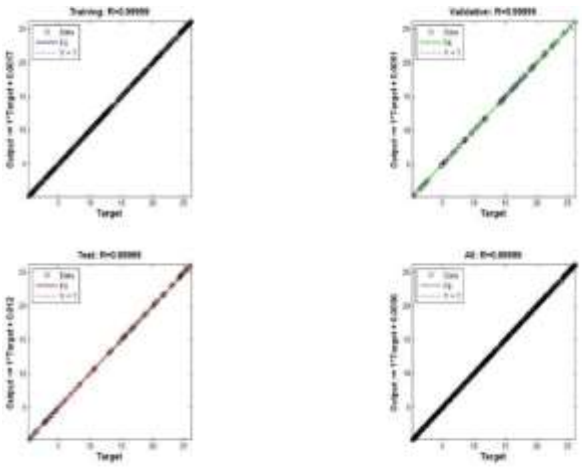

Figure 4.2.: Performance Regression plot

4.2. Model Performance and Validation

Several methods exist for NN model validation such as graphical, empirical, numerical and statistical methods. In this work, the graphical and practical approach were used to validate the trained model. First, the model output was compared with different set of data measured from experimental setup as shown in Fig 11. In the second validation stage, open-loop step test (Process reaction curve) was carried out to compare the NN trained model step response with plant open-loop step response, as shown in Fig 12. Both results from the two validation techniques indicated a very good NN model. Finally, as shown in Fig 13 empirical model, dynamic linearized model and NN non-linear models were compared to ascertain the validity of the trained model. The results indicated a very good trained model which can be used for control design.

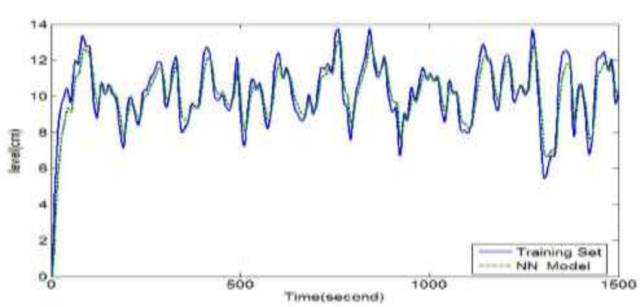

Figure 4.3 : NN Model and Training Data Evaluation

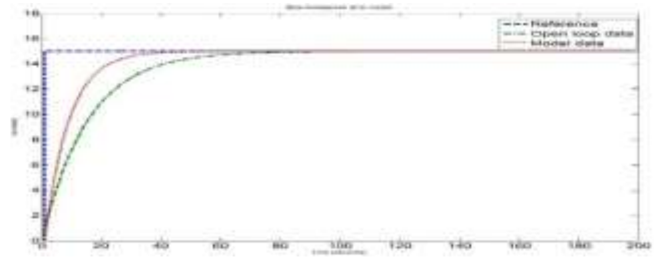

Figure 4.4. Open Loop Step Data (PRC) and NN Model Step Data Evaluation

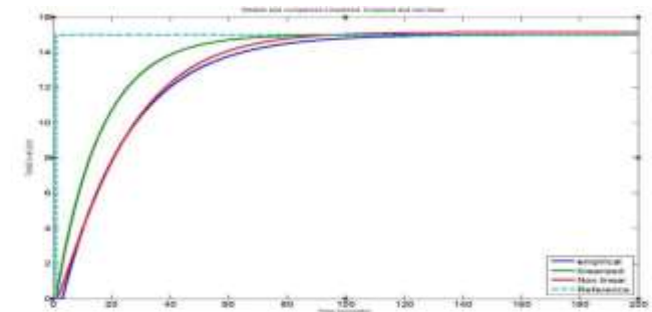

Figure 4.5. NN model, PRC and Mathematical Model Evaluation

4.3. Control Performance Evaluation

The Controllers settings for both set-point tracking and disturbance rejection are as Presented in table 2. The settings include filter setting for NNIMC design, 2DOF-IMC and conventional IMC for comparison purposes. Other controllers setting considered are the conventional PI gains according to the best turning methods obtained by reference [[6]]. All these were evaluated to ascertain the performance of the IMC control strategy.

