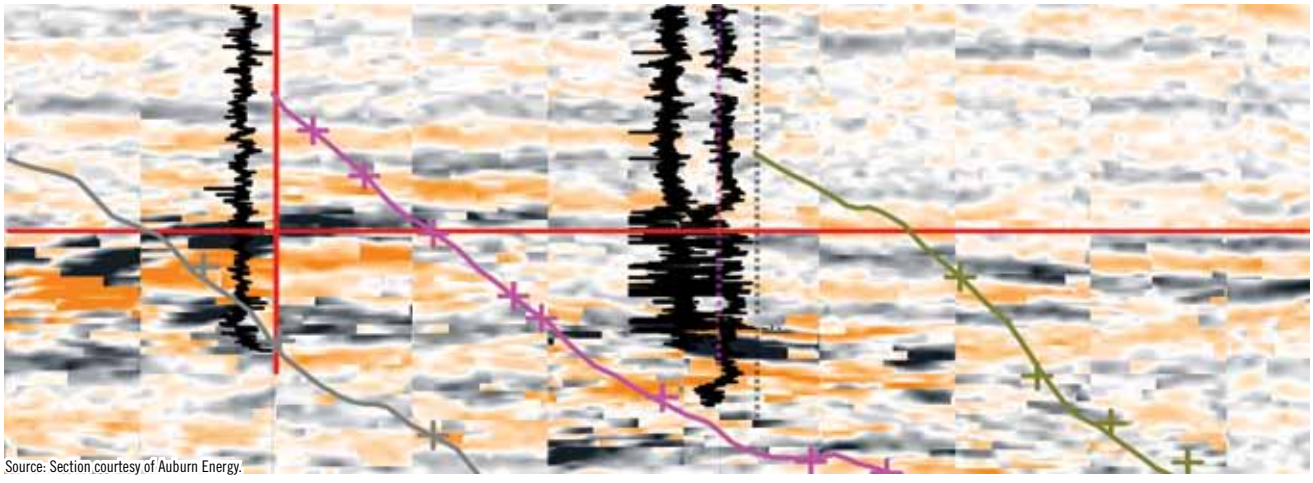
OIL&GAS JOURNAL

SPECIAL REPORT

A SECTION USING CONVENTIONAL SEISMIC INTERPRETATION SOFTWARE ANALYSIS

FIG. 1



Source: Section courtesy of Auburn Energy.

Unsupervised neural networks—disruptive technology for seismic interpretation

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The energy industry is faced with an exploding growth of information from a variety of sources: seismic surveys, well logs, and field production.

A step-change in technology is being developed that has the promise of geoscientists finding hydrocarbons more rapidly and with greater certainty by utilizing this large volume of data more effectively. Further, apart from automated tools to make better use of the data being collected, the industry risks wasting this valuable resource.

Supported by advanced software, a branch of neural networks is being found to be at least one practical solution for reducing the risk and time in finding oil and gas.

Neural network technology is used today in financial services software, pattern recognition systems, and many other settings. The general class of problems addressed by neural network technology in business is varied and diverse.

While there are several commercial tools in the upstream oil and gas industry that are based on "supervised" neural networks, this article describes how unsupervised neural network technologies can be used with "unclassified" data, a much more difficult problem having higher value results.

A supervised neural network operates on data that have been classified, i.e., the answer is known in specific locations, providing reference points for calibration purposes.

In the case of seismic data, for instance, a portion of a seismic survey at each logged well is known. The well log provides the ground truth.

Supervised neural networks link the seismic data at the well to the known results from the well. However, supervised neural networks have limited application since the earth is so heterogeneous, thus rendering classification away from boreholes difficult. In contrast, unsupervised neural networks do not require that the "answer" be known in advance and therefore are unbiased.

The other challenge working with supervised neural networks is that statistics grow more powerful as more wells provide more classified data. But that flies in the face of the more typical situation where our most important decisions need to be made when there are no or few wells.

