Parameters Estimation in petroleum wells using artificial intelligence

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Abstract: - In this work, the Parameters Estimation in petroleum wells is presented; it is based on Intelligent Systems (neural networks and fuzzy logic). For validating the results, the estimation is applied in wells that need artificial lift using well heading data (gas and production pressure).

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

1 Introduction

Nowadays, hydrocarbons reservoirs go together with technology. The possibility of installing devices for the bottom and surface variables measurement, allowing identifying the real contribution of the reservoir: across the production flow that comes from specific zones, the production flow displacement to the well and supervision and control at well head level [4].

The majority of well completation (tubing mechanical arrangement) traditionally there are no bottom technology that prove a quantity information reservoir. The use of this technology is highly expensive. As such as, its installation would require wells paralyzing, useful life (minor to 5 years) and maintenance costs. These are some of the reasons, exists wells that technology do not posses measure of bottom.

For these reasons, in this work it is proposed estimating the bottom pressure (PfINF) using Artificial Intelligence techniques. The validation of bottom variables estimation will be realized through an index, which consists in calculating differences between the Pressures: measured tubing production (THPM) and estimated tubing production (THPINF); if the result is minor that a β factor, it indicates that the bottom estimation (PfINF) is correct, reason for which it is proposed estimating this second variable (THPINF), since the structures of estimation are similar. This approach was applied and executed in PDVSA (Venezuelan Oil Company), realized in gas lift oil wells with promising preliminary results.

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 capability. With the purpose of taking advantage of artificial neural networks and the capacity of handling vague information provided by the fuzzy logic models, a structure called neo-fuzzy neuron has been proposed, which has demonstrated to give good results in behavior representation of complex systems [5, 6].

Neo-fuzzy systems 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. 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, 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 figure 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 posses a summing point that generates the output when adding the fuzzy logic model outputs for each input [6].

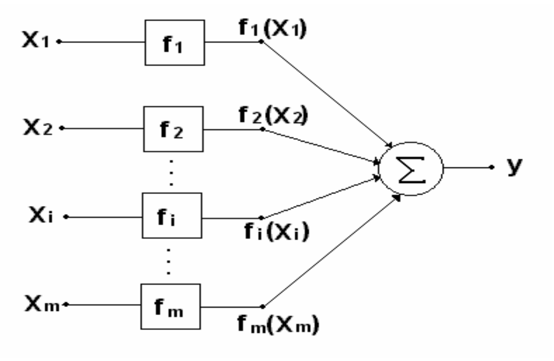

Fig. 1. Neo-fuzzy Neuron

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

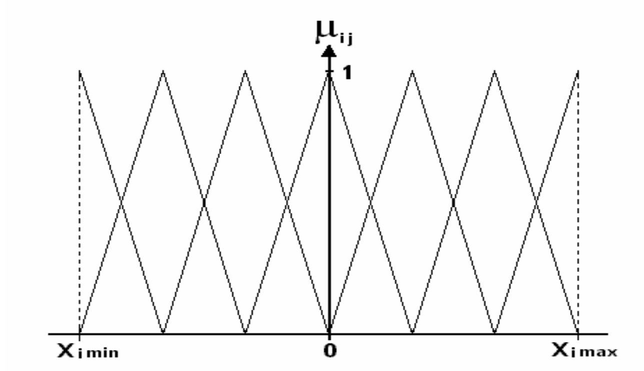

Fig. 2. Membership Functions

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 figure 3.

As in conventional artificial neural networks, learning in a Neo-fuzzy neuron consists about synapse modification in such a way that the errors between the desired outputs of the neuron outputs are minimized. Considering, that 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 constant weight of each synapse, corresponding to the activated rules related to a specific input, until obtaining the desired output. This is made by means of gradient descendent algorithm with the objective of minimizing an error functional.