Remarks

The performance indices set to evaluate the performance of the control algorithm can be described as:

Integral Squared Error (ISE): Defined as the integral square of error over time given by $\int e^2(t)dt$.

Integral Absolute Error (IAE): Define as the integral absolute of the error over time given by the expression $\int |e(t)|dt$.

*Integral Time Absolute Error (ITAE)***:** Define as $\int |e(t)|dt$.

ITAE can also be referred as time weight IAE or integral absolute value of the error multiply by time. Large of ITAE indicate poor performance of the controller while small values signify good performance of the control algorithm.

IAE: Allows larger deviation than ISE (Smaller overshot) therefore tend to indicate slower response than ISE over time.

ISE: Tend to have a longer time, and it has the effect of penalizing large errors. Controller with smaller value of ISE will tend to eliminate large error quickly but tolerate small error for a longer time.

ITAE: It has the effect of penalizing errors which exist for a longer time. This means weights error occurring later more heavily.

4.4. Tracking Performance

The tracking performance of the proposed control algorithm NNIMC compared with PI experimental benchmark controller is presented in Fig14. As it can be seen from the plot and tracking performance in Table 3, the NNIMC has improved tracking performance, rise time, settling time and with very small overshot compared to system benchmark PI controller. Furthermore, comparison analysis for tracking performance of the NNIMC with 2DOF-IMC, conventional IMC, and PI+NNFF were presented in Fig 15. While Table 4 shows the tracking performance for both controllers in terms of ITAE, IAE, and ISE. As it can be observed from the tracking performance in Table 4, the two-degree IMC with improved filter design has a better tracking performance than NNIMC. Similar properties have been observed with the used of conventional filter design for both set point and disturbance rejection controllers. The tracking performance of NNIMC when compared to conventional IMC and PI+FF shows a superior performance.

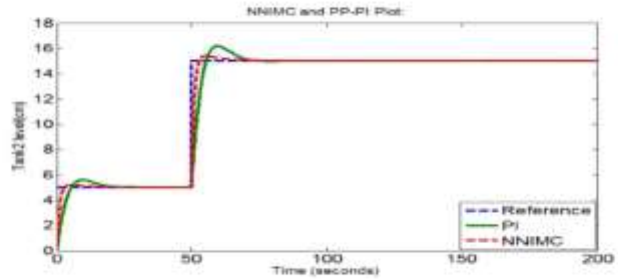

Figure 4.6.: Bench mark PI and NNIMC Tracking Performance

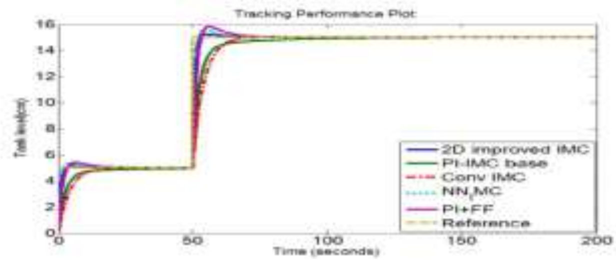

Figure 4.7. IMC strategy Performance Evaluation

Table 2: Tracking Performance Evaluation

Criterion	2DOF-IMC	NNIMC	C-IMC	PI+NNFF	PI-IMC
Rise Time	7	8	18	9	20
Settling Time	13	18	22	20	35
Overshot	2	4	0	6	0
ITAE	510	665.9	2245	1093	2749
IAE	13.81	18.12	60.09	28.53	59.63
ISE	44.43	53.86	250.2	84.36	175.9

