

Intelligent Supervision Systems for Improving the Industrial Production Performance in Oil Wells

EDGAR CAMARGO*, JOSÉ AGUILAR**, ADDISON RÍOS**, FRANCKLIN RIVAS***, JOSEPH AGUILAR-MARTIN[^]

*Doctorado en Ciencias Aplicadas, Facultad de Ingeniería
Universidad de los Andes
Mérida 5101
VENEZUELA

**CEMISID, Facultad de Ingeniería,
Universidad de los Andes
Mérida 5101
VENEZUELA

***Laboratorio de Sistemas Inteligentes
Universidad de los Andes
Mérida 5101
VENEZUELA

[^] Grup SAC, Universitat Politècnica de Catalunya
Campus de Terrassa
ESPAÑA

edgarc@ula.ve, aguilar@ula.ve, aguilar@laas.fr, ilich@ula.ve, rivas@ula.ve

Abstract: An Intelligent Supervision Scheme for the Industrial Production is presented in this work. Such scheme is tested for gas lift (GL) oil wells. The proposal is based on the possible production assessment, the process variables (specifically, the bottom-well pressures), and the operational scenarios detection for the process (in the case of study, as an oil producing well), with the objective of optimizing the producing performance of the well. The proposal combines intelligent techniques (Genetic Algorithms, Fuzzy Classification, Neo-Fuzzy systems) and Energy Mass Balance. The scheme in this specific study allows establishing the oil or gas flow that a well can produce, taking into account the completion geometry and the reservoir potential, as well as the financial criteria related to the well's performance curves and the commercialization cost of the oil and gas. The possibility of estimating bottom-well variables gives it a great operational significance to the presented approach; due to installation costs and bottom-well technology maintenance are very high, turning out to be unprofitable to produce the well.

Key-words: nodal analysis, supervision system, gas lift wells, automation, fuzzy logic, neo-fuzzy systems, evolutionary computation.

1 INTRODUCTION

With an increase of the degree of dependency of the society on complex technological systems and processes, their availability and right functioning have become a strategic matter. This fact holds true for a multitude of industrial domains: production systems, aeronautical and aerospace industry, among others. In all cases, the wrong functioning of these systems can cause financial and human losses, undesired environmental impacts, among others. Many of these systems are highly associated to automation. Automation of such systems through automatic control, although it has freed the human operators of their control and manual operation, it has not immunized them against operational failures.

Therefore, with the objective of finding the highest possible availability of the systems and processes, it is necessary to complement the industrial automation systems with potent and accurate supervision tools that allow indicating undesired or unpermitted performance states, as well as taking the proper measures in order to keep the system within the optimal performance states.

On the other hand, the use of the Intelligent Systems (IS) on supervision tasks in production systems is becoming an area of great interest at industrial level [1,3,5]. The IS have particularly started to gain more and more influence in the oil industry, as they allow approaching the problem of handling the complexity of the hydrocarbon production systems [1,2]. This

represents an attractive alternative to deal with highly varying, complex, and confusing problems [7, 9].

So, in this work it has been proposed an Intelligent Supervision System for optimizing continuous production processes, specifically for Gas Lift wells. It has been introduced the intelligent supervision notion, from the perspective that “intelligence” must be located at the well level. This intelligence is understood as the well’s capacity for self-organizing according to its conditions and the conditions of its environment. In this approach, the production demand is determined by the proposed mathematical model, as well as by the bottom-well variables, regarding the present operational scenario at operational level. Additionally, this approach propose a mathematical model to allow optimizing the gas and oil production planning for several wells, in which there is a known demand and a cost coefficient associated to each well in the objective function.

