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State of the Art of Artificial Intelligence and Predictive Analytics in the E&P Industry: A Technology Survey

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Abstract

Artificial intelligence (AI) has been used for more than two decades as a development tool for solutions in several areas of the E&P industry: virtual sensing, production control and optimization, forecasting, and simulation, among many others. Nevertheless, AI applications have not been consolidated as standard solutions in the industry, and most common applications of AI still are case studies and pilot projects.

In this work, an analysis of a survey conducted on a broad group of professionals related to several E&P operations and service companies is presented. This survey captures the level of AI knowledge in the industry, the most common application areas, and the expectations of the users from AI-based solutions. It also includes a literature review of technical papers related to AI applications and trends in the market and R&D.

The survey helped to verify that (a) data mining and neural networks are by far the most popular AI technologies used in the industry; (b) approximately 50% of respondents declared they were somehow engaged in applying workflow automation, automatic process control, rule-based case reasoning, data mining, proxy models, and virtual environments; (c) production is the area most impacted by the applications of AI technologies; (d) the perceived level of available literature and public knowledge of AI technologies is generally low; and (e) although availability of information is generally low, it is not perceived equally among different roles.

This work aims to be a guide for personnel responsible for production and asset management on how AI-based applications can add more value and improve their decision making. The results of the survey offer a guideline on which tools to consider for each particular oil and gas challenge. It also illustrates how AI techniques will play an important role in future developments of IT solutions in the E&P industry.

Introduction

While there is hardly a rigorous definition of the term artificial intelligence (AI) that is unequivocally accepted, the tools of AI and its intended uses have been well studied for decades and many applications have appeared. Loosely speaking, AI is the capability of machines (usually in the form of computer hardware and software) to mimic or exceed human intelligence in everyday engineering and scientific tasks associated with perceiving, reasoning, and acting. Since human intelligence is multifaceted, so is AI, comprising goals that range from knowledge representation and reasoning, to learning, to visual perception and language understanding (Winston 1992). AI techniques have been present in the E&P industry for many years. A quick literature search reveals application of AI in SPE scientific and engineering papers as early as in the 1970s. There are numerous references about the applications of neural networks, fuzzy logic, genetic algorithms, expert systems, and other artificial techniques in the resolution of problems in diverse areas, such as reservoir simulation, production optimization, process control, and fault detection and diagnosis, among many others.

AI is an area of great interest in the E&P industry, mainly in applications related to production control and optimization, proxy model simulation, and virtual sensing. The most popular techniques are artificial neural networks, fuzzy logic, and genetic algorithms, with interesting developments in hybrid and nontraditional techniques. There has been recent increase in such AI-based commercial applications for production management. While the full impact of such applications is still being realized, there are already solutions in the market with a positive impact in the E&P industry.

Recently, the term "artificial intelligence and predictive analytics" (AIPA) has been used to embed AI techniques into a broader set of techniques aimed at processing and data analysis, business process automation, and advanced visualization. In addition to the classical techniques of AI, AIPA includes data mining, automatic process control, workflow automation, and virtual environments, among others.

With the implementation of digital oilfield (DOF) programs in several oil and gas companies, application of AIPA technologies seems to be increasing. Application of heuristic techniques in the processing and analysis of data, physical modeling, processes prediction, and optimization, is often in DOF implementations. It is widely accepted that data management is a common challenge in the petroleum industry.

This paper presents a study about how AIPA technologies have penetrated and impacted the petroleum industry. To do this study, a survey was developed and conducted on the broad community of Society of Petroleum Engineers (SPE) professionals. Approximately 10,000 requests were sent out during October 2011 and 612 responses were received.

The survey aimed to capture the level of AIPA knowledge in the industry, including the most common application areas, the most popular techniques, and the expectations of the users for AI-based solutions. Also, the paper presents an analysis about the state of the art and the trends in AIPA technologies, within and outside the E&P industry. Many applications have become ubiquitous outside the industry. Is there additional value in comparing the differences (i.e., the gap between the E&P industry and US Department of Defense, the finance industry, or Google)? Outside the oil industry, there appears to be significantly greater activity in AI that could be indicative of opportunities for E&P industry. There is a significant amount of value that has been documented outside the industry ranging from disruptive to continuous daily support and knowledge bases like Google AI.

Several hypotheses were to be validated or rejected in regard to the perceived impact of AIPA techniques: (i) managers do not see the value, but engineers do; (b) information sources are perceived differently at different organizations; (c) data mining is more popular than other AI techniques because it has more available commercial tools; (d) AI knowledge and information are more readily available to managers, consultants, students and professors rather than they are to engineers; and (e) the perceived impact of AIPA techniques on the production and operation challenges and the available tools and knowledge about the techniques seem to be too small nowadays.

The goal of this study is to present the results as a guide for personnel responsible for production and asset management on how AI-based applications can add value and improve their decision making. The study also illustrates how AI techniques can play an important role in future developments of IT solutions in the E&P industry. The analysis of the future plans of major operators in the E&P industry indicates that the ultimate objective of their DOF plans entails the use of AI and intelligent systems.

Background

Members of SPE involved in AI created an AIPA subcommittee in 2009 as a part of the SPE Digital Energy Technical Section, with the objective of promoting the applications, research, and developments in artificial intelligence and petroleum analytics, in the context of the oil and gas industry. The AIPA subcommittee organized forums and special sessions at SPE conferences to increase the interest of AIPA technologies in the industry. Some of the events in which the AIPA subcommittee has participated are: the forum "Artificial Intelligence in the E&P Industry" (Colorado Springs, Colorado, USA, 2009); the Intelligent Energy Conference 2010 (Firenze, Italy, 2010); the Digital Energy Conference & Exhibition 2011 (Houston, Texas, USA, 2011); and the SPE Annual Conference and Technical Exhibition 2011 (ACTE, Denver, Colorado, USA, 2011). At the 2011 SPE ACTE, the subcommittee was promoted as a new technical section (TS) named "Data to Action (D2A)" within the SPE Information & Management technical discipline.

This paper is an effort of the D2ATS to study the impact of AIPA technologies in the industry, the level of knowledge and perceptions about these technologies, the main areas of interest, and the main problems faced by the industry that could be solved using AIPA technologies.

AIPA State-of-the-Art Review

This section provides an overview of the state of the art in each of the AIPA technologies considered in our survey. Basic definitions for each AIPA are included in the glossary. For the purpose of this review, AIPA technologies have been grouped in seven (7) themes or families.

I. Computational Intelligence. Computational intelligence focuses on problems that theoretically only humans and animals can solve, problems requiring intelligence. It is a branch of computer science studying problems for which there are no effective computational algorithms. The term acts as an umbrella under which more and more methods have been added over time.

I.A Neural Networks (Back-propagation, Hybrid, Recurrent, Self-organizing Maps). This is one of the most widely used AI techniques with many journals and books dedicated to its study (Appendix A) and numerous related conferences. There are several artificial neural network software tools for developing applications, and some of them are designed for industrial use. A Matlab toolbox is also available. The main use of a neural network is as an all-purpose (hence its popularity) nonlinear function approximator, for modeling and classification tasks. The development of a neural network usually requires large amounts of data to ensure spanning of a large enough area for an application and use of prior knowledge for structuring a neural network is not uncommon. It should also be mentioned that a crucial feature of neural networks, namely their ability to be trained and to compute using parallel computation, is hardly ever capitalized on in most engineering applications, which perform computations on standard serial machines (e.g., PCs). Applications of neural networks have been in pattern recognition, virtual sensors, process control, prediction, and modeling, among others.

A criticism of neural networks is that they are "black boxes" (i.e., it is difficult to determine exactly why a neural net produces a particular result). Certain neural network applications have produced very valuable results within certain ranges but have ceased working and giving good results without explanation. Management usually perceives neural network as AI, and, therefore, the failure of neural networks has had a negative impact on the management's perception of the potential of AI in the industry.

I.B Fuzzy Logic. This is a technique for representing inexact linguistic arguments and making inferences based on them. Nearing 50 years since its inception, it is perhaps the most widely used technique in daily activities. Refrigerators, washing machines, and automobile suspension systems are some of its applications. This AI technique has also many journals and books dedicated to its study (Appendix A) and many related conferences. There are software packages for developing applications that employ fuzzy logic, and some of them are designed for industrial use. A MATLAB toolbox is also available. The main applications of fuzzy logic have been in pattern recognition, virtual sensors, automatic control, prediction, and modeling, among others.

I.C Evolutionary Computation. Evolutionary computation is the collective name for a range of problem-solving techniques based on principles of biological evolution, such as natural selection and genetic inheritance. These techniques are being increasingly widely applied to a variety of problems, ranging from practical applications in industry and commerce to leading-edge scientific research. Here is a list of the most popular technologies.

Neural networks, genetic algorithms and intelligent agents are often classified as machine learning techniques. Agents may use co-occurrence matrices to learn how the attributes in data sets are related. Agent memories can be used in various ways—for diagnosis, for pattern recognition in multichannel signal data, and for workflow monitoring. In contrast to neural networks, associative memories are "white boxes"—they can be configured to explain their decisions. Stephenson et al. (2010) describe the use of an associative memory for gas lift well diagnosis. The machine learning processes in intelligent agents entail human-directed "machine learning".

I.C.1 Genetic Algorithms. Genetic algorithms comprise a class of optimization techniques that cleverly mimic the process of evolution (hence the term genetic) in a computer to let an initial population of possible solutions converge to optimal solutions. While convergence may be slow, there are no requirements on the structure (e.g., continuity, differentiability, convexity, etc.) of the optimization problem to be solved. There are a few journals dedicated to the exclusive study of genetic algorithms and some related conferences. There are some software packages for developing applications that employ genetic algorithms and some of them are designed for industrial use. A MATLAB toolbox is also available. The main applications of genetic algorithms have been in optimization and search activities, among others.

I.C.2 Machine Learning. Machine learning refers to algorithms that allow computers to learn behaviors by generalizing from data, often through reinforcement but without supervision (i.e., without being told what the behavior to be learned should be , for example, learning how to play backgammon by playing lots of games and figuring out winning strategies). Machine learning partially overlaps with data mining, but differs from it in that the latter focuses on pattern discovery, while the former is mostly concerned with producing desirable patterns. There are not many books and journals or conferences purely dedicated to this topic. However, there is substantial literature on machine learning in many disciplines.

