An Intelligent Distributed System Applied on Automated Lift System

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Abstract: This paper introduces the application of Symbolic Neural Network in an intelligent distributed system for automated petroleum lift systems. It also introduces the application of a special kind of perceptron for the pattern recognition of graphic cards applied on the lift system analysis. Applications on rod-pumb wells are illustraded

Key-Words: - Neural Networks, Intelligent Distributed System, Perceptrons, Pattern recognition.

1 Introduction

The analysis and management of complex systems are very hard tasks to solve. Conventional techniques based on analytical approaches frequently do not work very wel1. In these cases, intelligent computing approaches can be used to attain effective sollutions and the technical literature has presented some good examples. Additionally, as support for its applications, the literature also presents some interesting analysis and design tools.

This paper introduces the application of Symbolic Neural Network (SNN) as an agent in intelligent distributed system for automated petroleum well lift Systems. It is also presented the application of a special kind of perceptron for pattern recognition of graphic cards used on the lift system analysis.

Lift systems management are complex. They deal with a great amount of data and they show different behavior depending upon well characteristics. In addition, the decision system involves a great deal of empiricism and demands a rigorous data collecting and analysis. This makes oil the well artificial lift a suited for the Artificial Intelligence (AI) techniques application and it. has been the main subject of a lot of papers in the last few years. In the references below a few examples may be finded relating AI techniques applied to Rod Pumping (RP) and Intermittent Gas Lift (IGL) systems.

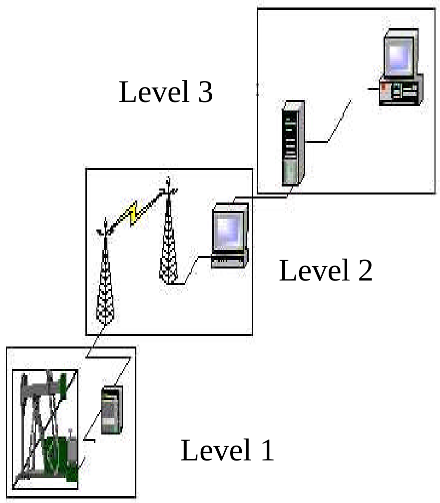

Figure 1 – SGPA levels

Recent developments in automation and tele-communications brought an ever growing application development to the oil industry, involving industrial programmable logic controllers (PLC) with bigger processing capabilities. The data analysis deployed by these PLCs taking account the experience and skills of lift system experts are one of the main goal of the proposed automated intelligent system. It can be seen (figure 1) as an intelligent distributed system with three distinct levels: Local (1), where the actions on the well are performed by the PLC without human interference; Supervision (2), where human actions are restricted to emergencies, like oil leakage or vandalism supervision; Analysis (3), where human deals with diagnostics and treatment of deviations from expected operation, as suggested by the AI specific module.

What makes the proposed system a distributed intelligent one is its ability to act over a well without local human interference, acquire human knowledge and skill and to optimize the well as a consequence.

2 Symbolic Neural Networks

Figure 2 shows a graphic representation of the Symbolic Neural Networks (SNN) with four levels, known as input level, aggregation level, decision level and output level [1].

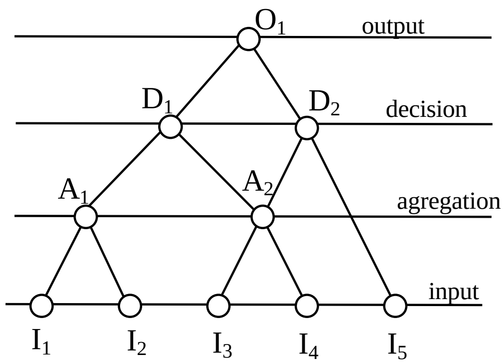

Figure 2 – SNN model

This neural net (NN) is made of layered neurons in which each neuron from a lower layer is linked to each one of the next layer by a connection called "synapses". To each link is given a relevance (r) which represents the neuron relevance to the hypothesis under analysis. Each neuron has also processing capabilities so fuzzy functions (FF) can also be used in the node processing. This kind of NN is known as symbolic neural net (SNN), and will be referred as such in this work. This concept can be applied in the knowledge representation from expert and to identify the system behavior. Several structures based on the model above were developed to deal with the most important problems that have been found in a artificial lifted well [2].