As the number of wells increases, the value of a supervised

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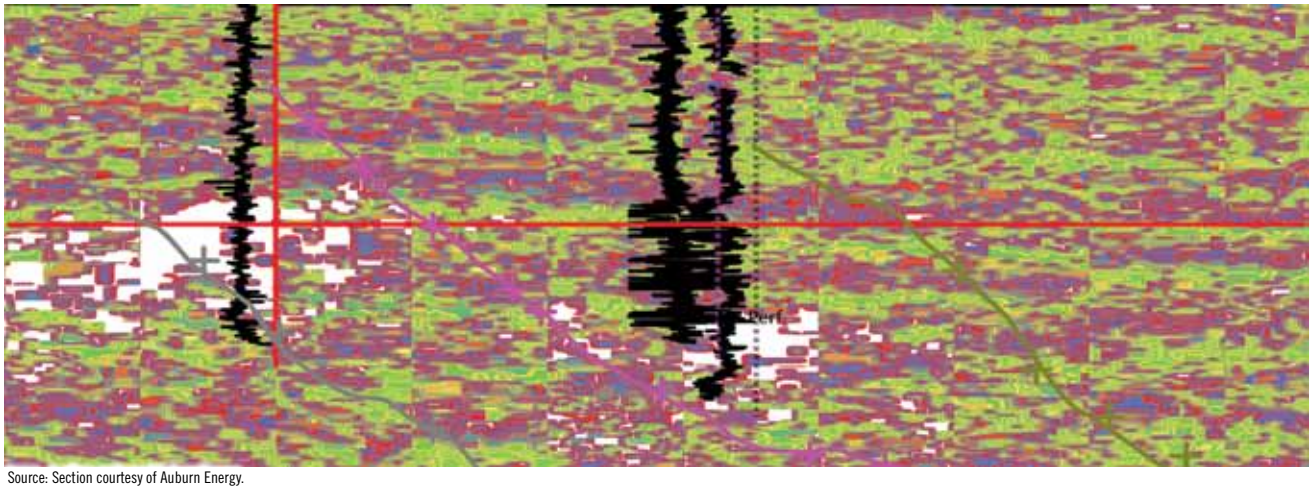
SECTION IN FIG. 1 ANALYZED USING NEURAL NETWORK TECHNOLOGY

FIG. 2



Source: Section courtesy of Auburn Energy.

neural network diminishes. In contrast, unsupervised neural networks do not require drilled wells and can be run against seismic reflection data alone.

The balance of this article describes how unsupervised neural network technology can be used to identify seismic anomalies through the use of multiple seismic attributes and how these anomalies may reveal the presence of hydrocarbons, often when conventional methods fall short.

The new technology may also find application in prediction of lithologies and fluid properties; perform comparative analysis of wells; and select the best seismic attributes for interpretation.

In seismic interpretation, unsupervised neural networks can be used to reveal subtle geologic features that may have been missed by conventional analytic methods. Through the balance of the article the term "neural network" will refer to only the unsupervised form of the technology.

Case study: Auburn Energy

Four wells have been drilled since 2006 in the "study area" of northern Wharton County, Tex.

Using a popular industry suite of seismic interpretation software, the company interpreted several locations to be lower-risk gas prospects.

The first well drilled encountered a formation that flowed. A large quantity of gas was found; however, much of that gas was not economically recoverable.

A second well was drilled 2 years later that found an economic gas reservoir that has produced for more than 3 years.

Two subsequent wells have been drilled that did not find economic reserves. In all but one case of these wells, the original seismic interpretation indicated the presence of gas reservoirs.

"From the neural network interpretation it was clear that the two dry holes were drilled in locations that were not in economic gas concentrations," said Deborah Sacrey, owner of Auburn Energy. "Applying the Geophysical Insights neural network technology to some 13 attributes, we can now see that two of the four wells would not have been drilled, saving investors about $8 million.

"I had included all of the AVO attribute analysis for the area of study available at the time. The neural network attribute analysis went well beyond conventional analysis by assimilating many more attributes than conventional software tools. We are now expanding the study area using the neural network technology to confirm additional exploratory prospects."

As an indication of the effectiveness of the neural network technology, Fig. 1 is seismic data from the existing gas field referenced above in Wharton County. The figure is comprised of seismic reflection data and fault interpretation using conventional, commercially available, seismic interpretation software.

Since two wells were dry holes, only two of the four wells drilled in the field are shown in Fig. 1. The conventional analysis in Fig. 1 indicates both reservoirs, one of which could not be produced because of very fine formation particles flowing along with the gas. The well on the left resulted in a gas 'show' only, while the well on the right has been producing for 3 years.

In Fig. 2, the original data are replaced with a neural network analysis based on a combination of 13 seismic attributes, revealing two seismic anomalies located near the two wells shown in Fig. 1.

Fig. 1 vs. Fig. 2 effectively compare conventional ("before") and neural network ("after") on the field of study. Since the neural network analysis resulted in only two anomalies being indicated, it is likely that only two wells would have been drilled out of the four. Also of interest is the position of the two wells near the edge of the two seismic anomalies, suggesting a potential "near miss" in the location of the wells.

