GENETIC MODEL FOR GAS RESERVOIR SIMULATION

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ABSTRACT: A general application model applied to gas reservoir simulation merging elements of the evolutionary and object-oriented paradigms is shown. The model works in three ways: 1. Make an adaptive grid partition of the 3D structure based on a non-linear function. 2. Solve the non-linear algebraic equation systems in each block, which are generated for the gas properties calculation, taking advantage of the object-oriented programming and genetic algorithms, this method is mainly advised when there are problems with traditional methods like Newton Method. 3. Find out an adaptive pressure distribution through of the reservoir based on a double exponential function, this distribution is more real and easy to understand and interpret that those gotten by others models. Finally, the model integrate the three sub-models to solve the non-linear equations system depicting the gas flow through the gas reservoir. This model exposes a novel representation method of individuals specifying the reservoir, equations, blocks, etc., and their components as object classes, following a complex system simulation model which take advantage of a genetic algorithm developed in oo-programming and fed with a population of those classes to attain a suitable solution. Expansion of the model to others more complex problems in different areas and the introduction of the genetic programming are discussed.

Key words. Gas Reservoir Simulation, Complex Systems, Genetic Algorithms, Object Oriented Modeling.

INTRODUCTION

Two successful models, independently developed, were merged to produce a new model of general application. The object-oriented conceptual modeling (O.O.) is well known for his closeness to natural cognoscible processes and Genetic Algorithms (G.A.) are known for giving good solutions to new and traditional issues with a marked non-linear behavior.

Our object-oriented genetic model (OOGM) is very easy to implement due to the confluence of both the objectual representation of the system's elements under analysis and the construction of a G.A representing its own evolution. This model, which combines current simulation techniques and modeling techniques of evolutionary computing [Mitchell 97] [Angeline 96] can be applied to a large quantity of problems in complex systems [Sánchez, 2001] [Torres, 2000 a, b, c, d]. Its performance is evaluated through the simulation of the GÜEPAJÉ-AYOMBE gas reservoir, which is handled by the columbian oil company ECOPETROL. The simulation is carried out within a framework of equations a little deviated respect to the traditional linearization equations methods, and the final outcome to be solved is a strongly non-linear system. Even though the system was approached with some restrictions for its real complexity (monophasic flux, absence of capillary pressures and some heterogeneities), the method used here will permit oncoming works to utilize other tools of evolutionary computing such as genetic programming, evolution strategies, etc, which will allow to expand and corroborate the prediction of this study on far more complex problems.

1. PROBLEM DESCRIPTION

The model was tested through the simulation of a complex system which was a typical gas reservoir, satisfying non-linear conditions of turbulence. The research was applied to a real case of a columbian reservoir in order to provide a practical projection so that it can be continued in the future.

ECOPETROL, oil columbian federal company supplied information over the gas reservoir GÜEPAJÉ - AYOMBÉ, located near the limits between the states of Sucre and Bolívar in the Ciénaga de Oro sedimentary layer, in Columbia. The reservoir holds three wells which have been drilled since 1992 with approximately every three years between each one.

Gas flux through a porous medium exhibits a turbulence level that can be regarded as chaotic, which tends to be a no linear model when it is going to be simulated. The process of simulation of this phenomenon depends on multiple factors and assumptions necessary to construct a model that converges in the shortest time without loss of validity or precision. Thus, the problem will be to simulate the future behavior of the reservoir, providing important information about a real problem of forecasting the economic life of a oil field to be managed.

2. OBJECT -ORIENTED EVOLUTIONARY MODEL FOR GÜEPAJÉ - AYOMBÉ GAS FIELD SIMULATION.

Inherent complexity of modern methods for systems modeling and simulation, stems from the great amount of information and related elements. Figure 1 shows all of the disciplines that must be accounted for altogether to make a oil reservoir simulation project [Salery, 98]. In view of the heterogeneous and extensive areas of engineering involved, and according to the characteristics and way followed by the systemic thinking, the necessity for integration of the these systems has arisen [Peebler, 98; Cooper, 97].

Types of complexity

Natural systems are in continuous evolution, making adaptation and interaction in relation to its surrounding environment, which in turn is evolving itself. This combination of interdependent mutual evolution, yield a high level of complexity in the formulation of one solution. Furthermore, the representation of the elements of a natural system is multidimensional and including features such as the component geometry, directionality, neighborliness or closeness, similarity, energy fluxes, etc. Nowadays it is proposed, like in [Salery, 98], and formerly in [Senge, 94], that there are two types of complexity in simulation projects:

