# Multiobjective Optimization Model using Genetic Algorithms for Oil Wells based on Electro Submersible Pumps

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*Abstract*— **The processes of optimization of oil wells involve an objective function that maximizes the production and minimizes the energy of lift. For the solution of this type of multi-objective problem, in the last decade the evolutionary technologies have demonstrated to be an effective and efficient tool. In this work is presented an evolutionary approach, in order to improve the performance of the Industrial Production in petroleum wells based on electro submersible pumps (ESP). The production is modeled using Numerical Methods based on Ordinary Differential Equations (ODE).**

*Keywords—evolutionary computation, multi-objective problem, production of well.*

## I. INTRODUCTION

The electric submersible pump (ESP), a tried and true workhorse of artificial lift systems, has a long track record for improving production and recovery rates in oil fields worldwide. As the industry has moved into more challenging frontiers and pushed to boost production from brownfields, ESP technology has evolved with the development of increasingly robust mixed flow systems that can handle varied flow rates and provide expanded operating ranges for a wide variety of hydrocarbon environments [1].

The decline of "easy" oil, however, has raised the bar even higher for artificial lift, including ESP performance. Many production companies are finding that the typical for ESP is a limitation, especially in complex, remote locations where intervention costs are high and lead to poor field economics. In these intervention constrained markets, the expense of ESP replacement, including workover costs and deferred production. The risks of early ESP failure and inconsistent performance in high intervention cost environments in challenging fields are the reasons many producers often choose alternative mechanism such as gas lift for artificially lifting their wells that typically do not deliver the highest recovery rates. That conundrum has led operators to put the need for a consistently reliable, longer lasting ESP systems at the top of their wish lists as they strive to maximize efficiency and reduce their total cost of ownership [2].

In response to that, this article presents the design and implementation of a computational tool for the optimization of systems lift of oil. Particularly, the oil and gas companies carry out constant efforts to optimize their systems of production. These efforts are directed to maximize the total daily production of hydrocarbons, minimizing the environmental costs, between others aspects, that extends the run life over conventional ESPs.

On the other hand, the Evolutionary Algorithms (EA) are technologies of optimization and search inspired by the natural evolution. There are other techniques in the literature that can be compared with EA [12], [13]. These algorithms define a population of individuals, each of them representing a possible solution to the proposed problem. Every individual of the population is defined genetically, this way, the best individuals are those that possess better genes. The best individuals are combined between them so that they form new solutions that possess better genes that their antecessors [3]. These new solutions generate a new population of individuals replacing the previous one ([3], [4], [11]).

The Evolutionary Algorithms (EA) is robust and effective methods for the resolution of problems of optimization. In [4] is presented an example of application in the petroleum industry, for the development of the concept "intelligent fields", in which it is used for the analysis and interpretation of a great quantity of information, combined with neural networks. So, A concept of industrial automation for control and optimization of the production of hydrocarbon based on genetic algorithms is presented [4].

So, in this work we propose a system for the optimization of wells using the Evolutionary Algorithms, specifically for wells based on electro submersible pumps (ESP). In this case,

we have determined two objectives to optimize: maximize the production of hydrocarbons and minimize the energy lift, which generates a zone of negotiation that allows finding the ideal production. The optimization system is composed of one first phase (component) of well model generation (using techniques of mass and energy balance), and one second phase (component) of optimization of the productive process for the identified scenario [5]. This paper is structured as follows: Theoretical aspects about Evolutionary Algorithms and the Production Process of well are presented in Section 2. The design of the Evolutionary Optimization System and the Model of the Well is presented in Section 3, while the results are shown in Section 4. The paper ends with conclusions.