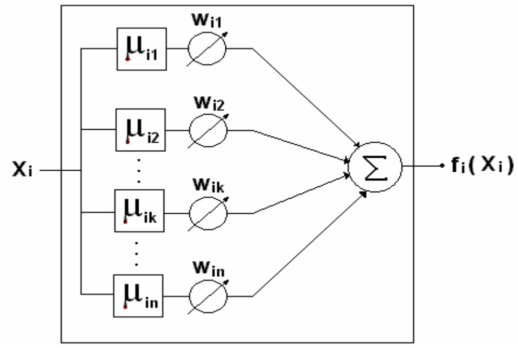

Fig. 3. Neo-Fuzzy Neuron Synapse

The process of training consists of the presentation of each one of the pattern and the weight of the synapse fits, denoted by w_{ik}. Every value of a sign of input activates only two rules, as it will be observed late, which indicates that to applied the process of inference in every fuzzy model, the constant weight of every synapse that influence the exit by one or two, and these are must be modified to achieve the wished exit. The adjustment of this weight is done whenever it appears a pattern of training 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 before a specific entry, up to achieving the desirable output.

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

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

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

3 Gas Lift Method

Gas lift is a technology for producing 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 figure 4). The gas reduces the density of the fluid in the tubing, which reduces the downhole pressure, Pf, and thereby increases the production from the reservoir. The lift gas is routed from the surface and into the annulus, the volume between the casing and the tubing. The gas enter the tubing through an injection orifice valve.

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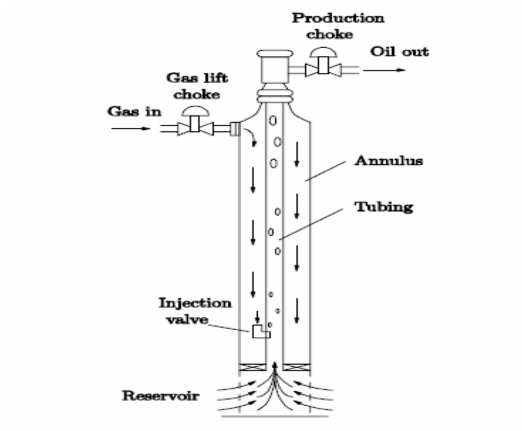

Fig. 4. Artificial Gas Lift

The Artificial Gas Lift (AGL) well behavior's model (figure 5), indicates that: when the gas injection rate increases, the production also increases until reaching its maximum value; but additional increases in the injection will cause a production diminution [2, 3, 5]. The figure 5 shows 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"). Large oscillations in the flow rate from the well causes lower total production, poor downstream oil/water separation, limits the production capacity and causes flaring. A reduction of the oscillation increases processing capacity because of the reduce need for buffer capacity in the equipment process [3].

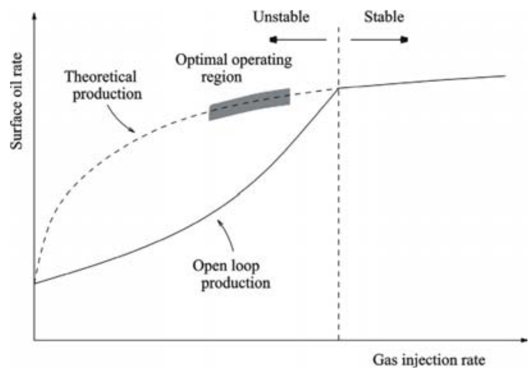

Fig. 5. Artificial Gas Lift well behavior's model

To this respect, for the implantation in field of this method AGL it is needed an instrumentation arrangement and control [1], for such task, there is needed the measurement and control of the following variables (see Figure 6): Gas flow of lift (FGL, expressed "mpcgd" thousands cubic foot gas day), Rate of Production (Qprod, expressed "BNPD" barrels net daily production), Pressure of the Injected Gas (GLP), Differential Pressure of the Injected Gas (GLDP), Pressure of the Casing (CHP), Pressure Tubing of Production (THP). The measurement of the injected flow is realized using the GLP and GLDP variables. The measurement of the pressure casing (CHP) allows to know the pressure that the gas to exercises in the casing, and (THP) the pressure exercised by the fluids multiphase in the pipeline and line of production (PLP).