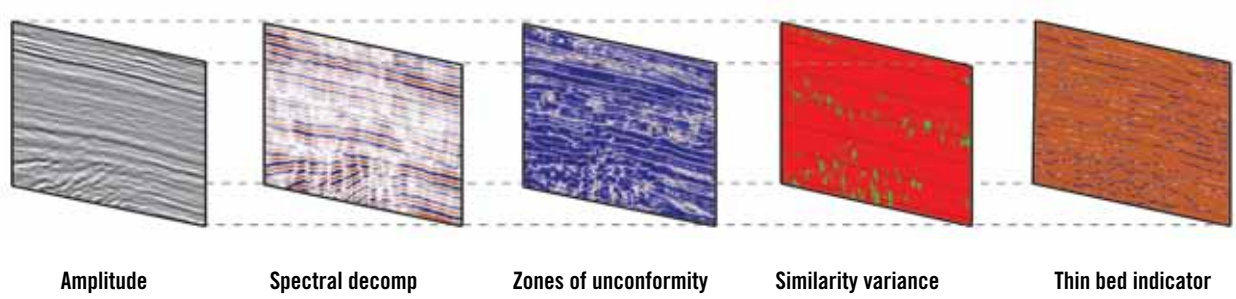
Applying self-organizing maps

Nature is full of examples of how animals, following a few simple rules, organize themselves into assemblages such as moving flocks, schools, and herds. Moreover, they reorganize themselves after a disruption to their normal pattern of movement.

Consider a flock of migratory geese and a school of fish. After taking flight, the flock of geese quickly organizes into the

EVALUATING MULTIPLE SEISMIC ATTRIBUTES

FIG. 3



familiar 'V' flying pattern. A school of fish forms and moves about as a protection against predators. In either the case of flying geese or school of fish, the assemblage quickly disperses at the threat of a predator and quickly reassembles once the threat is past. In both instances, the assemblage is robust yet each individual in the group is behaving according to a few simple instructions, i.e., "if not the leader, follow the individual ahead and remain to the left or right."

The neurons in a neural network are presented with data and adapt to the data following a set of simple rules. The neural network becomes in essence a "learning machine" whereby the network adapts to the characteristics of the data resulting in what are called self-organizing maps (SOMs). The input data are unclassified, and the learning process is unattended.

The SOM is a powerful cluster analysis and pattern recognition method developed by Prof. Teuvo Kohonen of Finland during the 1970s-80s. In the case study shown above, we present results based on SOM on a 3D seismic survey consisting of a large number of seismic attributes. These results constitute an ongoing portion of our research in this area.

Neural networks offer an automated process to assist seismic interpretation for instance, accelerating prospect evaluation by:

- Enabling the rapid comparison of large sets of seismic attributes.
- Identifying combinations of attributes that reveal seismic anomalies.
- Distilling the interpretation process to identify hydrocarbons with greater speed and certainty.

Consider for a moment the quantity of data available from a single seismic survey and how neural networks may be applied to reveal insights in the seismic reflection data.

The main task facing a geoscientist is to identify and ascribe the geologic meaning to observable patterns in the data. The most obvious patterns are found in seismic reflections, but in recent years the industry is using more subtle patterns and relating them to such features as porosity, lithology, and fluid content, as well as underground structure.

The isolation of such patterns and their use as possible identifiers of subsurface characteristics constitutes attribute analysis, which is a standard tool in the geoscientist's toolkit. Over the past several years, growth in seismic data volumes has multiplied many times in terms of geographic area covered, depth of interest, and the number of attributes.

Often, a prospect is evaluated with a primary 3D survey along with 5 to 25 attributes serving general and unique purposes. A group of just five typical seismic reflection attributes is shown in Fig. 3.

For illustration purposes, Fig. 4 (left) depicts three attributes from a single 3D survey. The three points near the center highlight one data sample for three associated attributes, aligned as parallel rectangular blocks.

Converting the three attributes into a SOM attribute perspective, as shown in Fig. 4 (right), each point sample is plotted in attribute space along three attribute axes, resulting in a natural cluster of similar characteristics. The natural clusters constitute regions of higher information density and may indicate seismic events or anomalies in the data.

Two additional natural clusters are illustrated in Fig. 4 (right) as well. Initially, neurons are randomly placed by the algorithm in attribute space. In the "learning" stage, neurons are attracted to the data samples in the clusters in a recursive process. Ultimately after neuron movement has finished, the neurons reveal subtle combinations of attributes that may highlight the presence and type of hydrocarbons.

While details of the algorithm are available in the technical literature, suffice to say that Figs. 1 and 2 compare a conventional seismic data display, offering limited resolution to a neural network classification of the same data. The neural network depiction dramatically increases the resolution and insight into the data.