3 Knowledge Representation

These structure are refereed as agents. The agents are grouped according to its common characteristics. Each agent groups communicates to each other using the blackboard concept [3].

Supervisor structures are designed to activate the agents in a way programmed by the specialist to deal with each type of information available (figure 3). Supervisor_0 analyses what information is available and decides what analyses is possible to be made with that information. Supervisor_1 decides which agents of the group 1 should be activated, and in what order. The agents classified as group 1 analyses the operational conditions of the system.

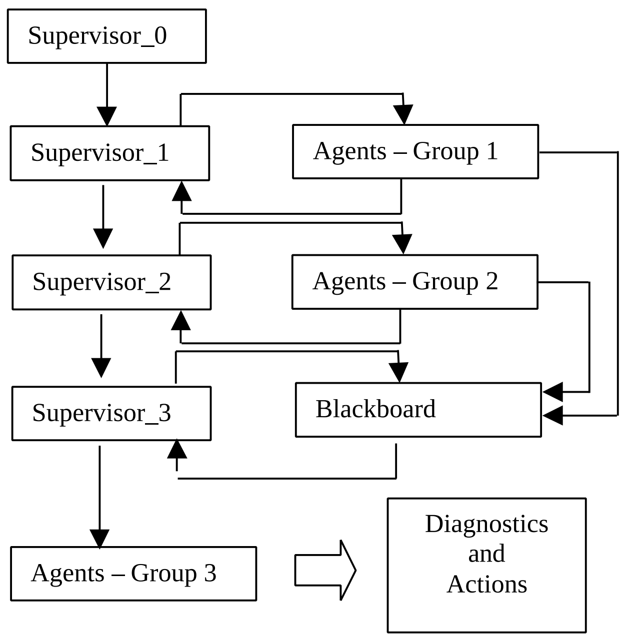

Figure 3 – Communication structure

The agents of the group 2 are activated by the supervisor_2 to complement the analysis of the operational conditions of the system. For this, it are done the inclusion of the other information do not get from real system. Supervisor_3 is the structure designed to propose the agents responsible for each diagnostic and to propose the action necessary to restore system.

4 Pattern Recognition

The system behavior can be identified by pattern recognition. It is made by a special Perceptron. This Perceptron is a kind of neural net in which there is only two layers. The upper layer has only one neuron and the lower layer has as much synapses and neurons as input values (figure 4).

The system behavior can be represented by pattern graphics. The analysis of the operational conditions of the system can be made by matching between the pattern graphics and the system behavior graphics. Each Perceptron can represent a specific system condition. Each relevant point of the pattern graphics is represented into neuron by its relevance and its variance [1]. Each input neuron has a fuzzy function in which the input data is the distance from the system behavior graphic point to each relevant points of the pattern graphic.

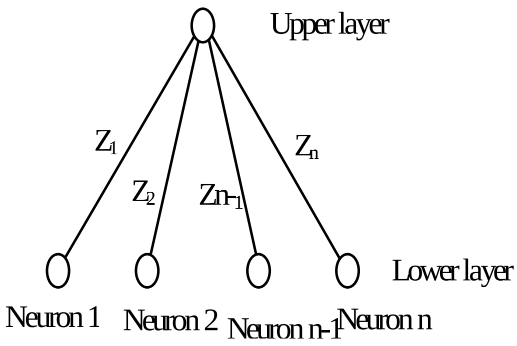

Figure 4 – The Perceptron.

In lower layer, fuzzy functions are used to calculate the matching of the system behavior graphic points with the closest pattern graphic points. In the upper layer, the output of the Perceptron calculates the matching of the pattern graphics and the system behavior graphics using a relevance center average.

5 Application on Automated Lift System

The cost necessary to optimize the well production are incremented by the difference between foreseen results in lift well project related to the obtained in production.

