A Neo-Fuzzy Approach for Bottom Parameters Estimation in Oil Wells

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Abstract: - In this work, an approach for the bottom parameters estimation in oil wells is presented. It is based on neural networks and fuzzy logic, specifically on the neo-fuzzy-neuron model. We propose a neo-fuzzy system compose by two neo-fuzzy neurons. For validating the results, the estimation is applied in oil wells based on the artificial gas lift method, using variables of the head of the wells, particularly the gas and production pressures.

Key-Word: - neuro-fuzzy models, oil system production, artificial gas lift wells, parameters estimation, neo-fuzzy neurons, oil wells.

1 Introduction

Hydrocarbons are produced from wells that penetrate geological formations rich on oil and gas. The wells are perforated in the oil and gas bearing zones. The hydrocarbons can flow to the surface if the reservoir pressure is enough to overcome the pressure from the flowing fluid column in the well and the pressures in the surface facilities. Detailed information on wells completion can be found in [2,4].

The possibility of installing devices for the bottom and surface variables measurement, allows identifying the real contribution of the reservoir in the production flow that comes from specific zones, in the production flow displacement on the well, and in the supervision and control at level of the head of the wells [4].

The majority of well completions (tubing mechanical arrangement) traditionally do not use bottom technology, which give quantity information about the reservoir. The use of this technology is highly expensive: its installation would require wells paralyzing, the useful life is very short, (minor to 5 years) and the maintenance costs are high. These are some of the reasons for which existing wells do not use that technology to measure the bottom variables.

For these reasons, in this work we propose the estimation of the bottom pressure (Pwf_{INF}) using Artificial Intelligence techniques. Specifically, we use the neo-fuzzy neuron model [6, 13, 14, 15]. We propose a neo-fuzzy system compose by two neo-fuzzy neurons. In general, neuro-fuzzy systems have been develop for control and supervision of industrial processes, and they have demonstrated to be very effective, particularly when the managing of the knowledge, or the decisions making, play an important factor [3, 6, 7, 8, 9, 10, 11, 12]

The validation of bottom variables estimation will be realized through an index, which consists in calculating the differences between the following Pressures: the measured tubing production pressure (THP) and the estimated tubing production pressure (THP_{INF}); if the result is minor that a β factor, it indicates that the bottom estimation (Pwf_{INF}) is correct. For this reason, we need to estimate this second variable (THP_{INF}), and then to use it to estimate Pwf_{INF}.

This approach has been used in PDVSA (Venezuelan Oil Company), specifically in gas lift oil wells. The gas lift method consist of injecting gas to a pressure determined in the low part of the column of fluid of the tubing of the well, to different depths,

2 Neo-Fuzzy Neuron Models

Artificial neural networks consist of a system that tries to emulate the biological neural networks behavior concerning the learning and the generalization capabilities. With the purpose of taking advantage of artificial neural networks, and the capacity of handling vague information provided by the fuzzy logic models, a new structure, called neo-fuzzy neuron, has been proposed, which has demonstrated to give good results in the behavior representation of complex systems [5,6, 13, 14, 15].

Neo-fuzzy neuron constitutes a tool that offers great advantages for modeling complex systems by the simplicity of its structure, consisting of a single neuron, which the difference enormously of the artificial neuronal networks, where several neurons are included, and can be numerous when the system to be modeled is very complex. Whereas in artificial neural networks it is necessary to change the number of layers, the number of neurons in each layer, and the activation function to find the structure that obtains a good adjustment to the modeled problem; in the neo-fuzzy neuron it is only necessary to change the number of fuzzy partitions in the input variables, allowing this way to find the most suitable structure with greater facility.

The structure of the neo-fuzzy neuron is shown in fig. 1, where the synaptic weights are not constant but nonlinear functions of the inputs, represented by fuzzy logic models based on a collection of “If – Then” rules, that use an approximated reasoning in the inference process. This structure does not have an activation function, but it has a summing point, which generates the output, adding the fuzzy logic model outputs for each input [5, 13, 14, 15].

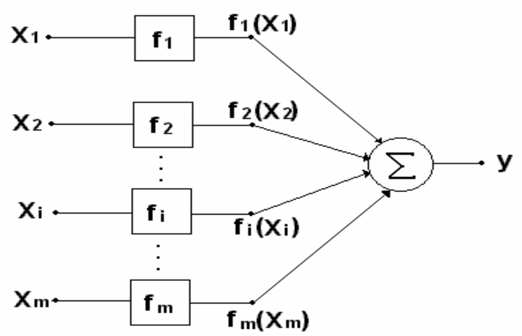

Fig. 1. Neo-Fuzzy Neuron

The input variables spaces are divided in several segments that will constitute the fuzzy subgroups of each variable. Each of these segments can be characterized by a triangular complementary membership function, as it is shown in Fig. 2.