I.C.3 Intelligent Agents. Intelligent-agent systems are computational systems comprising multiple agents which are capable of making decisions and taking actions in an autonomous way (e.g., in the same way that individual car drivers maintain traffic flow at a street intersection). Agents maintain information about their environment and make decisions based on their perception about the state of this environment, their past experiences, and their goals. Agents can also communicate with other agents and collaborate to reach common objectives. The paradigm of intelligent agents is ideally suited for systems that involve large amounts of data in physically distributed environments.

While it is possible to build intelligent agents that act autonomously, most intelligent agent systems are designed to support rather than replace users. Intelligent agent systems are particularly effective when there is a lot of data, when high degrees of expertise are required, or when response timelines are very short.

There are a number of research groups in the scientific community working on intelligent agents and there are standards and applications for multiagent system development. The most important standards for multiagent systems, such as the Agent Common Language (ACL) and the FIPA Interaction Protocols, are supported by the Foundation for Intelligent Physical Agents (FIPA), subscribed to the IEEE. Also, there are important scientific journals specializing in intelligent-agent systems

There are several references about the use of multiagent systems in the industrial world, mainly in the manufacturing industry (PABADIS, 2005)(Marik and Vrba, 2005). Common applications are distributed decision-making systems and distributed control systems. In the E&P industry, there are few references about applications of multiagent systems; three examples are the agent-based information management system for oil dispatch and sales workflows (Ølmheim et. al 2008), the application of multiagent systems in subsea facility modeling and the usage of agents in reservoir simulation history matching (Zangl et al. 2011). Nevertheless, the application of intelligent agents in the industry is being actively explored.

I.C.4 Swarm Intelligence. Swarm intelligence is an AI technique based around the study of collective behavior in decentralized, self-organized systems. Although there is normally no centralized control structure dictating how individuals should behave, local interactions between those individuals lead to the emergence of global behavior. Not many applications have been seen so far in the industry, although there is a huge potential. Some papers have been published in the area of history matching of simulation models (e.g.. Hajizadeh 2010).

II. Data Mining. Data mining by itself is not an AI technique; rather, it uses AI techniques together with statistics and other formal techniques to find interesting features from data sets. Nowadays it is a well-consolidated area with journals dedicated to its study (Appendix A) and some conferences concerning that topic. There is some software for developing applications, some of it designed by universities, and there is a MATLAB toolbox available. The main applications of data mining have been in prediction, classification, and segmentation, among others.

III. Rule-based Case Reasoning. This is not a different AI technique, because it does not emulate different intelligent activities from those used by the other techniques. It can be implemented using expert systems or fuzzy logic systems with a particular goal on case reasoning on if-then rules and is based on similar past problems. For example, rule-based case reasoning is often used in help-desk environments to support diagnosis of problems with consumer products. There are very few journals, conferences, and books related exclusively to this area, but it is a very common topic in more general AI events. In the same way, the implementation could be done using software for other techniques, so there are not many specific toolboxes. This technique can be widely used in diverse types of applications including industrial, process, fault detection and isolation, prediction, and any other area where there is knowledge available concerning the appropriate ways previously used for solving related problems.

III.A Bayesian Networks: Bayesian networks are computer models of probabilistic systems—that is, real-world systems operating under uncertainty. Bayesian networks have been applied successfully in the industry in many different areas. They are used in diagnostics in process control, implemented in expert systems for probabilistic decision support, and used for optimization. Standalone software tools are available. However, most implementations are done in custom development projects.

III.B Expert Systems. Expert systems are the oldest artificial intelligence technique according to applications development. Often, they are rule based. In essence, an expert system is a programming paradigm, focusing on declarative rather than procedural programming issues, namely how knowledge is represented and structured (e.g., in terms of objects) rather than how elaborate computations are performed. It was the most widely used AI technique during the 1970s and 1980s, spanning many areas of applications. In the oil and gas industry, drilling operations management was the primary target of the AI activity at that time. The intense interest in that time was followed by rapid decline, as methodology frameworks were very restricted, and this almost made interest in expert systems disappear during the early 1990s. Of course, as a tool for acquiring and representing knowledge handled by a human expert, an expert system can be very useful in a wide range of applications. Nowadays is a very well-consolidated area with journals dedicated to its study (including publications from Elsevier and Wiley) and many conferences dedicated to that area. There are many expert system software packages for developing applications, and some of them are specifically designed for industrial use. Expert systems have had diverse applications in health, industry, finance, security, and fault detection and diagnosis, among other areas.

New players, such as GE, are penetrating the E&P industry. They will bring significant experience in the use of expert systems in the continuous surveillance and management of rotating equipment. The provenance is from aircraft engines and locomotives. Is it of interest that GE predictive analysis are still in grounded in usage-based maintenance which by definition is parametric based and does not attempt condition-based maintenance.

IV. Automatic Process Control. Automatic process control is the most studied area of the entire list presented here, with decades of experience and improvements. Strictly speaking, it is not an AI technique but can use AI in some schemes. There is a well-developed body of theory on automatic control, with several varieties placing particular emphasis on various aspects of interest, including classical, robust, adaptive, model predictive, and intelligent, among others. There are many associations around the world, including IEEE and IFAC, that have entire chapters dedicated to automatic control. There are numerous journals and books on the subject (Appendix A) and a variety of conferences concerning this area. There is also abundant computer software created for developing applications for either educational or industrial use. A MATLAB toolbox and Simulink are quite popular. There is ample experience on automatic control in many industries that may share some characteristics with oil and gas (e.g., oil refining and chemicals, aerospace, and automotive). Tools for activities that are essential for automatic control, such as system identification, modeling, prediction, and optimization are well developed**.**

V. Workflow Automation. Workflow automation (WFA) is a set of techniques and tools that allow the integration of several data sources and applications and the collaboration among members of a team, though a well-defined sequence of activities (potentially assisted by a computer), to automate operations in an enterprise. Complex event management tools provide techniques for monitoring activities such as workflows and for responding dynamically to abnormal conditions. WFA is also called business process management. In the E&P industry, WFA has become a major driver of the DOF. Since processes in the E&P industry are complex and require the use of several applications and the access to multiple and diverse information sources, nowadays WFA is one of the areas of major interest in the industry (Biniwale et al. 2010; Sankaran et al. 2009; Szatny 2007; Moridis et al. 2011).

VI. Proxy models. Proxy models are approximate representations of a system inside a boundary of pre-defined conditions. These models are used when there is not enough information to build a full model, or if the only model required is a representation of the system around an operation point. The use of AIPA techniques, such as neural networks, genetic algorithms, data mining and system identification is common for the development of proxy models. In the E&P Industry there are many recent references about proxy models [Mohaghegh, et al, 2011; Zangl et al, 2006, Saputelli et al, 2003].

VI.A Surrogate Reservoir Models. Surrogate Reservoir Models (SRM) that are developed using AIPA technologies, may be considered as a form of proxy models that have recently been introduced (Mohaghegh 2012). SRM are distinguished from proxy models since they do not approximate the problem. They are built to accurately replicate reservoir simulation models for fast track analysis and quantification of uncertainties.

VI.B Top Down Models. Top-Down Models (TDM) are reservoir simulation models that are developed using measured field data such as well location, well trajectories, well logs, core analysis and well tests, seismic data and Production and injection rates. Since TDM is built using field data it is only applicable to brown fields. TDM attempt to deduce physics from measured field data (Mohaghegh 2011a).

VII. Virtual Environments. Virtual environments are physical or digital spaces where companies try to mimic remote operations while providing engineering support and subsurface interpretation, which would become more obvious with the evolution of computing power and telecommunications. Virtual environment technology has also been a flagship in the DOF technology offerings. The ability to make decisions is enhanced because of the use of a collaborative environment which brings together experts from different locations, computers and data from different networks and domains, as well as real-time predictive analytical and expert systems. There are many types of virtual environments in the oil and gas industry, with applications such as remote drilling operations support, production surveillance and optimization support, operator training simulators, geology and geophysics interpretation, logistics and combinations of the previous.

World Wide Web versus Petroleum Industry AIPA Technology Trends

Fig. 1 shows the relative position of each of the AIPA technologies within the global (number of World Wide Web search results in millions) or the petroleum industry context (petroleum industry search results in thousands). The number of results is just a very rough number to indicate the degree of development and use of each technology based on documents, links, citations, etc. This analysis was not intended to be conclusive or rigorous, but is nevertheless informative of the current trends over the internet. Themes or families in the previous section were not considered in this independent hit analysis.

Process control, data mining, and expert systems are the top three AIPA technologies in both the petroleum industry and World Wide Web trends (upper right corner of Fig. 1), whereas proxy models and workflow automation are the bottom two most popular technologies in both sectors (bottom left corner of Fig. 1).

The pseudo 45° dashed line indicates the expected behavior in both sectors (global and petroleum) follow the same trends in technology use: process control, data mining, expert systems, virtual environments, intelligent agents, workflow automation, and proxy models. However, those technologies which highly deviate from the 45° line are likely to be lagging in the oil industry. Therefore, it is expected to find more applications in process control, data mining, and expert systems in the petroleum industry, simply based on global trends.

