Artificial Neural Network Control of the Recycle Compression System

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Abstract: This paper presents results from an investigation on a nonlinear compressor control. The useful range of operation of turbo compressors is limited by choking at high rate flows and by the onset of instability known as surge at low rate flows. Traditionally, this instability has been avoided by using control systems that prevent the operating point of the compressor to enter in the unstable region. It is not efficient to apply classical controllers, such as simple P, PI and PID when the parameters of compression system change frequently. The aim of our work is to design and simulate an intelligent controller. A simulation part is clearly presented with the advantages of the intelligent system.

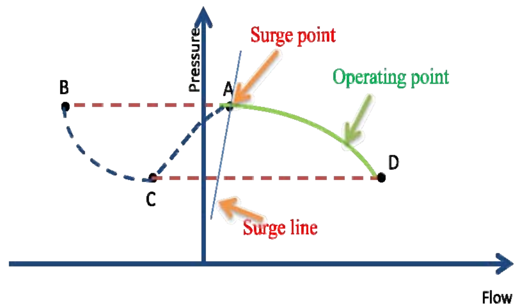
Keywords: Compression system, PID controller, Fuzzy logic control, Neural predictive controller, NARMA L2 Control.

1. Introduction

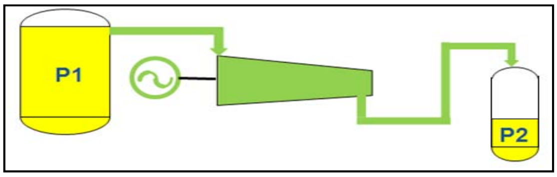
This work is motivated by the fact that the compressors are used in a wide variety of applications such as: power generation using industrial gas turbines, pressurization of gas in the process industry, transport of fluids in pipelines, and the fundamental instability problem known as surge limits the operation range for compressors at low mass flows. This instability problem has been studied and a surge avoidance solution is established. This solution is based on keeping the operating point at the right side of the surge line. There is a potential for increasing the efficiency of compressor by allowing the operation point closer to the surge line, which is the case in industrial current systems. The increase in efficiency range is possible with compressor designs where the design is done with such controllers. However, this raises the need for control techniques, which stabilize the compressor when disturbances occur or set point is changed, otherwise, the operating point may cause a crossing of the surge line. This approach is known as artificial intelligent active surge control. In recent years intelligent active surge control has been an active area of research as in [1,2,3,4] have been focused on modelling and control. Active surge control has showed the ability to extend the operating range significantly [3,4]. This study presents a solution to this problem based on intelligent neural network controller.

2. Description of the Surge Phenomena

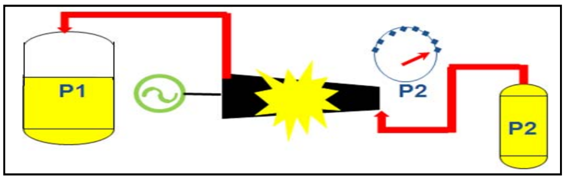
In compression systems, instabilities occur during operation close to their peak pressure-rise capability [5,6,7].However, the peak efficiency of a compression system lies close to this region of instability. Surge is an unstable flow situation that appears when the flow is too low and the head too high per unit of compressor speed. Under normal conditions, the compressor operates to the right of the surge line. However, as fluctuations in flow rate occur, or under startup/shutdown, the operating point will move towards the surge line because of reduced flow. If conditions are such that the operating point approaches the surge line, the impeller and diffuser begin to operate in stall, and flow recirculation occurs. The flow separation will eventually cause a decrease in the pressure and flow from suction to discharge. When a centrifugal compressor reaches its surge limit, the flow pattern through the compressor collapses and a sudden backwards flow of gas occurs from the discharge to the suction side of the compressor through the forward spinning impeller (Figure 1.c). This violent mode of instability causes a total breakdown of flow in the system and loss of the pressure-rise capability.



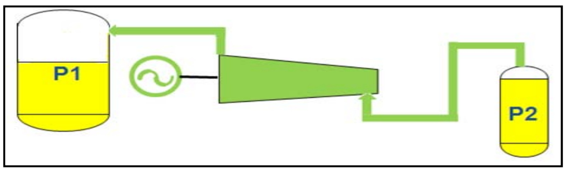
(a) Deep surge in centrifugal compressor



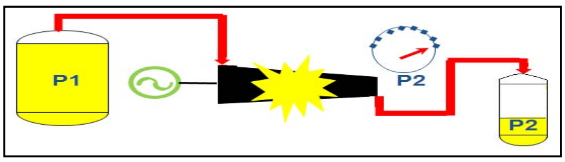
(b) From D to A: stable operation of the compressor from the suction tank to the discharge tank



(c) From A to B: rapid transition to the unstable region; From B to C: Vibration and unstable operating of the compressor from discharge tank to the suction tank;



(d) From C to D: stable operation from discharge tank to suction tank;



(e) At the point D: Vibration of the compressor and the cycle repeats again.

Figure 1. The cycle of the surge phenomenon

Generally, all compression systems operate with a surge margin. It is important to study the surge of the compression system to understand its dynamics in order to operate it close to the surge limit for achieving high efficiency. This surge phenomenon causes a reversal of the thrust loads and causes severe damage to the thrust bearings, seals, and the impeller. For these reasons, surge must be avoided during centrifugal compressor operation.

The complete characteristic of a compressor is shown as the S-shaped curve; it represents the pressure ratio or pressure rise as a function of the flow through the compressor (Figure 1.a). For a constant speed the compressor develops a compression ratio increasing to the maximum compression which is limited by the surge line. Then to move to the region where the compressor is completely unstable and the surge appears.

3. Operating Region of a Centrifugal Compressor and Protection Limits

Protective devices against the surge are installed so that the compressor does not reach the surge line, even during transient operation. A margin is required between the operating point and surge line defined as surge control line (Figure 2).

