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Artificial Neural Network Approach for Parameter Estimation in PI Self Tunning Regulator (PI-STR) method on Process Rig 38-714 Pressure Control

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***Abstract*—In a pressure process control system when the system is loaded or when the load is released from the system, there will be a change in the system response form. Changes in the form of the response because the load or release of the load changes the dynamics of the system. In the controller industry commonly used are conventional PI or PID. However, due to the large variations in load, the PID controller is unable to meet the specifications. Adaptive settings are one of the regulatory methods in which controllers can respond to modify their behavior due to changes in dynamics due to loading and characteristics of interference. Self-Tunning Regulator (STR) is an adaptive arrangement scheme. Parameter estimation is one part of STR. In this paper the implementation of STR with parameter estimation using the neural network approach (NN STR) is carried out on the pressure regulation system in the Process Rig 38-741. The test results showed that the nominal load condition of NN STR with learning rate = 25 had the closest performance to the design results with a overshoot value of 23.7% and the settling time of 283.8 seconds was in accordance with the specifications of the desired range. In testing with the condition of changes in NN STR load with a learning rate = 20 shows the best performance against all the criteria used. While for testing the nominal load on the variation of NN set-point STR with learning rate = 10 shows the best performance on all the criteria used.**

Keywords: PI, Self-Tunning Regulator, Pressure Process Rig 38-714, Artificial Neural Network

I. Introduction

Adaptive control is a control method where the controller can respond to modify its behavior because of changes in the dynamics of the process and characteristics of the disorder [2]. Adaptive control is a controller with parameters that can be changed. Adaptive settings can be used in plants that have variations in process dynamics. Variations in process dynamics can be caused by several factors, namely nonlinear actuators, variations of flow and speed, variations in disturbance characteristics, as well as variations in load characteristics and many other variation factors and also usually a mixture of several different phenomena. Thus adaptive control can be used to be used in a plant that has a variety of load characteristics so that the system reaches the desired specifications.

Some of the processes in the industry have a nonlinear nature, where during operation the nature or dynamics changes with the state of load and time [3]. In the process control system the problem that often occurs is the change in load or changing process dynamics because of several factors, for example the appearance of interference or the age of the equipment. Changes in load cause changes in the characteristics of the plant. The emergence of these changes will provide obstacles that must be considered if you want to achieve good performance and a simple controller design is not enough to overcome it. Self-tunning regulator (STR) is one type of adaptive control. STR can do tuning automatically when there is a change in the dynamics of the plant. One part of the STR is the plant model parameter estimate. To achieve a good STR performance, the right parameter estimation needs to be designed.

In this paper, we focus on analyzing the comparison of parameter estimation methods in the pressure control system in the self-tunning regulator controller that experiences changes in load characteristics. The plant used is the PROCON Process Rig 38-714 production of Feedback Inc. system. Minimum root mean square error (RMSE) criteria, integral time square error (ITSE), integral time absolute error (ITAE) and square time multiplied by square error integral (ISTSE) are used as comparison criteria between the parameter estimation methods used. The parameter estimation method to be tested is recursive least square (RLS) and artificial neural network approaches. The implementation of the control method design was carried out in National Instrument's LabVIEW software.

STR parameter estimation with recursive least square and artificial neural network in nominal load conditions, changes in load and variation in set points for PROCON Pressure

Process Rig 38-714 try to be applied and analyzed so that the advantages and disadvantages of both are known.

II. System Design

Modeling is an important stage in the control system design cycle. To get a model from the Pressure Process Rig plant 38-714, a system identification is carried out which is one way to get a model from the system. Figure 1 shows the system identification scheme carried out. The method used is static identification.

Figure 1 System identification scheme

2.1. Static Identification of Open Loop Systems

Static identification is one method of identification, which is done by giving input or set value in the plant in the form of a constant signal. The signal that can be used is the unit step signal. The system that will be identified is an open loop system from the Plant Process Rig 38-714. Plant response data will then be collected and then analyzed to obtain a model from the plant. Identification is carried out with the following plant conditions:

1. Input *plant* : 15,2 mA (3 psi)
2. Amount of data taken : 30000 sample
3. Nominal conditions :
   Open valve : V1, V3, V4, and V5
   Closed valve : V2 and V6
4. *Air receiver* : used

