Lessons Learned During the Development of a Gas Lift Troubleshooting Expert System: A Case History

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ABSTRACT

In 1986 a team of gas lift troubleshooting engineers realized that procedural programming was not the answer in trying to preserve practical knowledge in a computer for future generations.

Looking for innovative solutions we engaged in an ambitious project with the purpose of developing an expert system that could help in preserving the know-how of a gas lift specialist, transmit this knowledge to future novice engineers and more importantly be able to perform effectively as a tool in solving operational problems.

This paper describes the evolution and progress of this project with the first prototype called DIALOGO in 1987, the first operational version SEDILAG 1.0 completed in 1991, and the last two achievements in 1992: TRINEXUS intended to interact with an SCADA system and the gas lift optimization system called SOLAG, and NetLAG 1.0 which is an application of neural networks for recognizing pressure vs. time patterns from a gas lift pressure chart.

Finally a general overview of the current stages of the project will be given: (1) DIDACTICO that will speed up the process of training novice engineers in troubleshooting and optimizing gas lift wells, and (2) NetLAG 2.0 or the operational version of the gas lift pattern recognition system.

INTRODUCTION

A well producing by gas lift will eventually present one of the following problems:

- Gas lift gas injection operation stops and well ceases to produce.
- Well does not produce but gas injection operation continues.
- Well Produces by continuous, intermittent, slug or any other gas lift method, but oil flow rate has decreased significantly.
- Productivity index or reservoir pressure declines and a change from continuous to intermittent gas lift is needed to improve oil flow rate.

When performing the analysis in any of the previous problems, the types of knowledge used are: model, and practical knowledge.

Model knowledge relates to mathematical models that describe the gas lift process in continuous, intermittent, slug or any gas lift method. These models allow us to predict the depth of injection when dealing with injection through a gas lift valve, annulus-tubing communication, hole in casing, etc.

For a gas lift expert the most important qualification is his practical knowledge related to one or more of the following tasks:

- Selection of appropriate field data to be used in the mathematical model. In some cases it is necessary to draw inferences from uncertain or incomplete well data.
- Interpretation of results from mathematical models.
- Interpretation of surface pressure charts to recognize the gas lift method (continuous, intermittent,etc). Some of the troubles can be detected from a direct interpretation of the surface pressure charts.
- Recommendation of the best course of

actions to solve a problem.

After studying profiles of several production engineers, it became obvious for us that a gas lift expert became one only after at least 8 to 10 years of training and experience. On the other hand, we were planning to increase the number of wells to be gas lifted, and an increase in the number of intermittent and slug gas lift wells was expected.

There was an ideal situation for new ideas and technologies to solve the problem of availability of gas lift expertise for the future.

SYSTEM DEVELOPMENT

In 1986 we decided to apply artificial intelligence to develop a gas lift troubleshooting expert system to preserve practical knowledge from a gas lift specialist close from retirement.

From the beginning the project was conceived in phases. Each phase intended to serve as the justification of the next.

FIRST PROTOTYPE: DIALOGO (1987)

In 1987 the first prototype called DIALOGO[1] was ready to be tested by engineers.

The development environment was chosen after an extensive evaluation exercise. AI languages were rejected as being too risky for a limited time and cost project as it was thought this first phase of the project.

An expert system shell called M.1. developed by Teknowledge Inc. was selected [2] .This tool used backward chaining as inference mechanism.

DIALOGO served not only the purpose of verifying the feasibility of applying artificial intelligence to develop a troubleshooting expert system, but also to select the most appropriate technique for knowledge acquisition.

During the development of DIALOGO it was realized that the knowledge engineer could achieve a better level of performance working with a production engineer. Therefore the development team was organized as follows: the knowledge engineer, an experienced gas lift engineer as project leader, and the gas lift specialist.

The roles of the development team are indicated in figure 1.

Review sessions between knowledge engineers from Teknowledge Inc. and ours were included in the budget as an important part of the project.

DIALOGO's knowledge base had 50 rules. The user interface was developed using the capabilities of the M.1. expert system shell. Each session between the user and the system was highly interactive. To complete a consultation session, the user had to answer several questions pertaining field data, and other "yes" "no" questions related to well producing conditions.

As a result of the evaluation of this first prototype the following conclusions were draw:

- Highly interactive systems were not practical for diagnosing a high number of wells, due to the time users had to spend during each consultation. Communication with existing data bases were necessary.