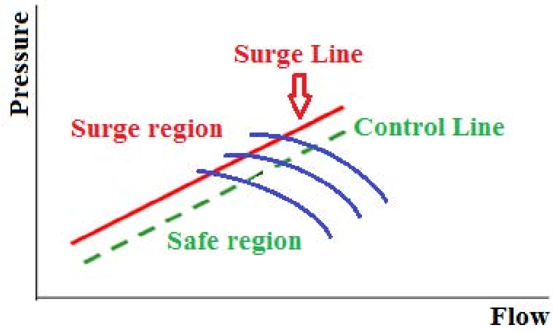


Figure 2. Representation of the surge line and surge control line

Moreover, the characteristic curves of the pressure/volume also represent significant operating limitations. The most important is the surge line limit in which the compressor becomes unstable. This instability is manifested by pulsations in the flow and pressure that can cause serious damage to the compressor. For this reason, we use an anti-surge system to maintain constant flow nearest the limit of the surge. The surge zone and its limits are clearly indicated on the curves (Figure 2); the left end of the curves corresponds to the surge limit. In the right side, the curves are limited before reaching the stone-wall (or strangulation). To control the system manually with a great degree of protection, manufacturer visualizes for engineer in the control room two other lines of protection DSLL (Low Low Deviation to the Surge with color blue), DSL (Low Deviation to the Surge line, with color green), SCL (Surge Control Line with yellow) and DSH (High

Deviation between operating point and Surge control line with color red) shown by Figure 3.

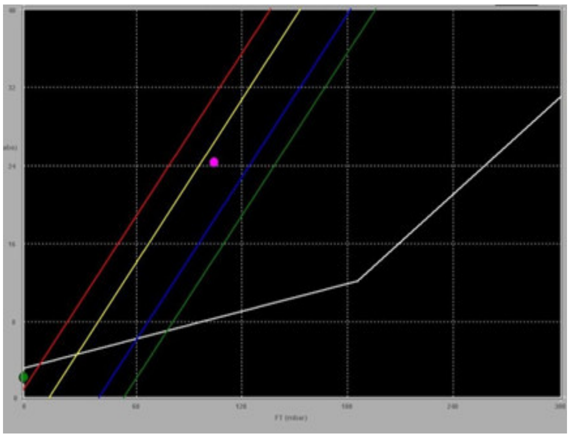


Figure 3. Compressor's operating point of Algerian Company

Figure 4 shows the operating region of the compressor, which is limited at

- The left by the surge line;
- The top by the maximum rotational speed;
- The right by the stone wall (white);
- The Bottom by the minimum rotational speed.

4. Modeling of the Recycle Compression System

The compression system is modelled as in Figure 5, with a compressor, a duct of length L, a plenum of volume V_p, a throttle, and a drive unit imparting a torque on the compressor.

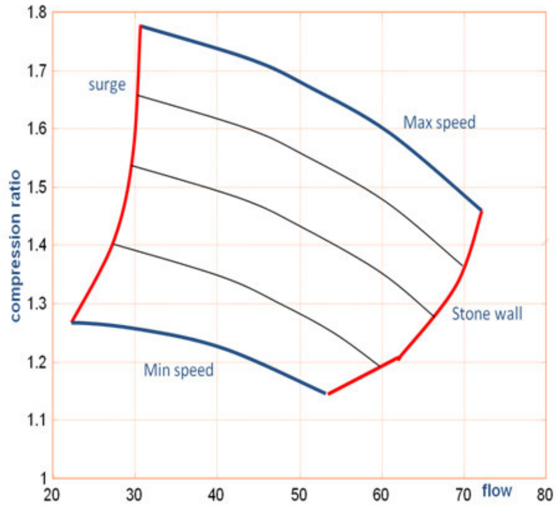


Figure 4. The operating region of a centrifugal compressor

According to Greitzer [7], Egeland and Gravdahl [8], the model of recycle compression system is:

$$\dot{P}_1 = \frac{a_p^2}{V_1}(Q_f + Q_r - Q) \tag{1}$$

$$\dot{P}_2 = \frac{a_p^2}{V_2}(Q - Q_t - Q_r) \tag{2}$$

$$\dot{Q} = \frac{A}{L}(\Psi_c(Q,N)P_1 - P_2) \tag{3}$$

$$\dot{N} = \frac{1}{J}(\tau_m - \tau_c) \tag{4}$$

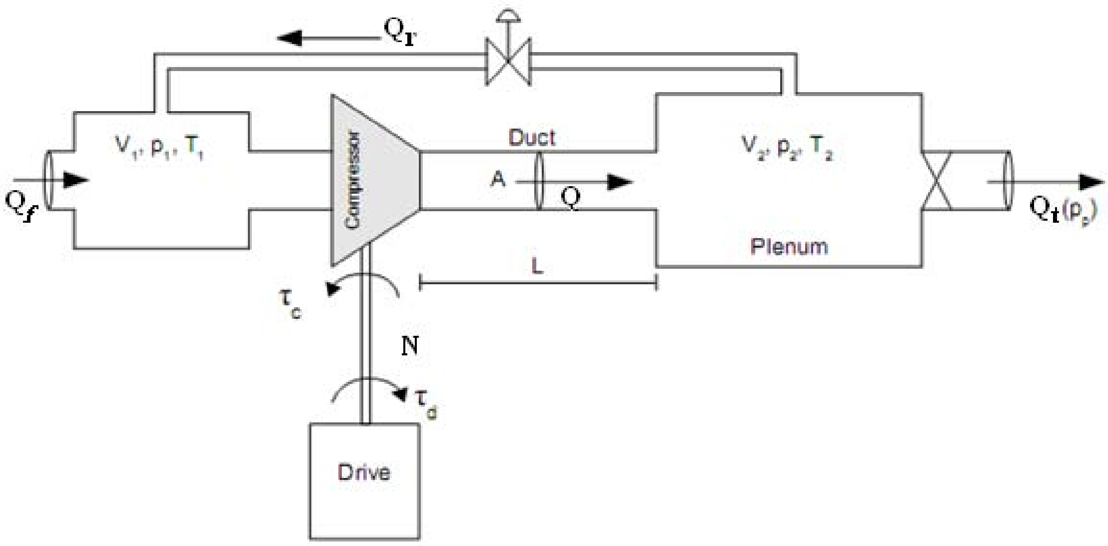


Figure 5. The compression system model

Notations are defined in Table 1.