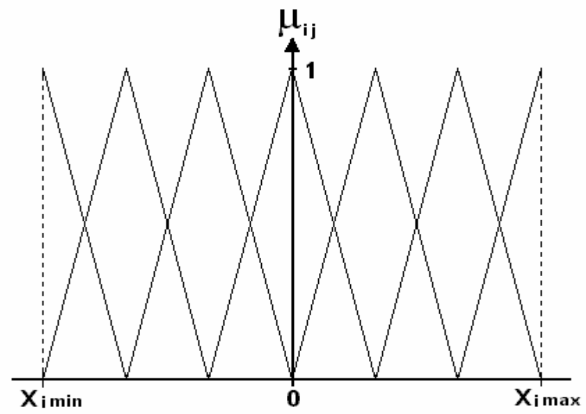

Fig. 2. Membership Functions

The output synapses of each fuzzy logic model is obtained by means of an inference mechanism using fuzzyfication and defuzzyfication processes, as is shown in Fig. 3.

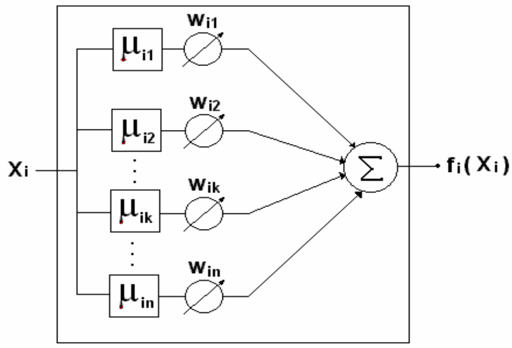

Fig. 3. Neo Fuzzy Neuron Synapse

As in conventional artificial neural networks, learning in a Neo-fuzzy neuron consists on synapse modification, in such a way that the errors between the desired outputs and the neuron outputs are minimized. Whereas in Neo-Fuzzy neurons the synapse is represented by a fuzzy logic model with a set of “If – Then” rules, whose consequent are constant weights, and for a single signal input two rules are always activated, the constant weights of each synapse that influence the output are two and these are due to modify to obtain the desired output. This way, the learning for a Neo fuzzy neuron consists of modifying two weights of each synapse, corresponding to the activated rules related to a specific input, until obtaining the desired output. This is made by means of a classical gradient descendent algorithm with the objective of minimizing the error between the desired outputs and the neuron outputs [7, 8, 9, 10, 11, 12] .

The process of training consists of the presentation of each one of the patterns. Every pattern of input activates only two rules, as it will be observed late, which are the weights of every synapse that influence the exit, for this reason these must be modified to achieve the wished exit. The adjustment of weights is done according to the equation (1). During the training of a fuzzy neuron, several cycles of training must be executed, up to achieving a good adjustment of the model. Therefore, the learning for a fuzzy neuron consists in modifying one or two weight of every synapse, correspondent to the rules activated due to a specific input, up to achieving the desirable output.

$$W_{ik}(T+1) = w_{ik}(T) + \Delta w_{ik}(T) \quad (1)$$

The fuzzy neuron output "y" is given by the following equation:

$$y = f1(x1) + f2(x2)..+ fm(xm) = \sum_{i=1}^{m} fi(xi) \quad (2)$$

Where f(x) is a classical defuzzyfication function [6, 13, 14, 15].

3 Production Process of an Oil Well

One of the most important components in the well system is the reservoir. Unless accurate predictions can be made as to what will flow into the borehole from the reservoir, the performance of the system cannot be analyzed. The flow into the well depends on the bottom pressure in the well (Pwf), and the static pressure of the reservoir (Pws). The relationship between flow rate and these pressures occurring in the porous medium, can be very complex, and it depends on parameters such as rock properties, fluid properties, flow regime, fluid saturations in the rock, formation damages or stimulations, turbulence and drive mechanisms, etc. It also depends on the reservoir pressure itself and, depending on the drive mechanisms, this may decrease with the time or the cumulative production.