2. THEORETICAL FRAMEWORK

2.1. Gas Lift Method

The Gas Lift method consists of injecting gas at an established pressure at the lower part of the well pipe’s fluid column, at different depths, with the purpose of decreasing its weight, helping the reservoir fluids rise from the bottom of the well to the surface. The production curve of a well that produces by the gas injection method (see Figure 1), indicates as the Gas Lift Flow increases (GLF, expressed “mpcdg” thousands of gas cubic feet days), the production rate (Q_{prod} , expressed “BNPD” Daily Production Net Barrels) also increases until reaching its highest value (Stable Region); such that additional increases in the injection or below the necessary injection will cause a decrease in the production (Unstable Region) [1,2].

The mechanical completion installed at the bottom and surface of the well and the characterization of the physical properties of the fluid (Gravity of the oil, water cut, Bottom-well pressure, Gas-liquid ratio) is identified in the characterization; all of this is done because the oil production behavior in the wells injected with gas depends of variables, both of the reservoir and of the mechanical design (valves, production pipes, among others) [1]. After that, techniques based on Mass and Energy Balances called Nodal Analysis will be applied [1,4]. For its calculation, a node (point of implementation of the energy balance) must be chosen at any place of the production system.

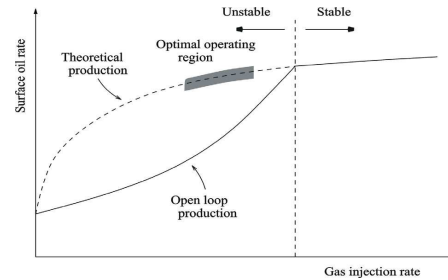


Figure 1: Artificial Gas Lift well behavior’s model

2.2 Intelligent Supervision

The IS allows us to incorporate skills to a Supervision System in order to confer the following qualities to the system being supervised: Autonomy in the decision making process, anticipating the effect of the supervision tasks on itself; Adaptive capacities for the possibility of learning from the occurrence of events on the industrial system under supervision; Self-diagnosing and self-organizing capacities. Additionally, the possibility for the intelligence distributing at process level, for the decision making to be made locally, thus minimizing the response times of the supervision tasks. All this will allow to the supervised system function autonomously in dynamic (changing) environments.

This approach exceeds the classical approach of the Data Control and Acquisition Systems (SCADA) that limit them to supervision and control tasks, from the following idea: it is based on a self-regulation process in the wells, from the information they handle (status-actions), which allows them to anticipate situations, have a proactive knowledge, without losing the global vision of the business. In that sense, our approach is autonomous and distributed.

Generally, in this work we will call the supervision systems with abilities for conferring these qualities Intelligent Supervision Systems. This proposal is oriented towards the provision of intelligence to the well by giving it onsite self-diagnosing characteristics, giving the production method better performance and financial profitability. This is done through the proposed supervision system. Wells with these characteristics would be called “conscious wells”, meaning by this term a well that, based on its profitability, regulates its production, self-diagnoses, controls its damages, watches and supervises the behavior of its subsoil/surface infrastructure, among other things [1].

3. SUPERVISION SYSTEM SCHEME

The Intelligent Supervision System proposed in this work is shown in Figure 2. Such Intelligent Supervision System, at wellhead level, has been designed for Gas Lift wells (“GL”), and confers capacities for measuring, controlling, diagnosing, identifying, and optimizing the GL process, in its respective operational states. This way the well has self-adapting and self-diagnosing capabilities (it supervises the behavior of its subsoil/surface infrastructure, watches the injection of external fluids, among other things). Thus, the Intelligent Supervision scheme has the virtue of being integrated by the elements of the surface infrastructure, including the reservoir model, with the purpose of sharing information, which allows, for example, considering production goals, surface and reservoir infrastructure restrictions, among other things. Such scheme proposed and implanted in this work, confers the above qualities to the supervised system (in our case, GL wells) at field level.