2.2. System Model Formulation

The model of the system is approached by the first order system model because after seeing the response from the system shows the similarity of the first order system. Delay on the system is not modeled because the value is so small that it can be ignored. In general, a first-order system can be expressed with a transfer function written in the equation as follows:

$$G(s) = \frac{K}{\tau s + 1} \quad (1)$$

The system response graph of the data retrieval is illustrated in Figure 2

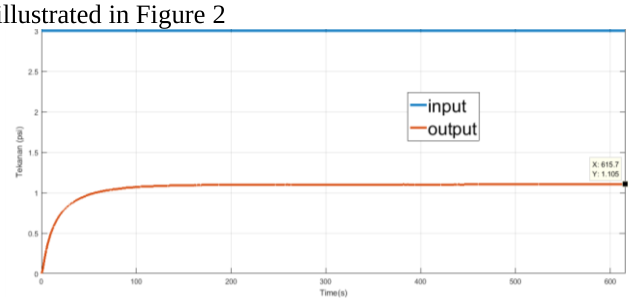

Figure 2 Graph of the open loop response of Pressure Process Rig 38-714

Thee process of finding parameters from the system is carried out in several stages below. First, the overall gain (K) calculation can be calculated using Equation (2).

$$K = \frac{Y_{ss}}{X_{ss}} \quad (2)$$

where Y_ss is the response of the system at steady state conditions and X_ss is the input system in steady state conditions. The output response of the system experiences steady state conditions when it is valued at 1,105 psi while the system input experiences steady state when 3 psi. Thus the overall gain is obtained

$$K = \frac{Y_{ss}}{X_{ss}} = \frac{1.105}{3} = 0{,}36833 \quad (3)$$

After getting the gain overall value from the system model is a search for the time respone value (τ) of the system. The value of τ can be searched through the value of time when the response reaches 63.2% from the steady state state. The steady state value of the system is 1,105 so 63.2% of the value is 0.69836 psi. The time when the response reaches that value is 18.12 seconds. Thus the transfer function of the plant can be stated in Equation (4).

$$G(s) = \frac{0.36833}{18.12s + 1} \quad (4)$$

2.3. Model Validation

Figure 3 shows a comparison between the system models obtained in system identification section and real response. When using the mean square error (MSE) criterion to compare the model and the open loop response from the plant the value is $3{,}5435\times 10^{-4}$.

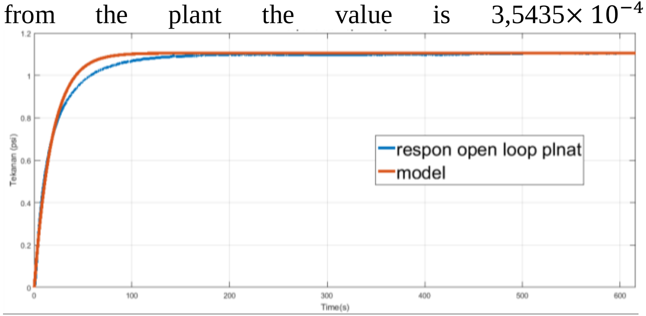

Figure 3 Comparison of the open loop plant response with the model obtained

2.4. Determination of Sampling Frequency

Determination of sampling frequency in a digital regulation system is an important problem. Sampling frequency affects many properties of a system, such as measurement noise and sensitivity to dynamics that have not been modeled. Thus the sampling frequency selection becomes a problem in the design system design stage.

One rule to determine which is useful for the design method is to choose the sampling interval h chosen in such a way as to fulfill

$$\omega_o h \approx 0{,}2 - 0{,}6 \quad (5)$$

where ω_o is the dominant natural pole frequency of a closed-loop system [2].

2.5. *Estimation of System Parameter*

One part of the self-tunning regulator is the system model parameter estimator. In this section we will discuss the design of parameter estimators with two methods, namely recursive least square and artificial neural network.

2.6. *Recursive Least Square (RLS) Model Estimation [2]*

A mathematical model can be expressed in form

$$y(k) = \varphi_1(k)\theta_1 + \varphi_2(k)\theta_2 + \ldots + \varphi_n(k)\theta_n = \emptyset^T(k)\theta \quad (6)$$

where y is the output of the system, θ is a parameter of an unknown mathematical model, and φ is a regression variable consisting of input and output system data.

$$\emptyset^T(k) = [\varphi_1(i) \quad \varphi_2(i) \quad \ldots \quad \varphi_n(k)] \quad (7)$$

$$\theta = [\theta_1 \quad \theta_2 \quad \ldots \quad \theta_n]^T \quad (8)$$

$$\theta(k) = \theta(k-1) - P(k)\big(\varphi(k)\varphi^T(k)\theta(k-1) + \varphi(k)y(k)\big) \quad (9)$$