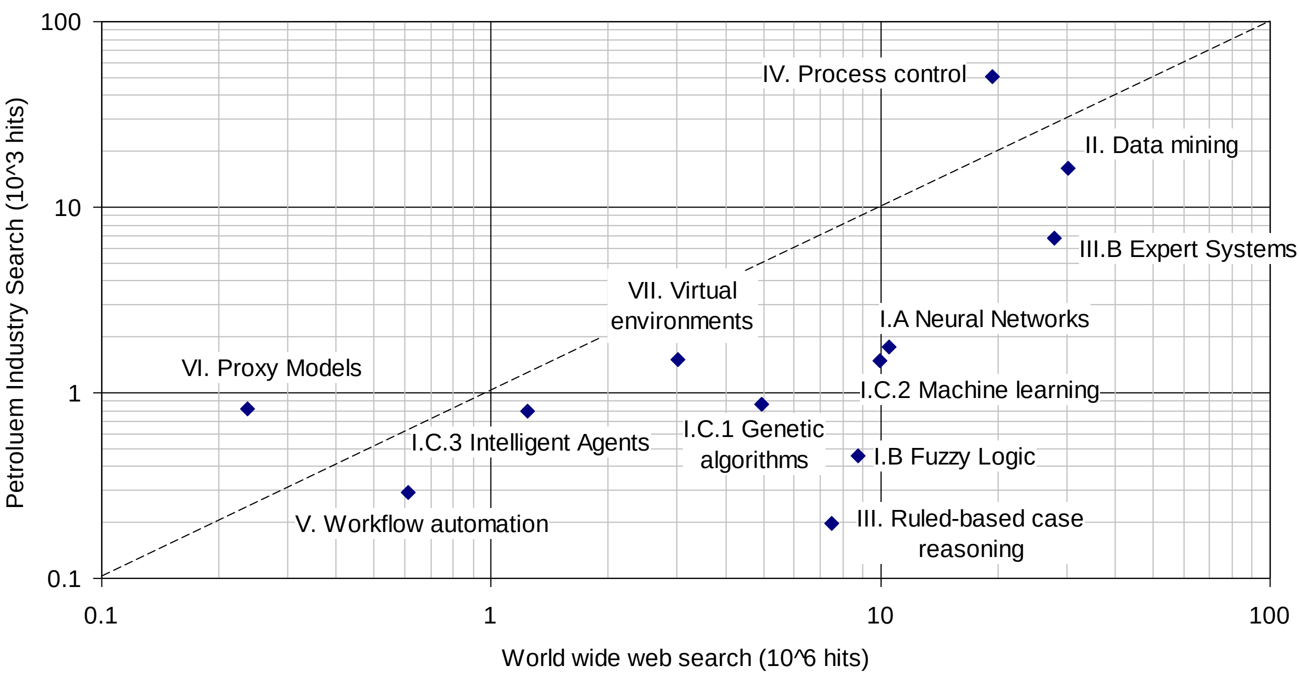


Fig. 1—Results of searches on AIPA technologies in petroleum industry versus global search sites (as of November 2011).

Purpose and Structure of the Survey

The purpose of the survey was to capture the level of AIPA knowledge in the industry, including the most common application areas, the most popular techniques, and the expectations of the users for AI-based solutions. This survey was directed to a broad group of professionals involved with information management, exploration and production operation, management, and optimization in both operations and services E&P companies. This survey was distributed to SPE members with the support of the SPE board.

The survey was composed of nine multiple-choice questions and four additional open-answer questions. The questions were designed to capture information about these topics:

- Information management and analysis challenges in the industry
- Level of knowledge about AIPA techniques
- Most commonly applied AIPA techniques
- Application areas of AIPA techniques
- Level of perceived value and areas of impact of AIPA techniques
- Perceived level of knowledge available about AIPA techniques
- Perceived maturity of AIPA techniques
- AIPA commercial tools
- Demographic information

In the multiple-choice questions the respondent could select only one of the answers. The four open questions could be answered in a free and unstructured way. At the end of the survey, the respondent could answer demographic questions about job classification, company type, age group, and career background. This information was very important for the analysis of the survey results.

Survey Results

The survey was made available to general SPE members (i.e., all professionals from all disciplines who were related to any of the four main SPE disciplines) during October 2011. In total, 612 answered surveys were received. Appendix B shows the details of the survey. Appendix C summarizes the demographic information from the respondents.

Information Management and Analysis Challenges in the Petroleum Asset. Approximately 72% of respondents answered that data management and integration is a challenge in information management and analysis in the petroleum industry. Similarly, approximately 50% responded that managing large volumes of data and lack of integration between work processes are also challenges **(Fig. 2).** These results showed how common these challenges are among all kinds of surveyed professionals.

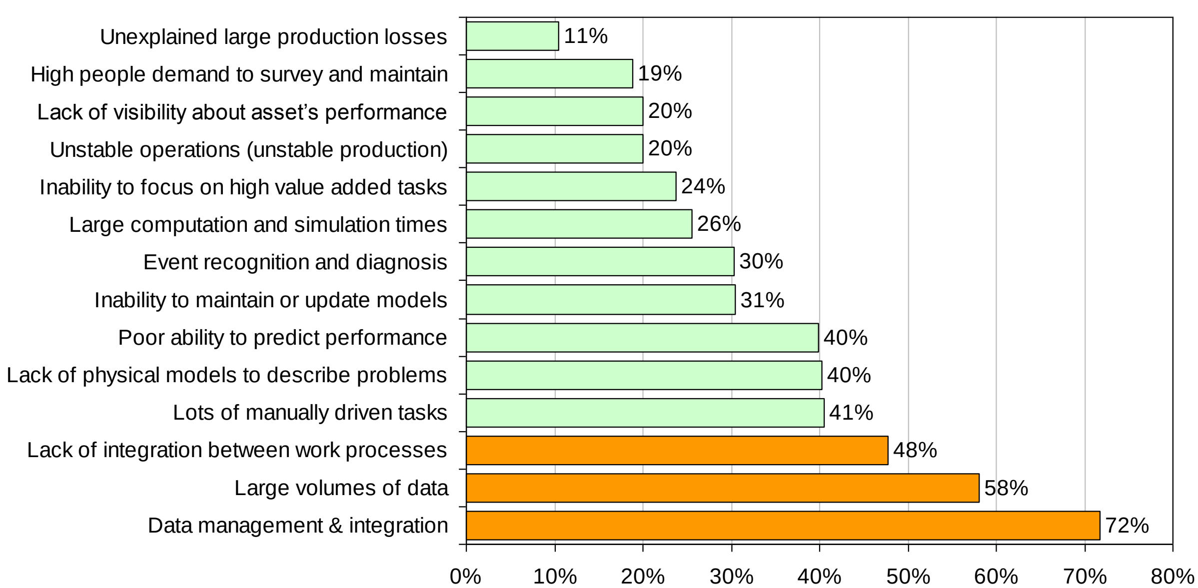


Fig. 2—Which challenges occur in information management and analysis?

How Important are these Challenges? All of the different challenges shown in Fig. 1 were characterized as major challenges or as having some or no challenge realized **(Fig. 3).** Of all challenges characterized as major, the following were the top five: (1) data management and integration, (2) managing large volumes of data, (3) large computation times, (4) lots of manually driven tasks, and (5) lack of integration between work processes. Management of unstable operations had the smallest score (22%) as a major challenge in information management and analysis.

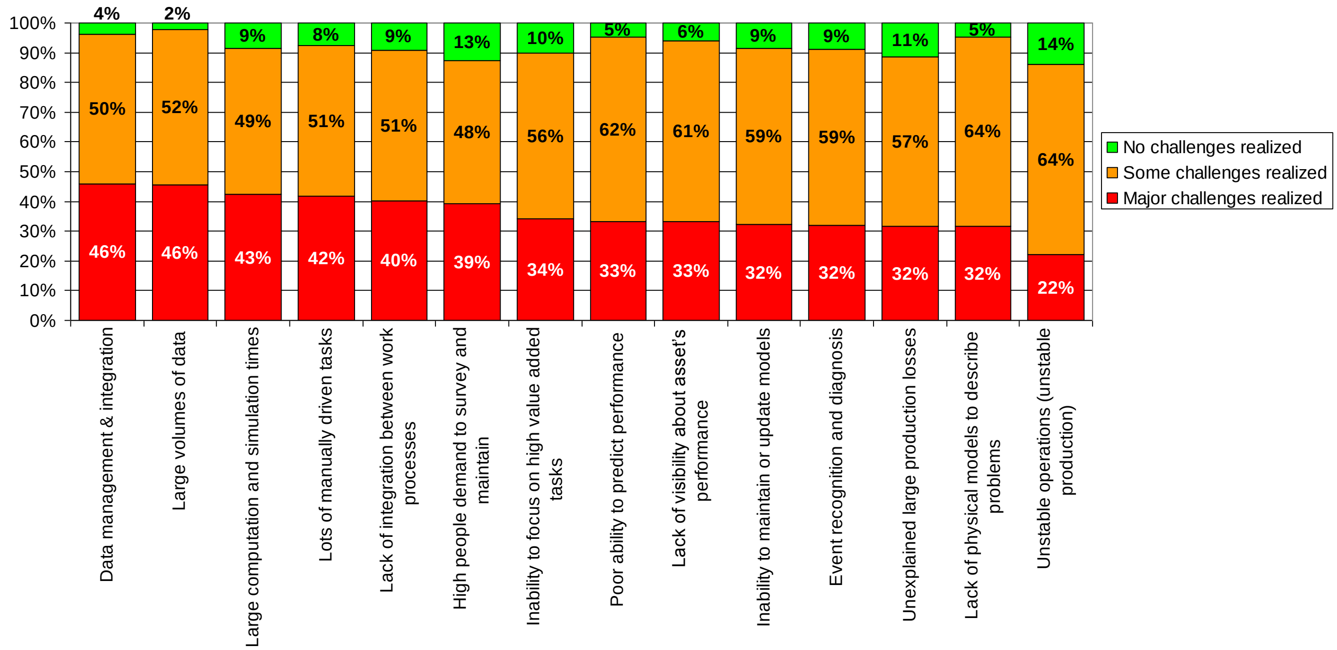


Fig. 3—How great are the challenges in common information management and analysis challenges?

In addition to the above challenges, lack of physical models to describe problems, personnel training, and data quality were mentioned as open answers.

Artificial Intelligence and Petroleum Analytics Applications Awareness. The purpose of this question was to rapidly screen the individuals according to whether they were "personally familiar" with AIPA applications in the petroleum industry, and if so, which ones. If the answer to this question was “None”, then the individual did not have to answer the question and was directed to bypass the six following questions on AIPA application use.

