Optimization of an Oil Production System based on Neural Networks and Genetic Algorithms

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Abstract— *This paper proposes an optimization strategy which is based on neural networks and genetic algorithms to calculate the optimal values of gas injection rate and oil rate for oil production system. Two cases are analyzed: a) A single well production system and b) A production system composed by two gaslifted wells. For both cases an objective function is maximized to reduce production cost. The proposed strategy shows the ability of the neural networks to approximate the behavior of an oil production system and the genetic algorithms to solve optimization problems when a mathematical model is not available.*

Keywords— Genetic algorithms, injection gaslift, neural network, optimization, oil production system, perceptron multilayer.

1 Introduction

The daily operation of an oil and gas production system, have many decisions, which affect the volumes produced and the cost of production oil. These decisions are taken at different levels in the organization, but eventually they will reach the physical production system [1]. Fig. 1 gives an overview of a physical gas lift production system. For such oil production systems, the decisions are related to find the lift gas rate for each well giving the maximum total oil production rate at very instance of time.

An objective function is a single-valued and well-defined mathematical function mapping the values of the decision variables into a performance measure. Examples of such performance measures are the total oil production rate, net present value (profit), or the recovery of the reservoir. To improve the performance of the production system, a question to be answered is: what decisions are better to maximize or minimize the objective function?. In the process of making good decisions, information about the production system is used. This information may include the physical properties such as pipe diameters and lengths, or it may include measurements from the production system.

To support making good decisions, well models may be used to develop the production plans. Typically, well test are performed to determine the gas to oil ratio, water cut, and production rates of each individual well. Well test are performed by routing a well to a dedicated separator. This separator will separate three phases, and a rate transmitter is connected to the outlet for each phase. The well model is update using the measurements taken during a test. Fluid sampling may be used to obtain the fluid composition including the water cut.

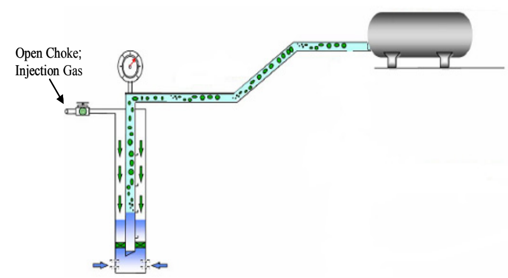

Figure 1: Gas lift production system of a single well.

The objective of gas lift is to increase oil production or allow nonrateing wells to rate by reducing the hydrostatic head of the fluid column in the well [2]. By injecting gas into the tubing, the density of the wellbore fluid decrease; thus, the pressure-drop component resulting from gravity is reduced. However, the gas lift also gives a larger pressure-drop component resulting from friction, giving some optimal gas lift rate for the well. Usually, the available lift-gas for a group of wells is less than the sum of the individual optimum lift-gas rates for each well. The gas-lift optimization problem is established to find the lift gas rates for each well giving the maximum total oil production rate subject to a gas lift processing capacity constraint and possibly other operational and processing constraints.

In this paper, a model-based optimization via neural networks and genetic algorithms is developed and used to calculate the optimal values of gas injection rate and oil rate of a gas lift production system. Two cases were analyzed: a) A single well production system and b) A production system composed by two gas lifted wells. For both cases maximize the objective function to reduce production cost. The proposed strategy shows the ability of the neural networks to approximate the behavior of an oil production system and to solve optimization problems when a mathematical model is not available.

This paper presents a methodology of hybrid computational intelligent using neural networks and genetic algorithm. Others related references for example; genetic algorithms for neural network training on transputers, neural network weight selection using genetic algorithms, studies on the speed of convergence of neural network training using genetic algorithm, automatic generation of neural networks with parameter setting based on genetic algorithms, evolutionary algorithms for neural network design and training, others.

2 Optimization strategy based on a neural network and genetic algorithms

In order to solve the gas-lift optimization problem, an optimization procedure based on a neural network and genetic algorithms was developed. The strategy selected is based on three components as illustrated in Fig. 2. The first one is a neural network which is used to approximate the gas lift performance curve, the second one uses an objective function to satisfy a performance index and the third one is used to solve the optimization problem via genetic algorithms.