Table 1. Table of parameters & acronyms

Param.	**Meaning / Values** [5,9]
Q	The mass flow (kg/s)
Q_f	The feed flow (kg/s)
Q_r	The recycle flow (kg/s)
Q_t	The throttle flow (kg/s)
a_p	The speed of sound=343 m/s
c_p	Specific heat at constant pressure 1005(J/kg.K)
V_1	Suction plenum volume 0.05 m^3
V_2	Discharge plenum volume 0.1 m^3
P_{01}	Ambient pressure 101.325 Pa
P_1	Section plenum pressure (Pa)
P_2	Discharge plenum pressure (Pa)
T_{01}	Ambient temperature 20 Celsius
A	Duct area 0.07m2
L	Duct length 2.85m
$\psi_C(Q,N)$	The pressure rise
τm	Drive torque
τc	Compressor torque
μ	Energy transfer coefficient 0.99
r_1	Inducer perimeter radius 0.0395m
r_2	Impeller perimeter radius 0.0565m
α	Constant of incidence loss
k_f	Friction constant
k_t	The area of the throttle opening valve.
ξ	1000
c_f	The percentage feed opening valve
c_r	The percentage recycle opening valve
c_t	The percentage throttle opening valve
N	The speed (rad/s)
J	The impeller inertia 5e^{-4} kg m^2
α	Constant of incidence loss
C	Flow coefficient

The complete recycle compression system is modelled and simulated. The throttle and recycle valves are modelled by:

$$\begin{aligned} Q_t &= \tanh(\xi(P_2 - P_{01}))k_t * \\ &\quad * \sqrt{(P_2 - P_{01})\tanh(\xi(P_2 - P_{01}))} \\ &= C_t\sqrt{(P_2 - P_{01})} \end{aligned} \tag{5}$$

$$Q_r = C_r\sqrt{P_2 - P_1} = C_r\sqrt{\Delta P} \tag{6}$$

Where: C_t and C_r are constants which represent the percent of the area of the valve to be opened.

ΔP : is the pressure drop across the valve.

In the case of compressor deep surge, we'll have a flow reversal [8,9]. Finally the torque acting on the impeller blades is:

$$\tau_C = |Q| r_2^2 \mu . N \tag{7}$$

The model uses the pressure ratio of the compressor ψ_C. The compressor characteristic derived from enthalpy transfer in Egeland and Gravdahl [10] is:

$$\Psi_C(Q,N) = \left(1 + \frac{\mu . r_2^2 N^2 - (1/2) r_1^2 (N - \alpha Q)^2 - k_f Q^2}{c_p T_{01}}\right)^{\frac{k}{k-1}} \tag{8}$$

This expression is also valid in the unstable area to the left of the surge line.

5. Data Measurement of the Recycle Compression System

The industrial compression system is shown by the Figure 6, with a compressor, a duct, Feed flow valves, a throttle valve, recycle valve, coolers, drive unit imparting a torque on the compressor, and plenums of volume.

The compressor is protected against surge by an anti-surge valve connecting the

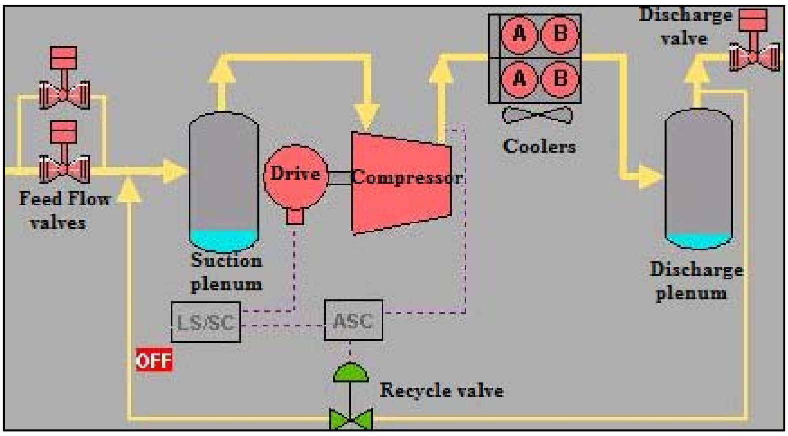


Figure 6. Industrial recycle compression system

compressor's discharge to the suction plenum, thus increasing the flow in the compressor to return it out of the surge area. The surge regulation is intended to open this valve as soon as the flow in the compressor is getting too close to the surge flow. Anti-surge control has the function of maintaining the compressor in a stable operating range assuring a higher suction capacity than the surging rate whatever the compression ratio may be [11,12].

When the compressor flow rate is below the specific flow for the protection margin at a given pressure ratio (Figure 2), the controller should send a control signal to the valve to open [12]. The rate of opening or closing should be based on the speed required to protect the compressor. The compression system is a complex industrial process and very dangerous due to the high pressure in petroleum companies. The neural network is used to simulate non-linear systems, therefore this technical approach can be implemented to identify and control the recycle compression system.

The identification of the compression system is the determination of the model parameters of a dynamic system from inputs (Flow and Speed)/output (Pressure ratio) data. We measure the discharge pressure (compression ratio) for different flow rates and velocities. We plot in a coordinate system (flow, compression ratio) for different speeds. Some measurements are given by the characteristic map of the manufacturer and are shown by Figure 7.