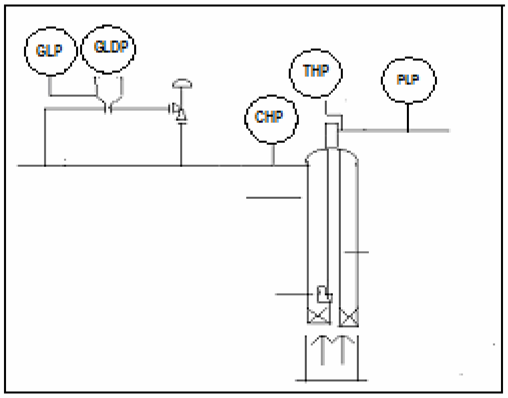

Fig. 6. Schematic design of the Well with Extraction Gas Lift Method

4 Neo-fuzzy System Application Results

4.1 Case Study: Gas Lift Well

Figure 7 shows neo-fuzzy structure, these are some of the functions: the identified with ND1 the will allow estimating THP with the variables of surface GLP, GLDP and CHP. The identified with ND2 will estimate the pressure of bottom, which will take as an entry the variables ND1 and THPM. Finally, to validate inference values of the pressure bottom (PfINF) it proposes an index, which consists of calculating the difference between ITHPM-THPINFI; If it is minor to β, indicates that the value is correct, if not new values of bottom must be registered due to the presence of an operational scene of bottom different that was used to train the neo-fuzzy system.

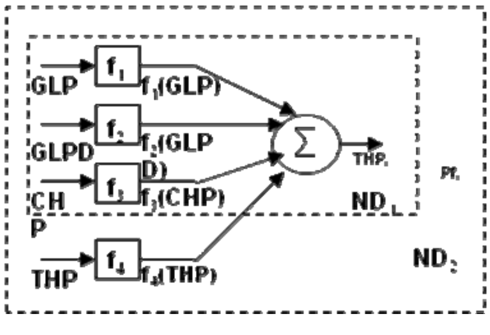

Fig. 7. Neo-fuzzy Scheme for the Surface Pressure (ND_1) and Bottom Pressure (ND_2) Estimation

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The well characteristics where the system was implemented are the following: It flows without reducer 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 25 API crude Gravity, 6% water Cut and 3489ft. The completation of the producing vertical well of 3489 ft and valves to 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

The well shows level of production in the order of (250±5) BPND, with a gas injection (0,5±0,1) mpcgd, the values have been obtained from the level of flow station (see figure 8).

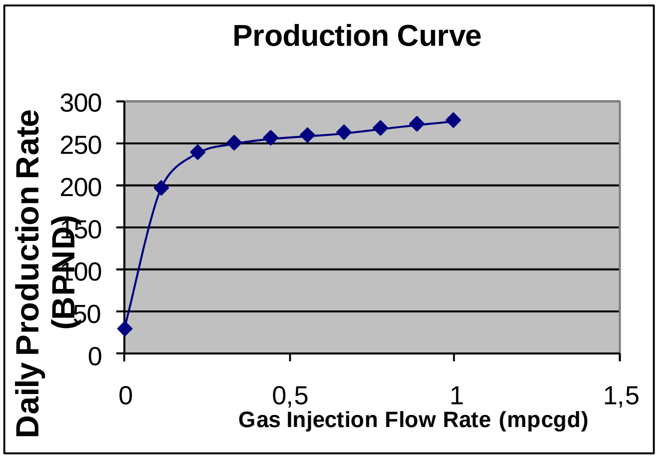

Fig. 8. Production Curve

In Figures 9 and 10 appear the records of the bottom and surface variables, which will agree the pattern to being used in the training of the fuzzy neurons. In the Figure 9, it is presents the profile tubing pressure of production (THP), obtained with the system of intelligent instrumentation implanted in field [1], where the behavior of the THP is observed, presenting 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].

On the other hand, well surface level installs a portable system "FGS" (optical fibre device that registers values of pressure and temperature to level of bottom-hole), which consists: optical fiber, a source laser, an analyzer, and transmitters of temperature and pressure in the surfaces of the well. The source laser sends pulses of light for a directional optical along the fiber. Every pulse of laser is dispersed by the variation of pressure and temperature at the back of the well. In the Figure 10 it is presents the profile pressure of bottom to depth of 3400 ft. It is important to indicate that this system "FGS" was in use for taking record temporary of the pressure of bottom.