- Connecting rules to mathematical models was essential to get a closer representation of the specialist's methodology.

- Backward chaining did not reproduce the analysis of important cases.

- Field data were not always complete, or an extensive analysis were needed to select data for mathematical models.

SEDILAG (1991)

SEDILAG [3] was developed from 1989 to 1991.

The first year of the project we used an expert system shell (NEXPERT 1.0), to represent the knowledge using rules and objects. Given the number of wells we were trying to cover with this system, the time needed to complete the analysis for one well forced us to review the scope of the project.

We decided to split the project into two parts. The first intended to develop an efficient expert system, capable of analyzing 4000 wells a day (SEDILAG) and the second to develop a system for training novice engineers (DIDACTICO).

During the knowledge formalization process we realized that the gas lift specialist used underlying statistical models to generate solutions when analyzing field data. We decided to separate the problems into two parts: data analysis and troubleshooting.

After an extensive knowledge elicitation process we came up with a system as described in figure 2.

One knowledge base contains 200 rules for data filtering, while the other knowledge base contains 630 rules for interpreting results from mathematical models, and producing the diagnosis and recommendation.

Knowledge base's basic decision tree is described in figure 3. Six cases can be recognized from the tree. If the well is not producing, then there are two cases: M-I if the well does not take gas, and M-II if the well does receive gas.

If the well is producing, then it is very important the interpretation of both surface pressure recorder and injection flow meter charts. From gas injection charts three cases are defined: P-I for good injection operations, P-II for irregular injection, and P-III if well does not take gas.

Case P-I is broken into two more cases according to the interpretation of the surface pressure vs. time chart which allows us to identify the gas lift method: continuous, or intermittent flow. Moreover, this interpretation plays an important role in confirming if there is a good valve operation or injection through a hole.

The knowledge base was finally was developed using a procedural language: PL1. When taking this decision we were clear that representation of the knowledge was not going to be as explicit as we originally wanted. But for the team the development a system that could be fast and reliable in existing mainframe became a priority.

Then we sacrificed knowledge representation but we got speed and reliability instead. All expectation about having an explicit knowledge base was left for the next part of the project: DIDACTICO.

Another important lesson we learned in testing SEDILAG was the importance of the interpretation of surface pressure vs. time, and gas injection flowmeter charts. It was obvious for us that we had to automate this interpretation to give SEDILAG's knowledge base, important pieces of information needed in the troubleshooting process.

On the other hand there was another system called SOLAG (Gas Lift Optimization System), which needed the classification of surface pressure vs. time charts in the calculation process.

Results achieved with the use of SEDILAG are better than expected. A team of gas lift troubleshooting engineers (most of them with less than 5 years of experience) study between 150 to 200 wells/month additional to the previous figures. By detecting and solving problems associated to the gas lift equipment or changing the gas lift method an increase of 1.5 MSTBD in oil production have been obtained during the past 14 months.

TRINEXUS

We decided that we had enough justification to start a project to develop a neural network pattern recognition system that could be part of an integrated system called TRINEXUS[4].

TRINEXUS as shown in figure 4, integrates three main systems: SOLAG, SEDILAG and netLAG.

The main characteristic of TRINEXUS is its communication capabilities with existing gas lift data bases (gas lift design, reservoir data and mechanical completion), and the SCADA system (well test, gas lift flow rate and pressure).

NetLAG classifies for each well surface pressure vs. time shapes (both casing and tubing pressures). This classification is then used by SEDILAG to establish the depth of injection.

Given depth of injection, well test data, and the pressure vs. time shape classification, SOLAG estimates the recommended ga injection rate for the productivity index of the particular well.

With TRINEXUS' architecture we will be able to expand and insert any future development since all existing gas lift tasks have been very well defined independently one to the other: gas lift pressure and injection chart interpretation, troubleshooting and optimization.

NetLAG

NetLAG stands for neural networks applied to gas lift.

The main goals of this project were: (1) To implement an efficient mechanism to digitize surface pressure charts and to code the image in some way for storage or transmission, (2) to implement a neural networks based pattern recognition system to classify casing and tubing surface pressure vs. time (from pressure recorders) as well as static and differential pressure vs. time (from orifice plate meters) shapes, (3) to implement a friendly user interface with useful on line helps, and (4) to implement an interface with the existing expert system SEDILAG.