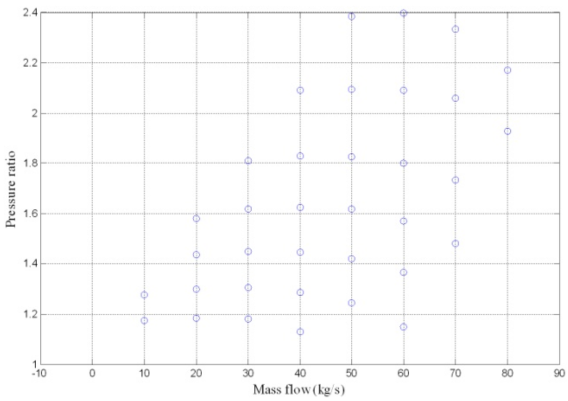


Figure 7. Manufacturer measurements compressor data map

Egeland and Gravdahl [8] uses a method where approximations of the measurements are based on polynomial curve fitting is done, to make the characteristic continuous in both mass flow and speed. Two stages are required. First, each speedline is approximated as [8,9]:

$$\psi_c(Q) = C_0 Q^3 + C_1 Q^2 + C_2 Q + C_3 \quad (9)$$

According to Gravdahl and Egeland [8], the negative flow points are chosen such that the 3rd order polynomial obtains the right form. Q is the mass flow and C_i, i = 0; 1; 2; 3 are the coefficients corresponding to a given rotational speed.

Next, the coefficients are approximated as:

$$c_i(N) = C_{i0} N^3 + C_{i1} N^2 + C_{i2} N + C_{i3} \quad (10)$$

Where: N is the rotational speed. The approximation can now be written as:

$$\psi_c(Q,N) = C_0(N)Q^3 + C_1(N)Q^2 + C_2(N)Q + C_{3(N)} \quad (11)$$

And by this interpolation we can determine a data base: pressure ration, speed, and flow; this can be used for the step of identification to train the neural network.

6. Artificial Neural Network of the Recycle Compression System

Artificial neural networks (ANN) have been successfully applied to many engineering and science fields [13,14]. It is a processing that is inspired by the biological nervous systems, such as the brain, process information.

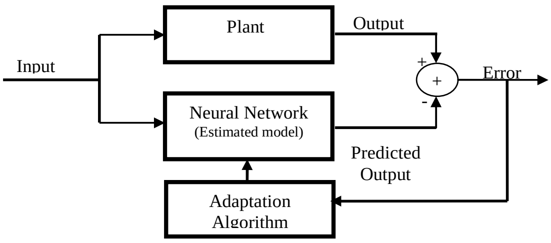


Figure 8. Estimation of the compression model by Neural Network

A neural network is a system with inputs and outputs that consists of many simple and similar processing elements with a number of internal parameters called weights [13]. The principle of regulation is illustrated in the Figure 8.

As shown in Figure 8, we have an unknown function that we wish to approximate. We want to adjust the parameters of the network so that it will produce the same response as the unknown function, if the same input is applied to both systems. For our compression system, the unknown function corresponds to a system we are trying to control. To identify the model of the compression system, we consider the mass flow and speed as inputs and the pressure ratio as output of the system. The program written to create a feed forward network is as follows:

```
% Neural Network using feed forward
  backpropagation network
% We import the inupts (Qs,S) and the
  output Tc from the compression system. P
  is the matrix of inputs data
P = [Qs';S'];

% Creation of the network with one hidden
  layer of 10 neurons.
net = newff(P,Tc',10);

% The network is simulated and its output
  plotted against the targets.
Y = sim(net,P); plot(P,Tc',P,Y,'o')

% The network is trained for 1000 epochs.
  Again the network's output is plotted.
net.trainParam.epochs = 1000;
net = train(net,P,Tc'); Y = sim(net,P);
plot(P,Tc','*',P,Y,'o'); gensim(net)
```

After simulating the above program, the results are illustrated in the Figure 9 and Figure 10.

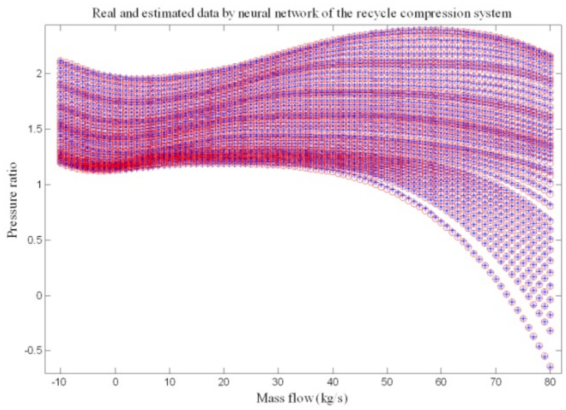


Figure 9. Real and NN estimated curves characteristic of centrifugal compressor

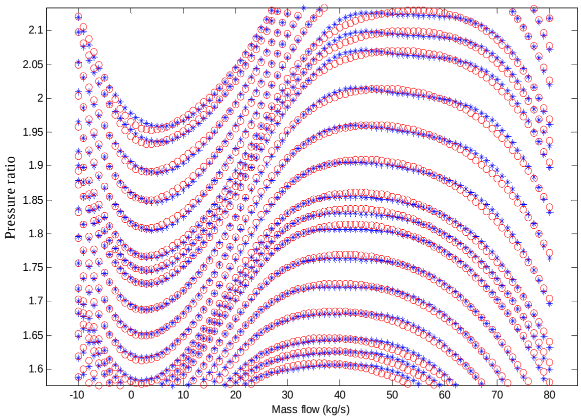


Figure 10. Zoom of curves characteristic of centrifugal compressor

The rounded points show the estimated model and the star points show the real output of the centrifugal compressor. Until now, the neural networks have been used to identify our system by generating a functional block representing the input/output relationship. However, using this block will create troubles in controlling the system mainly in choosing the type of the controller that has to be used. For this purpose, we have chosen a controller that performs both tasks: the identification and the control at the same time. The NN predictive and NARMA L2 controllers respond to these needs because they use the learning algorithm based on neural networks inside the controllers themselves. The parameters of these controllers are set manually in such a way that the system operates as close as possible to its desired operating performance.

As we have already said, there are typically two steps involved when using neural networks for control:

1. System identification
2. Control design.

In the system identification stage, we develop a neural network model of the compression system that we want to control. In the control design stage, we use the neural network compression system model to design (or train) the controller.

The most common technique for training neural networks is by studying the variations of the gradient descent [14]. And the control systems must have the capability to identify defects, to isolate the damaged elements and to reconfigure the architecture in real time [15].