## II. THEORETICAL FRAMEWORK

### A. Evolutionary Algorithms

The Evolutionary Algorithms (EA) simulates the process of natural evolution [4]. They consist of an iterative technology that applies operators over a set of individuals of the population with the intention of improving their "fitness", a measure related to the objective function of the problem in question. Every individual of the population represents a potential solution of the problem. Initially, the population is generated randomly, and then it evolves by means of operators', which include recombination of individuals, crossover and mutations. This evolution is guided by a strategy of selection of the individuals most adapted to the resolution of the problem, according to their values of fitness. The Figure 1 presents a generic scheme of an EA. The intention of the Selection is to emphasize in the most capable individuals of the population, hoping that their children have fitness better than that of the parents. The crossover operator combines several individuals to generate new individuals, and the mutation is a random process where a gene is replaced by other for producing a new genetic structure. The Replacement is a process that substitutes individuals of the population (normally the worst) for the new individuals created (normally the best). As soon as a new population has been produced, the "fitness" of the individuals in the new population can be determined and restarts the process ([3], [4], [11]).

```
Begin (P(0))
generation=0
Test (P(0))
While  (no CriterionStop) do
    Father = Selection (P(generation))
    Sons = Operators of Reproduction (Father)
    NewPop = Replacement (Suns, P(generation))
    generation ++
    P(generation) = NewPop
```

Figure 1. Scheme of an AE

### B. Electrical Submersible Pump Method

ESPs are turbo machines that transfer energy to fluids by means of stages conformed by one impeller and one diffuser. These devices, as any centrifugal devices, are highly affected by changes in the viscosity of the fluid that is being pumped. For a centrifugal pump, as the viscosity of the fluid increases, the required brake horsepower increases as well; whereas, head capacity and efficiency decrease. There are tools that allow

engineers to evaluate the effects of viscosity of fluids in the pump with a reasonable accuracy. The pump of an ESP system may have a significant number of stages spinning at high velocities. As a result, a volume of fluid is exposed to a considerable amount of shear force that induces increments on the fluid temperature. Consequently, and according to the liquids that are being pumped, there might be a considerable difference between the viscosity of the fluid at the inlet of the pump and viscosity of the fluid at the outlet of the pump. Therefore, the stages of pumps should not have the same performance, resulting in an increase of the capacity to generate pressure in the upper section of the system ([1], [2], [10]).

So, the ESP process of transforming mechanical energy into hydraulic energy is characterized by the pump performance curves Figure 2, given at a operational speed that is often expressed in terms of frequency (f). The hydraulic energy that an ESP system is able to deliver is expressed in Height (ft) and Flow Rate(Q); The Energy that a pump demands of the motor is represented by the Brake Horsepower Curve (Potency,Hp), and the Curve of Efficiency ($\eta$,%) is a representation of how much efficient this energy transformation.
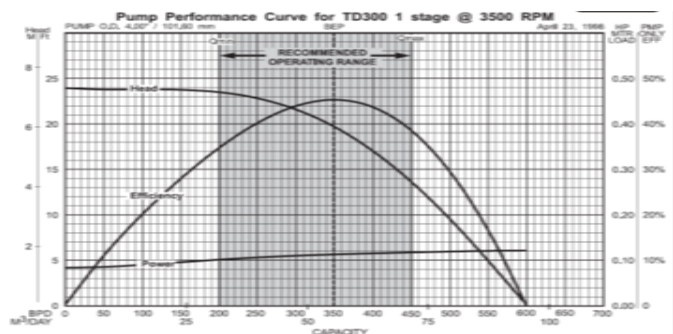


Figure 2. Curve of Performance of Pump a One Stage in 3600 RPM (60 Hz)

## III. DESIGN OF THE EVOLUTIONARY OPTIMIZATION SYSTEM

### A. First Phase: Generation of the Well Production Model

The mathematical models presented in this work are inspired on ([5], [6], [10]), and basically consist of checking the pressure profile from the head (Pwh) to the bottom (Pbh) of the well, to determine the current production capacity (Q), which exhibits the well through the pumping system. For this purpose, the method called nodal analysis is used  ([5], [6], [7]). Thus, a simple model of production by artificial lifting by electric submergible pump is proposed: the inflow of crude oil and gas of the reservoir is modeled by the use of the productivity index (relationship between the production rate (Q) and the differential Between the reservoir pressure (Pr) and the flowing pressure at the bottom of the well (Pbh), using Equation 1, which determines the capacity of the oil reservoir. It is normal for this capacity to decrease over time, for the reduction of the permeability in the vicinity of the well, and for the increase in the viscosity of the well. This Equation 1 is inflow referred to as the energy supply curve, or flow of fluids, that the reservoir delivers to the well (Pbh vs q).