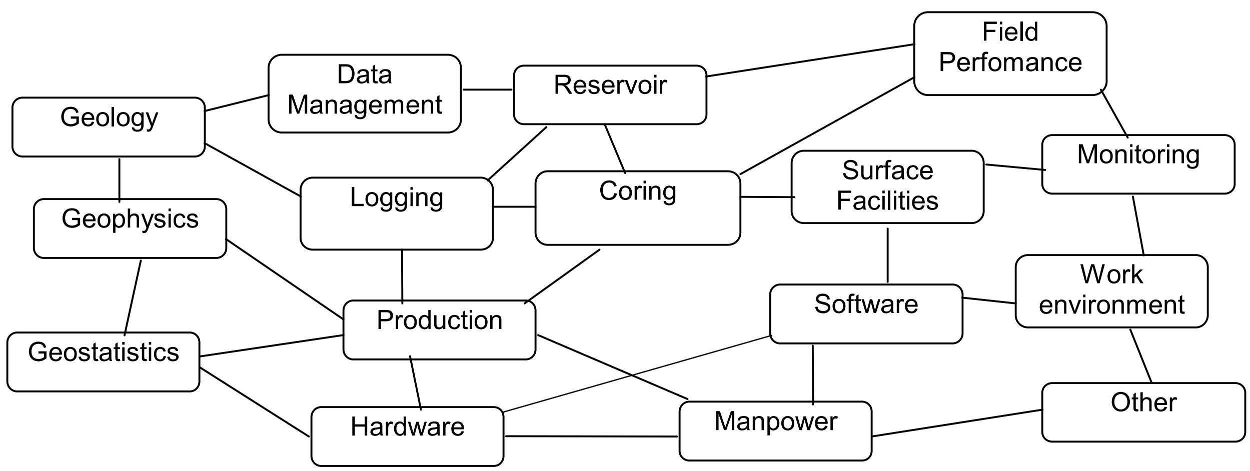


Figura 1. Managing Reservoirs in a multidiscipline data environment [Salery, 98],.

Detail complexity: it is related to the detail definition, structuring and management of the static individual components of the project.

Dynamic complexity: it deals with the dynamic consequences of the interactions between the individual components of the system. This is the kind of complexity with a major importance in order to understand a natural system since the consequences or results of the interrelationships are generally unpredictable.

We try to put together the detail complexity of a system with its dynamic complexity through its simulation. Nevertheless, the actual control of most of the projects, lies in the understanding of the latter instead of the former type of complexity. [Salery, 98] [Senge, 94].

Object oriented genetic model (OOGM)

An object-oriented evolutionary model developed to model complex systems, namely natural systems, may represent the structure and dynamics of the system.

The system components can be represented along with its properties and functions by using the O.O paradigm. This paradigm, not only has shown its worth in the last decades due to its modeling capabilities but when it is extended and integrated with other paradigms as the evolutionary computing, it has proved to be a simple natural way of representing complex systems whose components evolve into a satisfying solution to the system as a whole. This integration was proposed in [Torres, 2000a, b, c, d] as the Object-Oriented Genetic Model (OOGM), useful to model dynamic systems accounting for both its dynamic complexity and detail complexity by representing the transformation of the objects together with its traits and functions into new stages determined by non-linear trends (as in a ecosystem) or either into improved stages or nearer an optimum overall stage (in case of quest of the optimum stage of a non-linear system). The advantages of combining OOP with Artificial Intelligence, were first investigated in [Tello, 89], who applied this association to expert and learning systems. Even though this field has as a main drawback that there are rather few publications and it constitutes a base for a new generation of scientific languages.

Dorsey and Hudicka [Dorsey, 99], also give us a good example of the integration of another two different paradigms, They merged the OO modeling with the relational paradigm for databases, making the most of the unified modeling language (UML) and ORACLE technology. Regarding this topic, they stated:

> "Logically, the data and codes are not to be taken into account in a separate manner. The underlying idea of object orientation that the entities and their corresponding operations and methods must be considered altogether, is a much more logic and natural approach"
> "Improvements expected in the development and maintenance speeds are going to be a consequence of this more natural philosophy of modeling. The stronger the disconnection between the way we think of our systems and the tools we use, the longer it will take us to reach a good development. If we get that the Relational Database Management System (RDBMS) and the tools to be more consistent with this object oriented methodology, we will be able to construct better systems a lot of faster."

They also show the way in which the universe of modeling and simulation of the real world by computers moves swiftly toward the paradigms integration. They also noted some restraints, that even today are in store to be satisfactorily addressed, as the type of relations that may be represented and the modeling of systems of dynamic information. The OOGM object genetic model moves into this direction. Even though it is not initially bound to solve all these difficulties, it opens up a wide route that may be used as support for this purpose.

As it was previously noted, the following five steps or submodels, are a simple specific application of the general OOGM model.