The process of production in a well of oil or gas begins from the external radius of drainage in the reservoir to the tanks where the oil is stored. The Fig. 4 shows the complete system with four clearly identified components: the Reservoir, the Completion, the Well and the Flow Surface Line. In in the above mentioned process, the initial pressure is Pws, and the final pressure is the pressure of the separator on the station of flow, Psep.

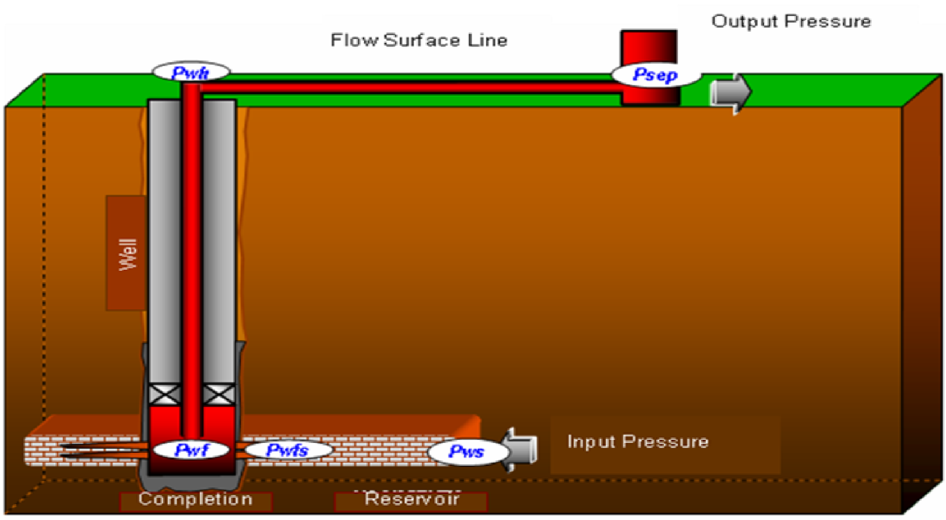

Fig. 4. Productive Process of a Well

The movement of the fluids begins in the reservoir to a distance "re" of the well, where the pressure is Pws. The fluids travel across the porous medium up to coming to the face of the sand or radius of the hole, "rw," where the pressure is Pwfs. In this area, the fluid loses energy in the measure that the medium is of low capacity of flow (Ko), there are restrictions in the proximity of the hole (damage, S) and the fluid offers resistance (mo).

The bigger it is the hole, better will be the communication between the reservoir and the well, increasing the index of productivity of the well. On having crossed the completions, the fluids enter to the bottom of the well with a pressure Pwf. Inside the well, the fluids ascend across the pipeline of production conquering the force of gravity and the friction in the internal walls of the pipeline. In the well head, the resultant pressure is identified as Pwh.

The loss of energy in the shape of pressure across every component (see Fig.5), depends on the characteristics of the produced fluids, and specially, the transported flow, in such a way that the capacity of production of the system is equal to the balance between the capacity of energy input of the reservoir and the demand of energy of the installation to transport the fluids up to the surface.

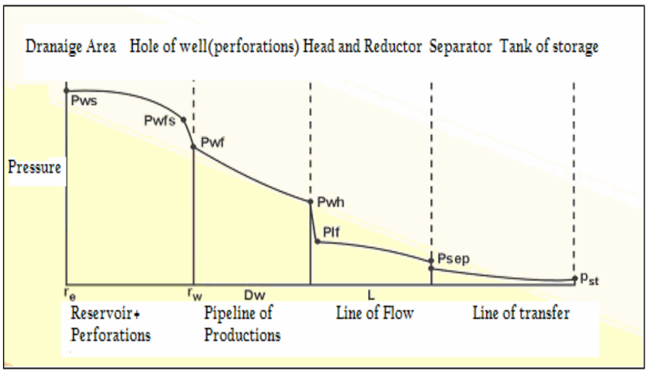

Fig. 5. The loss of energy in a Systems of Production

3.1 Gas Lift Methods

Gas lift is a technology to produce oil and gas from wells with low reservoir pressure, by reducing the hydrostatic pressure in the tubing. Gas is injected into the tubing, as deep as possible, and mixes with the fluid from the reservoir (see Fig. 6). The gas reduces the density of the fluid in the tubing, which reduces the bottom pressure, Pwf, and thereby increases the production from the reservoir. The lift gas is routed from the surface to the annulus, the volume between the casing and the tubing. The gas inputs the tubing through a valve, an injection orifice.