$$\frac{dp_{bh}}{dt} = \frac{\beta_1}{V_1}(q_r - q) \qquad (1)$$

As for the outflow, described by Equation 2, the pump transfers kinetic energy to the fluid, reducing the weight of the column, increasing the head pressure in the well, allowing to establish a certain production rate in which the fluid supply capacity of the reservoir equals the fluid extraction capacity of the well.

$$\frac{dp_{wh}}{dt} = \frac{\beta_2}{V_2}(q - q_c) \qquad (2)$$

Thus, the production of the system responds to a balance of energy in the form of pressure, between the capacity of energy reservoir and the lifting system, expressed in Equation 3 ([2], [5]).

$$\frac{dq}{dt} = \frac{1}{M}(P_{bh} - P_{wh} - (\rho_1 g h_1 + \rho_2 g h_2) + \Delta P_p - \Delta P_f) \qquad (3)$$

Where:
Pbh = Bottom Pressure
Pwh = Head Pressure
$\beta_1$, $\beta_2$ = Volumetric Module
V1, V2 = Volume Multiphase
qr = Input Flow
q = Flow of well
qc = Flow of Valve
$\rho_1$, $\rho_2$ = Density of flow
g = gravity
h1, h2 = Vertical Distances
$\Delta$Pp = Differential of Pressures
$\Delta$Pf = Total Pressure Loss in the Well

So, in the case of the pump, the production curve is used in function of the efficiency indicated by the manufacturer, to which a polynomial adjustment is applied, to determine the Differential equation (ED), which describes the production curve in terms of [6]: the efficiency of the pump to proper operating conditions of the well (variables surface and bottom), API grades (measure of how heavy or light a petroleum liquid is compared to water) and kinetic viscosity ($\nu$, is the ratio of the dynamic viscosity $\mu$ to the density of the fluid $\rho$). Thus, API and $\nu$ are data obtained in crude sample at the laboratory level, Equation 4.

$$H_0(q) = aq^5 + bq^4 + cq^3 - dq^2 + eq - f \qquad (4)$$

Where a, b, c, d, e and f are constants characterized for a specific pump.

So, to model the production lift system according to the above (Equations 2, 3, 4), we will use numerical methods based on Adams - Bashfort of fourth order predictor and Adams - Moulton corrector, with initial values obtained with the Runge - Kutta method of the fourth order [8].

*B. Second Phase: Optimization of the Production Process*

The optimization problem of ESP wells consists of increasing the production of oil and minimizing the energy, based on three variables: Height (H,ft), Production (Q,BPD) and Efficiency ($\eta$,%). 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 pumping of the bottom well", as it was previously explained.

The restrictions are contextualized in the operational scenarios and the reservoir conditions. We assume that: $\rho$, g are constant, due to the slow dynamics of the reservoir. From the well model, we establish the maximum production capacity that a reservoir can contribute, Qmax. Below, we present the objective function with its respective restrictions:

$$\eta(\%) = \frac{\rho g Q H}{\text{Potency power for the pump} * 1{,}000 \text{ W/KW}} \qquad (5)$$

Where:

Hmin < H < Hmax $\rightarrow$ 10.000(ft)<H<14.000 (ft).

Potencymin < Potency <Potencymax $\rightarrow$ 20(Hp) < Potency < 40(Hp).

Qprod min < Qprod < Qprod max $\rightarrow$ 6000(BPD) < Qprod < 8000(BPD).