Steps followed in an object - oriented evolutionary simulation

To cope with the complexity mentioned above in the gas reservoir, a general model was constructed to represent the detail and dynamics complexity in a complex system, which can be observed in figure 2. This model is the conceptual base for the submodels and applications made to solve the problem system described in the before section. Solution to this problem was worked out in 5 steps:

Step 1. A novel general scheme is proposed, shown in figure 2, which models the dynamic and detail complexity in complex systems. The model was named OOGM [Torres, 1999]. In the three subsequent steps this general model is separately applied to every subproblem, integrating finally their solutions into the final step.

Step 2. An evolutionary submodel was set up for space discretization, which "intelligently" divides the reservoir based upon the behavior of the flux equations. Figure 3 depicts the flowchart of the implementation of OOGM model for this case. Figure 4 shows the graphic results.

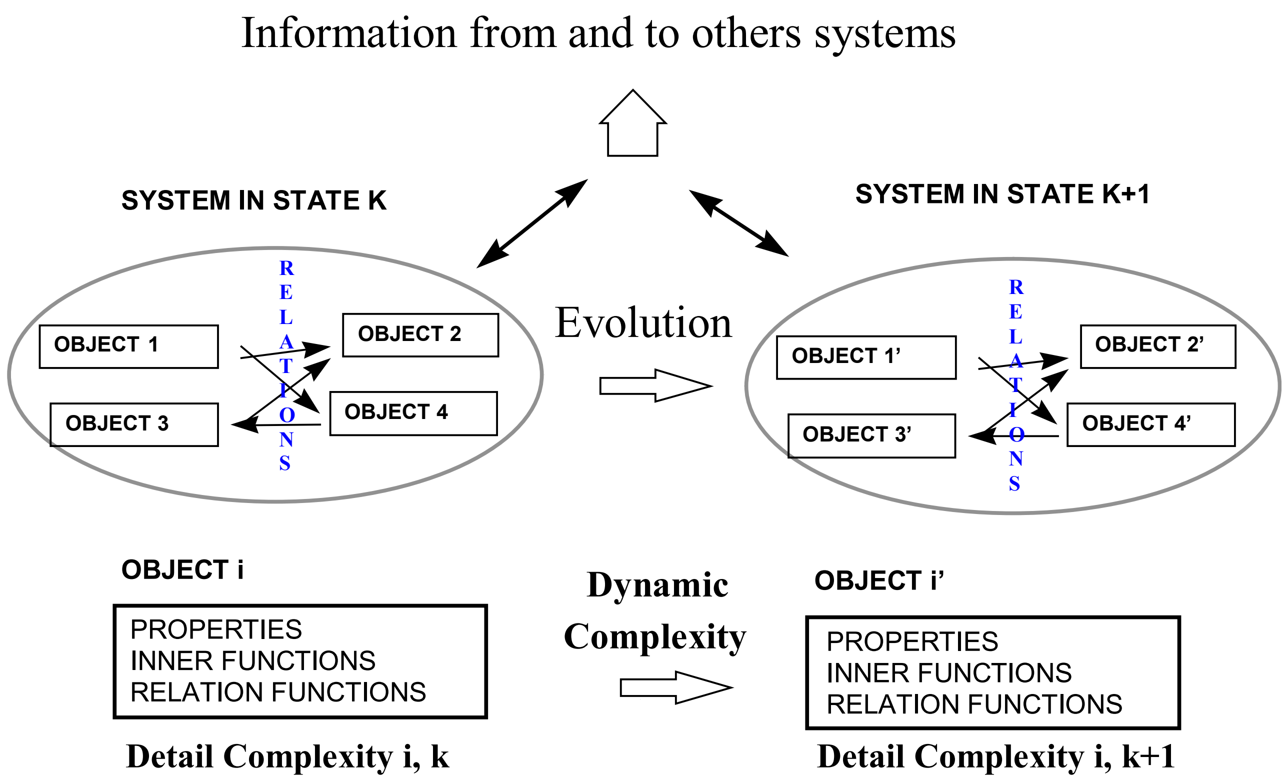


Figure 2. Object-oriented genetic model (OOGM) used to optimize a complex system.

The evolutionary submodel for space discretization get the optimal division from an starting population, randomly chosen, to which a heuristic non-linear space interval distribution is applied, and that evolves according to a fitness function, which has as main component the number of spatial intervals, into the directions where there is the major flux variation [Torres 2001a, b, c]. It is also easy to include time intervals if stability analysis of the convergence of the solution of the application model are required.