The supervision system is composed of one phase (component) of well model generation (in this work is proposed the utilization of techniques of Mass and Energy Balance in this phase); one phase (component) of Operational Scenario identification (in this work is proposed the utilization of fuzzy logic in this phase); and one phase (component) of optimization of the productive process for the identified scenario (in this work is proposed the utilization of evolutionary techniques based on process restriction and operational production cost [2] in this phase). Also, it has an instrumentation component that allows it to capture the variables of the system (in our particular case, variables of injection and production); and a control component (not developed in this work, but in our particular case it would be applied to the gas injection rate through the PID control [1,2]). Below, the phases (components) of the Intelligent Supervision System that are developed in this work are described.

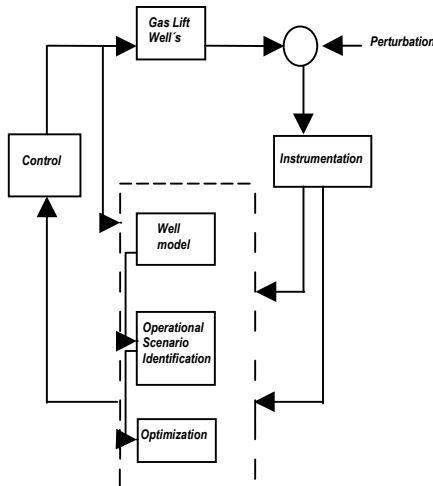


Figure 2: Intelligent System Supervision for Production System Oil proposed in this work (well LG)

3.1. First Phase: Generation of the Well Production Model

It Obtains the Production Model of a Well at field level, that consists of comparing the pressures profile from the wellhead (P_{thp}) to the bottom (P_{wf}) of the well, in order to determine the real capacity of production (Q_{prod}) the well exhibits through the gas injection rate (Q_{iny}). In order to do that, the method called Nodal Analysis [1, 2] is used. Thus, a simple gas lift model is proposed: the oil and gas “Inflow” of the reservoir is modeled by the use of the productivity index (existing ratio between the production rate (Q_{prod}) and the differential between the reservoir pressure (P_{ws}) and the flowing pressure at the bottom of the well (P_{wf}). To that, the equation (1) is used, which determines the capacity of contribution of the oil reservoir. This equation represents an instant snapshot of such capacity of contribution of the reservoir towards the well, in a given time of its productivity life. It is normal for such capacity to decrease through time, for reduction of permeability of the well surroundings, and for the increase of viscosity of the oil as its light fractions vaporize. This equation is considered as the energy offer, or fluid affluence curve, that the reservoir yields to the well (P_{wf} vs Q_{prod}).

$$P_{wf} = P_{ws} * \left[\left(1,266 - \frac{1,25 * Q_{prod}}{Q_o} \right)^{0,5} - 0,125 \right] \quad (1)$$

Where Q_o represents a base production rate, which is determined through reservoir core tests. As for the “outflow”, gas is injected at a given depth to reduce the weight of the column and reducing the bottom pressure of the well, thus allowing to establish a given production rate in which the capacity of fluid contribution from the reservoir equals the capacity of fluid extraction from the well. In this sense, in order to inject gas, it is assumed that the pressure at the level of the bottom injection valve located in the casing must be greater than the pressure in the space of the production pipe at the injection point ($P_{g,iny} > P_{T,iny}$), in order to ensure a displacement of the gas towards the production pipe. This is described by the following restrictions:

$$Q_{iny} = \begin{cases} c\sqrt{\rho_g(P_{g,iny} - P_{T,iny})} & \text{if } P_{g,iny} > P_{T,iny} \\ 0 & \text{else} \end{cases} \quad (2)$$

Where:

$P_{g,iny}$ = Pressure of Injection Gas to the Valve

$P_{T,iny}$ = Pressure of the Production Pipe at the Point of Injection

ρ_g = Gas Density

c = Constant related to the characteristics of the valve

Q_{iny} = Gas Injection Rate

For the model, the node at the gas injection valve is assumed in order to establish the capacity of production of the lifting system [1,7,8].