Criteria used in classifying pressure charts were based on one suggested by Ortiz [5].

The most difficult problem encountered in the development of NetLAG was digitizing surface pressure vs. time values from circular charts. This became the major bottleneck and time consuming task due to the noisy nature of data.

As shown in figure 5, circular charts record casing pressure and tubing pressure values. When looking at these charts color is an important issue. Background color is usually green. Casing pressure is recorded with red ink and tubing pressure with blue ink. We had to solve the problem of separating these two curves from the noisy green background which also contains red and blue pixels.

Several brainstorming sessions were held between engineers from the consulting company and ours.

Different approaches were tried. Finally a novel filtering mathematical algorithm was developed which resulted in a very close reproduction of the original shape. This algorithm is a combination of two techniques: interpolation grids and resampling [6].

A process diagram from NetLAG is shown in figure 6. There are three main processes: digitalization, encoding, and neural network. Information flows through training and operation.

The neural network architecture selected for training was MHC created by Ramirez [6], and is suited for hybrid training. .

As development platform C++ was used. User interfaces were created with MS C++ v7.0.

The first version of NetLAG proved to be successful in recognizing the patterns used in the first training sessions.

Collecting charts that can cover all the classification criteria has not been an straight forward task. Since not all the cases are present with the same frequency. It is necessary to wait until an important number of cases are studied. Teamwork is very important in this part of the project. Each one of the 14 gas lift troubleshooting engineers have the compromise of collecting typical cases, validate the diagnosis, and then organize all the field data associated with the case.

As a result of testing the first version of NetLAG, we decided to start the development of the operational version (NetLAG 2.0) that will be interacting with SEDILAG, and will be operating in a network with multitasking capabilities (operation and training at the same time).

To illustrate the use of NetLAG, in figure 7 we show an actual image of a surface pressure vs. time circular chart already processed. In figure 8, the digitized version of the chart in terms of pressure vs. time pairs values is shown. The result of the classification is also indicated.

DIDACTICO

Instruction is an integral part to successful and productive use of gas lift troubleshooting and optimization existing tools. As we stated when discussing DIALOGO's experience, the following and perhaps the final step in the development of this integrated gas lift expert system, is to come up with an intelligent computer assisted instruction (ICAI) system to speed up the process of training novice engineers.

We are using our experience in a gas lift troubleshooting course that we offer to engineers of oil industry in Venezuela since 1984. An instructional design is available and has been proved, so learning objectives have already been established.

The characteristics of the system currently developed are: (1) Capability of continuing assistance to the engineer during long and complex problems, (2) Possibility of making a comparison between the solution proposed by the engineer and the solution given by SEDILAG, explaining the correct reasoning behind the analysis, and (3) Capability of accepting problems proposed by the engineer.

The conceptual ICAI system architecture is is similar to the one proposed by Crews [8]. There are two modules, one containing metaknowledge with teaching strategies and techniques, and the other one knowledge from SEDILAG.

First prototype of DIDACTICO will be ready for testing by october 1993.

CONCLUSIONS

- The application of artificial intelligence tools such as expert systems has proved to be successful in preserving the knowledge of a gas lift specialist.

-The use of a procedural language contributed to speed up the development of the system and to verify the rules. In this stage we sacrificed having the knowledge base totally explicit.

-A combination of a ruled-based expert with artificial neural networks allow us to reproduce completely the task of troubleshooting gas lift wells. The resulted system is practically independent of human intervention.

- It is important to clearly define the need for having practical knowledge explicitly represented. We realized we were looking for two systems: one for speeding the process of troubleshooting gas lift wells with the use of the specialist´s knowledge and the other for speeding training of novice engineers.

-Field data are not always complete and it is necessary to incorporate knowledge to perform an extensive analysis to select data for mathematical troubleshooting models.

ACKNOWLEDGMENTS

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REFERENCES

1 Bravo,C.T., Mata A., and Ortiz, J.L., Inteligencia Artificial Aplicada al Levantamiento Artificial Por Gas: Sistema DIALOGO, Paper presented in the 7th Lagovén Technical Conference, Amuay Refinery, Falcón, Venezuela, January 1988.