2.7. Model Parameter Estimation with Artificial Neural Network Approach

Artificial neural networks can be used to estimate the parameters of the ARX system model. One of the artificial neural network architectures that can be used to estimate parameters is shown in Figure 4

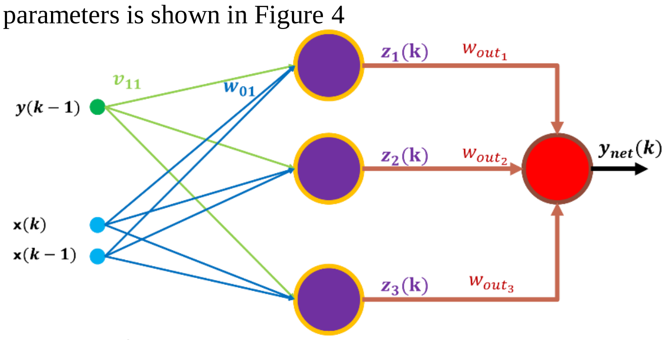

Figure 4 Artificial neural network architecture used

By using Equations (8) and (9) the model parameter values can be calculated as follows:

$$\widehat{a_1} = \frac{1}{4}\left(\sum_{h=1}^{H}(w_{out_h}\, v_{1h})\right) \quad (10)$$

$$\widehat{b_0} = \frac{1}{4}\left(\sum_{h=1}^{H}(w_{out_h}\, w_{0h})\right) \quad (11)$$

$$\widehat{b_1} = \frac{1}{4}\left(\sum_{h=1}^{H}(w_{out_h}\, w_{1h})\right) \quad (12)$$

2.8. Desain *Self-Tunning Regulator [2]*

After identification and known the system response resembles a first-order system, the plant transfer function can be expressed in equation (13) [12]. Where Y (s) is output and U (s) is input. The model

$$\frac{Y(s)}{U(s)} = \frac{K}{\tau s + 1} \quad (13)$$

will be expressed in discrete form because the parameter estimation results are discrete models. Equation (13) can be changed to a discrete model by using the Binier Transform which is defined in Equation (14)

$$s = \frac{2}{Ts}\left(\frac{1 - z^{-1}}{1 + z^{-1}}\right) \quad (14)$$

The substitution of Equation (14) in Equation (13) will get Equation (15).

$$\frac{Y(z)}{U(z)} = \frac{K}{\frac{2\tau}{Ts}\left(\frac{1 - z^{-1}}{1 + z^{-1}}\right) + 1} \quad (15)$$

$$y(k) = -\frac{\left(1 - \frac{2\tau}{Ts}\right)}{\left(1 + \frac{2\tau}{Ts}\right)}y(k-1) + \frac{K}{\left(1 + \frac{2\tau}{Ts}\right)}u(k) - \frac{K}{\left(1 + \frac{2\tau}{Ts}\right)}u(k-1) \quad (16)$$

In general, the shape of the model with the ARX structure (1.1) can be expressed by Equation (17).

$$y(k) = -a_1 y(k-1) + b_0 u(k) + b_1 u(k-1) + e(k) \quad (17)$$

Equation (17) has the same structure as the plant model that has been changed to a discrete form, namely Equation (16) when added to the noise component e (k). Thus it can be formulated in the following equations

$$a_1 = -\frac{\left(1 - \frac{2\tau}{Ts}\right)}{\left(1 + \frac{2\tau}{Ts}\right)} \quad (18)$$

$$b_0 = \frac{K}{\left(1 + \frac{2\tau}{Ts}\right)} \quad (19)$$

$$b_1 = -\frac{K}{\left(1 + \frac{2\tau}{Ts}\right)} \quad (20)$$

Equation (19) can be used to decrease the time constant value (τ) stated in Equation (21)

$$\tau = \frac{a_1 + 1}{\frac{2}{Ts}(1 - a_1)} \quad (21)$$

Equation (19) can be used to determine the gain value overall from the plant stated in Eq (22).

$$K = b_0\left(1 + \frac{2\tau}{Ts}\right) \quad (22)$$

Subtitution of Equation (21) to Equation (22), we will get Equation (23).

$$K = b_0\left(1 + \frac{2}{Ts}\left(\frac{a_1 + 1}{\frac{2}{Ts}(1 - a_1)}\right)\right) \quad (23)$$

The controller configuration used in the self-tunning regulator design is a PI controller which is expressed by the transfer function in Equation (24). Where U (s) states the control signal and E (s) declares an error signal. Controller parameters can be expressed in Equations (24) - (27).