The dynamics of highly oscillatory flow in a gas lifted well can be described as follows:

(1) Gas from the casing starts to flow into the tubing. As gas inputs the tubing the pressure in the tubing falls. This accelerates the inflow of gas.
(2) The gas pushes the major part of the liquid out of the tubing.
(3) Liquid in the tubing generates a blocking constraint in the injection orifice. Hence, the tubing gets filled with liquid and the annulus with gas.
(4) When the pressure on the injection orifice overcomes the pressure on the tubing side, a new cycle starts.

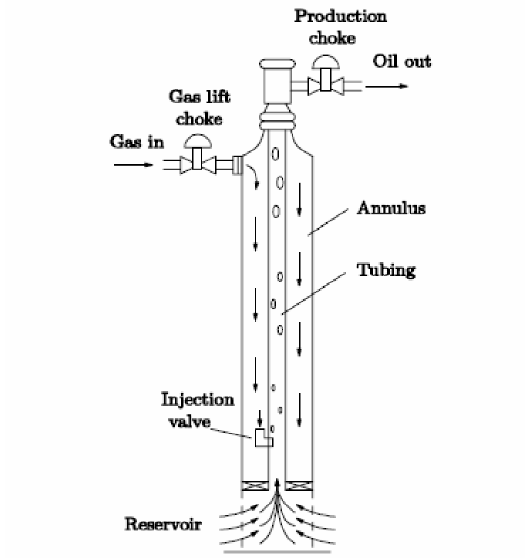

Fig. 6. The Artificial Gas Lift

The Artificial Gas Lift (AGL) well behavior's model (Fig.7) indicates that: when the gas injection rate increases, the production also increases until reaching its maximum value; but additional increases in the gas injection will cause a production diminution [3,5]. The curve shows under which conditions the well exhibits stable or highly oscillatory flow. It is important to note that the average production rate may be significantly lower with unstable (see the line "open loop production"), compared to stable well flow (see the line "theoretical production").

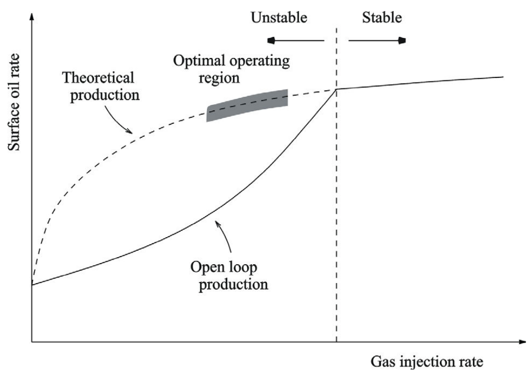

Fig. 7. Artificial Gas Lift well behavior's model

Large oscillations in the flow rate from the well cause lower total production, poor oil/water separation, limits in the production capacity, etc. A reduction of the oscillations increases the production capacity.

Unstable operational conditions may occur in a gas lift well because the characteristics of the systems are such that small perturbations can degenerate into huge oscillations in the flow parameters. Unstable production may lead to periods of reduced, or even no production.

At the highest gas injection rates, the pressure in the tubing is dominated by friction. If GOR (Gas Oil Ratio) rises, the tubing pressure will increase which will reduce the gas injection rate. This region therefore ensures stable production and explains why well stabilization by increased gas injection can be successful.

At low gas injection rates however, the hydrostatic pressure gradient dominates the pressure in the tubing. A small increase in GOR results then in a lower tubing pressure, which leads to a higher gas injection rate from the annulus to the tubing through the gas lift valve. Since the gas rate is restricted by a gas injection choke at wellhead, the gas pressure in the annulus will be reduced. After a time, the gas rate into the production tubing will therefore be reduced, with resulting lower oil production rates.

To illustrate the stability problem, a description of a heading cycle is given below (see fig. 6):

(1) Starting with an annulus pressure that is lower than the bottom pressure, there is no gas flow through the gas lift valve into the tubing. Production rate and gas/liquid ratio is low. Gas is injected through the gas injection choke and annulus pressure builds up.

(2) After some time, the annulus pressure exceeds bottom pressure, and gas is injected into the tubing through the gas lift valve.

(3) The injected gas lightens the tubing gradient so that bottom pressure begins to decrease. Simultaneously, the production rate of the wellhead tubing pressure begins to increase.

(4) Gas now flows from the annulus to the tubing at an increasing rate. Because insufficient gas can be supplied through the gas injection choke, annulus pressure decreases rapidly.