The majority of respondents (>50%) indicated knowledge of applications in data mining and neural networks. About 40% or more indicated awareness of workflow automation, fuzzy logic, expert systems, and automatic process control applications **(Fig. 4).**

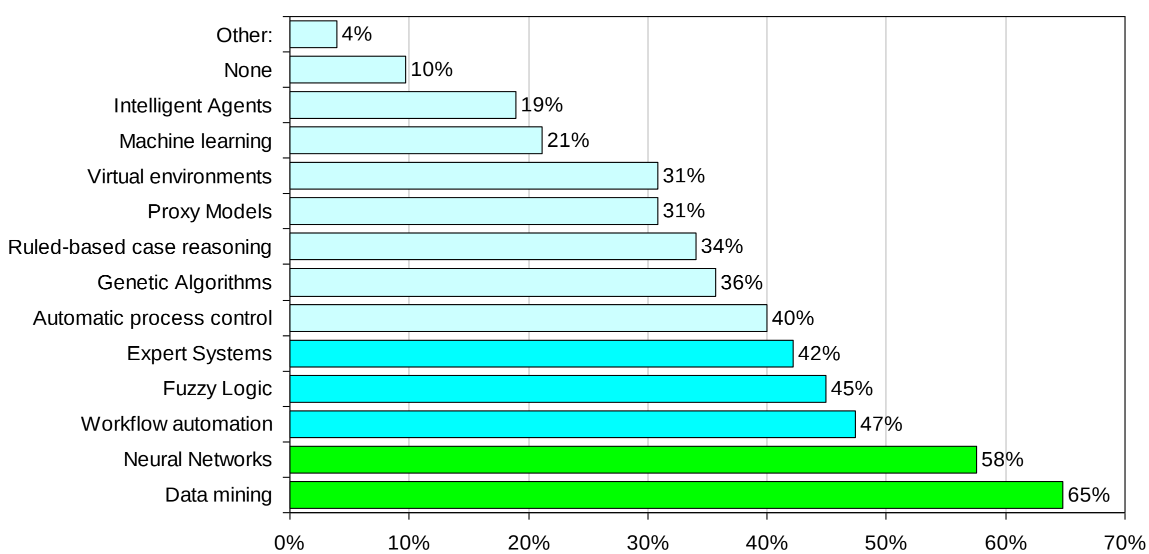


Fig. 4—AIPA applications in the petroleum industry that individuals are aware of.

Artificial Intelligence and Predictive Analytics Applications Level of Awareness. More than 50% of respondents declared that they are either fully engaged or frequently use applications in workflow automation and automatic process control. Between 40 to 50% declared themselves to be fully engaged in or to frequently use applications in rule-based case reasoning, data mining, proxy models, and virtual environments **(Fig. 5).**

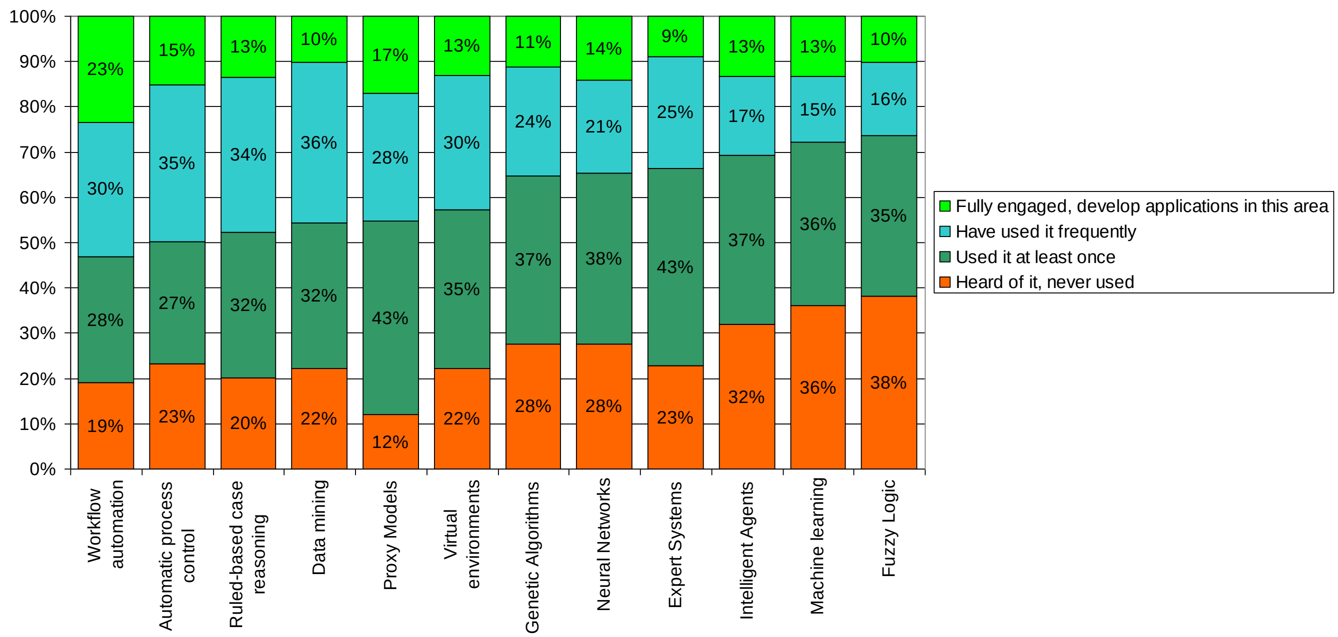


Fig. 5—Level of awareness with AI and petroleum analytics technologies.

How does this correlate to the professional level and amount of available information?

Fig. 6 shows the distribution (pie) chart for each of the job description categories. Managers and consultants surpass engineers in the use of AIPA applications. Those in education (students and professors) have the greatest level of "fully engaged or develop applications" in this area.

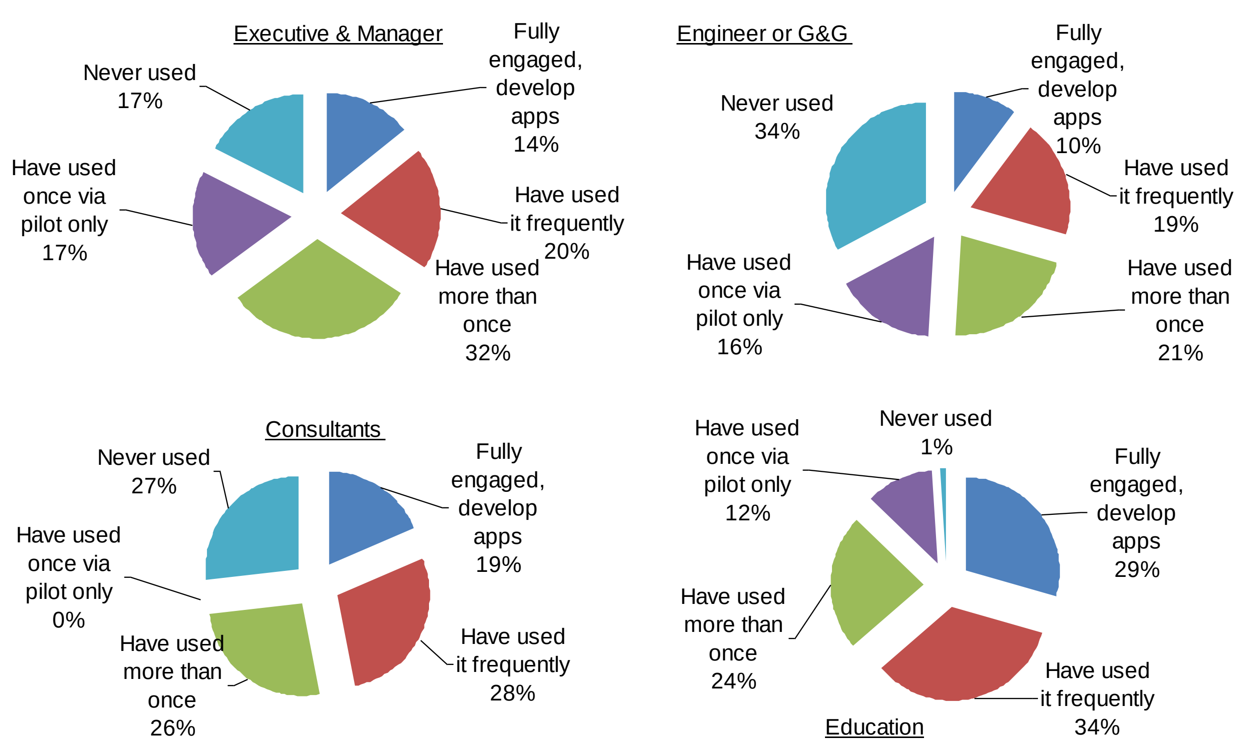


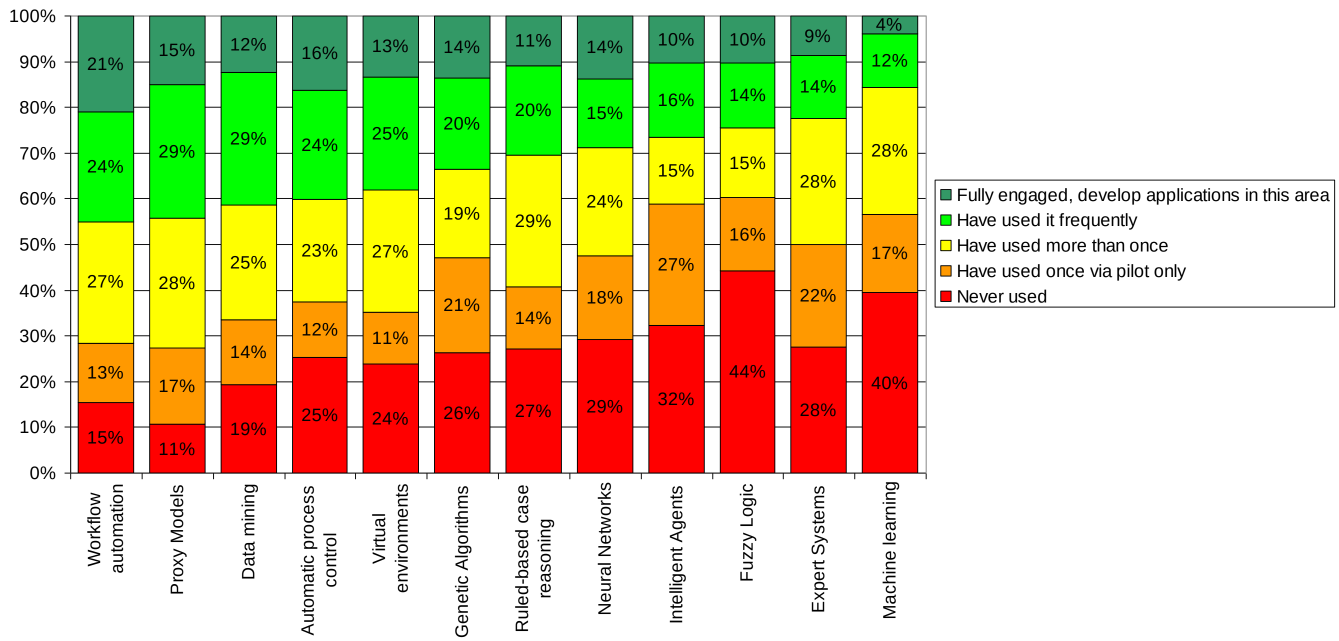
Fig. 6—Level of use by professional role.