The intervals regarding the restrictions in, Equations 4 and 5, depend on the identified operational scenario, which are characterized in the Equation 6. These ranges will be used by the optimization technique. In order to solve that problem, a genetic algorithm is used, which presents the following components.

Structure of individuals: is coded in real numbers composed of two fields, H and Hp, Equation 6. These variables are used, because they are related to the bottom behavior and surface level production, and they can be manipulated at an operational level with a field instrumentation arrangement. This is important, can be adjusted in terms of the optimum values recommended by the genetic algorithm, and thus achieve the best performances of the producing well.

Number of individuals: random between 2 and 10. Number of generations: 99, Objective function: Equations 4 and 5, including its respective restrictions. Crossover operator: single point cross with 0.7 probabilities. Mutation operator 30%: random with 100 probabilities. Space for search: a population of individuals was gathered with the set of values allowed to variables H and Hp, according to the operational scenario identified in the restrictions of the Equation 6.

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 the Equation 5 for that operational scenario.

## IV. RESULTS

### A. First Phase: Generation of the Well Production Model

This section presents the first result, which describes the effectiveness of the tool developed to determine the performance curve of an electric submergible pump (flow vs. efficiency) [6], that will generate the polynomial of the pump under study, following the same behavior of the Curve of the Fabricant, as well as the Curves of the Potency and Height, as a function of the flow rate (see Figure 3). So, the polynomial characteristic of the pump corresponding to the study is (see Equation 6)

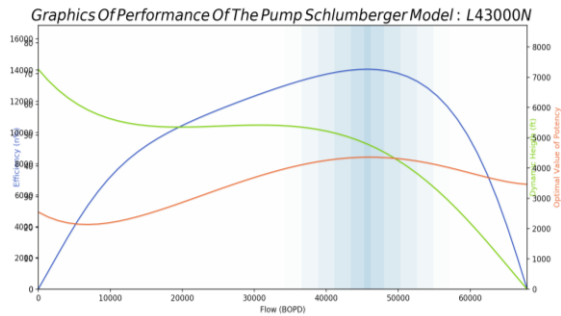$$H_0(q) = 9.3072e - 11q^5 + 4.7302q^4 + 0.0005q^3 - 0.004q^2 + 0.150q - 0.054f \qquad (6)$$



Figure 3. Experimental Curve of the Performance of the Electric Submergible Pump

### B. Second Phase: Optimization of the Production Process

This section presents initially an inference of the operational parameters of the bottom (Pbh), head (Pwh) pressures and of the production rate (Q), as a function of the measured variables with instrumentation of field (frequency,f) and pressure in the (production line, Pts), Thus, f and Pt, are real conditions of the well to study object, taking a history of 6900 instances, evaluated in the system developed based on Adams - Bashfort of fourth order predictor and Adams - Moulton corrector, with initial values obtained with the Runge - Kutta method of the fourth order [8].

Thus, the Figure 4 represent the behavior of the classic systems of an artificial lift system. So, for example when the bottom pressure decreases (Pbh) the rate of production (Q) must increase, likewise when the bottom pressure (Pbh) increases there is a significant drop in production.
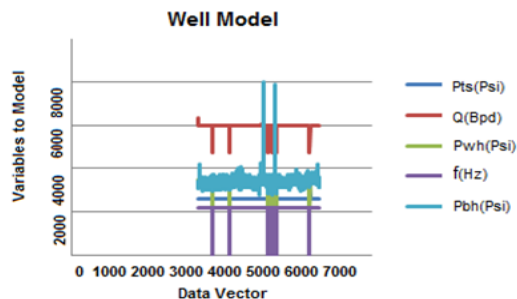


Figure 4. Modeling the Well to Study Object

Following, the Genetic Algorithm was applied for one of the operational scenarios identified in the first phase (see Equation 6). The final population given by the Genetic

Algorithm for that operational scenario is shown in Equation 5, which objective is the value of η(%). According to the results of the Figures 3 and 4, the production system presents an optimum behavior at a height 5000 to 6000 ft, Potency 35 to 45 Hp with an associated production of 7000 to 8000 BPD. So, according to Figure 3, the maximum production of the well is approximately 7500 BPD, with an efficiency level of the order of 70%. Thus, the genetic algorithm obtains a maximum efficiency value of 67%, in 55 generations, the Figure 5, which represents a production values of 7700 BPD (see Figure 6).