(5) Oil and gas are produced through the production choke at high rate. Wellhead tubing pressure passes through a maximum and bottom pressure passes through a minimum.

(6) With decreasing annulus pressure, gas flow through gas lift valve decreases. The gradient in the tubing becomes heavier and bottom pressure increases. The production rate and wellhead tubing pressure decreases again.

(7) When bottom-hole pressure exceeds annulus pressure, gas injection into the tubing stops. With continued gas injection rate at the wellhead, annulus pressure starts to build again.

Unstable production of gas lifted wells causes many drawbacks, and it implies safety aspects and shutdown risks. The total oil and gas productions must usually be less than the systems design capacity.

For the implantation in field of the AGL method, it is needed an instrumentation arrangement and control [1,2]; for such task, we need the measurement and control of the following variables (see Fig. 8): Pressure of the Injected Gas (GLP), Differential Pressure of the Injected Gas (GLDP), Pressure of the Casing (CHP), Pressure of the Tubing of Production (THP). The measurement of the injected flow is carried out using the GLP and GLDP variables. The measurement of the pressure casing (CHP) allows knowing the pressure that the gas exercises in the casing, and (THP) the pressure exercised by the fluids in the pipeline and the pressure of the line of production (PLP). Other important variables are: the Gas flow of lift (FGL, expressed as "mpcgd"-thousands of gas cubic foot per day), the Rate of Production (Qprod, expressed as "BNPD"-barrels net of production per day).

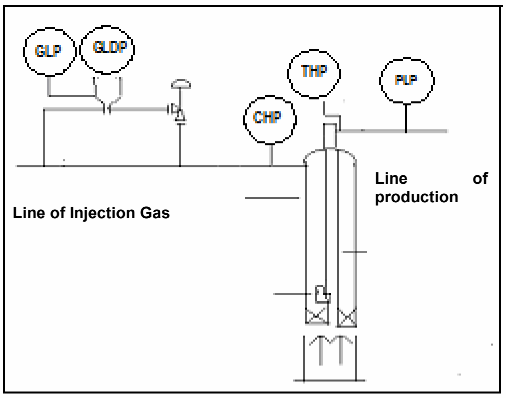

Fig. 8. Schematic design of the Well with the Extraction Gas Lift Method

4 Neo Fuzzy System Application

4.1 Study Case: Gas Lift Wells

Fig. 9 shows the neo fuzzy structure proposed in this work. There are two neo-fuzzy neurons: the identified as ND1 will estimate THP with the variables of surface GLP, GLDP and CHP. The identified as ND2 will estimate the pressure of bottom, which will take as input the variables ND1 (THP_{INF}) and THP. Finally, to validate the estimated values of the bottom pressure (Pwf_{INF}), we propose an index, which consists of calculating the difference between THP_{INF} and THP_{INF} ($|THP-THP_{INF}|$); If it is minor to β, indicates that the value is correct, otherwise new values of bottom must be registered, due to the presence of an operational scenario of bottom different to that used to train the neo-fuzzy system.

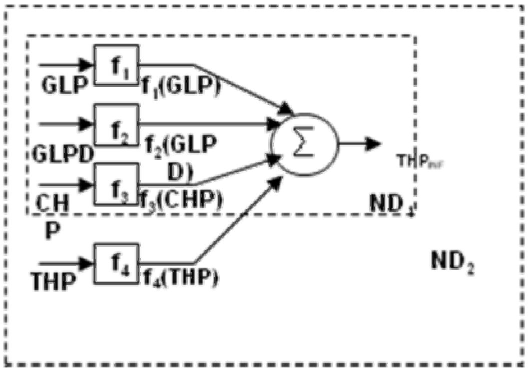

Fig. 9. Neo-fuzzy Scheme for the Surface Pressure (ND_1) and Bottom Pressure (ND_2) Estimation

The well characteristics where the system was implemented are the following: It flows towards the Flow Station located at 5360,89 ft, and receives gas lift from the gas Manifold located at 508,53 ft far from it. It presents a 25 API crude Gravity, 6% of water Cut, and the bottom of the hole is at 3489ft. The valve is at 3184 ft (see Table 1).