4.5. Disturbance Rejection Performance Evaluation

Disturbance rejection is one of the important aspects of process control. As such disturbance rejection of the proposed control algorithm has been investigated for +10% disturbance in the process. Fig 16 present disturbance rejection plot for NNIMC and experimental benchmark PI controllers. While Figure 17 present disturbance rejection performance plot for 2DOF-IMC, NNIMC, PI-IMC, conventional IMC and PI+NNFF. Table 4 present a summary of the control and disturbance rejection performances. From Table 4, it can be seen that 2DOF-IMC controller has the best performance with small values of ITAE, IAE and ISE. This means the 2DOF-IMC controller has the best disturbance rejection capability, then followed by NNIMC. Additionally, NNIMC and PI+FF showed a very similar performance even though NNIMC has little bit superior performance over PI+FF based on the set criteria of ITAE, IAE, ISE and overshot. This means, in terms of the selected criteria values of ITAE, IAE, ISE, the NNIMC controller has a smaller value compared to PI+FF. These clearly indicated the robustness of NNIMC over PI+FF. Furthermore, NNIMC has a small overshot, risen time and settling time compared to benchmark PI.

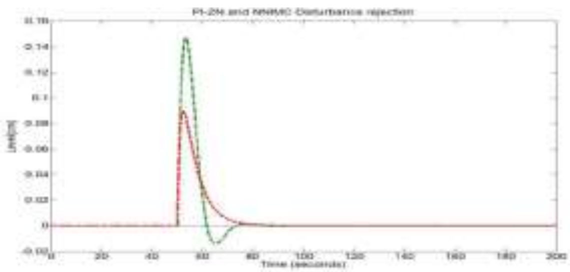

Figure 4.8.: NNIMC and PI-Benchmark Performance Evaluation

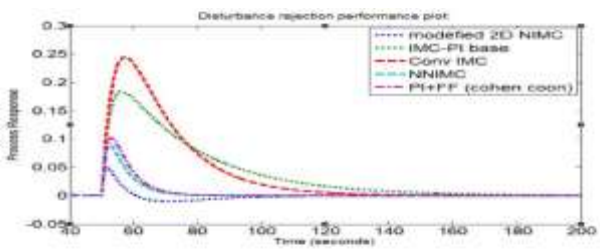

Figure : IMC Strategy Performance Evaluation

Table 3: IMC Strategy Performance Evaluation

Criterion	2DOF-IMC	NNIMC	C-IMC	PI+NNFF	PI-IMC
Overshot	0.05	0.08	0.25	0.1	0.19
ITAE	63.030	94.66	714.1	104.6	737.8
IAE	0.5405	0.8067	5.997	0.97	5.868
ISE	0.0119	0.0440	0.937	0.064	0.644

5. Conclusion

In this work, important ideas have been materialized such as non-linear NN model identification of the CTS, NNIMC, 2DOF-IMC, PI+NNFF and conventional IMC controllers for the control of non-linear CTS. The pilot plant CTS has been successfully modelled by NNARX model structure using NN system identification toolbox in Matlab. From this study, it can be observed that, 2DOF-IMC and NNIMC have better performance compared to PI, IMC and PI+FF under ITAE, ISE, ITA and overshot set criteria. Furthermore, NNIMC and 2DOF indicated a very small risen time and settling time both for tracking and disturbance rejection. However, 2DOF-IMC and NNIMC controllers produced almost similar results in terms of tracking performance with very small overshoot. The result shows that process engineers in industries can easily deploy 2DOF-IMC or NNIMC to either replace or complement the existing conventional controller's performance. Moreover, the existing industrial conventional PID controllers can be optimized through incorporating NN feedforward control block without adding much complexity to the existing control system.

Therefore, in this research work, similar properties have been found to hold for NNIMC and 2DOF-IMC strategy. The control algorithms showed better performance when compared with conventional IMC and PID families, which is according to [4-6]. While with the modification of the 2DOF-IMC block to include set-point tracking and disturbance rejection filter, the algorithm showed a significant increase in performance.

Feature research work will investigate more number of tanks such as quadruple tank system, conical coupled tanks and conical quadruple tank system due to highly increased in non-linearity nature of the system. Thus, this investigation work could serve as an important stage in exploring other process system configuration and control algorithm.

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