The second experiment is performed. Thus, the genetic algorithm obtains a maximum efficiency value of 68%, in 88 generations, Figure 7, which represents a production value of 3500 BPD. This result represents the effectiveness of the implemented algorithms (see Figure 8).
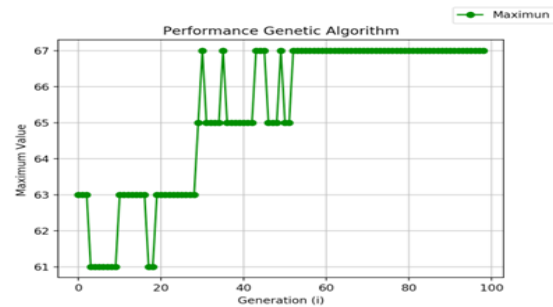


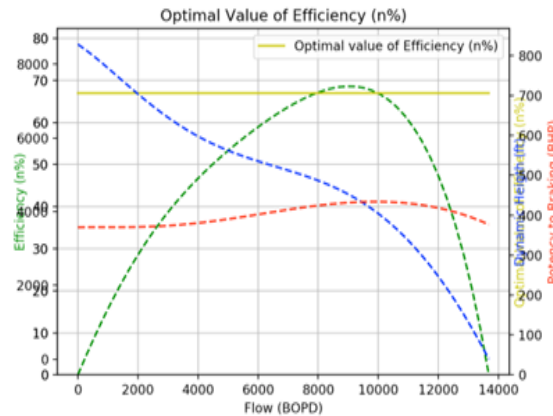Figure 5. Performance Genetic Algorithm, First Experiment



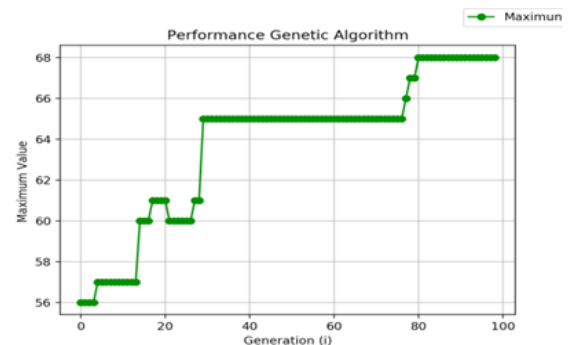Figure 6. Modeling the Well to Study Object with Genetic Algorithm, First Experiment



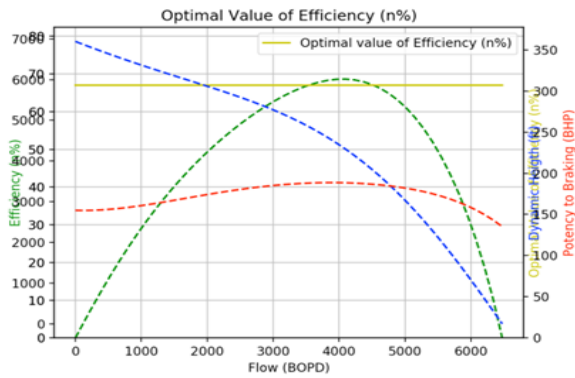Figure 7. Performance Genetic Algorithm, Second Experiments

Figure 8. Modeling The Well to Study Object with Genetic Algorithm, Second Experiments

## V. Conclusion

The production model obtained by using the characterization of the ESP Process using Nodal Analysis allows the prediction of the production rate that the well can produce. These models show the behavior from the "inflow" variables of the reservoir and surface pipe flow for any fluid. In our case, the Intelligent System allows obtaining similar results at reservoir and wellhead levels, in field operational.