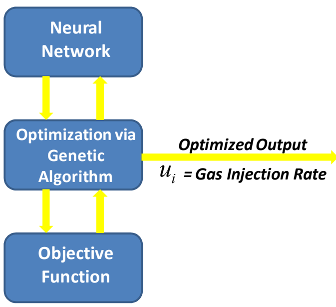

Figure 2: Strategy of optimization based on a neural network and genetic algorithms.

2.1 Neural Network

A Multi-Layer Perceptron (MLP) is selected. The use of this kind of networks to approximate functions and carry out identification process goes back to more than one decade [3]. The following equation is used to determine the structure of a MLP with a single hidden or intermediate layer, a neuron in the output layer with function of linear activation and M hidden neurons is used;

$$F(x_1,\ldots,x_P) = \sum_{i=1}^{M} \alpha_i g(\sum_{j=1}^{p} w_{ij} x_j - \theta_i) \tag{1}$$

The expression to define the neural network used in our strategy is given by

$$Q_i = g[u_i(i-1)] \tag{2}$$

where:

Q_i : is the estimated produced oil rate (STB/day).

u_i : is the Gas lift rate injected into the well (MMscf/day)

g: function activation

In this application, the approximation procedure is done using a neural network multilayer perceptron with three layers. The hidden layer has neurons using sigmoid activation function and the output layer has a unique neuron with linear activation function. Different MLPs are trained by means of Levenberg-Marquardt Algorithm, which uses the criterion of middle square error to update the neural network weights. The corresponding MLP is displayed in Fig. 3.

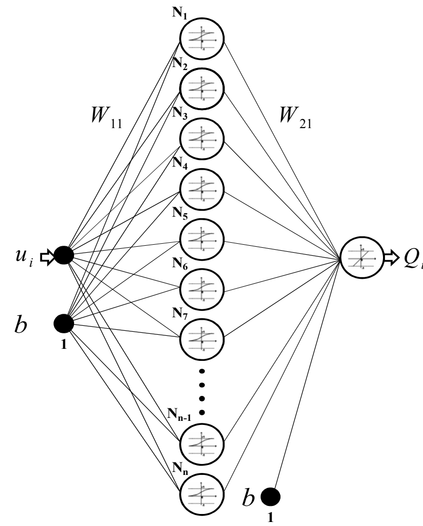

Figure 3: Neural network MLP.

2.2 Objective function

The expression to define the objective function used in our strategy of optimization is given by:

$$J(u) = \sum_{i=1}^{N} \alpha_i Q_i(u_i) - \beta_i u_i \tag{3}$$

where:

α_i : Production costs by 1 STB/day produced oil.

β_i : Supply costs by 1 MMscf/day injected gas.

N : amount wells.

α_i and β_i are required to balance units

[STB/day]/[MMscf/day]= STBD/MMscfd

The objective function given in (3) can give a net gain, relating adequately processes numerical comparison of the output of the desired product and quantity of flow of injection gas.

2.3 Optimization via genetic algorithms

In order to maximize the objective function, given in (3), the following simple genetic algorithm is applied [4].

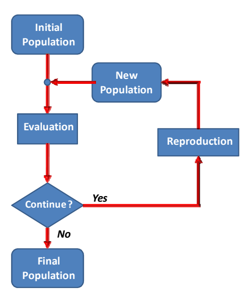

Figure 4: Simple genetic algorithm pseudocode diagram.

The properties of genetic algorithms which are applied are the following ones

- Type of genetic algorithm: Simple genetic algorithm [4].
- Amount of unit in population: 100 chromosomes
- Amount of units that contain "N" genes, to find the optimal value: 200 generations.
- Probability of mutation= 0.001.
- In order to select the units the match method is used.

In this application we take into account that the values of injection gas must satisfy the following conditions.

$$u_i = \{0.00, 0.01, 0.002, \ldots, 5.99, 6\} \tag{4}$$

The previous condition represents the precision considered when the injection gas is sampled.

Other conditions are:

- The rate of gas injection will be a value in the following interval (MMscf/day):

$$0.00 \le u_i \le 6.00 \tag{5}$$

- There is not mathematical model of the process; however, experimental data can be obtained from a well simulator.
- A neural network model of the process is available, which can be used to approximate its behavior and to construct the objective function.