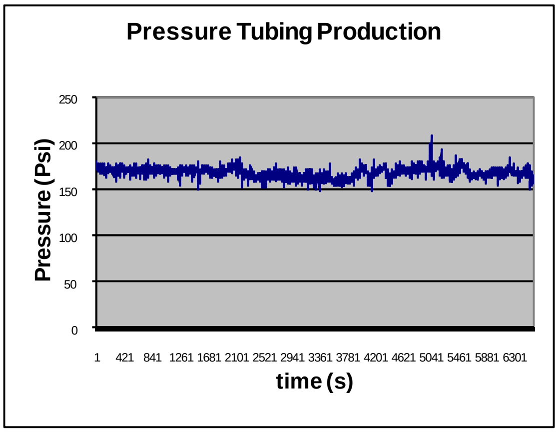

Fig. 9. Tubing Pressure Production

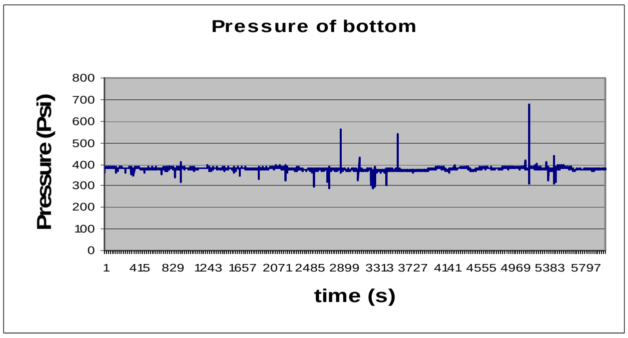

Fig. 10. Pressure bottom of well

4.2 Process Training

The first realized step was the sampling of the variables (input and output) in the same instant of time, for which each group of samples to be used in the training fuzzy neurons. Later were standardized the date of input and output (min, max), to realize the fuzzy partition. The fuzzy number of set was defined, associated with triangular functions of membership. The weight has 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).

System of three inputs and one output to be considered, this is proposed for the estimation pressure tubing (THPINF), where the variables of input are identified as GLP, GLDP and CHP, and the output THP presented in the table 2.

Table 2. Pattern of training

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

Taking three fuzzy values for the variables of input and initialized the weight with random values, the fuzzy neuron has the structure showed in Figure 11.

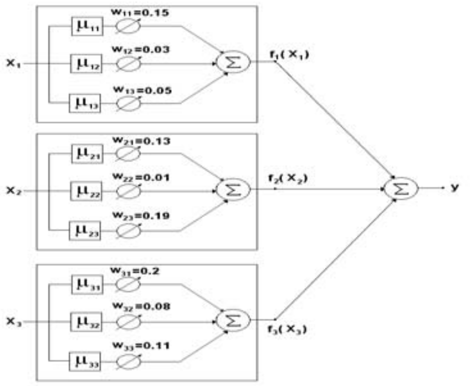

Fig. 11. Scheme Neo-Fuzzy with values random

The calculation of the degrees membership of value GLP =1705,88806 in each fuzzy set of this variable GLP denoted by $\mu 11$, $\mu 12$ y $\mu 13$, become as shown in figure 12. These degrees of membership have the following values: $\mu 11 =$ 0.608, $\mu 12 =$ 0.392, $\mu 13 =$ 0.

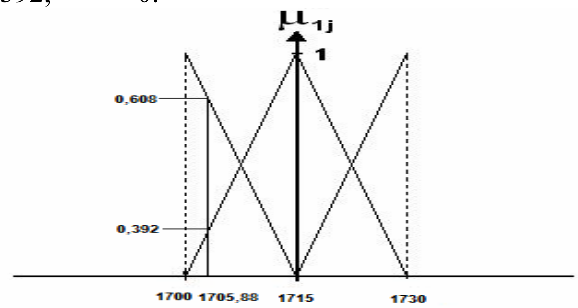

Fig. 12. Partition Fuzzy GLDP

The calculate the degrees of membership of the values GLDP = 9,57197762 y CHP = 1619,50378 in the respective fuzzy sets, the following results are obtained:

$\mu 21 =$ 0.2145, $\mu 22 =$ 0.785 $\mu 23 =$ 0; $\mu 31 =$ 0,5

$\mu 32 =$ 0.5 y $\mu 33 =$ 0.