Step 3. Another evolutionary submodel was created as a solution to non-linear algebraic equation systems. These systems frequently appear interacting with more complex systems of partial differential equations. Since this non-linear systems are to be solved for each block in every iteration (in an implicit or explicit model) and in every time, hence they are responsible, partially, for the extensive overall run time and the error increase of a simulator because they feed others simulator processes. Thus, it is proposed a rapid evolutionary model giving reliable results where other methods like Newton-Raphson´s, fail [Torres, 1999]. Equations and groups of members may be modeled in object classes [Brumbaugh, 94] [Pastor, 95], as well as unknowns, functions and their arguments; an instantiation for the objectual system will determine the fitness function which is equivalent to the instantiation error and will reveal if a solution has been reached. As observed in Figure 5, four objectual classes will be sufficient: ***Equation_individual*** class, ***Equation_member*** class, ***Solution_individual*** class and ***Genetic operator*** class. The ***Equation_member*** class displays two specializations, *the* ***unknown*** class and the ***function*** class, which in turn has a specialization: the ***argument*** class.

Step 4. An evolutionary submodel was created to represent the pressure distribution across the reservoir, which is similar to the solution to the non-linear implicit numeric equations obtained from the discretization of the original partial differential equation. It follows that for the monophasic case in question, the equation can be expressed as follows:

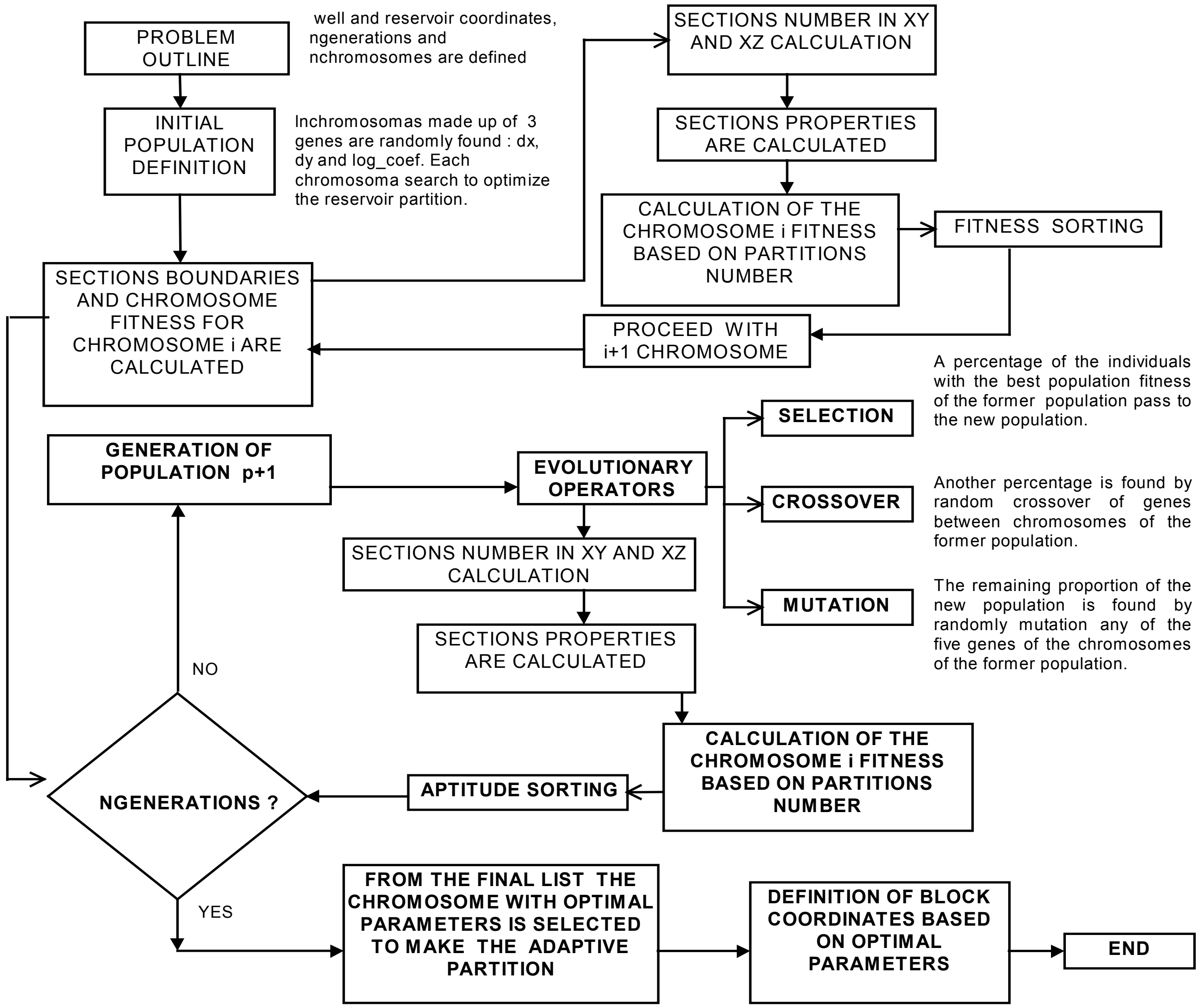


Figure 3. General algorithm for the evolutionary spatial divisor.

$$\frac{\partial}{\partial x}\left(\frac{P}{\mu z}\frac{\partial P}{\partial x}\right)+\frac{\partial}{\partial y}\left(\frac{P}{\mu z}\frac{\partial P}{\partial y}\right)+\frac{\partial}{\partial w}\left(\frac{P}{\mu z}\frac{\partial P}{\partial w}\right)=\frac{\phi}{K}\frac{\partial}{\partial t}\left(\frac{P}{z}\right) \qquad \textbf{(1)}$$

Where: P : Pressure, μ : Viscosity, z : Compresibilidad factor, ϕ : Porosity,. K : Permeability.