Observations from **Fig. 6** concerning use of AIPA applications include the following:

- Of the engineers, 50% have used applications more than once, or use applications frequently, or are fully engaged in developing applications.
- Of executives/managers, 66% have used applications more than once, or use applications frequently, or are fully engaged in developing applications.
- Of consultants, 73% have used applications more than once, or use applications frequently, or are fully engaged in developing applications.
- Of those in education and academia, 87% have used applications more than once, or use applications frequently, or are fully engaged in developing applications.

Most Common AIPA Applications and Solutions at the Company or Work Area. Fig. 7:shows which AIPA applications are most commonly used. Observations from Fig. 7 include the following:

- 70% or more have used workflow automation and proxy models
- 40% or more have used frequently or they are fully engaged in workflow automation, proxy models, data mining, and automatic process control
- 40% or more of the respondents used at least once (via pilot or not) all (or any) of the AIPA applications.
- 40% or more have never used fuzzy logic and or machine learning techniques.
- Machine learning, genetic algorithms, fuzzy logic and intelligent agents have the greatest number in pilot only applications.



	Never used	Have used once via pilot only	Have used more than once	Have used it frequently	Fully engaged, develop applications in this area
Workflow automation	15%	13%	27%	24%	21%
Proxy Models	11%	17%	28%	29%	15%
Data mining	19%	14%	25%	29%	12%
Automatic process control	25%	12%	23%	24%	16%
Virtual environments	24%	11%	27%	25%	13%
Genetic Algorithms	26%	21%	19%	20%	14%
Ruled-based case reasoning	27%	14%	29%	20%	11%
Neural Networks	29%	18%	24%	15%	14%
Intelligent Agents	32%	27%	15%	16%	10%
Fuzzy Logic	44%	16%	15%	14%	10%
Expert Systems	28%	22%	28%	14%	9%
Machine learning	40%	17%	28%	12%	4%

Fig. 7—Positive responses (100% stacked column) vs. AIPA technologies used in company or work area and level of use.

Ways AIPA Technologies have been Applied to Solve Problems in the Petroleum Industry. AIPA technologies are applied to solve problems in the petroleum industry in many ways. **Fig. 8** shows the percentage of responses versus industry applications in which AIPA technologies are applied. The possible AIPA technologies are given in twelve colors, and the numbers inside the bars indicate the count of valid responses.

The top areas, with 300 positive responses or more, are: (1) production optimization, (2) reservoir modeling and simulation, (3) data management and integration, (4) production management, (5) process control, (6) filtering/cleaning data, and (7) virtual metering and event recognition.

Data mining appears to be the most important technology provider for any of the areas contributing, with 13% or more of the positive responses. It also contributes with 30% or more for data management and integration, data filtering and cleansing, and information search.

Automatic process control appears to be the most important technology in the areas of process control (as expected because of its name similarity), and virtual environments appear to be the most important contributor to personnel training.

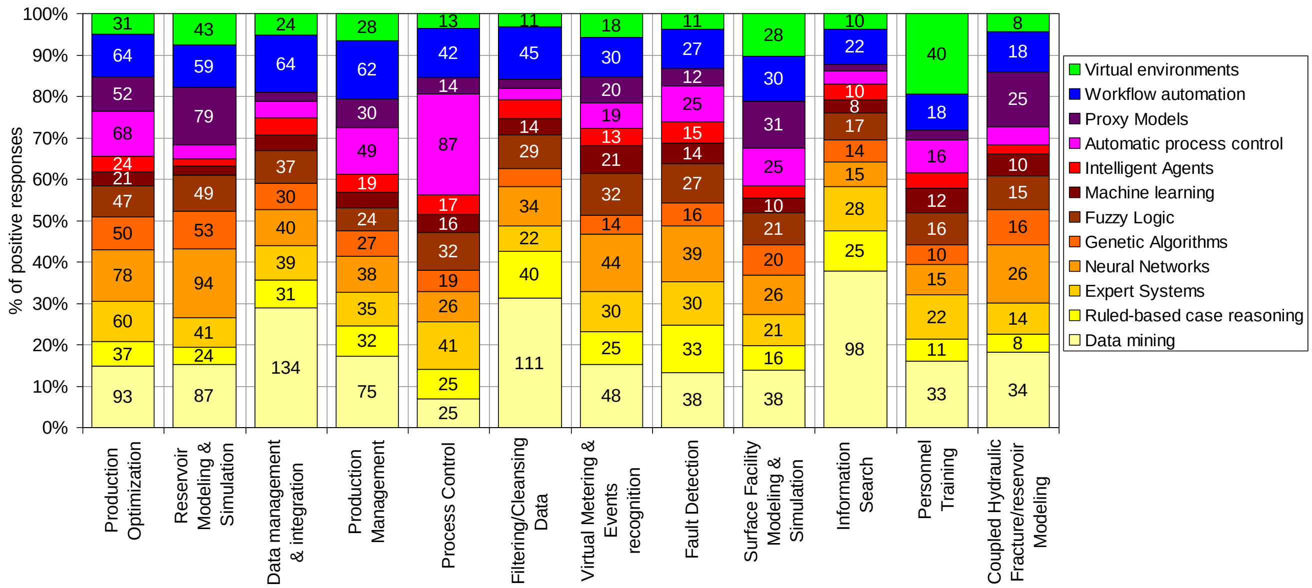


Fig. 8—Positive responses (100% stacked column) versus ways AIPA technologies are used in E&P industry.

What Value does each of these Technologies have, and What does it Potentially Impact? AIPA technologies are applied to add value in the E&P industry in many ways. **Fig. 9** shows the number of responses versus each of the impacted value areas (revenue, reserves, production, cost, and safety) in the application of data mining. The possible AIPA technologies are given in twelve colors, and the numbers inside the bars indicate the count of valid responses.

The top areas, with 600 positive responses or more, include (1) production, (2) cost, and (3) reserves. Data mining appears to be the most important provider for the areas of production, cost, reserves, and revenue contributing with 13% or more of the positive responses, except for safety. Neural networks appear to be the most important technology in the value area of reserves. On the other hand, automatic process control and workflow automation appear as the most important contributor (>13%) to safety.

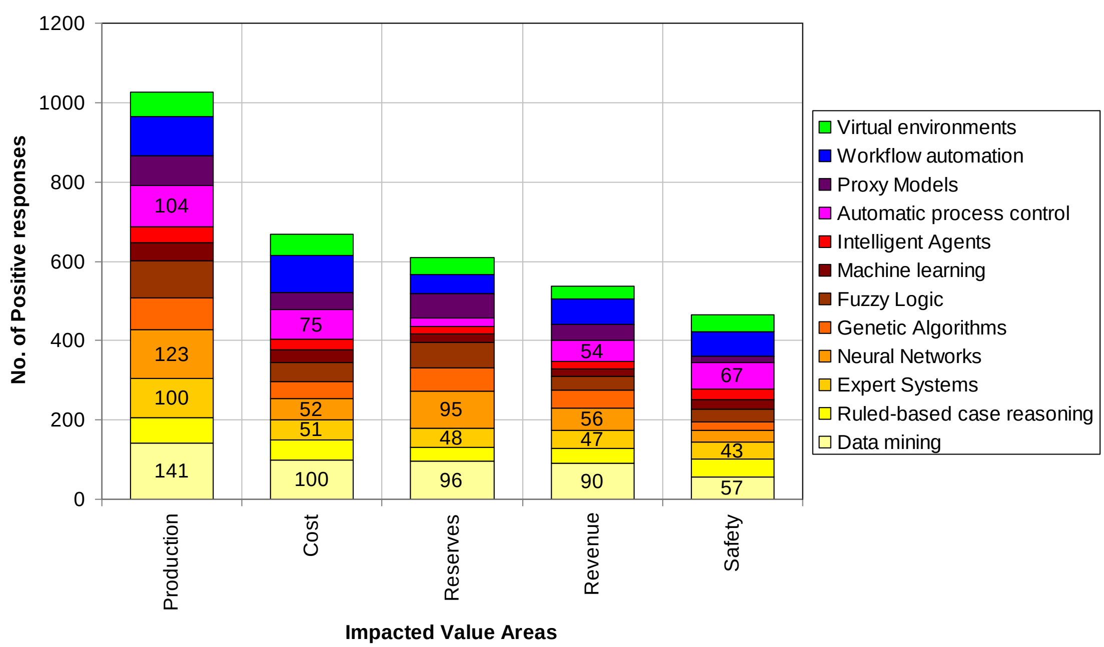


Fig. 9—Positive responses for each impacted value area for each of the AIPA technologies.

Fig. 10 shows the percentage of responses versus each of impacted value areas (revenue, reserves, production, cost, and safety) in the application of data mining. The possible responses are given in four colors and the numbers inside the bars indicate the count of valid responses. Approximately 85% to 90% of respondents perceive medium to high value added to any of the impacted value areas. Only about 10% of respondents indicated that there is no value or the value is not known in the application of data mining in any of the impacted value areas.

Not shown in this paper because of length limitations, about 85% of respondents perceive medium to high value added to some impacted value areas (revenue, reserves, production) in the application of rule-based case reasoning and neural networks. Workflow automation has the highest ranking in medium to high value creation for production and reserves.

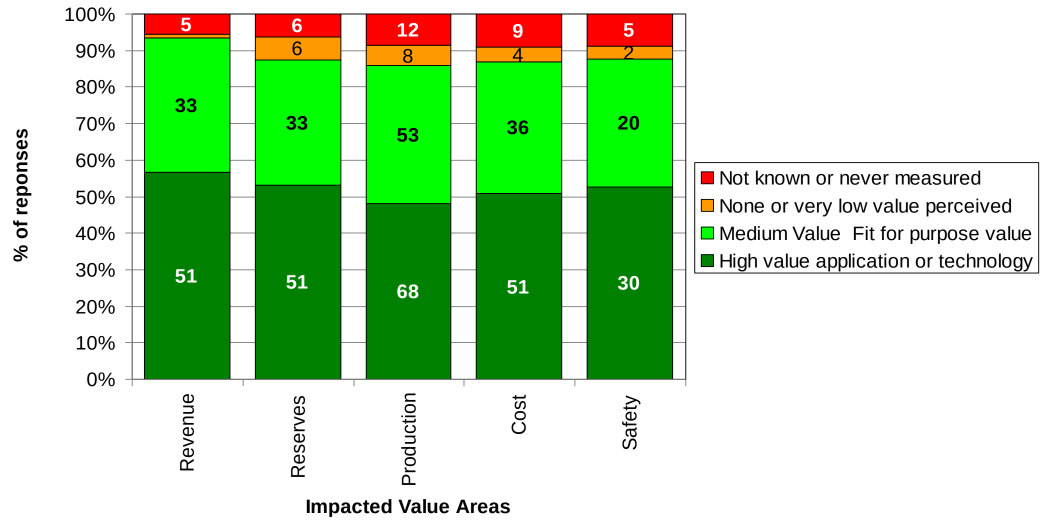


Fig. 10—Perceived value (100% stacked column) for data mining in each of the impacted value areas.