Once obtained the values of the degrees membership, the synapse for the input is 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 the ND values for input pattern 1 is given by:

THP = 0.10296+0.0356+0.14=0.278

At the first pattern presents must be updated only the weights associated with fuzzy sets in which the degrees of membership are different of zero. The update of the weights is done using the following equation:

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

In this way, the update for each weight with the pattern 1, 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 = 33,631

$w_{13} =$ 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 apply to other patterns, up to achieving a good fit. The number of training cycles is select by the user.

4.3 Obtained Results

The table 3 and the figures 13 and 14 present results obtained for the estimation of the pressures production and bottom with the neo-fuzzy system.

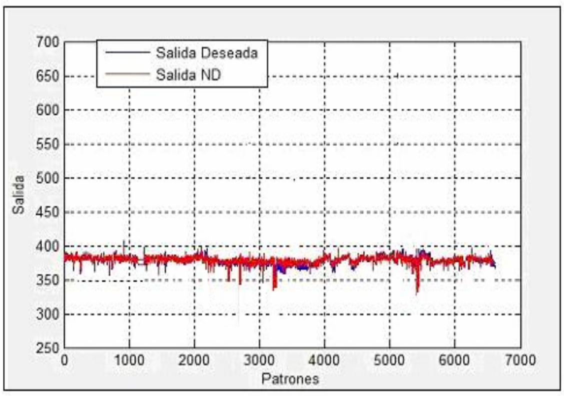

Fig. 13. Neo-Fuzzy Scheme for Estimating Pressure Bottom with 50%

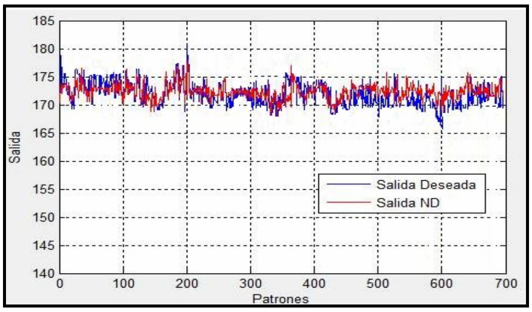

Fig. 14. Scheme Neo-Fuzzy by Estimation Pressure Tubing Production with 50%

Table 3. Pattern of training

Input	Output	Pattern training.	Pattern test	Mistake Quadratic
GLP, GLDP, CHP, THP	Pf_{INF}	3250 (50%)	3250 (50%)	0,294% 0,400%
GLP, GLDP, CHP	THP_{INF}	350 (50%)	350 (50%)	0,771% 1,305%

Obtained results in both neo-fuzzy models, give a satisfactory estimation of bottom and surface variables, the quadratic mistakes of the obtained training-test for the estimation of bottom pressure they were 0,235 % and 0,331 %. The quadratic mistake of training and test obtained for the tubing of production they were 0,727 % and 0,872 %, which Neo-Fuzzy indicates the efficiency of the networks. The value of β is minor to 5 psi in the whole cycle of training, reflecting the efficiency of the surface estimation.

4 Conclusion

The system used in this work for variables estimation, proves a great interest by its elaboration low-cost, by the current disposition of systems acquisition date and databases historical, which contribute the information needed for the design of these systems.

The results of the Neo-Fuzzy System to estimate bottom and surface variables is effective due to that follows the dynamics of the measured pressures. Its importance is in having the value of the bottom pressure to surface level, we can calculate the production of the well, its operational state, if the bottom of the well is under the presence of water, sediments, etc. This can change the rate of production of the well.

The use of this system to other wells where their production do not depend on the LAG Method, require that the neo-fuzzy model be trained with own conditions operation of the well, to obtaining reliable results.

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