$$Q_{iny} = C_{iv} \sqrt{\rho_{g,iny} (P_{g,iny} - P_{thp} + P_{wfp})} \quad (3)$$

From (1), (2) and (3) the mathematical model that describes the behavior of a well by gas lift is obtained:

$$Q_{prod} = \frac{Q_{iny} \left(\left(\frac{P_{thp} + P_{g,iny} - ((Q_{iny}/C_{iv})^2)/\rho_g + 0,125}{P_{ws}} \right)^2 - 1,266 \right)}{1,25} \quad (4)$$

3.2. Second Phase: Identification of Operational Scenarios

This phase establishes the operational scenario of the well by gas lift, starting from the value of its variables. These operational scenarios can be:

- Under-injected Operational Scenario: It takes place when the well generates a low production due to it receiving gas with low pressure that is generated because there is a fissure in the pipe, or there is an injection valve in poor condition, or there is a problem in the producing formation.
- Normal Operational Scenario: It takes place when the well generates the highest production with the minimum rate of gas injection.
- Over-injected Operational Scenario: It is identified when the well presents low

production, because it receives gas with high pressure, generated by the increase of water cut (it generates an increase in the weight of the fluid column in the production pipe, requiring greater amount of gas to lift the fluid up to the wellhead).

For that, a classification system based on the variables at reservoir level (bottom pressure), at wellhead level (pressure from the casing), and the gas lift flow is proposed. These variables guarantee obtaining the operational scenario, as they are related to the energy balance applied in the previous phase, both at bottom and surface levels. In order to design the fuzzy classification system, the set of fuzzy variables and the rules that will allow making the analysis of the GL wells have to be established. The fuzzy variables are: Pressure of the Casing, Bottom Pressure, and Operational Scenario.

Next, the rules of the fuzzy classification system for identifying the operational scenarios are described:

- *If (Low Bottom Pressure) and (Low Casing Pressure) then (Normal Operational Scenario),*
- *If (Low Bottom Pressure) and (Medium Casing Pressure) then (Normal Operational Scenario),*
- *If (Low Bottom Pressure) and (High Casing Pressure) then (Over-injected Operational Scenario),*
- *If (Medium Bottom Pressure) and (Low Casing Pressure) then (Normal Operational Scenario),*
- *If (Medium Bottom Pressure) and (Medium Casing Pressure) then (Normal Operational Scenario),*
- *If (Medium Bottom Pressure) and (High Casing Pressure) then (Normal Operational Scenario),*
- *If (High Bottom Pressure) and (Low Casing Pressure) then (Under-injected Operational Scenario),*
- *If (High Bottom Pressure) and (Medium Casing Pressure) then (Under-injected Operational Scenario),*
- *If (High Bottom Pressure) and (High Casing Pressure) then (Under-injected Operational Scenario).*

Followed, we show an example of one of the functions of membership for one of the fuzzy variables of the fuzzy classification system, the variable bottom pressure, by the rest to see [1].

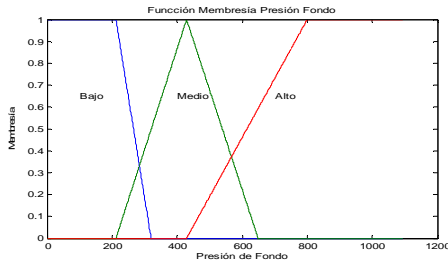


Figure 3: Variable Fuzzy Bottom Pressure

3.3. Third Phase: Optimization of the Production Process

The optimization problem of GL wells consists of Increasing the Production of Oil and Minimizing the Flow of injected Gas, based on three variables:

Q_{prod} , $Cost$ and Q_{iny} . This optimization problem is described by the objective function of the equation (5), with the respective restrictions of the process. The production pipe is modeled with the pressure gradients “Pressure Drop in the Reservoir” and “Pressure Drop in the Production Pipe”, through the well model presented in the first phase. The union of the pressure gradients is modeled as a “Node at the Injection Valve Level at the Bottom of the Well”, as it was previously explained.