2 Hayes-Roth, Frederick. The Knowledge-Based Expert System: A tutorial, Teknowledge Inc., September 1984, Pages 11-28.

3 Lagovén, S.A. Production Department. Western Division. Expert System for Gas Lift Wells SEDILAG. User Manual, August 1991.

4 Ortiz,J.L.. Application of Artificial Intelligence for the Diagnosis of Artificial Gas Lift Equipments, III LatinAmerican Petroleum Congress (Conexpo-Arpel 92), October 1992, Rio de Janeiro, Brasil.

5 Ortiz, J.L. An Artificial Intelligence Approach to Model-Based GasLift Troubleshooting, M.S. Thesis, Texas A&M University, December 1990.

6 Niblack, Wayne. An Introduction to Digital Image Proccessing, Prentice/Hall International, 1986.

7 Ramirez, José, MHC: A Connectionist Architecture for Hybrid Training, 18th LatinAmerican Conference on Informatics, Proceedings Panel'92, Las Palmas de Gran Canaria, 1992.

8 Crews, Phillip. Engineering Training: The Expert System Factor, The Fourteenth Annual Energy-Sources Technology Conference and Exhibition (ASME), January 1991.

FIGURES

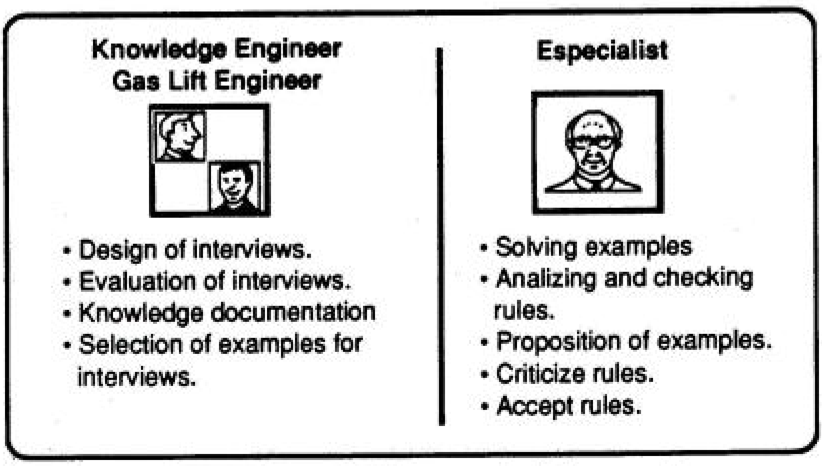

Figure 1: Knowledge adquisition methodology used to develop DIALOGO