What is the Level of Knowledge Available for each Technology? Fig. 11 shows the percentage of responses versus each of the AIPA technologies. The possible responses are given in three colors and the numbers inside the bars indicate the count of valid responses.

The perceived level of available literature and public knowledge in AIPA technologies is generally low. Except for automatic process control, more than 50% perceive that there are limited resources available in any of the AIPA technologies.

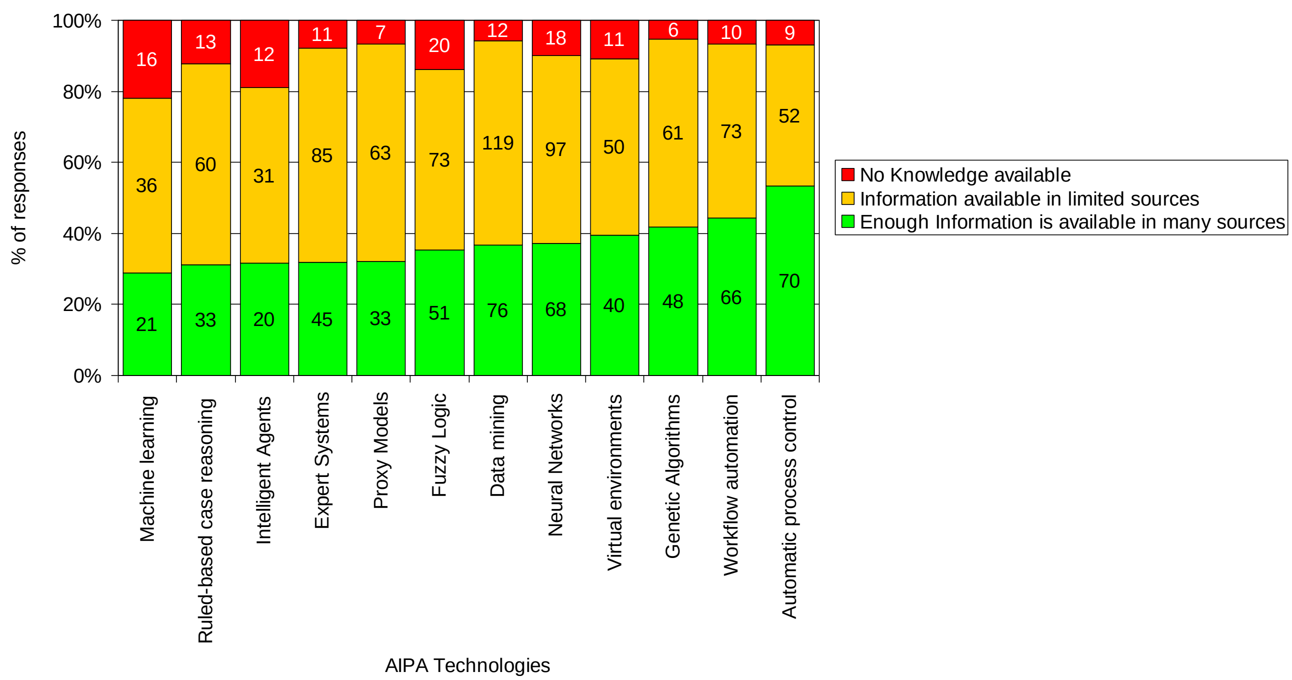


Fig. 11—Level of knowledge available (100% stacked column) for each technology.

Fig. 12 segregates the perceived level of knowledge for four different demographic groups. In all groups, 50% or more agreed that there are enough information sources in automatic process control. About 50% or more perceive that there are limited resources available in any of the AIPA technologies. In all, except for educators and students, roughly 60% or more perceived that there are limited to nonexistent resources in all AIPA technologies. Responses by group are summarized below.

- ***Executives and Managers***: 40% or more perceived that there are enough information sources in automatic process control, neural networks, genetic algorithms, fuzzy logic, and workflow automation; 20% or more perceived that the information related to fuzzy logic and machine learning is nonexistent.
- ***Engineers and Geologists and Geophysicists***: 40% or more perceived that there are enough information sources in automatic process control and virtual environments; 20% or more perceived that the information related to fuzzy logic and machine learning is nonexistent.
- ***Consultants***: 40% or more perceived that there are enough information sources in automatic process control, data mining, genetic algorithms, fuzzy logic, workflow automation, and virtual environments; approximately 50% or more perceived that the information related to rule-based case reasoning, expert systems, machine learning, intelligent agents, and proxy models is limited or nonexistent.
- ***Educators and Students***: 50% or more perceived that there is enough information, except for proxy models and virtual environments.

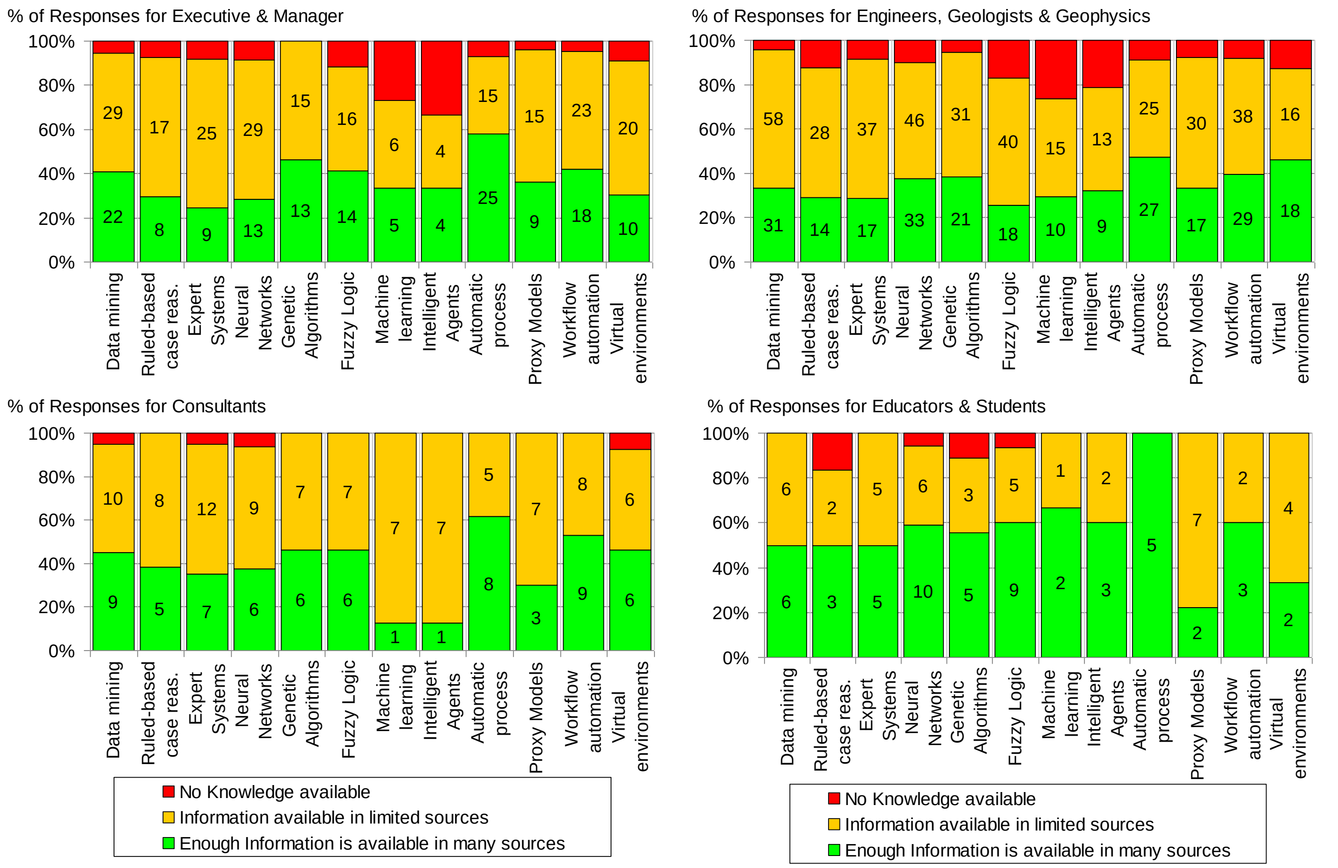


Fig. 12 Perceived level of knowledge available versus job title.

In most cases (Fig. 12) executives, managers, engineers, and consultants consider that there is information available about the AIPA techniques, but in limited sources. Only in the case of automatic process control all professionals consider that there is enough information in many sources; this is an expected response since automatic process control is a mature technique with presence in the industry for many years. Educators and students consider that in most of cases there is enough information available; only in the case of proxy models do they perceive that there are limited information sources. Professionals with job title of intermediate levels (engineers, and geologists and geophysicists) who work in operator companies, are the ones who have a lower level of knowledge about AIPA techniques and consider that there is not enough information available about them. In contrast, executives, consultants, and academic professionals (educators and students) have a high level of knowledge about AIPA techniques and consider that there are sources of information available.

What is the Perceived Level of Maturity for each Technology? Fig. 13 shows the responses related to perceived level of maturity for each technology. Observations from Fig. 13 include the following:

- For all technologies, "improving" level is the relatively greatest perceived level of maturity.
- 34% perceive automatic process control as the most mature "productive" technology.
- Approximately 50% or more perceive that proxy models and data mining are improving.
- Approximately 41 to 46% perceive that automatic process control, workflow automation, genetic algorithms, and

virtual environments are improving.

- The greatest levels of frustration (25 to 28%) occurred in expert systems, intelligent agents, and machine learning.
- The greatest levels of potential to grow and improve (21 to 22%) occurred in fuzzy logic and machine learning.