Two cases are simulated; the first one corresponds to a single well production system, then the equation (3) can be rewritten like:

$$Max[J(u)] = \alpha_1 Q_1 - \beta_1 u_1 \tag{6}$$

and the second one considers a production system composed by two wells, then the equation (3) can be rewritten like:

$$Max[J(u)] = \alpha_1 Q_1 + \alpha_2 Q_2 - \beta_1 u_1 - \beta_2 u_2 \tag{7}$$

3 Results and Discussions

3.1 First case: Produced oil by a single well

The corresponding oil production system is illustrated in Fig. 1. For this case, two single wells are considered. The first one has a pressure in the well head (P_{wh}) equal to 14 kg/cm^2 and the second one has 12 Kg /cm^2. A simulation program is used to collect data and to train neural networks using neural networks toolbox of Matlab.

The best trained neural networks are described in Table 1 and Table 2. Other parameters like the static pressure in the reservoir, lengths and diameters of the tubing and lines, chokes and others pipe components are also considered. Figure 5 illustrates the simulation for a well with P_{wh}= 14 kg/cm^2.

Table 1: Neural network architecture and obtained errors with P_{wh} = 14 Kg/cm^2.

Number of neurons		error	error (%)
Intermedia layer	Output layer		
30	1	0.1365	0.002

Table 2: Neural network architecture and obtained errors with P_{wh} = 12 Kg/cm^2.

Number of neurons		error	error (%)
Intermedia layer	Output layer		
30	1	0.0119	0.0004

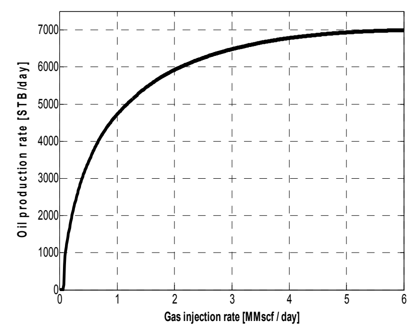

Figure 5: Estimated production curve oil production rate vs gas injection rate, P_{wh} = 14 Kg/cm2.

Figure 6 displays the obtained results when the gain of production for this well with P_{wh}=14 Kg/cm^2 is maximized. Furthermore, α_1=*28*USD/STBD and β_1=*5250*USD/MMscfd are considered in equation (6); α_1 *and* β_1 estimates cost for this year.

The obtained results in this case are contained in Table 3.

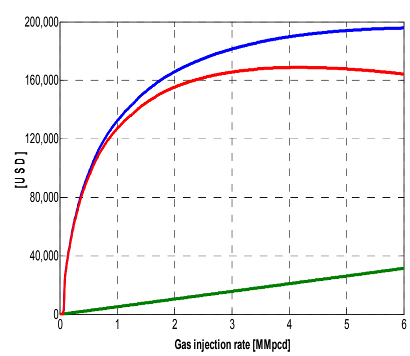

Figure 6: Optimization results; income of production (blue), costs by supply of injection gas (green) and objective function (Optimal gain-red).

Table 3: Gain of production results

Optimal gain production (USD)	Income optimal production (USD)	Costs by supply of injection gas (USD)	Obtained optimal gas injection rate (MMscf / day)
168,840	190,680	21,840	4.16

Figure 7 illustrates the simulation results for a well when P_{wh}=12 kg/cm^2 is used.

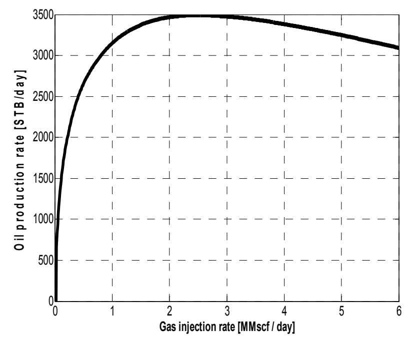

Figure 7: Estimated production curve oil production rate vs gas injection rate, P_{wh} = 12 Kg/cm2.

Figure 8 displays the obtained results via optimization procedure to maximize the gain of production for this well when P_{wh}=12 Kg/cm2 is used. As considered above, $\alpha_1=28$USD/STBD and $\beta_1=5250$USD/MMscfd are used in equation (6).

The obtained results in this case are contained in Table 4.