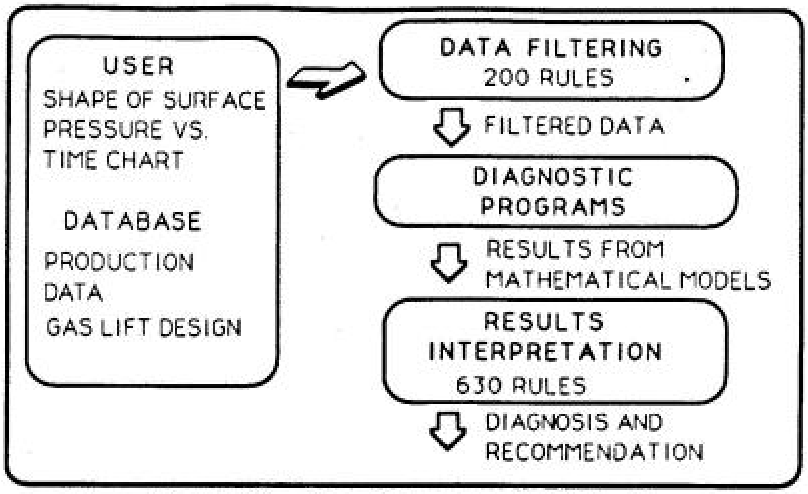

Figure 2: Flow Diagram of SEDILAG

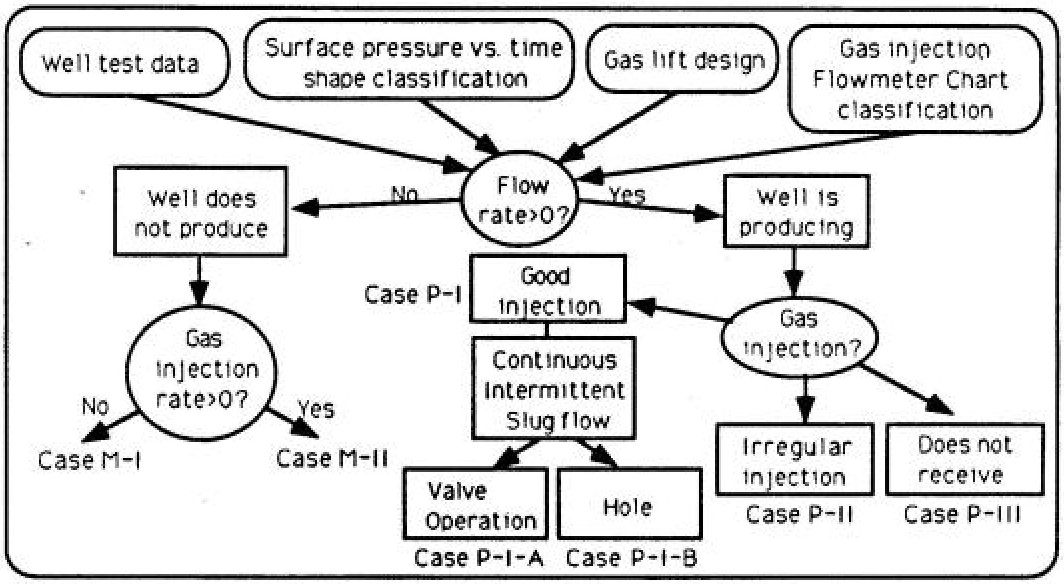

Figure 3: SEDILAG knowledge base's basic decision tree

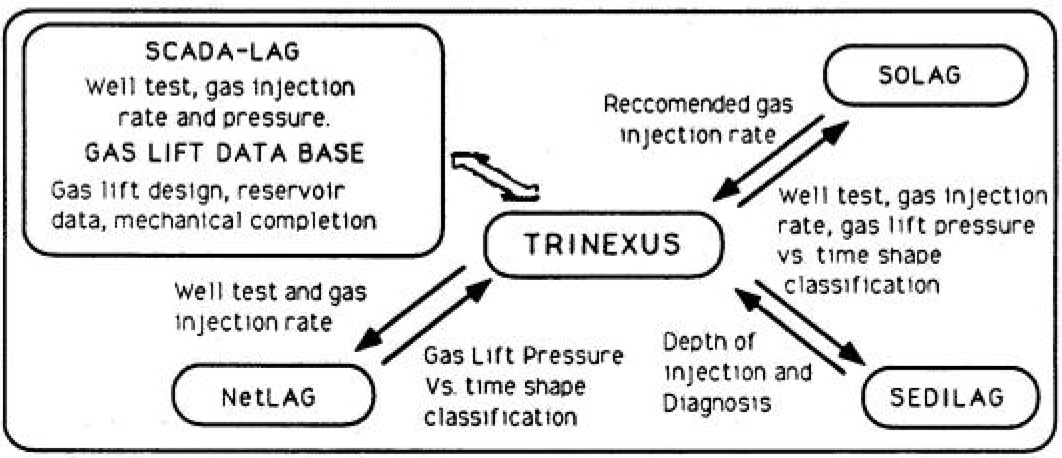

Figure 4: TRINEXUS conceptual diagram

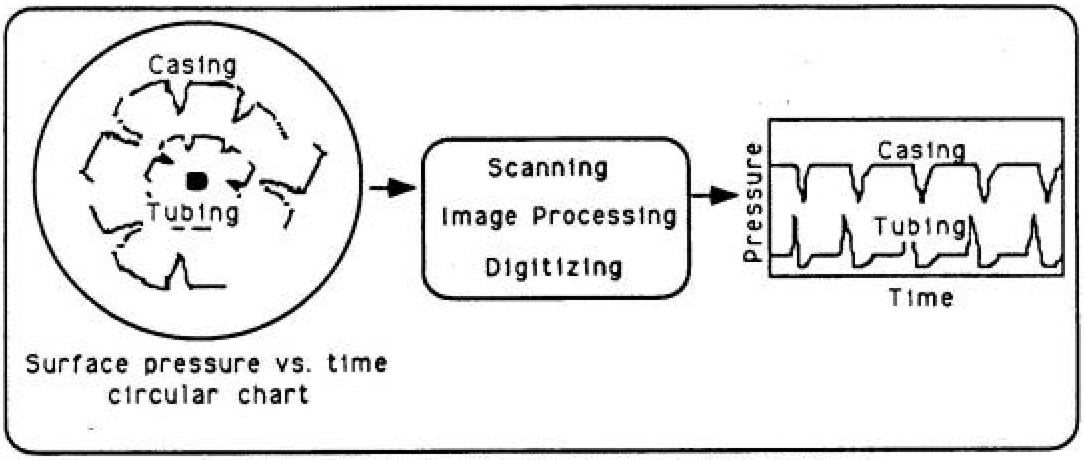

Figure 5: Digitizing pressure vs. time charts

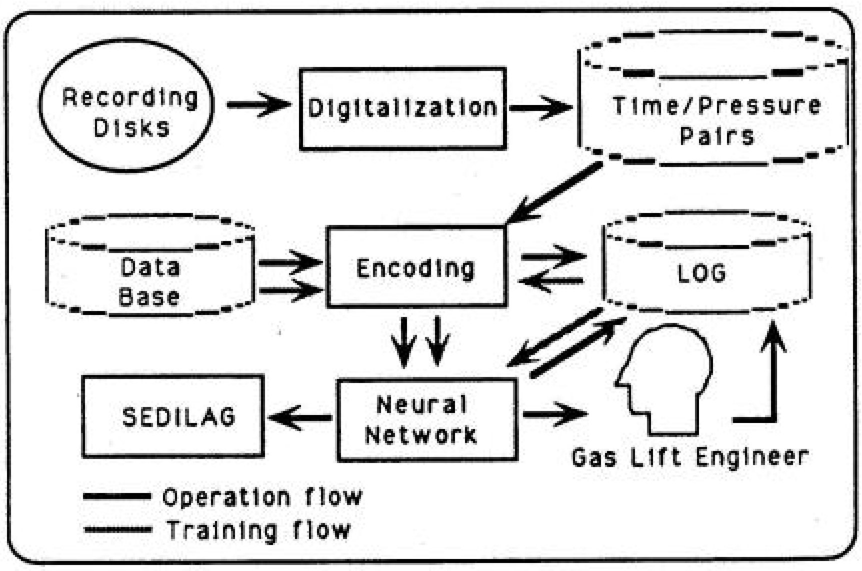

Figure 6: NetLAG process diagram

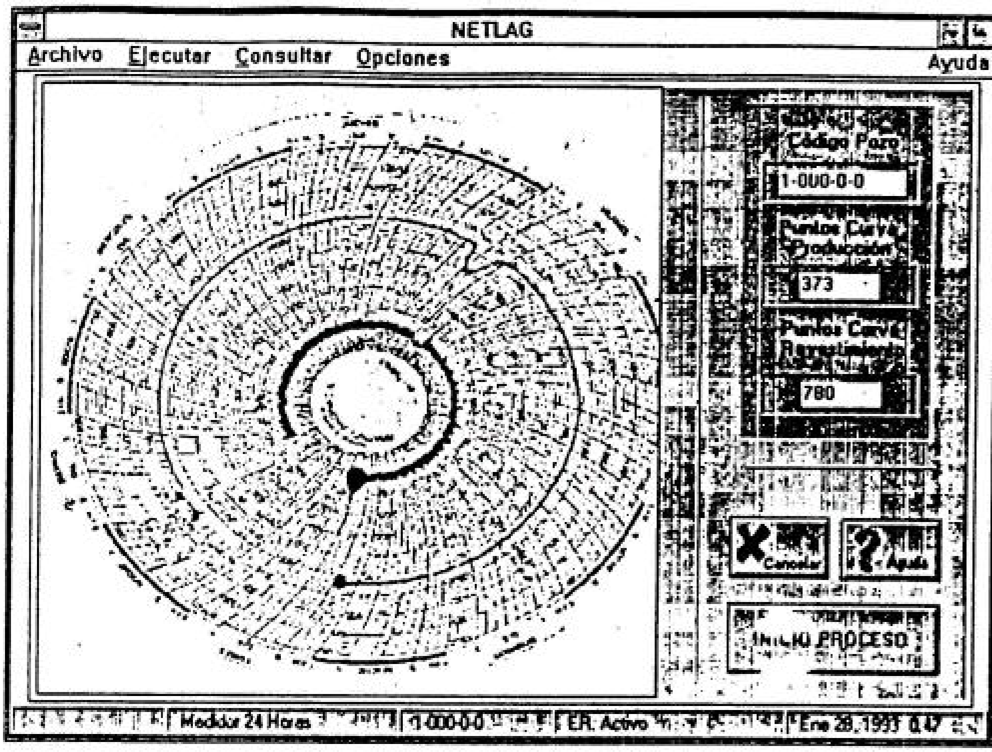

Figure 7: An actual surface pressure vs. time circular chart already processed.