The model developed in this research obtains the parameters, randomly generated, for a double exponential heuristic function of the form: $e^{f(p)^{a\_\exp}}$

Let us make f(p) a random value function:

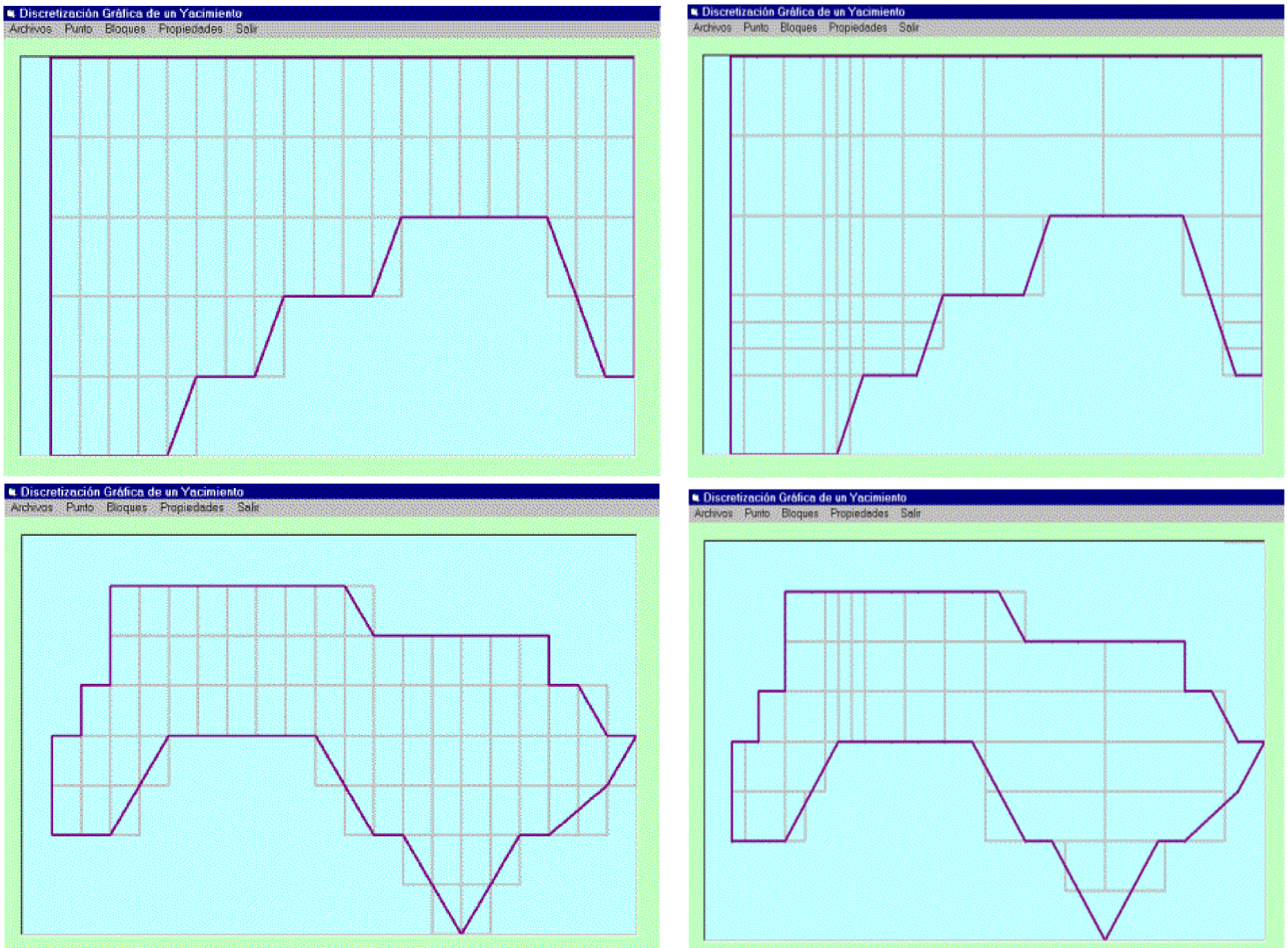
$$\mathbf{f(p) = factor\_dp * dp\_max * blocks\_base * (1- blocks\_fraction)} \qquad \textbf{(2)}$$

where (see figure 6):

blocks_base = maximum length of blocks of the field to the farthest block. If m>g, then blocks_base = m+1. Maximun pressure drop is found amidst them.