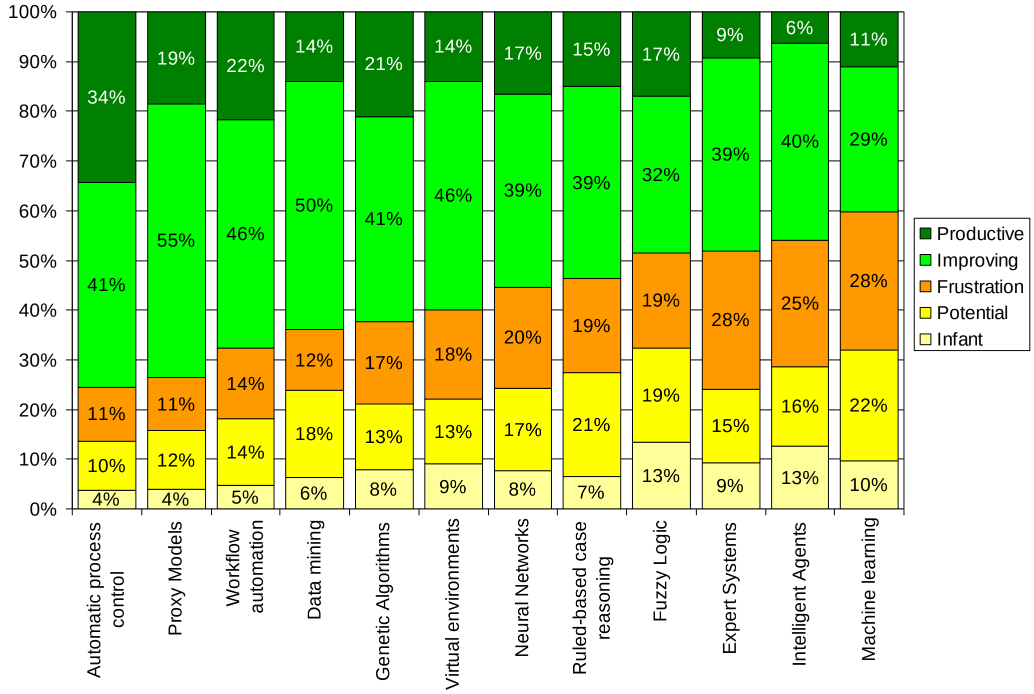


Fig. 13—Perceived level of maturity for each AIPA technology.

How Robust is our Survey with Respect to the Targeted People? We believe that only professionals interested in AIPA technologies were attracted to respond to the survey. People with no or little interest to AIPA technologies did not attempt to answer the survey. 58% of the respondents heard of used any of the AIPA technologies at least once. This could provide a bias and skewed results from people who know little or have little interest in AIPA.

Summary of Results

The survey was valuable in validating the following statistical results:

- Data management and integration is a common challenge in information management and analysis, with 75% of the respondents agreeing on this.
- Data management and integration, managing large volumes of data, large computation times, lots of manually driven tasks, and lack of integration between work processes were the top five of the "major challenge" list.
- Approximately 50% of respondents indicated knowledge of applications in data mining and neural networks.
- About 40% or more of respondents indicated awareness of data mining and neural networks, workflow automation, fuzzy logic, expert systems, and automatic process control applications.
- Between 40 to 50% declared that they are fully engaged or frequently use applications in workflow automation, automatic process control, rule-based case reasoning, data mining, proxy models, and virtual environments; 50% or more of all respondents have used more than once, frequently use, or are fully engaged in developing applications; 70% or more have used workflow automation and proxy models, and 40% or more have used frequently or they are fully engaged in proxy models, data mining, and automatic process control.
- Data mining appears to be the most important technology provider for any of the impacted value areas in E&P, contributing 13% or more of the positive responses. It also contributes with 30% or more for data management and integration, data filtering and cleansing, and information search. The value added by data mining to any of the impacted value areas in E&P was perceived as medium to high by 90% of respondents .
- The perceived level of available literature and public knowledge in AIPA technologies is generally low. Except for automatic process control, more than 50% perceive that there are limited resources available in any of the AIPA technologies. Executives, managers, engineers, and consultants consider that there is information available about the AIPA techniques, but in limited sources.

- Automatic process control is perceived as the most mature "productive" technology by 34% of the respondents; more than, 50% perceive that proxy models and data mining are improving, and the greatest levels of frustration (25 to 28%) occurred in expert systems, intelligent agents, and machine learning.
- Engineers and geologists and geophysicists working in operator companies had the lowest level of knowledge about AIPA and expressed that there is not enough information available. Executives/managers, consultants, and academics (educators and students), have a high level of knowledge about AIPA techniques and consider that there are enough or limited sources of information available.

Conclusions

AIPA technologies have penetrated the oil and gas industry in many ways. To increase such penetration further and reap expected benefits, there is a need for illustrative literature, clear accounts of case histories, and industrially hardened software tools. While most of the techniques have been available for several years, acceptance varies by the type of organization. This phenomenon is a recurring theme that has attracted considerable attention and has been analyzed by industry experts (Daneshy and Donnelly 2004).

The survey presented in this paper shows how AI-based applications can add value to operations and offers a guideline on which tools to use for each particular oil and gas challenge.

Some AIPA technologies tend to be more accepted by academia (educators and students), for many possible reasons, such as academic emphasis on fundamental research and novelty (albeit with focus on long-term industrial relevance); few immediate constraints on the economic viability of proposed solutions (albeit with serious constraints on available research funding); ability to work on “sanitized” versions of industrial problems that may retain many of the essential features but lack some of the intricacies of real-world problems; and reliance on the a strong theoretical background that makes some AI solutions, such as automatic process control, neural networks, genetic algorithms, fuzzy logic, machine learning, and intelligent agents somewhat easier to grasp. At the same time, technologies that are more heuristically or more practical (through relation to daily operations), such as data mining, workflow automation, proxy models, and virtual environments, appear to be less easily accessible to academia, possibly for the same reasons as stated above.

Acknowledgments

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Glossary

Artificial neural networks (ANN): Mathematical models or computational models that are inspired by the structure and/or functional aspects of biological neural networks. A neural network consists of an interconnected group of artificial neurons, and it processes information using a connectionist approach to computation.

Fuzzy logic: Multivalued logic that deals with reasoning that is approximate rather than fixed and exact. In contrast with traditional logic theory, where binary sets have two-valued logic (true or false), fuzzy logic variables may have a truth value that ranges in degree between 0 and 1.

Genetic algorithms A search heuristic that mimics the process of natural evolution. This heuristic is routinely used to generate useful solutions to optimization and search problems. Genetic algorithms belong to the larger class of evolutionary algorithms (EA), which generate solutions to optimization problems using techniques inspired by natural evolution, such as inheritance, mutation, selection, and crossover.

Machine learning: A scientific discipline concerned with the design and development of algorithms that allow computers to evolve behaviors based on empirical data, such as from sensor data or databases.

Intelligent agent: An autonomous entity which observes and acts upon an environment. Intelligent agents may also learn or use knowledge to achieve their goals. They may be very simple or very complex: a reflex machine such as a thermostat is an intelligent agent, as is a human being, as is a community of human beings working together towards a goal.

Swarm intelligence: The property of a system whereby the collective behaviors of (unsophisticated) agents interacting locally with their environment cause coherent functional global patterns to emerge. Swarm intelligence provides a basis with which it is possible to explore collective (or distributed) problem solving without centralized control or the provision of a global model.

Data mining: The process of discovering new patterns from large datasets involving methods from statistics and artificial intelligence but also database management.

Rule-based case reasoning: A particular type of reasoning that uses "if-then-else" rule statements. Rules are simply patterns and an inference engine searches for patterns in the rules that match patterns in the data. The "if" means "when the condition is true," the "then" means "take action A", and the "else" means "when the condition is not true take action B".

Bayesian networks: Computer models of probabilistic systems. Bayesian networks work by efficiently automating probability updating given observations. A Bayesian network can be used to learn causal relationships, and hence can be used to gain understanding about a problem domain and to predict the consequences of intervention.

Expert systems: Software solutions that use a knowledge base of human expertise for problem solving or to clarify uncertainties where normally one or more human experts would need to be consulted.

Automatic process control: Engineering-based discipline (architecture, mechanisms, algorithms) for maintaining the output of a specific process within a desired range, by moving field actuators following predetermined error correction algorithm. The objectives are to proactively keep a process in statistical control, maintain certain operating point, keep process safety, or optimize asset performance. The control signal may be computed from field measurements and an optimum expected performance target which are derived using physics-based or data-driven analytical methods or artificial intelligence techniques such as neural networks, fuzzy logic, and others.

Workflow automation: A set of methodologies and technologies, which aim to integrate data and applications into automated workflows, which reflect the business processes developed in a company over a well-structured information management platform. Workflow automation has been one of the main areas of interest of the E&P industry in the last 5 years, since it is one of the key elements of the digital oil field (DOF) and integrated production operations (IPO) trends.

Proxy models: Simplified representations of the response surface of numerical models, used commonly to make an approximate simulation model of a physical process (reservoir models, well models, surface models, advance process control) in a specific boundary of time and restrictions. Surrogate reservoir models are proxy models that are developed using machine-learning technology. They are also classified as AI-based reservoir models.

Virtual environments: The combination of simulation, computation, and visualization technologies to reach partial or total immersive environments for the analysis of production and reservoir data.

Appendix A: AI Resources

This appendix provides the names of journals and books that are resources for AI techniques.

Papers

Al-Kinani, A., Nunez, G., Stundner, M. et al. 2009. Selection of Infill Drilling Locations Using Customized Type Curve. Paper SPE 122186 presented at the SPE Latin American & Caribbean Petroleum Engineering Conference, Cartagena, Colombia, 31 May–3 June.

Berka, P. 2011. NEST: A Compositional Approach to Rule-Based and Case-Based Reasoning. *Advances in Artificial Intelligence*,. **2011**, Article ID 374250, http://www.hindawi.com/journals/aai/2011/374250/.