Table 1. Physical Properties of the Flow

PVT	
Oil Gravity (API)	25°
Water Cutr (%)	6,02
Depth Perforation (ft)	3489
Temperatura (F)	60
Valve (ft)	3184

One of the most used techniques for optimizing the crude and gas production systems, considering its verified effectiveness, is the Nodal Analysis [1,2]. In order to optimize the Production system using this technique, it is necessary describing the production system, making emphasis in the required energy balance between the reservoir and the installed infrastructure, for establish the production capacity of the well. For this, it is necessary to construct a well model with the reservoir and production variables.

Using the Nodal Analysis technique, at the well head, the energy balances were made with several gas injection flow rates, and for each one of the reservoir pressures. That gives the volume of production of the well and the pressure required in the well output for transporting it to the separator. The well shows level of production in the order of (250±5) BPND, with a gas injection of (0,5±0,1) mpcgd, the values have been obtained from the level of the flow station (see fig. 10).

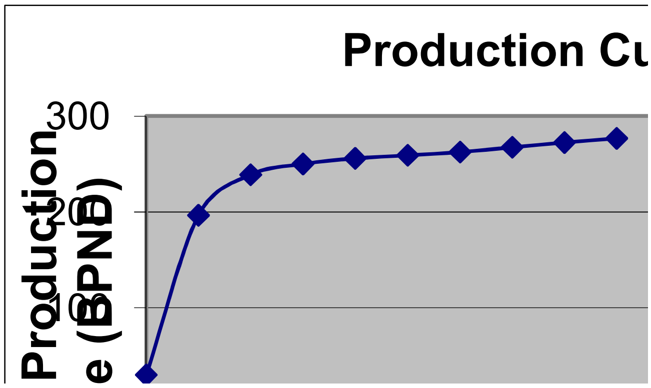

Fig. 10. Production Curve

In (Figs. 11 and 12) appear the records of the bottom and surface variables, which will be used like patterns in the training of the fuzzy neurons. In the Fig. 11 we present the profile of the tubing pressure (THP), obtained with the system of intelligent instrumentation implanted in field [1], where the behavior of the THP is observed that has a stable behavior, with oscillations minor to 5 % with regard to the value of reference (175 psi) obtained across the Model of Production of the Well [2].

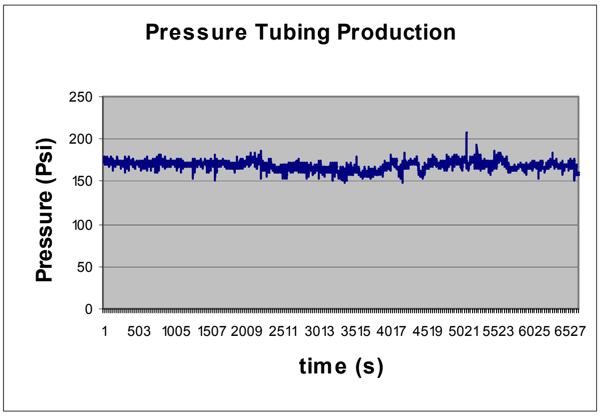

Fig. 11. Tubing Pressure

On the other hand, at the level of the well surface we have installed a portable system "FGS" (optical fiber device that registers values of pressure and temperature at level of the hole bottom), which consists on an optical fiber, a laser source, an analyzer, and transmitters of temperature and pressure to the surface of the well. In the Fig. 12 we present the profile of pressure of bottom to a depth of 3400 ft. It is important to indicate that the "FGS" system was used to record temporarily the pressure of bottom, because the utilization of this device is very expensive.

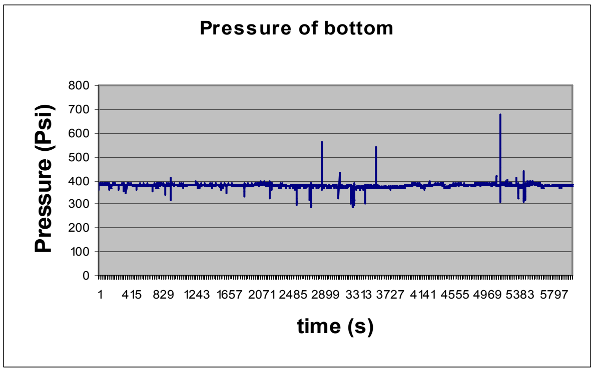

Fig. 12. Bottom Pressure of the well

4.2 Process of Training

The first step is the sampling of the input and output variables in the same instant of time, for each group of samples to be used in the training of the neo-fuzzy neurons. Later, we need to normalize the inputs and outputs (min, max) to carry out the fuzzy partition. We are used triangular functions of membership. The weights have been modified to achieve the desirable output, changing also the fuzzy partitions. Finally, the model was validated by values not used during the process of training (30% of the total pattern).