To help in this task, the automation of petroleum wells has grown expressively. For example, over 700 wells in Brazil, at Bahia State, are provided with PLCs using an embedded intelligent distributed system for their control. This kind of automation generates an expressive amount of data that can be used to enhance the lift systems production. Besides this, it also allows local control and remote observation of many wells in real time basis.

Researchers of Universidade Federal da Bahia, jointly with engineers of brazilian petroleum company, PETROBRAS, have applied the concept presented above into an automated lift well management system, called SGPA.

SGPA supports diagnosing and proposes solutions to optimize automated wells production. It focus mainly on Rod-Pump wells management. However, other lift systems can be managed using the same principles. SGPA operates under three main subsystems, see Figure 5:

(1) Data consistency module – It makes the acquisition data from different sources and verify consistency these information. The information are treated and shown in a integrated interface (GUI);
(2) Dynamometric Cards module - It module allows the user generate pattern graphics of the behavior de lift system, called dynamometric cards. These patterns graphics can be used by the PLC which control the well, and by the SGPA into pattern recognition subsystem to supply the well diagnose and improve the well lift;
(3) Knowledge module – It makes the well analysis. The knowledge module determine symptoms, makes diagnostics and propose actions to improved lift system performance.

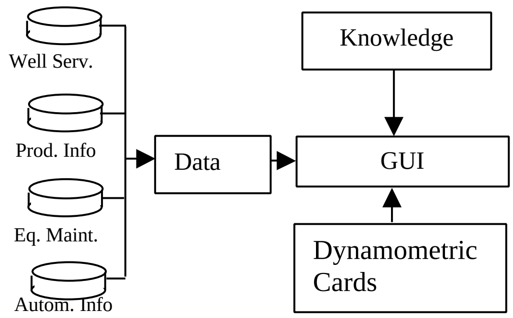

Figure 5 – SGPA modules.

5.1 Knowledge module

During the development of the Knowledge module, It was used SNN conceptions to represent the knowledge expert about rod-pumping (RP), for example (see figures 6 – 8).

In figure 6 are shown the Supervisor_1 and Agent-Group 1 responsible for determination of the RP symptoms [4].

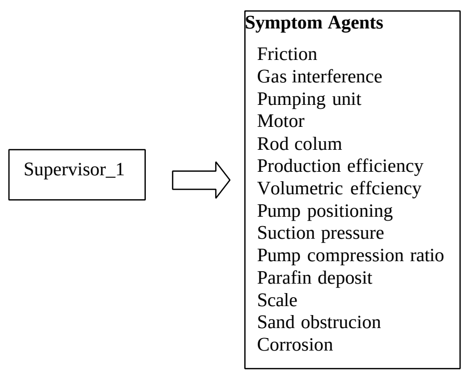

Figure 6 – Supervisor_1 and Agent-Goup 1 - Symptoms for RP.

In figure 7 are shown the Supervisor_2 and Agent-Group 2 responsible for the complementary analysis of the operational conditions by RP dynamometric graph.

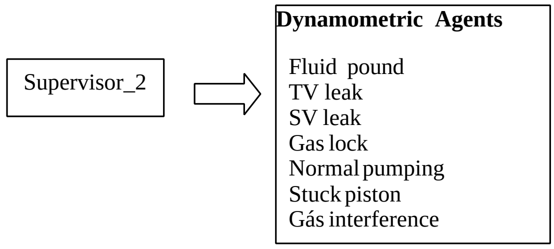

Figure 7 – Supervisor_2 and Agent-Goup 2 – RP Dynamometric

In figure 8 are shown the Supervisor_3 and Agent-Group 3 responsible for determination of the diagnostics and actions for RP.