Other applications of neural networks

Large volumes of seismic data are typically good candidates for using neural networks to identify anomalies in the data.

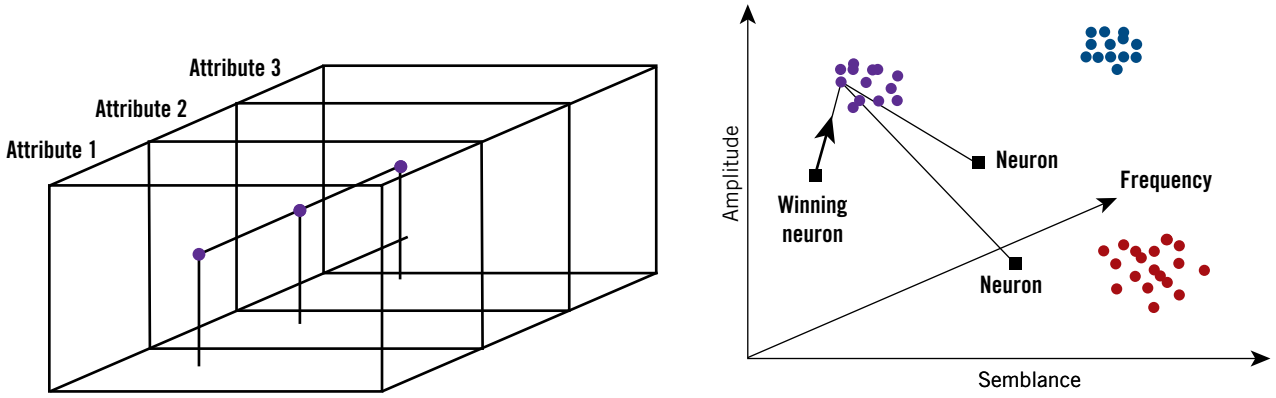
Beyond the most immediate opportunity of using neural networks to aid seismic interpretation, other valid applications of the technology include:

- Identifying errors and gaps in data for quality assurance.
- Analyzing seismic attributes with well log data for better predictions away from the wells.
- Integrating seismic data in reservoir characterization and simulation.
- Incorporating microseismic events with other seismic data for better fracture prediction.

Fortunately, large sets of data can be evaluated by a neural network rapidly, typically in a matter of minutes to a few hours,

THREE SEISMIC ATTRIBUTES (LEFT) SORTED BY SOM TECHNIQUE (RIGHT)

FIG. 4



making their use quite practical. They can also be programmed to run unattended and report by exception when anomalies are encountered.

Getting started with the technology

Continuing with the example of seismic interpretation, the following basic steps are recommended when planning a neural network application.

Since neural networks are highly specialized technology, having a thorough understanding of the methodology of neural networks and the appropriate choice of parameters for neural network classification is strongly encouraged. The following four general tasks outline the key steps in conducting a neural network analysis.

1. Perform an assessment that reveals the right choice of seismic attributes.
2. Conduct an appropriate interpretation of attributes for the geologic trends of interest.
3. Select the well information, where available, for calibration purposes to bring ground truth to the seismic response.
4. Generate new attribute volumes—the neural network classification and a classification reliability.

One of the keys to a successful project is selecting the best choice of seismic attributes, revealed by a thorough assessment of the data. This step will require a deep knowledge of geophysics, of course, and is optimally conducted by domain experts.

As the neural network operates on the data, visual output from various attributes will require an interpretation of the attributes for the geologic trends of interest. Where available, well information is then used for calibration purposes to bring the all-important ground truth to the seismic response. The complete analysis will result in two new attribute volumes—a neural network classification and a classification reliability, which identifies uncertainty in the classification.

A major change is needed to take full advantage of the explosion of data in the oil field. Neural network technology enables greater insights into all types of data, but has its greatest value when applied to seismic interpretation.

Neural networks are proving their value to reduce the time and costs for the interpretation process while increasing the dependability of the results. The technology can also be used to correlate well information with well log data and enhance the quality of reservoir simulation.

Neural networks have the promise of being a disruptive technology that will accelerate and improve the industry's use of data from the field. OGJ

The author

Tom Smith (tsmith@geoinsights.com) is president and chief executive officer of Geophysical Insights. He began work in the industry with Chevron Geophysical as a processing geophysicist. He founded Seismic Micro-Technology in 1984 and there led the development of the KINGDOM software suite for seismic interpretation. He launched Geophysical Insights in 2010 to tackle fundamental geophysical problems and develop advanced technology for practical solutions in the energy industry. He has BS and MS degrees in geology from Iowa State University and a PhD in geophysics from the University of Houston.

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