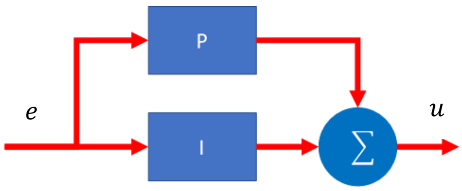

Figure 5 PI Controller

Figure 5 shown structure PI controller that used in the system. From the figure we can drawn equation (24).

$$\frac{U(s)}{E(s)} = K_p\left(1 + \frac{1}{\tau_i s}\right) \tag{24}$$

Equation (24) is converted to a discrete equation using the Binier Transform where the results are expressed in Equation (3.90).

$$\frac{U(z)}{E(z)} = \frac{K_p \tau_i \frac{2}{Ts}\left(\frac{1-z^{-1}}{1+z^{-1}}\right) + K_p}{\tau_i \frac{2}{Ts}\left(\frac{1-z^{-1}}{1+z^{-1}}\right)} \tag{25}$$

$$u(k) = \left(u(\mathrm{k}-1) + \frac{\left(K_p \tau_i \frac{2}{Ts} + K_p\right)}{K_p \tau_i} e(k) + \frac{\left(K_p - K_p \tau_i \frac{2}{Ts}\right)}{K_p \tau_i} e(k-1) \right) \tag{26}$$

After the controller configuration has been formulated in Equation (26) the PI controller parameters can be calculated. The analytical approach is used to find controller parameters which if the desired stedy state error is zero then the value of the parameter τ_i is the same as the time value of the contant of the open loop system formulated in Equation (27).

$$\tau_i = \tau \tag{27}$$

Where the value of the open loop system time constant is expressed in Persaman (21), thus the equation τ_i is obtained in the function of the system model parameter which is expressed in Equation (28).

$$\tau_i = \frac{a_1 + 1}{\frac{2}{Ts}(1 - a_1)} \tag{28}$$

The proportional constant value of the controller can be found with Equation (29).

$$K_p = \frac{\tau_i}{\tau^* K} \tag{29}$$

Equation (29) can be changed by doing substitution Equations (28) and (23) in this equation to get the relationship between the constant values proportional to the parameter values of the system model.

$$K_p = \frac{\left(\frac{a_1 + 1}{\frac{2}{Ts}(1 - a_1)}\right)}{\tau^* \left(b_0 \left(1 + \frac{2}{Ts}\left(\frac{a_1 + 1}{\frac{2}{Ts}(1 - a_1)}\right)\right)\right)} \tag{30}$$

Where is τ^* specification time constant desired closed loop system response. The desired specification value τ^* in this design is 50 seconds.

III. Result and Discussion

In this section, we will discuss the results of system testing that has been designed previously to determine the performance of the plant if a self-tunning regulator method is applied with recursive least square parameter estimation (STR RLS) and self-tunning regulator with parameter estimation of neural network approach (NN STR). Testing with changes in load. The values of RMSE, ITSE, and ITAE and ISTSE from the system are used as comparative criteria, then do not forget to see other system performance that has been designed such as settling time (t_s) and overshoot percentage, peak percentage, and recovery time percentage.

3.1 System test by changing the load

The problem highlighted in this section is knowing the performance of the system when a load changes. The initial conditions of the system are as follows:

a) Set point : 15,2 mA (3 psi)
b) Amount of data taken : 5000 sample
c) Nominal conditions :
   i. Valve open : V1, V3, V4, and V5
   ii. Valve close : V2 and V6
d) Air receiver : used
e) Sampling period : 300 ms
f) Initial condition of output : 0 psi

Load changes are made by deactivating one of the manual valves. The manual valve V5 is deactivated or closed when the system has been operating for 600 seconds.