blocks_fraction = distance between the block in question and the farthest block divided by blocks_base, so that blocks_fraction = (m-j)/(m+1)

factor_dp = ln(dp_max)/blocks_base. It calculates a logarithm factor for the maximum random pressure drop between the well and the farthest block, with values ranging between 0 and 1000 lpca.



a) b)

Figure 4. Discretization of the Güepajé-Ayombé gas reservoir, on xy y xz planes respectively.
a) Using a traditional uniform model, b) Using OOGM model.

dp_max = random value ranging between 0 y 1 that changes the shape of the logarithm distribution curve when multiplied by factor_dp.

where ***a_exp***, is a random value producing the biggest variation near the well, as it may be seen in figure 7. Figure 8 shows the flowchart upon OOGM implementing to simulate the evolutionary distribution of pressure in the reservoir.

Step 5. The three previous submodels were finally integrated (step 2 through 4) to solve the complex flux problem, represented by equation 1, for the gas reservoir described above [Torres, 2001a].

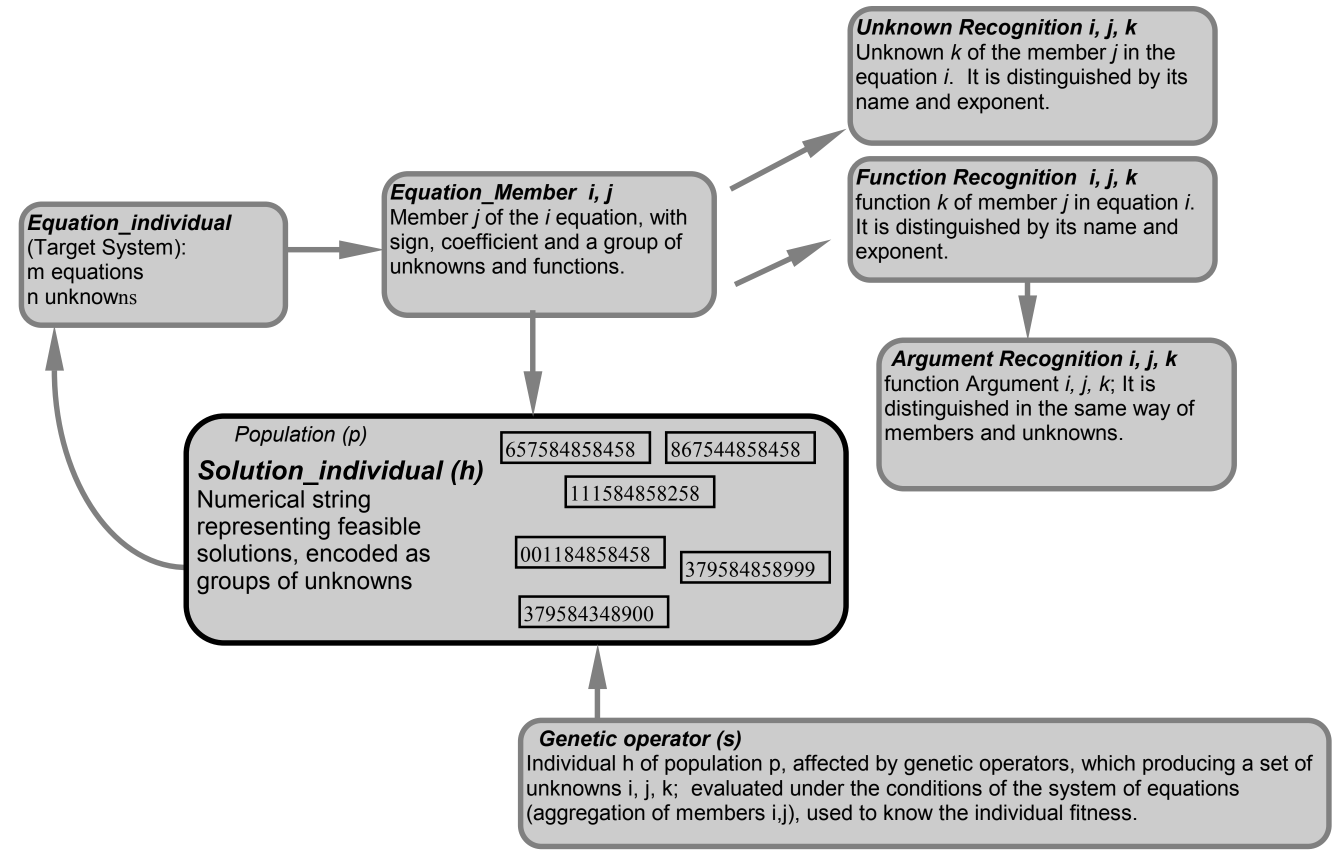


Figure 5. Information flux of the OOGM model used to solve non -linear equations systems.