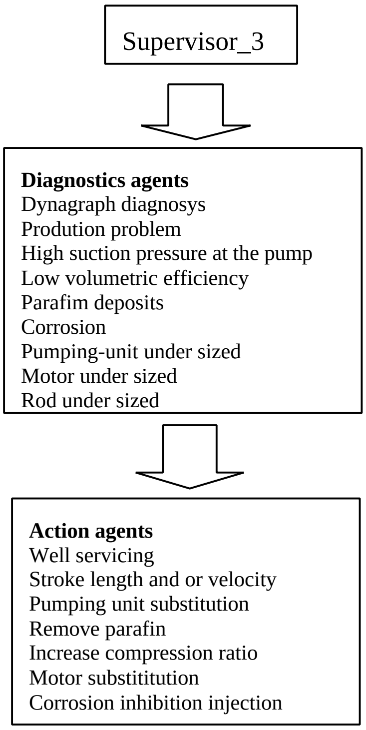

Figure 8 – Supervisor_3 and Agent-Goup 3 - Diagnostics and Action for RP

In the figures 9 and 10 are shown the Symptom Agent responsible for gas interference and friction analysis of the RP, respectively.

Gas interference agent determines the reliable value in the hypothesis of severe gas interference. The analysis is made from the comparison between loads in the column of connecting rods in the surface and corresponding calculated loads. These last ones are calculated for one determined relative density of the fluid in which the connecting rods are immersed. The difference between both allows to conclude regarding real the relative density of the fluid, and therefore to classify the severity of the gas interference.

The analyzed loads are the following ones: load measured in the test of the foot valve (SVm) and load calculated for this same test (SVc), load measured in the test of the traveling valve (TVm), and load calculated for this same test (TVc); beyond that, the information about the amount of gas present in the produced fluid (RGL) is also used.

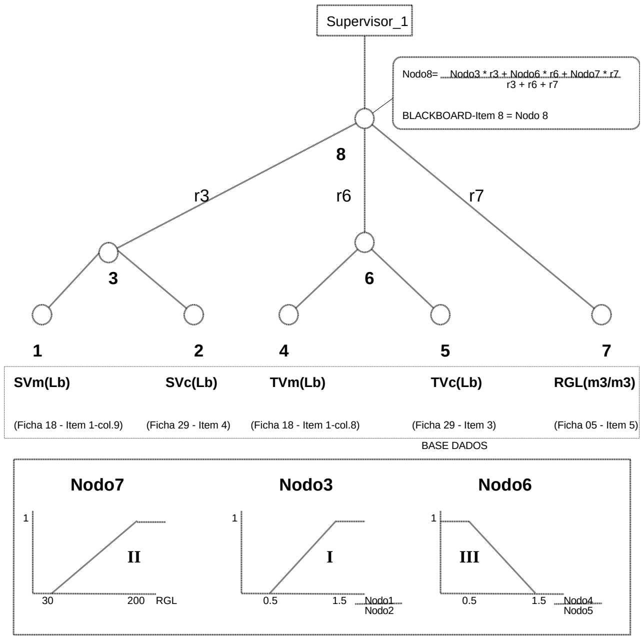

Figure 9 - Gas interference agent

Friction agent used the same parameters in the previous agent to evaluate the friction in the rod column. The reasoning is similar, only come back toward the hypothesis of severe friction:

The rule:
If SVm < SVc then the friction is severe;

It is represented by nodes 1, 2 and 3 of the SNN of the figure 10. The function of relevancy I supplies an intermediate reliable value to the hypothesis of severe friction in node 3. This function represents the minor concept, for this context, supplied by the specialist.

The rule:
If TVm > TVc then the friction is severe;

It is represented by nodes 4, 5 and 6, and the function of relevancy II supplies another reliable value (intermediate) to the hypothesis of severe friction in node 6. This function represents the greater concept, for this context, supplied by the specialist.

The implementation of the Knowledge Kernel was based on a tool specially designed for this purpose. The knowledge is coded in Microsoft VBscript language, witch can be executed by the SGPA interface.