Daneshy, A. and Donnelly. J. 2004. A JPT Roundtable: The Funding and Uptake of New Upstream Technology. *J. Pet Tech* 56 (6): 28–30.

de la Vega, E. Sandoval, G., Garcia, M., Nunez, G, A. Al-Kinani, A., Holy, R.W., Escalona, H., Mota, M. 2010.. Integrating Data Mining and Expert Knowledge for an Artificial Lift Advisory System. Paper SPE 128636 presented at the SPE Intelligent Energy 2010 Conference, Utrecht, The Netherlands, 23–25 March

Ella, R., Reid, L., Russell, D. et al.. 2006. The Central Role and Challenges of Integrated Production Operations. Paper SPE 99807 presented at the 2006 SPE Intelligent Energy Conference and Exhibition, Amsterdam, The Netherlands, 11–13 April.

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Féret, M.P., and Glasgow, J.I. 1997. Combining Case-Based and Model-Based Reasoning for the Diagnosis of Complex Devices. *Applied Intelligence* **7**. (1): 57–78.

Gayer, G., Gilboa, I., Lieberman, O. 2007. Rule-Based and Case-Based Reasoning in Housing Prices. The B.E. Journal of Theoretical Economics **7** (1). Article 10.

Kravis, S. and Irrgang, R. 2005. A Case Based System for Oil and Gas Well Design with Risk Assessment. *Applied Intelligence*. **23** (1).

Journals

Expert Systems: The Journal of Knowledge Engineering, Wiley (http://www.wiley.com/bw/journal.asp?ref=0266-4720)
Expert Systems with Applications, Elsevier (http://www.journals.elsevier.com/expert-systems-with-applications/)
Neural Networks, Elsevier (http://www.journals.elsevier.com/neural-networks/) [SLD: *IEEE Transactions on Neural Networks*, IEEE (http://www.ieee-cis.org/pubs/tnn/)
International Federation of Automatic Control (IFAC) publications (www.ifac-control.org)
International Journal of Control, Taylor & Francis, UK (http://www.tandf.co.uk/journals/journal.asp?issn=0020-7179&linktype=1)
Journal on Data Mining and Knowledge Discovery, Springer (http://www.springerlink.com/content/100254/)
Journal on Machine Learning, Springer (http://www.springerlink.com/content/100309/)
Journal on Neural Computing and Applications, Springer (http://www.springer.com/computer/theoretical+computer+science/journal/521)
Journal on Statistical Analysis and Data Mining, Wiley (http://onlinelibrary.wiley.com/journal/10.1002/(ISSN)1932-1872)

Books

Akerkar, A.R. and Sajja, P. 2009. *Knowledge-Based Systems*. Sudbury, Massachusetts: Jones & Bartlett Publishers.

Berry, M. and Linoff, G. 2000. *Mastering Data Mining*, John Wiley & Sons.

Dunham, M. 2003. *Data Mining Introductory and Advanced Topics*. Prentice Hall..

Durkin, J. 1994. *Expert Systems Design and Development*. Prentice Hall. New York: Macmillan.

Giarratano, J.C., and Riley, G.D. 2004. *Expert Systems: Principles and Programming*, fourth edition. Course Technology.

Hagan, M.T., Demuth, H.B., and Beale, M.H. 2002. *Neural Network Design*. Hagan Publishing.

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Lebart, L., Morineau, A., and Warwick, K. 1984. *Multivariate Descriptive Statistical Analysis. Correspondence Analysis and Related Techniques for Large* Matrices. New York: John Wiley & Sons.

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Nise, N. 2003. *Control Systems Engineering*, fourth edition. John Wiley.

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Appendix B: Artificial Intelligence and Predictive Analytics Industry Survey

1. Which are the most common information management and analysis challenges in your petroleum asset?

Possible answers: Data management and integration, large volumes of data, lack of physical models to describe problems, event recognition and diagnosis, poor ability to predict performance, lots of manually driven tasks, lack of integration between work processes, inability to maintain or update models, unstable operations (unstable production), lack of visibility about asset's performance, large computation and simulation times, unexplained large production losses, inability to focus on high value added tasks, high people demand to survey and maintain, and other (open answers).

2. Are you personally familiar with AIPA applications? Which ones? (If the answer to this question is all "Never heard about it", then go to question 9.)
   Possible answers: Data mining, rule-based case reasoning, expert systems, neural networks, genetic algorithms, fuzzy logic, machine learning, intelligent agents, automatic process control, proxy models, workflow automation, virtual environments, and other (open).
3. What are the most common AIPA applications and solutions in your company or work area?
   Possible answers: Never used, have used once via pilot only, have used more than once, have used it frequently; and fully engaged, develop applications in this area.
4. In which areas have you applied or you know that there have been AIPA technologies applied to solve problems in your industry?
   Possible answers: Data management and integration, filtering/cleansing data, virtual metering, events/patterns recognition and diagnosis, fault detection, process control, production optimization, production management, surface facility modeling and simulation, reservoir modeling and simulation, coupled hydraulic fracture/reservoir modeling, information search, personnel training, and other.
5. What is the perceived value or impact in each of these applications? (The technologies the person chose in question 2 were listed.)
   Possible answers: Value level answers could be one of the following: not known or never measured, none or very low value perceived, medium value—fit for purpose value, and high value application or technology. Impacted area possible answers were: revenue, reserves, production, cost, and safety.
6. What is the level knowledge available for each technology? (The technologies the person chose in question 2 were listed)
   Possible answers: No knowledge available, information available in limited sources, enough information available in many sources.
7. Which technology has seen some evolution/change/development in the last years
   Possible answers: Not aware or cannot provide an opinion; no evolution in the last years; some evolution, change, and development in the last years; a lot of evolution and development in the last years.
8. What is the perceived maturity for each technology?
   Possible answers: Infant: very early stage of development; potential: the potential has been demonstrated; Frustration.
9. Which commercially available products for the E&P industry based on AIPA do you know (if any)?
   Possible answers: Commercial application: (App1, App2, App3) Knowledge about commercial application: just heard about it; have used it once or more; fully engaged, develop applications in this area. Potential to add value: Cannot provide an opinion yet, none or low potential to add value to oil and gas problems, and high potential to add value.
10. Do you know success cases of the application of AI solutions in your enterprise?
    Possible answers: Open answer.
11. Which far market technologies must be considered as game changers in AIPA?
    Possible answers: Open answer.
12. Which competing technologies may provide solutions to the information management and analysis challenges in your petroleum asset?
    Possible answers: Open answer.
13. Open comments: Is there any other topic you would like to discuss?
    Possible answers: Open answer.
14. What is your job classification?
    Possible answers: Executive, manager, engineer, geologist or geophysicist, superintendent or foreman, educator, consultant, student, and other
15. What is your age group?
    Possible answers: < 26, 26–35, 36–45, 46–55, 56–65, 65+
16. How many years have you worked in the E&P industry?
    Possible answers: 0–4, 5–9, 10–14, 15–19, 20–25, 26+
17. What is your primary area of technical interest?
    Possible answers: Drilling and completions; health, safety, security, environment, and social responsibility; management and information; production and operations; projects, facilities, and construction; and reservoir description and dynamics.
18. What category of company do you work for?
    Possible answers: National oil company, independent oil company, international oil company, integrated (major) oil company, technology/service provider, consultancy
19. What is your company's annual sales volume?
    Possible answers: Above USD 1 billion, USD 500 million to 1 billion, USD 250 million to 499 million, USD 100 million to 249 million, USD 50 million to 99 million, USD 25 million to 49 million, and below USD 25 million.
20. In which geographic region do you work?
    Possible answers: Sub-Saharan Africa, North Africa, Asia/Asia Pacific, Australia/New Zealand, Europe/Russia/Caspian, Middle East, North America, and South America/Caribbean/Mexico

Appendix C: Demographic Information

The following tables show the demographic information for the respondents. In each table, the answer with the highest response is in bold and shaded pink in the chart column.

TABLE C-1: JOB TITLE			
Response	**Chart**	**Frequency**	**Count**
Executive		6.7%	20
Manager		18.7%	56
Engineer		**49.3%**	**148**
Geologist or geophysicist		5.7%	17
Superintendent or foreman		0.0%	0
Educator		4.0%	12
Consultant		10.3%	31
Student		2.0%	6
Other		3.3%	10
		Valid Responses	**300**

TABLE C-2: AGE			
Response	**Chart**	**Frequency**	**Count**
< 26		4.3%	13
26–35		21.0%	63
36–45		20.7%	62
46–55		22.7%	68
56–65		**23.3%**	**70**
65+		8.0%	24
		Valid Responses	**300**

TABLE C-3: YEARS OF EXPERIENCE			
Response	**Chart**	**Frequency**	**Count**
0–4		13.3%	40
5–9		15.0%	45
10–14		11.0%	33
15–19		9.0%	27
20–25		11.3%	34
26+		**40.3%**	**121**
		Valid Responses	**300**

TABLE C-4: PRIMARY AREA OF TECHNICAL INTEREST			
Response	**Chart**	**Frequency**	**Count**
Drilling and Completions		8.3%	25
Health, Safety, Security, Environment, and Social Responsibility		0.7%	2
Management and Information		8.0%	24
Production and Operations		33.3%	100
Projects, Facilities, and Construction		3.0%	9
Reservoir Description and Dynamics		**46.7%**	**140**
		Valid Responses	**300**

TABLE C-5: COMPANY CATEGORY			
Response	**Chart**	**Frequency**	**Count**
National Oil Company		12.7%	38
Independent Oil Company		21.7%	65
International Oil Company		9.7%	29
Integrated (Major) Oil Company		13.7%	41
Technology/Service Provider		**28.7%**	**86**
Consultancy		13.7%	41
		Valid Responses	**300**

TABLE C-6: COMPANY ANNUAL SALES VOLUME			
Response	**Chart**	**Frequency**	**Count**
Above USD 1 billion		**49.3%**	**148**
USD 500 million–1 billion		10.3%	31
USD 250 million–499 million		4.3%	13
USD 100 million–249 million		7.7%	23
USD 50 million–99 million		3.3%	10
USD 25 million–49 million		6.7%	20
Below USD 25 million		18.3%	55
		Valid Responses	**300**

TABLE C-7: GEOGRAPHIC WORK AREA			
Response	**Chart**	**Frequency**	**Count**
Sub Saharan Africa		2.3%	7
North Africa		1.7%	5
Asia/Asia Pacific		8.3%	25
Australia/New Zealand		3.7%	11
Europe/Russia/Caspian		20.7%	62
Middle East		9.3%	28
North America		**45.3%**	**136**
South America/Caribbean/Mexico		8.7%	26
		Valid Responses	**300**