In each of the two control architectures, the system identification stage is identical. The control design stage, however, is different from each other. The next part of the paper, we discuss the model predictive control and NARMA-L2 control.

6.1 Neural network predictive control

The first step in model predictive control consists to determine the neural network compression system model by identification. Next, the compression system model will be used by the controller to predict future performance.

The prediction error between the compression system output and the neural network output is used as the neural network training signal. The process is represented by Figure 11.

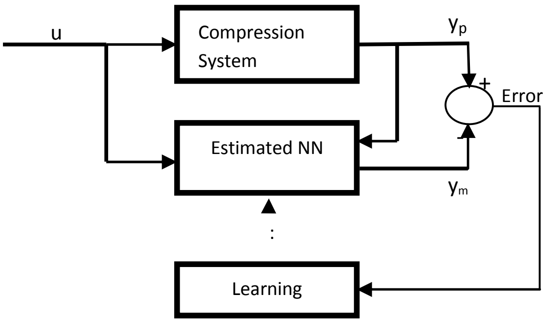


Figure 11. Identification of the recycle compression system

One standard model that has been used for nonlinear identification is the Nonlinear Autoregressive-Moving Average (NARMA) model [13]:

$$y(k+d)=h\left[y(k), y(k-1),\ldots, y(k-n+1), u(k), u(k-1),\ldots, u(k-m+1)\right] \tag{12}$$

Where *u(k)* is the system input, *y(k)* is the system output and "*d*" is the system delay of the predictive controller. For the identification phase, we train a neural network to approximate the nonlinear function "*h*". The structure of the neural network plant model is given in Figure 11 and the equation for the plant model is given by:

$$y_m(k+1)=\hat{h}\left[y_p(k), y_p(k-1),\ldots, y_p(k-n+1), u(k-1),\ldots, u(k-m+1); X\right] \tag{13}$$

Where "$\hat{h}$" is the function implemented by the neural network, (*n*, *m*) represent the order of the recycle compression system which is known, "*x*" is the vector containing all network weights and biases.

The neural network model predicts the plant response over a specified time horizon [13].

$$J = \sum_{j=N_1}^{N_2} \left(y_r(k+j)-y_m(k+j)\right)^2 + \rho \sum_{j=1}^{N_u} \left(u(k+j-1)-u(k+j-2)\right)^2 \tag{14}$$

Where N_1, N_2 and N_u define the horizons over which the tracking error and the control increments are evaluated. The y_r is the desired response and y_m is the network model response. Figure 12 illustrates the model predictive control process.

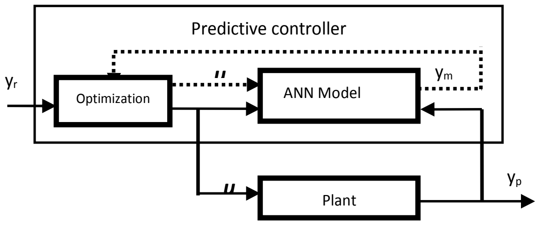


Figure 12. Neural Network Predictive Control Model

Classification of data was performed using the MATLAB Neural Network Toolbox. A feed forward network with a pure line transfer function in last neuron was created (Figure 13) and used for the experiment [13].

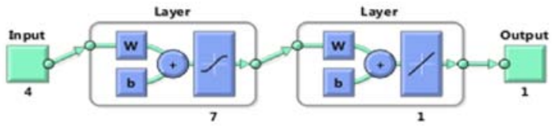


Figure 13. Architecture of artificial neural network

The results of simulation of the recycle compression system by Predictive identification are shown by Figure 14

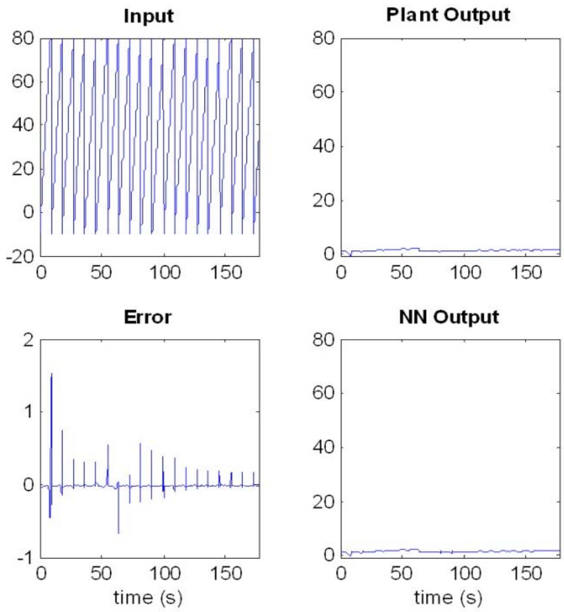
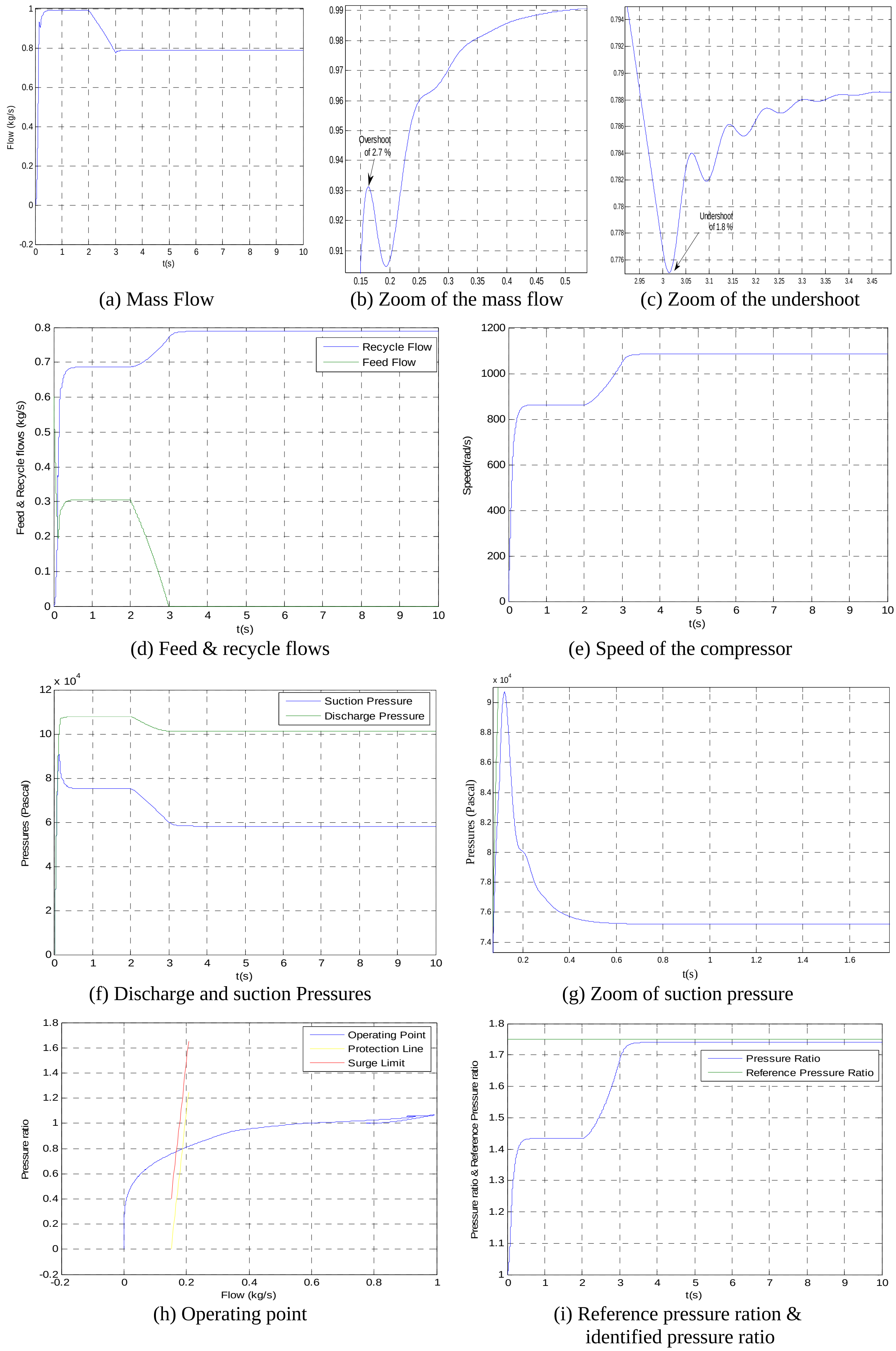