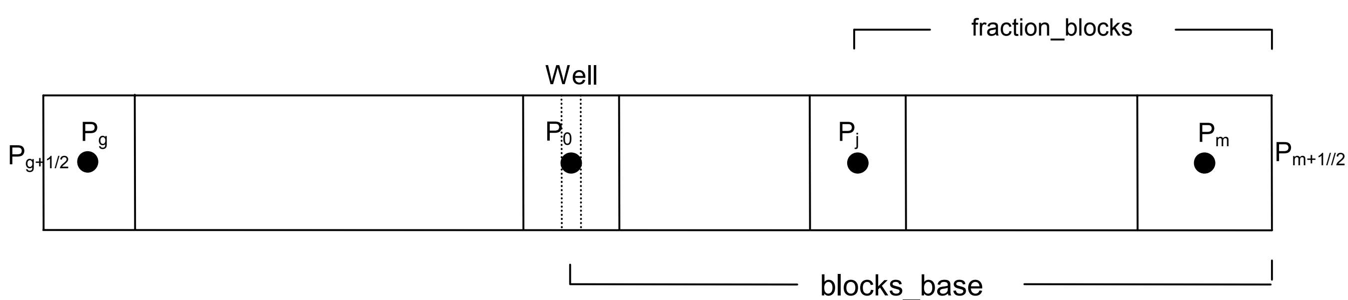


Figure 6. Model used to calculate a adaptive pressure distribution based on the well distance.

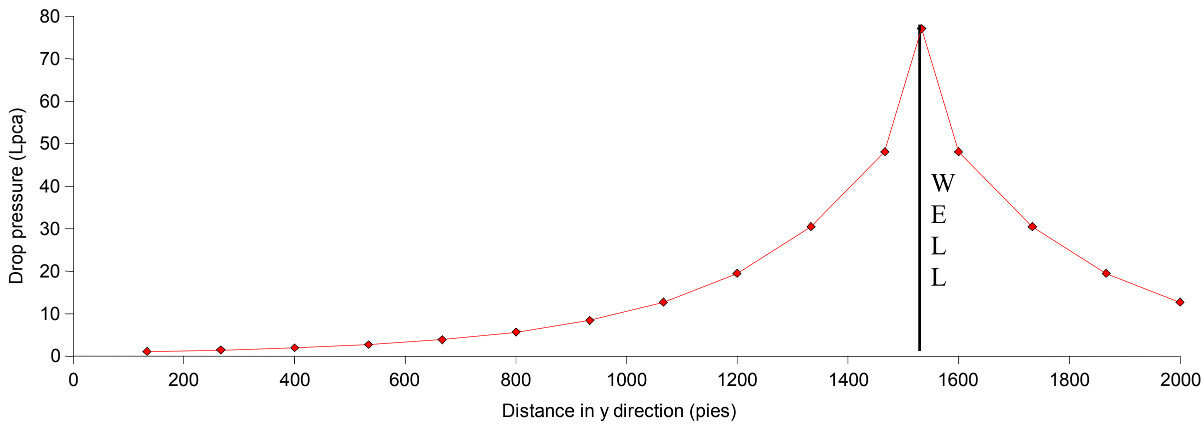


Figure 7. Drop pressure distribution using a double exponential scheme.

3. CONCLUSIONS AND ONCOMING WORKS

In order to evaluate the model, the GÜEPAJÉ-AYOMBE gas reservoir was initially simulated for the monophasic production of the well GÜEPAJÉ 1, then it was compared to a traditional implicit simulator with actual data. To go further with this investigation simulations will be made for all wells and for the multiphasic phenomenon.

The OOGM model was successful in modeling in a natural, real, easy and understandable manner, the behavior and distribution of pressures through the GÜEPAJÉ-AYOMBÉ gas reservoir, in relation to a typical implicit simulator also implemented. In addition, it allows for a more optimal discretization of this and the solution to conflicts in the calculation of some inconsistent properties such as the compressibility gas factor. As for the issue of pressure distribution, an evolutionary pressure distributor was developed; for the case of discretization the reservoir, an spatial evolutionary divisor, and for the solution to non-linear equations of the block properties, an evolutionary optimizer of non-linear systems, respectively. Each of them was successfully tested in its respective area and because of their integration it was possible to simulate the whole gas reservoir. The OOGM model can be easily extended to represent not only a non-linear distribution of pressure, but also other properties like temperature, viscosity, permeability, and so forth, based on other functions of distribution. This is specially important since by spatial discretization and distributing pressures merely based on the change of a logarithmic or exponential function of pressure (depending how it is done), other properties might by roughly distributed.