The restrictions are contextualized in the operational scenarios and reservoir conditions. We assume that:

P_{ws} is a constant, due to the slow dynamics of the reservoir; P_{wf} must be lesser that of the reservoir, for oil displacement to be generated towards the bottom valve. From the well model we establish the maximum production capacity that a reservoir can contribute $Q_{prod,max}$ and the gas lift flow Q_{iny} , that at an operational level it is a limited resource and of variable availability, which depends on the gas plant assignment. The objective function, with its respective restrictions, is:

$$f = (PVPPetroleo - CostoProducciónCrudo) * Q_{prod} - (CostoCompresiónGas) * Q_{iny}$$

Subject to:

$$\begin{aligned} P_{ws} &= Const, \\ P_{wf} &< P_{ws}, \\ Q_{prod} &\leq Q_{prod,max}, \\ Q_{iny,min} &\leq Q_{iny} \leq Q_{iny,max} \\ P_{wf,min} &\leq P_{wf} \leq P_{wf,max} \end{aligned} \tag{5}$$

Where:

$PVPPetroleum$ = Selling price of oil in terms of the daily barrel, Bs/bl,
 $Cost Production$ = Production Cost,

$$CostGasCompression = \ln Bs/Mpcn,$$

The $Cost$ is defined in terms of the $Cost ProductionCrudeOil$ and the $CostGasCompression$. The intervals regarding the restrictions in (equation 5) depend on the identified operational scenario, which are characterized in the following table:

These ranges will be used by the optimization technique to use, according to the operational scenario identified in the previous phase.

Table 1: Values of the Variables according to each operational scenario

Operational Scenario	Q_{prath}	$Q_{inj,min}$	$Q_{inj,max}$	$P_{wf,min}$	$P_{wf,max}$
Under-injected	235	291	681	410	1100
Normal	244	682	793	200	630
Over-injected	250	764	818	0	300

4. EXPERIMENTATION WITH THE INTELLIGENT SUPERVISION SYSTEM

A possible implementation of the intelligent supervision system for GL wells, we tests our system for the validation of GL wells from an oil field of the Venezuelan oil industry. But this procedure would be followed for any GL well.

4.1. FIRST PHASE: GENERATION OF THE WELL'S PRODUCTION MODEL

The identification of the mathematical model of the well by GL constitutes an important step towards the operation of the supervision system. For the purposes of the construction of the GL well mathematical model, as it was previously indicated, the node in the gas injection valve is assumed, with the purpose of establishing the production capacity of the lifting system. The pressures at which the reservoir yields the production rate at the entrance and exiting of the node, the energy “Inflow” of the reservoir, and the energy “Outflow” of the surface

installation are established. To establish the “Inflow” of oil and gas used in the equation (3), that determines the capacity of contribution of the oil reservoir. If a constant reservoir pressure is assumed $P_{ws} = 2400$ psi, and for a base production rate $Q_o = 150$ bpd, the results of the “Inflow” of the reservoir. In order to establish the “Outflow” of energy from the installation, equation (3) is used, which says that gas (Q_{iny}) must be injected with a fixed density, as it will not change the concentration of the gas (the way it is done in an experimental manner, where $\rho_{g,iny} = 0,8$ lbs/pt³), to decrease the bottom pressure (P_{wf}), so as to extract the oil up to the wellhead generating a production pipe pressure P_{thp} . C_{iv} corresponds to the valve adjustment constant.

The behavior of the gas lift injection versus the production in such well is as follows: it operates at a gas injection rate between 550 and 650 mpcndg, and the production associated to the well ranged between 190 bnpd and 220 bnpd. Thus, in Figure 4 the real curve is presented (measured at flow station level with a bottom pressure of 2400 psi), the established curve using the oil and gas injection flow measured at station level and evaluated in equation (4), and the theoretical curve according to our model (equation 4).