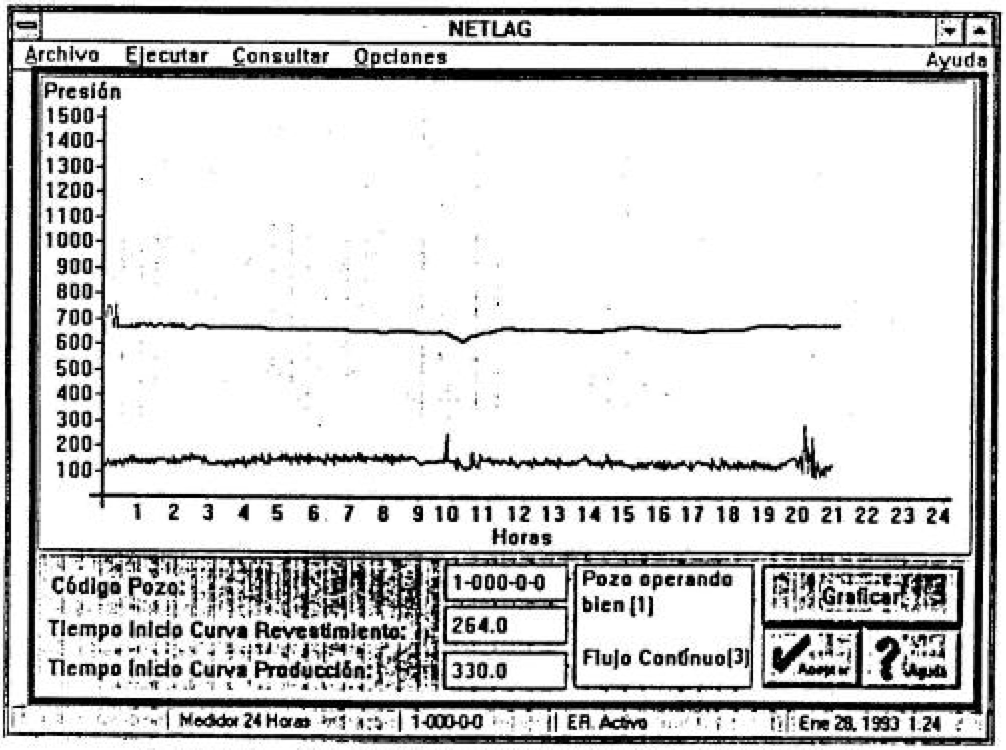

Figure 8: Values of pressure vs. time digitized and classified by NetLAG. "Pozo Operando Bien" and "Flujo Continuo" is the result of that classification.

Chart Category	Description
1	Well does not take gas lift gas
2	Not feed in. Well is circulating gas
3	Producing by continuous gas lift
4	Intermittent gas lift. Choke control of injection gas
5	Intermittent gas lift. Surface time cycle controller
6	Intermittent gas lift. Chamber lift
7	Well is producing by natural flow

Type Chart	Description
1	Good operation
2	Communication annulus-tubing (leak, hole,valve,etc)
3	Valve throttling
4	Excessive tubing back pressure
5	Unloading
6	Low reservoir deliverability
7	Restrictions in gas lift injection
8	Improper time cycle or cycle frecuency
9	Faulty controller or intermitter
10	Fluctuating gas line pressure
11	Changes in gas lift valve pressure operation
12	Intermittent well interference
13	Improper gas lift design
14	Problems in pressure recorder
15	Injection operation through different valves
16	Improper injection gas liquid ratio (IGLR)
17	Effect of size of annulus space (casing-tubing)
18	Changes in gas lift method
19	Changes in well test separator pressure
20	Well closed in
21	Valve port diameter too large

Table 1: Criteria used for pressure chart classification