For ND_1, we propose a neo-fuzzy neuron of three inputs and one output, to estimate the tubing pressure (THP_{INF}), where the variables of input are GLP, GLDP and CHP, and the output is THP (see Table 2).

Table 2. Examples of Training Patterns for ND_1

Pattern	GLP	GLDP	CHP	THP
1	1705,88	9,57	1619,50	171,71
2	1723,91	11,33	1624,37	174,12
3	1720,50	10,49	1627,59	178,82

For each input fuzzy variable we suppose three fuzzy values and initialize their weights with random values. The neo-fuzzy neuron has the structure showed in Fig. 13.

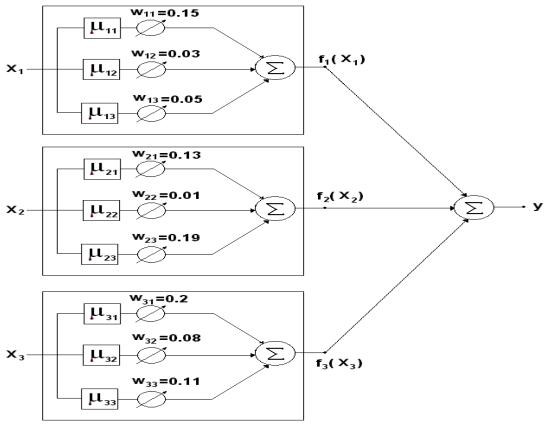

Fig. 13. Scheme of the first Neo Fuzzy Neuron

Now, we give an example of fuzzification of the variable values. The calculation of the membership degrees for GLP =1705,88806 in each fuzzy set of this variable, denoted by $\mu 11, \mu 12$ y $\mu 13$, is shown in Fig.14. These degrees of membership have the following values: $\mu 11 = 0.608$, , $\mu 12 = 0.392$, $\mu 13 = 0$.

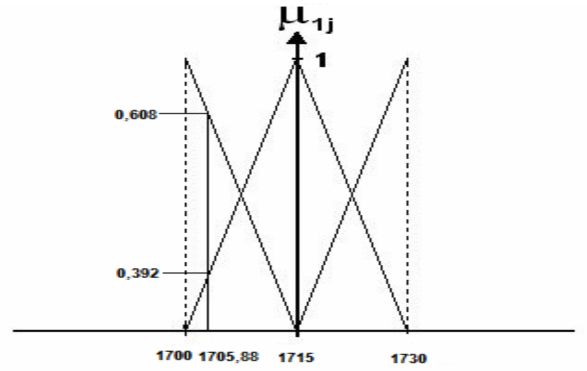

Fig. 14. Fuzzification of GLDP

The calculation of the degrees of membership for GLDP = 9,57197762 and CHP = 1619,50378 in their respective fuzzy sets, give the following results: $\mu 21 = 0.245$, $\mu 22 = 0.785$, $\mu 23 = 0$; $\mu 31 = 0.5$, $\mu 32 = 0.5$ and $\mu 33 = 0$.

Once obtained the values of the membership degrees, the synapse for the inputs are given by:

f_1(GLP) = 0.15 * 0,608 + 0.03* 0,392 + 0.05* 0 = 0.10296

f_2(GLDP) = 0.13* 0.214 + 0.01* 0.785 + 0.19* 0 = 0.0356

f_3(CHP) = 0.2 * 0.5 + 0.08* 0.6 + 0.5* 0.11*0 = 0.14

Therefore, the output of ND_1 for the input pattern 1 is given by:

THP = 0.10296+0.0356+0.14=0.278

When the first pattern have been presented, the system must update only the weights associated with the fuzzy sets in which the degrees of membership are different of zero. The update of the weights is done using the following equation:

$$w_{ik}(T+1) = w_{ik}(T) - \alpha(y_i - y_{di})\mu_{ik}(x_{ij}) \quad (4)$$

In this way, the update for each weight with the pattern 1, and α= 0.5, is the following:

w_{11} = 0.15 − 0.5 * (0.278 − 171,71666)* 0.608 = 52,267

w_{12} = 0.03 − 0.5 * (0.278 − 171,71666)* 0.392 = 33,63

w_{13} = 0.05 − 0.5 * (0.278 − 171,71666) * 0 = 0,05

w_{21} = 0.13 − 0.5 * (0.278 − 171,71666) * 0,2145 = 18,516

w_{22} = 0.01 − 0.5 * (0.278 − 171,71666) * 0,785 = 42,901

w_{23} = 0,19

w_{31} = 0.2 − 0.5 * (0.278 − 171,71666)* 0.5 = 43,059

w_{32} = 0.08 − 0.5 * (0.278 − 171,71666)* 0.5 = 42,939

w_{33} = 0,11 - 0.5* (0.278-171,7166)* 0 =0,11

The same procedure showed previously for the pattern 1, must be applied for the rest of the patterns, up to achieving a good fit. The number of training cycles is select by the user.