Figure 14. Real output and neural network estimated output of the recycle compression system

Now we will demonstrate the predictive controller by applying it to a compression system where the objective is to maintain the compressor working in the stable region. To keep the compression system in the stable region of the compressor map, initially, for simulation, the pressures in the two volumes are set to ambient pressure while the compressor speed and the mass flow are both set to zero. In the other hand, the throttle and the feed flows are taken at their initial states.



(a) Mass Flow (b) Zoom of the mass flow (c) Zoom of the undershoot

(d) Feed & recycle flows (e) Speed of the compressor

(f) Discharge and suction Pressures (g) Zoom of suction pressure

(h) Operating point (i) Reference pressure ration & identified pressure ratio

Figure 15. The closed loop compression system with the predictive controller

Next, we close the feed flow valve at the time t=2sec to disturb the system (Figure 15d). At this moment the tuned predictive controller opens gradually the recycle valve (Figure 15d) to compensate the flow in the suction plenum (Figure 5 and Figure 6) in order to stabilize the system, as a result:

– The mass flow decreases to 0.788 kg/s with an undershoot of less than 1.8% (Figure 15a)
– The suction pressure decreases from 7.53 x 10^4 Pa and stabilizes at 5.82 x 10^4 Pa (Figure 15f);
– The discharge pressure decreases from 11.78 x 10^4 Pa and stabilizes at 10.13 x 10^4 Pa (Figure 15f);
– The rotation speed increases from 863 rad/s and stabilizes at 1085 rad/s without overshoots (Figure 15e).
– The pressure ratio of the compression system reaches the reference pressure ratio after 3 second (Figure 15i);

We observe that the operating point never reaches the surge line (Figure 15h). The operating point is situated to the left of the surge line only during starting of the compression process, so it is better to start the compression system manually.

6.2 Neural network NARMA L2 control

The neuro-controller represents a feedback linearization control where the nonlinear system dynamics are transformed into linear dynamics by cancelling the nonlinearities.

The first step in using NARMA-L2 control is to identify the system to be controlled. The NARMA-L2 approximate model is given by [9] (Eq. (15)):

The model of NARMA-L2 is in companion form, where the next controller input *u(k)* is not contained inside the nonlinearity.

Figure 16 represents the block diagram of the NARMA-L2 controller.

The form of NARMA-L2 controller [9] is Eq. (16):

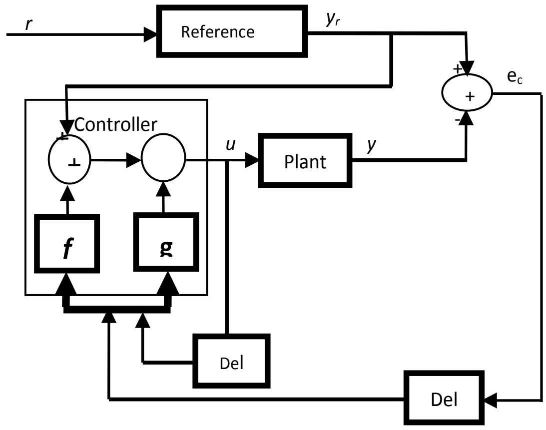


Figure16. Structure of NARMA-L2 Controller

The real data and estimated output of the recycle compression system obtained by NARMA identification are shown by Figure 17.