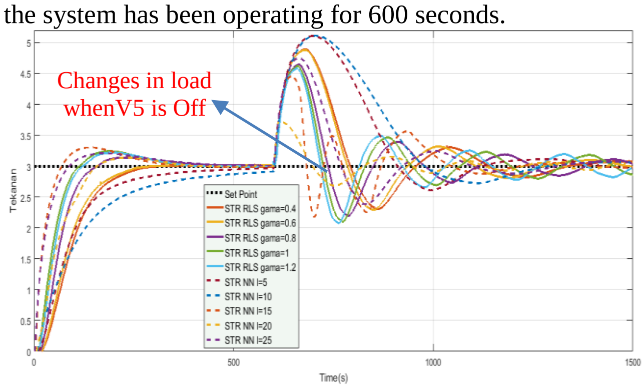

Figure 6 System response conditions for load changes

The system response resulting from the implementation of the method tested in the event of a change in load. That is shown in Figure 6 show the system performance from the tests carried out in the event of a change in load. Figure 7-Figure 12 illustrates the response of the K_p and T_i values obtained. Table 1 - Table 2 presents a normalized system performance table and given criteria weights.

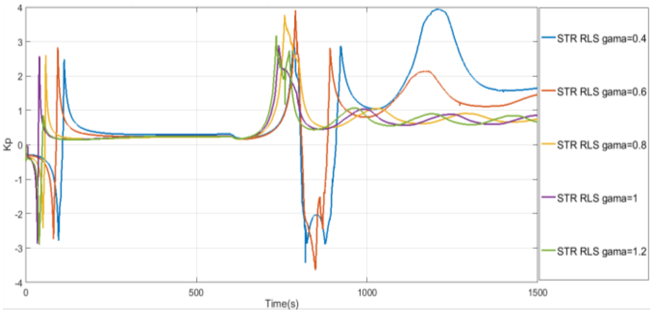

Figure 7 Response to Kp STR RLS values under load change conditions

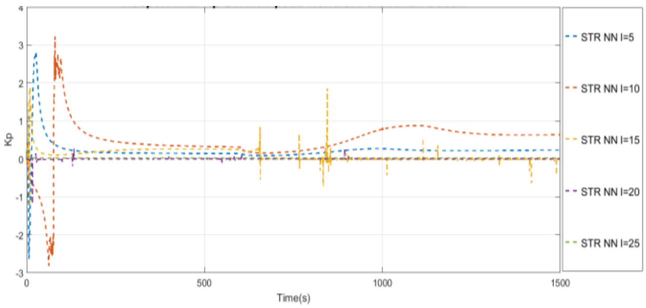

Figure 8 Response Kp STR NN under load change conditions

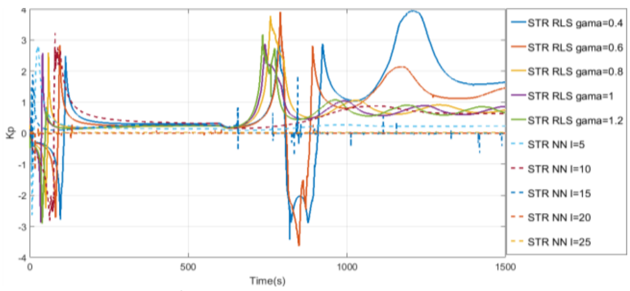

Figure 9 Response of Kp value under load change conditions

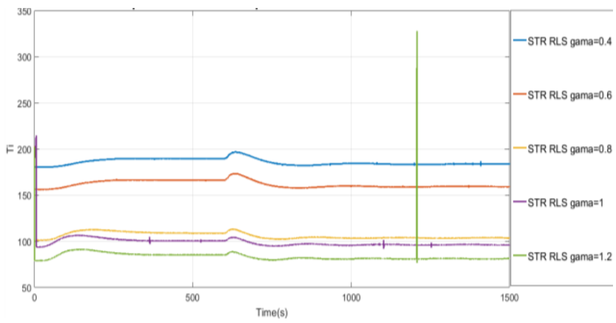

Figure 10 Response of the RLS STR Ti value under load change conditions

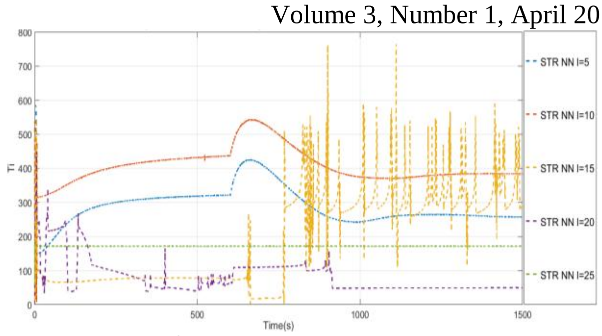

Figure 11 Response of Ti NN STR under load change conditions

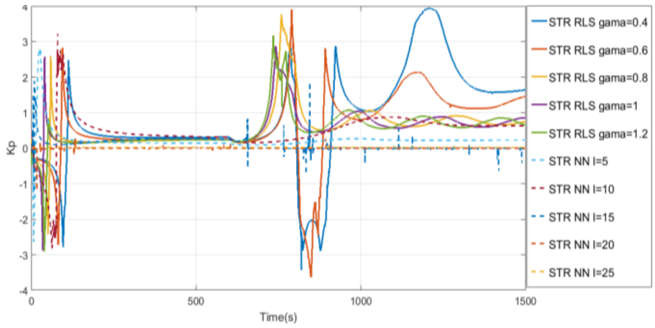

Figure 12 Response value under load change conditions

Table 1 System performance as a result of STR testing with recursice least square parameter estimation in the condition of a load change

STR RLS	g=0,4	g=0,6	g=0,8	g=1	g=1,2
RMSE	0,4401	0,4178	0,3363	0,3133	0,3163
ITSE	$3,0450 \times 10^5$	$2,8968 \times 10^5$	$1,8187 \times 10^5$	$1,7260 \times 10^5$	$1,6498 \times 10^5$
ITAE	$3,1020 \times 10^5$	$2,9710 \times 10^5$	$2,5068 \times 10^5$	$2,5650 \times 10^5$	$2,5501 \times 10^5$
ISTSE	$2,0299 \times 10^8$	$1,9408 \times 10^8$	$1,2369 \times 10^8$	$1,2267 \times 10^8$	$1,1721 \times 10^8$
% Peak	63,0333	62,7667	54,9333	54,1667	52,9333
Recovery time ($\pm$ 5%)	600,5s	617s	721s	811s	865s

Table 2 System performance results from STR testing with parameter estimation of artificial neural network approach in the condition of a load change

STR NN	L=5	L=10	L=15	L=20	L=25
RMSE	0,5341	0,6172	0,2371	0,2043	0,2794
ITSE	$5,3761 \times 10^5$	$6,2660 \times 10^5$	$1,2528 \times 10^5$	$0,3281 \times 10^5$	$2,0671 \times 10^5$
ITAE	$4,1076 \times 10^5$	$4,7990 \times 10^5$	$1,9943 \times 10^5$	$1,0000 \times 10^5$	$2,4580 \times 10^5$