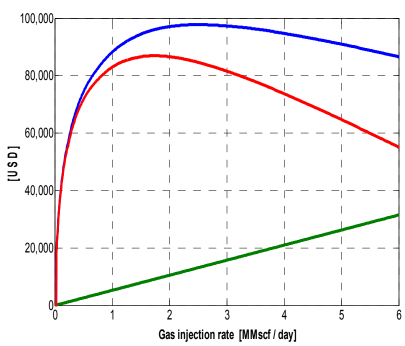

Figure 8: Optimization results; income of production (blue), costs by supply of injection gas (green) and objective function (Optimal gain-red).

Table 4: Gain of production results

Optimal gain production (USD)	Income optimal production (USD)	Costs by supply of injection gas (USD)	Obtained optimal gas injection rate (MMscf / day)
86,921	96,004	9,082	1.73

3.2 Second case: Produced oil rate by a production system based on two wells.

In Fig. 9 is shown an oil production system of two wells. Production system made up of wells of 12 kg/cm^2 and 14 Kg /cm^2. A simulation program is used to collect data and to train neural networks using neural networks toolbox of Matlab. The best trained neural networks is described in Table 5.

Table 5: Neural network architecture and obtained errors, two wells.

Number of neurons		error	error (%)
Intermedia layer	Output layer		
30	1	-0.3702	-0.0037

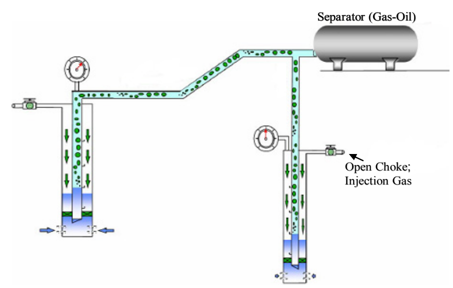

Figure 9: Gas lift production system composed by two wells.

3.2.1 Sub case 1. $u_i = u_1 = u_2$

The Fig.10 illustrates the simulation for a system composed by two wells (Black).

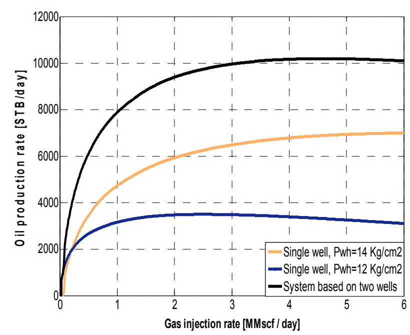

Figure 10: Estimated production curve oil production rate vs gas injection rate. System composed by two wells.

Figure 11 displays the simulation results of maximizing of the gain of production for two wells. Assume that $\alpha_1=\alpha_2=28$USD/STBD and $\beta_1=\beta 2=5250$USD/MMscfd are considered in equation (7). Furthermore, objective function is subject to the next constrains:

$$0.00 \le u_i \le 6.00 \text{ and } u_2 = u_1.$$

The obtained results in this subcase are contained in Table 6.

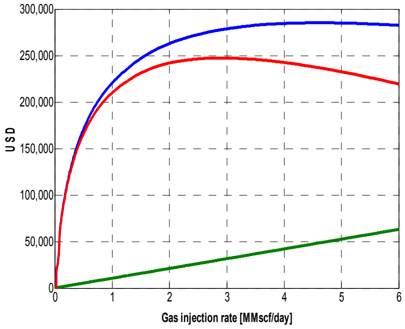

Figure 11: Optimization results; income of production (blue), costs by supply of injection gas (green) and objective function (Optimal gain-red).

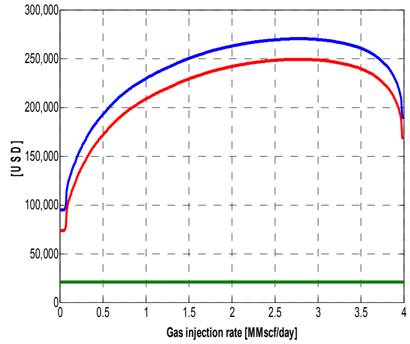

Figure 13: Optimization results; income of production (blue), costs by supply of injection gas (green) and objective function (Optimal gain-red).

Table 6: Gain of production results

Optimal gain production (USD)	Income optimal production (USD)	Costs by supply of injection gas (USD)	Obtained optimal gas injection rate (MMscf / day)	
247,260	277,550	30,240	2.88	2.88

Table 7: Gain of production results

Optimal gain production (USD)	Income optimal production (USD)	Costs by supply of injection gas (USD)	Obtained optimal gas injection rate (MMscf / day)	
249,360	270,360	21,000	2.79	1.21

3.2.2 Sub case 2. $u_1+u_2=K$

The Fig. 12 illustrates the simulation for a system composed by two wells (Black).