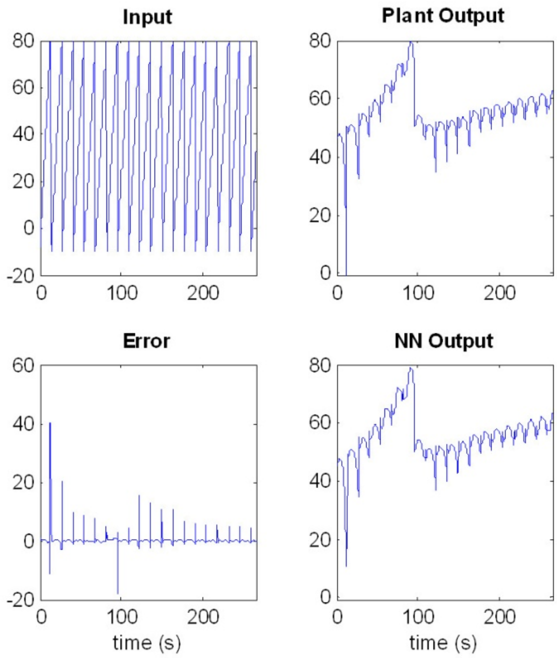
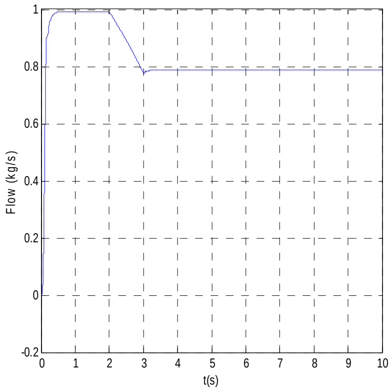


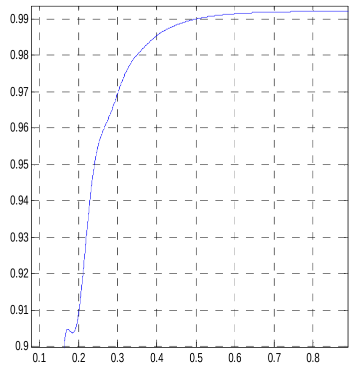
Figure 17. Real output, and NARMA estimated output of the recycle compression system.

$$\hat{y}(k+d) = f\left[y(k), y(k-1),....,y(k-n+1),u(k),u(k-1),....,u(k-m+1)\right] + g\left[y(k), y(k-1),....,y(k-n+1),u(k),u(k-1),....,u(k-m+1)\right].u(k) \quad (15)$$

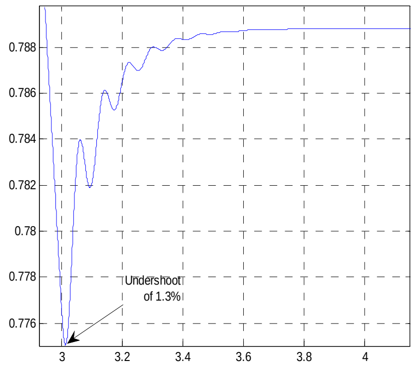
$$u(k)=\frac{y_r(k+d)-f\left[y(k),y(k-1),....,y(k-n+1),u(k),u(k-1),....,u(k-m+1)\right]}{g\left[y(k),y(k-1),....,y(k-n+1),u(k),u(k-1),....,u(k-m+1)\right]} \quad (16)$$