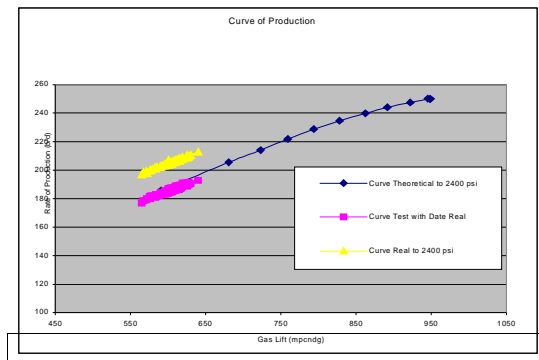


Figure 4: Curve of Production Theory, Real and Test

4.2. SECOND PHASE: IDENTIFICATION OF OPERATIONAL SCENARIOS

Values of casing pressure, production rate, bottom pressure, and gas injection were identified through the well model obtained in the first phase [1,3,5]. These values correspond to different operational scenarios to be used in the validation of the Classification System. In Table 2, the Input/Output variables are shown with their respective operational states, corresponding to the different scenarios identified through the production model, which will be used for validating the fuzzy classification system.

The fuzzy classification (FC) system allows to identify operational scenarios (“normal, under-injected, and over-injected”), giving a production value the defuzzification process of the classification model very close to the theoretical, which indicates the effectiveness of the fuzzy classification system.

Table 2: Results given by the FC, compared with the theoretical model.

Pressure Casing (Psi)	Pressure Bottom (Psi)	Rate Injection of Gas (mpcndg)	Operational Scenarios	Q_{inj} (Theory Model)	Q_{inj} (Fuzzy System)
1020	10	766,57	Normal	766,57	766,66
1190	200	754	Normal	754	766,66
1250	100	806	Over-	806	799,66
1090	420	640	Normal	640	633,33
1130	270	710	Normal	710	728,88
1320	630	648	Under-injected	648	500
1190	1050	308	Under-injected	508	500
1120	620	540	Under-injected	540	536,51

The fuzzy classification (FC) system allows to identify operational scenarios (“normal, under-injected, and over-injected”), giving a production value the defuzzification process of the classification model very close to the theoretical, which indicates the effectiveness of the fuzzy classification system.

4.3. THIRD PHASE: OPTIMIZATION OF THE PRODUCTION PROCESS

The optimization problem of GL wells consists of increasing the Oil Production and minimizing the Gas Lift Flow, based on the objective function and the operational restrictions described in equation (5). In order to solve that problem a genetic algorithm is used, which presents the following components:

- Structure of individuals: coded in real numbers composed of two fields, Casing pressure ($P_{g,iny}$) and Tubing pressures (P_{thp}). These variables are used because they are related to the gas behavior and surface level production, and they can be manipulated at an operational level with a field instrumentation arrangement.

This is important, because in the implementation of the intelligent supervision system at operational level such pressures can be adjusted in terms of the optimum values recommended by the genetic algorithm, and thus achieve the best performance of the producing well.

- Number of individuals: random, between 2 and 10,
- Number of generations: 25,
- Objective function: equation (5), including its respective restrictions
- Crossover operator: single point cross, with 0.7 probability
- Mutation operator: random, with 0.03 probability
- Space of search: a population of individuals was gathered with the set of values allowed to variables P_{thp} y $P_{g,inj}$, according to the operational scenario identified in the previous phase (the specific values for variables $Q_{iny,min}$, $Q_{iny,max}$, $P_{wf,min}$, $P_{wf,max}$ for the restrictions of equation (5) are determined according to the operational scenario (see table 2)). That means, the population of individuals will be specific to the operational scenario identified in the previous phase, so that the genetic algorithm may establish the optimum value of equation (5) for that operational scenario. To evaluate equation (5), the equations (3) and (4) are required to use. By optimizing (5), the optimum value of production and injection are established in the operational scenario identified.