The new model was used, and can be used in the future, in the purpose to evaluate traditional or other emergent models, as well as the effects of either considering or not the variability of lithological properties (permeability and porosity) through the reservoir.

The OOGM model turns out to be a viable alternative for the solution of complex problems common in the majority of scientific disciplines. The mere application of the OOGM model helps to comprehend nature and to quantify non-linear problems, generally solved forcibly by linearization. The new evolutionary paradigms, as genetic programming, are promising tools in the study of complex systems, still expecting to be evaluated. [Velásquez, 1998] [koza, 1996] [Koza, 1992].

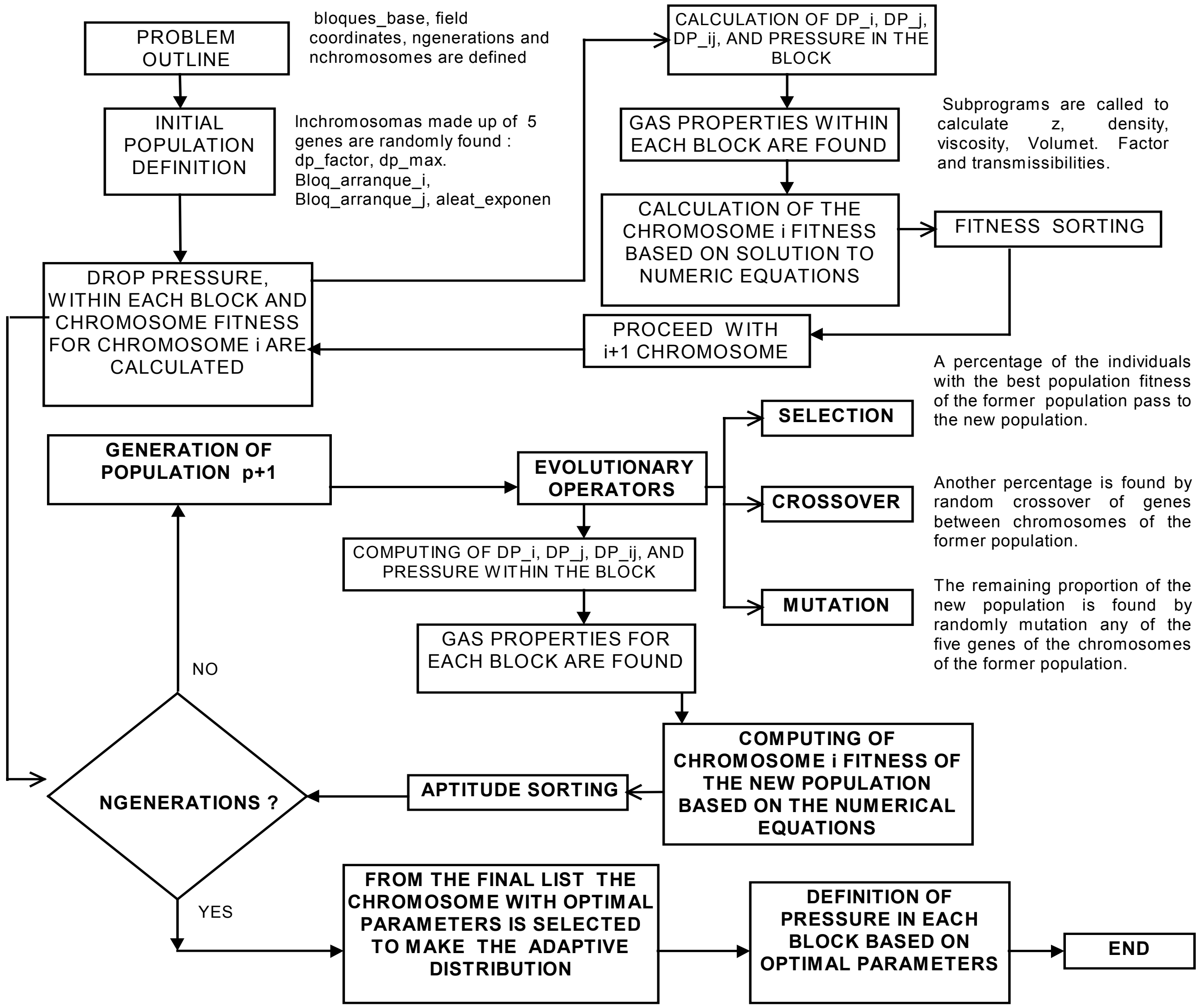


Figure 8. General algorithm for the evolutionary pressure distributor.

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