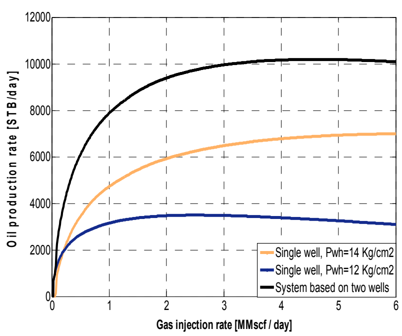

Figure 12: Estimated production curve oil production rate vs gas injection rate. System composed by two wells.

Figure13 presents the results of maximizing of the gain of production for two wells. α_1 *and* β_1 considered in objective function subject to constrains :

$$0.00 \leq u_i \leq 6.00$$

and

$$u_2 + u_1 = K$$

where $K = 4$. Furthermore, $\alpha_1=\alpha_2=28$USD/STBD and $\beta_1=\beta_2=5250$USD/MMscfd are considered in equation (7).

The obtained results in this subcase are contained in table 7.

4 Conclusions

The obtained results shows that neural networks and genetic algorithms are useful to optimize the costs and gains in an oil production systems. The implementation of these methodologies to be applied in petroleum industry allows to increase the gains, to reduce the costs, save natural elements and to extend the life of wells.

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References

[1] H.P. Bieker, O. Slupphaug, and T. A. Johansen, "Real-Time Production Optimization of Oil and Gas Production Systems: A Technology Survey," *SPE Production & Operations Journal*, vol. 22, no. 4, pp. 382-391, November 2007.

[2] A. Vasper, "Auto, Natural, or In-Situ Gas-Lift Systems Explained," *SPE Production & Operations Journal*, vol. 23, no. 1, pp. 75-80, February 2008.

[3] J. Nocedal, and S.J. Wright, *Numerical Optimization*. New York: Springer, 1999. K Narendra, and K. Parthasarathy, "Identification and control of dynamical systems using neural networks". IEEE Transactions on Neural Networks, vol.1, no 1. pp. 4-27, 1990.

[4] D. Goldberg, (1989). Genetic Algorithms in Search, Optimization, and Machine Learning (Addison-Wesley, Readings, MA).

[5] W.Y. Fang, and K.K. Lo, "A Generalized Well-Management Scheme for Reservoir Simulation," *SPE Reservoir Engineering Journal*, vol. 11, no. 2, pp. 116-120, 1996.

[6] E.P. Kanu, J. Mach, and K.E. Brown. "Economic Approach to Oil Production and Gas Allocation in Continuous Gas Lift," *Journal of Petroleum Technology*, vol. 33, no. 10, pp. 1887-1892, 1981.

[7] K Hornik, M. Stinchcombe, and White H. “Multilayer Feedforward Networks are Universal Aproximators”, Neural Networks, vol. 2, no. 5, 1989.

[8] M. Norgaard, O. Ravn; Poulsen, N. K., y L. K., Hansen, “Neural Networks for Modelling and Control of Dynamic Systems”, Springer-Verlag, London, 2000.

[9] Prosper. Petroleum Experts Ltd. User’s Guide IPM V5.3Build #173 Jun 6, 2006.

[10] J. A. Ruz-Hernandez., D. A. Suarez, E. Shelomov. and A. Villavicencio, “Predictive Control Based on an Auto-Regressive Neuro-Fuzzy Model Applied to the Steam Generator Startup Process at a Fossil Power Plant”, Revista de Computación y Sistemas, vol. 6, no. 3, CIC-IPN, ISSN 1405 5546, Mexico, pp.204-212, 2003.

[11] E. N. Sánchez, G A. Alanís, “Redes Neuronales, Conceptos Fundamentales y Aplicaciones al Control Automático”, Prentice Hall, 2006.

[12] J. M. Corchado, F. Díaz. “Redes Neuronales Artificiales, un enfoque Practico”. Universidad de Vigo. ISBN. 848158145-3.

[13] G. Cybenko, “Aproximation by superpositions of sigmoidal function”, Math. Control, Sygnals and System, vol. 2, nº 4, 1989.