For example, our genetic algorithm was applied to one of the operational scenarios identified in the previous phase (normal). The final population given by the genetic algorithm for that operational scenario is shown in Table 5 (an individual is the value of (P_{thp}) and ($P_{g,inj}$) specified on a row of that table).The optimum values of that operational scenario, of the variables Tubing Pressure (P_{thp}) and Casing Pressure ($P_{g,inj}$) shown in Table 3, are used in the models of the gas injection well, giving the results of Q_{inj} , Q_{prod} and $Profits$ shown in the same Table 3.

Table 3: Results Obtained.

$P_{thp}(psi)$	$P_{g,inj}(psi)$	$Q_{inj}(mpcndg)$	$Q_{prod}(b/d)$	$Profit(Bs/d)$
170	1022	596,6	232,0	29794346
170,4	1109,8	619,1	230,2	29544303
172,5	1226,3	689,1	233,7	29959487

According to the results, the production system presents an optimum behavior at a gas injection rate of about 596,6 mpcndg, with an associated production of 232,06 b/d, and a casing pressure of 1022 psi and production pipe of 170 psi. On the other hand, for a gas flow of 619,1 mpcndg its production rate is 230,21 b/d, generating a smaller profit and greater consumption of gas with regard to the case of 596,6 mpcndg. Regarding to the gas flow of 689,1 mpcndg, a production of 233,71 b/d is expected, higher than the one of 596,6 mpcndg (1,64892 b/d), but more gas flow is required. Now, the profit differential in its favor is 165141 Bs/d, which indicates that this case could be interesting (more optimum) as it better combines the two costs.

5.- CONCLUSIONS

Some specific conclusions of our work are:

1. We have proposed an Intelligent Supervision System for the optimization of processes of continuous production, specifically for Gas Lift wells. The Intelligent Supervision notion has been introduced from the perspective that “the intelligence” must be located at well level. This intelligence is understood as the capacity of the well for self-organizing according to its conditions as well as its environment. This approach improves the classic approach of the Data Control and Acquisition Systems (SCADA) that limit themselves to supervision and control tasks, from the following idea: it is based on a self-regulation process in the wells, from the information they handle (states-actions), which allows them to anticipate situations, have a proactive behavior, without losing the overall vision of the business. In that sense, our approach is autonomous and distributed.

2. The Production Model obtained by using the Characterization of the GL Process using Nodal Analysis allows predicting the production rate the well can produce. Similar results are obtained with commercial applications [15], which are used for modeling and optimizing the behavior of a well.. The advantage of our well model is that it is implanted at wellhead level and not at a distant computer (which would generate delays in the decision making processes).
3. The Fuzzy System for Well Analysis allows us to analyze the data coming from the By-phase Fluids extracted from the well. It generates information from the reservoir variables (bottom-well pressure), from wellhead (casing pressure) and gas flow. Normally, these variables are not used together for not having the bottom measurement. This will allow the well to self-diagnose, control its damages, watch and supervise the behavior of its subsoil/surface infrastructure, all this at real time. This is currently done through commercial centralized applications that depend on Communication Systems and large Databases, generating delay in the decision making processes and possible operational impacts (low production, gas recirculation, oil leaks, etc.).
4. The production of the GL method was optimized in terms of the integrated subsoil and surface information, which will allow minimizing costs and guaranteeing the best distribution of the injecting gas, maximizing the production of oil. The subsoil-surface integrated approach is innovative in the sense that it integrates the reservoir/wellhead infrastructure behavior. This is done through an objective function, with the respective restrictions of the process, which allows contextualizing such objective function to the operational scenario and the reservoir conditions identified in the previous phases of the supervision scheme. The genetic algorithm establishes the production and gas injection value optimum for the identified operational scenario. That optimization scheme reduces the production costs and optimizing the gas injection.

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