The production of the ESP method was optimized in terms of the integrated subsoil and surface information, which will allow guaranteeing the best distribution of the energy in 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 in the operational scenario and the reservoir conditions identified in the supervision scheme. The genetic algorithm establishes the optimum production and efficiency value for the identified operational scenario from the relationship of the two productive processes: reduce the energy and optimize the efficiency and maximize of productions.

Finally, our multiobjective optimization model system must be proved using other method of lift, compared with other intelligent techniques [9], [12], [13] and parallelized [11], in order to analyze and improve its system performance (at level of the results quality and execution time).

### References

[1] A. AI-Jasmi, K. Goel, G. Moricca, and A. Carvajal. ESP Smart Flow Integrates Qualiy and Control Data for Diagnostics and Optimization in Real Time, SPE 163809. 2013.

[2] C. Bravo. J. Aguilar, J. Aguilar-Martin, F. Rivas, A. Rios, and L. Saputelli. An implementation of a Distributed Artificial Intelligence Architecture to the Integrated Production Management, Journal of Natural Gas Science & Engineering, Vol. 3, No. 6, pp. 735-747, 2011.

[3] R. Leal, J. Aguilar, L. Trave-Massuyes, A. Rios, and E. Camargo. Genetic Algorithm Approach for Diagnosability Analysis, International Journal of Engineering Development and Research, Vol. 2, No. 4, pp. 3786-3799, 2014.

[4] E. Camargo, J. Aguilar, A. Ríos, F. Rivas, and J. Aguilar-Martin. Optimization Model based on Genetic Algorithms for Oil Wells, Proceeding 9th WSEAS International Conference on Computational Intelligence, Man-Machine Systems and Cybernetics, pp. 173-178, 2010.

[5] E. Camargo, J. Aguilar, A. Ríos, F. Rivas, and J. Aguilar-Martin. Nodal Analysis-Based Design for Improving Gas Lift Wells Production, WSEAS Transactions on Informations Science & Applications, Vol. 5, No. 5, pp. 706-715, 2008.

[6] E. Camargo, J. Aguilar, E. Aceros, and H. Lozada, Implantación de un Sensor Virtual en Procesos Operacionales, Sociedad Chilena Mecánica Computacional, Vol. 14, No. 1, pp. 68-77, 2017.

[7] E. Camargo, J. Aguilar, and E. Aceros, Intelligent Well Systems, Proceeding IEEE Asia-Pacific Conference on Computer Aided System Engineering, pp. 13-18, 2015.

[8] R. Burden and D. Faires. Análisis Numéricos, Séptima Edición, International Thomson Editores, S.A., 2002.

[9] E. Camargo and J. Aguilar. Advanced Supervision of Oil Wells Based on Soft Computing Techniques, Journal of Artificial Intelligence and Soft Computing Research, Vol. 4, No. 3, pp. 215-225, 2014.

[10] E. Camargo, J. Aguilar, A. Rios, and F. Rivas. Un Modelo de Producción de Pozos por Levantamiento Artificial Utilizando Análisis Nodal. Revista Ciencia e Ingeniería, Vol. 30, No.1, pp. 23-28. 2009.

[11] F. Hidrobo and J. Aguilar. Toward a Parallel Genetic Algorithm Approach Based on Collective Intelligence for Combinatorial Optimization Problems, Proceeding IEEE International Conference on Evolutionary Computation, pp. 715-720, 1998.

[12] J. Aguilar. A General Ant Colony Model to Solve Combinatorial Optimization Problems. Revista Colombiana de Computación. Vol. 2, No. 1, pp. 7-18, 2001.

[13] J. Aguilar. Definition of an Energy Function for the Random Neural to Solve Optimization Problems, Neural Networks, Vol. 11, No. 4, pp. 731-738, 1998.