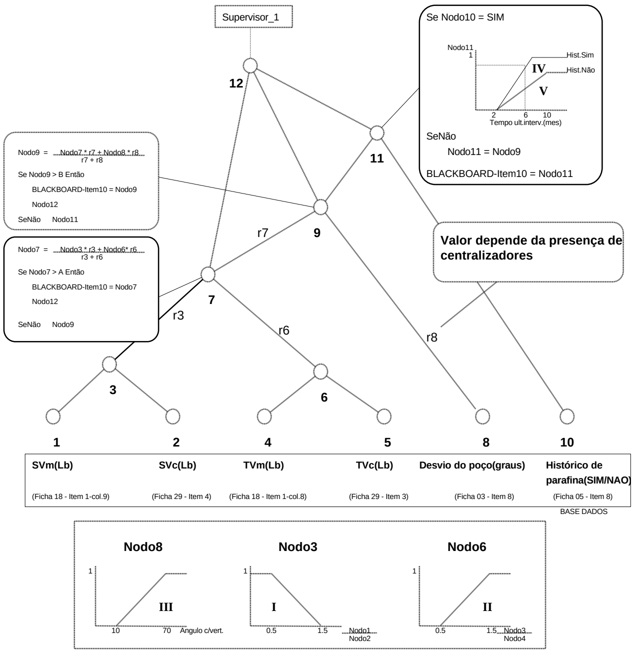

Figure 10 – Friction agent.

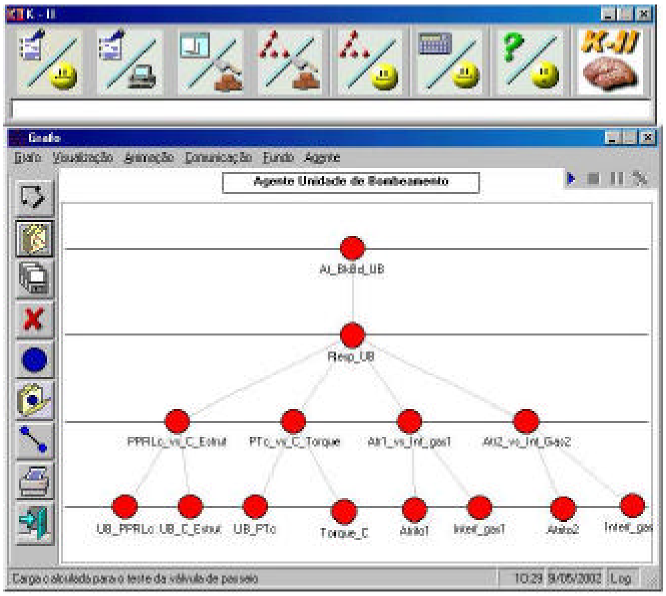

Figure 11: Knowledge Kernel development tool interface (pumping unit analysis agent).

The figure 11 shows an example of the GUI used to develop an SNN to analyze the proper pumping unit design. This tool is a freeware academic software and it is available in the site http://www.eina.com.br.

5.2 Dynamometric Cards module

In the Dynamometric Cards module was used the Pattern Recognition approach, described in section 4. The RP behavior was modeled from the dynamometric graphics pattern shown in figure 12.

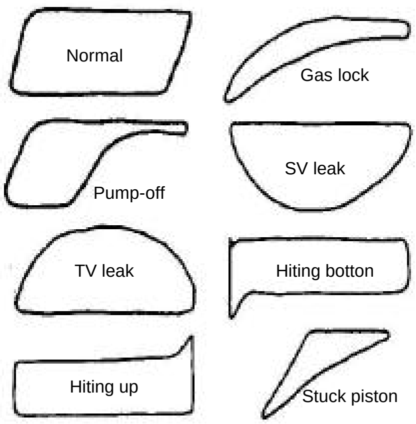

Figure 12 – Dynamometric graphics patterns.

6 Conclusion

Symbolic neural nets and fuzzy logic concepts were suited to the development of SGPA. The easy implementation and maintenance achieved with the use of such concepts allows the adaptation of the coded knowledge to local cultures and procedures and, most important, it allows easy aprehention of the new knowledge as a consequence of the systematic SGPA use. The application of SGPA has been well succeed in tests on sites at Bahia State, Brazil.

The codification of the knowledge done by the specialist itself is a powerful technique that allows not only to code his knowledge and experience but to systematize it. This technique is also economical because the adjustment or the evolution of the knowledge can be done by several users without external help.

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