ISTSE	$3,7918 \times 10^8$	$4,4754 \times 10^8$	$0,9044 \times 10^8$	$0,1686 \times 10^8$	$1,4395 \times 10^8$
% Peak	70,2000	70,4333	48,5667	23,7000	5,.3667
Recovery time	471s	589s	407,5s	283,8s	449,5s

(± 5%)					

In this test the NN STR with the learning rate = 20 has the lowest RMSE, ITAE, and ITAE and ISTSE values. If only the RLS STR is reviewed, the lowest RMSE value is owned by the RLS STR with forgetting factor = 1 and the lowest ITSE, ITAE, and ISTSE values are owned by the RLS STR with the value of forgetting factor = 1.2.

For the condition of load changes the smallest% peak value is owned by STR NN with a learning rate = 20. If only the RLS STR is observed the smallest peak value is owned by STR by forgetting factor = 1.2. On the RLS STR to test the condition of changes in load the value of the% peak is getting smaller with the greater value of forgetting factor.

The fastest recovery time value is obtained from the NN STR test with a learning rate = 20. If only the RLS STR is examined, the lowest recovery time value is owned by the RLS STR with forgetting factor = 0.4. On the RLS STR the smaller the value of forgetting factor, the faster the recovery time value of the system.

IV. Conclusion

After doing the testing on this Project using Artificial Neural Network Approach for Parameter Estimation in Self-Tunning Regulator (STR) method on Process Rig 38-714 Pressure Control can be drawn the following conclusion:

1. When the load is nominally STR NN, the learning rate = 25 shows the performance closest to the design results, with the fastest time settling and the small overshoot, which is 0.9%.
2. Under conditions of changes in load NN STR with learning rate = 20 shows the best performance on all the criteria used, namely RMSE, ITSE, ITAE, and ISTSE and with% pertubation peak = 23.7% and recovery time = 283.8 seconds.
3. In the situation of nominal loads with variations in the NN set-point STR with a learning rate = 10 showing the best performance for all the criteria used, namely RMSE, ITSE, and ITAE and ISTSE.
4. Artificial Neural Network Approach for Parameter Estimation can be used for tuning a STR-PID

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