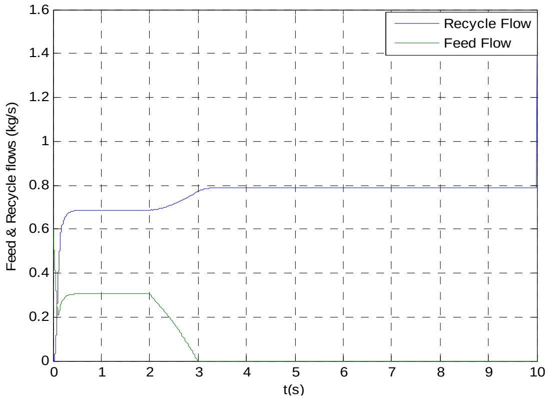
(a) Mass Flow



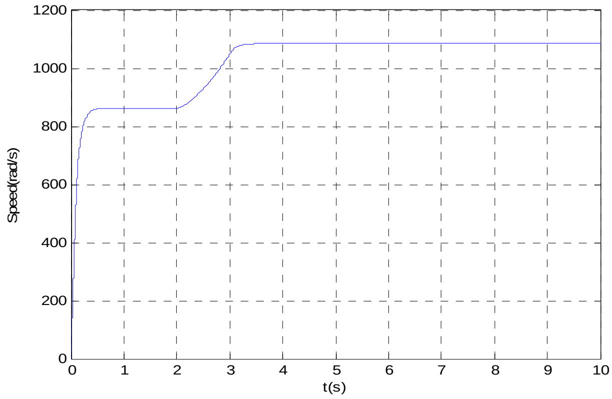
(b) Zoom of the mass flow



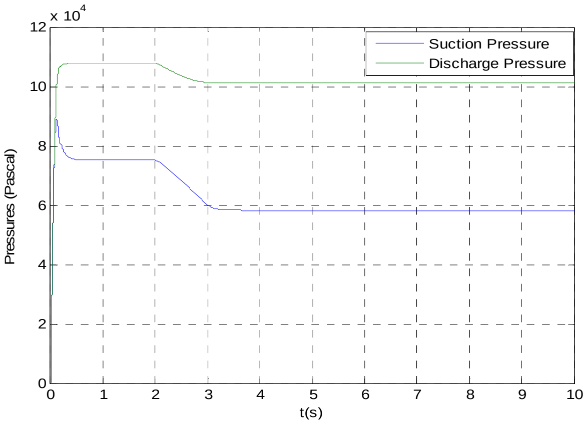
(c) Zoom of the undershoot



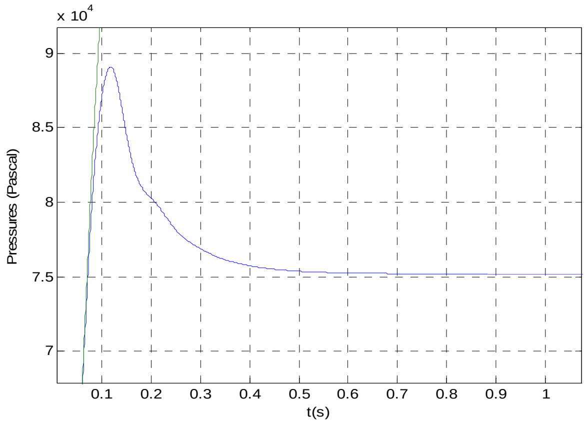
(d) Feed & recycle flows



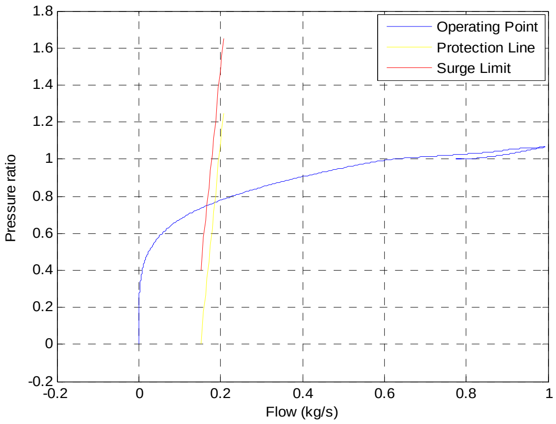
(e) Speed of the compressor



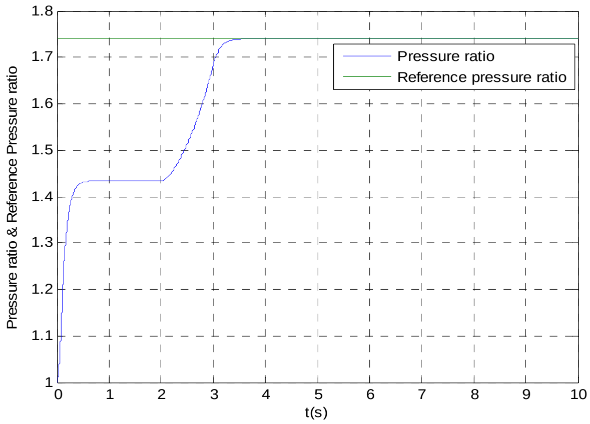
(f) Discharge and suction Pressures



(g) Zoom of suction pressure



(h) Operating point



(i) Reference pressure ration & identified pressure ratio

Figure 18. The closed loop compression system with the NARMA L2 controller

Now, we will explore the NARMA L2 Controller that is based on the use of neural networks to identify and control our compression system. Therefore, the objective is to maintain the compressor working in the stable region too.

Initially, for simulation, the pressures in the two volumes are set to ambient pressure while the compressor speed and the mass flow are set to zero. The throttle and the feed flows are taken at their initial states.

Next, we close the feed flow valve at the time t = 2 sec to disturb the system (Figure 18.d). At this moment the tuned NARMA L2 Controller opens the recycle valve to compensate the flow in the suction plenum (Figure 4) in order to stabilize the system, as a result:

- The mass flow decreases from 0.992 kg/s to stabilize at 0.788 kg/s with an undershoot of 1.3% (Figure 18a);
- The suction pressure decreases from 7.52 x 10^4 Pa to stabilize at 5.82 x 10^4 Pa (Figure 18f);
- The discharge pressure decreases from 10.78 x 10^4 Pa to stabilize at 10.13 x 10^4 Pa (Figure 18f);
- The rotation speed increases from 862.8 rad/s to stabilize at 1085 rad/s (Figure 18e);
- The pressure ratio of the compression system reaches the reference pressure ratio after 3 second (Figure 18i);
- The operating point never reaches the surge line (Figure 18h). Indeed, the operating point is far away from the surge line.

7. Discussion

NN Predictive control and NARMA-L2 algorithm are implemented using back-propagation networks. The number of neurons in the hidden layer represents the degree of complexity of the system, and the ability of input layer to store information.

Comparing now between the results got by the predictive controller and those of the NARMA L2 controller, we conclude the following:

- In the case of the predictive controller, the mass flow oscillates with a big undershoot after the automatic opening of the recycle valve (Figure 15b and Figure 15c);
- In the predictive controller, the compression system pressure ratio follows the reference pressure ratio after 3.6 sec, the time of closing the feed forward valve, with an error of 2%. While the NARMA L2 controller follows the reference pressure ratio after 2.6 sec with an error of 0%. Therefore, the NARMA L2 controller gives more accurate results than the predictive controller;
- The compressor speed: for the predictive and NARMA L2 controllers, notice that the high speed value that our compressor reaches is 1085 rad/s;
- The discharge pressure has the same behaviour in the predictive or NARMA controllers. But the suction pressure in the predictive controller starts with big oscillation comparing to the NARMA controller (Figure 15b and 18b);
- The operating point of the compressor: to ensure a safe operation of our compressor, this latter should not operate in a region of higher flows. In fact, it is to operate just in the safe region because operating in the surge region lead to compressor's damage;
- By comparing the performance of NN predictive controller, Fuzzy logic and PID controllers developed in reference [11], it is observed that NARMA-L2 controller is faster and has good set point tracking capability.

Thus, for identification based on neural networks, the NARMA-L2 controller is the best, more accurate and suited controller for our compression system.

Until now, we dealt with the NN predictive and L2 NARMA controllers in which the identification algorithm using neural networks is integrated with the control part.

8. Conclusion

The aim of all compression systems that exist in industry is to stabilize the operation of the compressor with maximum pressure ratio and performances. In this paper we have presented a brief introduction to identify and control the system by neural networks. Two different methods of identification by neural networks integrated with two controllers are presented in this paper. The first is using the predictive controller, and the second is using the NARMA L2 controller.

The NARMA L2 controller gives optimal results in terms of mass flow oscillations which are undesirable and lead to chocks waves of gases in recycle compression systems. So the implementation of artificial neural network in recycles compression system in petroleum companies is better than the actual control using PID controllers (developed in [11]).

Finally the neural network is successfully used to model and solve the problem of surge in centrifugal compressors by keeping the system at its stable region with optimum recycled gases.

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