We have followed a similar procedure to training the neo-fuzzy neuron ND_2. In this case, we have used the Pwf measured using the "FGS" system.

4.3 Obtained Results

In the Table 3 and the Figures 15 and 16 are presented the results obtained for the estimation of the tubing and bottom pressures with our neo-fuzzy system.

Table 3. Patterns of training

Inputs	Output	Training Pattern	Test Pattern	Quadratic Error
GLP, GLDP, CHP (throught output ND_1=> THP_{INF}), and THP	*Pwf_{INF} (ND_2)*	3250 (50%)	3250 (50%)	0,087
GLP, GLDP, CHP	*THP_{INF} (ND_1)*	350 (50%)	350 (50%)	0,59%

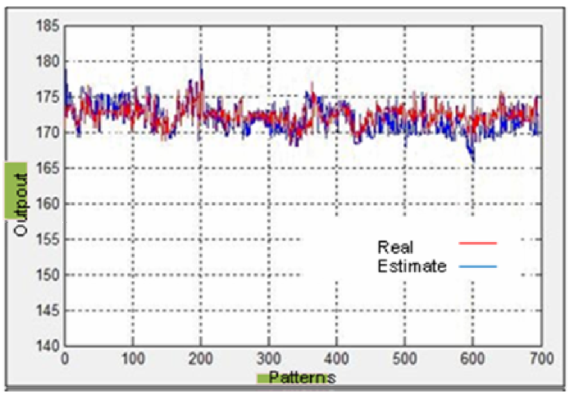

Fig. 15. Neo-Fuzzy Estimation of the Bottom Pressure

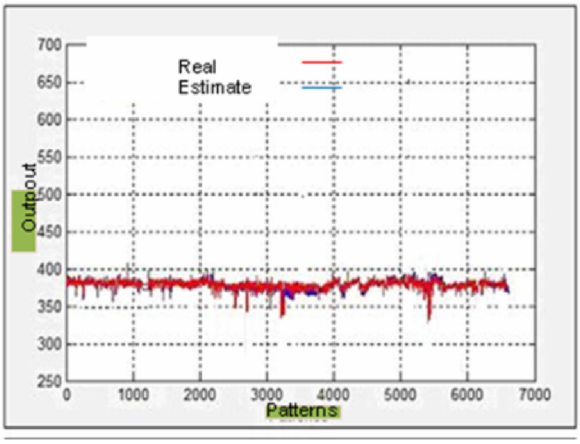

Fig. 16. Neo-Fuzzy Estimation of the Tubing Pressure

The obtained results in both neo-fuzzy neurons are satisfactory. The estimation of the bottom and surface variables are correct (the average error for each estimated variable, with respect to the real values are 0.023 and 0.031, respectively), and the quadratic errors of the training-phase were low.

The value of β is minor to 5 psi in the whole cycle of training, reflecting the efficiency of the surface estimation.

4 Conclusions

The system used in this work for variables estimation, is very interesting by its elaboration low-cost. The current data acquisition systems and the databases historical contribute with the information that we need to build these system.

The estimation of the bottom pressure using our system is effective due to follow the dynamic of the measured pressures. The importance of having the value of the bottom pressure at surface level is because it allows make decisions about the possible production of the well, determine its operational state, if the bottom of the well has presence of water, sediments, etc.

The use of the Neo-Fuzzy System allows estimate the variables of bottom and surface, with a quadratic erro minor to 1 %, which indicates the efficiency of the system.

The use of this system to other wells where their production method is different to the GAL Method, or in other reservoir, requires that the neo-fuzzy model be trained with the own operation conditions of the wells, to obtaining reliable results

Acknowledgment

This work has been supported in part by FONACIT under grant 2005000170, CDCHT-ULA under grant I-820-05-02-AA, and PCP Automation Integrated to Processes of Production No. 200500380.

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