**Neural Networks for the Practicing Engineer**

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Decision Precision

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This Microsoft Word document contains the slides and the non-SPE figures as used in the presentation.

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Excerpt from *Applied Decision Analysis with Portfolio and Project Modeling*

OUTLINE

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**SCOPE OF ARTIFICIAL INTELLIGENCE**

**artificial intelligence**

an engineering discipline devoted to designing ways to make computers perform tasks that were previously thought to require human intelligence.

The main subdivisions:

* natural language processing
* vision systems
* robotics
* expert systems (rule- and frame-based)
* neural networks

Expert systems and neural networks are commonly called
 “**knowledge systems**”

## OVERVIEW OF EXPERT SYSTEMS

**expert system** (ES)

a computer program that solves a particular procedural problem in much the same way as would a human expert.

The expert system allows a less-experienced person to perform a task in a manner similar to and with nearly the performance of a human expert.

Types of Problems Addressed

* diagnosis and prescription
* classification
* planning and configuring.

**In engineering, the computer can check designs against rules and design precedents. It can offer suggestions and assist in design calculations.**

**MACSYMA** system solves integral calculus.

**Dipmeter Advisor** for interpreting well logs.

**Wine Advisor** represents wine-choosing expertise of an expert.

Example Expert Systems in Petroleum Industry

* Interpreting logs
* Diagnosing and prescribing remedies for stuck drillpipe
* Locating mineral deposits
* Configuring seismic processing runs
* Selecting the optimal drilling mud; problem diagnoses
* Identifying the cause of a chemical spill and recommending action

Criteria for Employing Expert System Techniques

1. The problem is important.
2. A body of knowledge exists related to the problem.
3. There are recognized experts who are substantially better at solving the problem than non-experts.
4. A good solution can be recognized.
5. The skill can be taught, i.e., reasoning can be explained.
6. Experts are scarce and expensive.
7. Solving the problem takes several hours to several days.

Example Knowledge within an Expert System

 **Assertions**:

 (ABC\_COMPANY INDUSTRY

 PETROLEUM\_E&P

 GAS\_PIPELINE

 NGL\_EXTRACTION)

 (MAJOR\_PRODUCT OIL)

 (INJECTOR\_WELLS MORTON#1

 MORTON#15)

A key feature: **Explanation system**

 **Rules**:

 IF INDUSTRY IS OIL THEN

 PRODUCT-TYPE IS

 COMMODITY

 IF ASSET-TYPE = PLANT AND

 ACQUISITION-DATE > 1987

 THEN

 LIFE = 15

**Frames**:

####  MORTON#1

 IS-A WELL

 LOCATION T15N\_R15W\_S14

 PRODUCING-INTERVALS

 8520-8730 9540-9560

## OVERVIEW OF NEURAL NETWORKS

**neural network** (NN)

a simple arrangement of nodes, called neurons, used for pattern recognition, modeled after a simplistic representation of a living brain.

* Several to tens of neurons in NN’s
* 100 billion neurons in human brain, some connected to 10,000 other neurons.
* Parallel, distributed processing

The neural network allows mathematical processing of often-complex data. This is can be viewed as **massive, multi-variable, non-linear regression**.

Engineering principles are not programmed. The neural network finds—discovers—a solution by learning by example.

The learning process examines examples over and over, perhaps as many as 10 million times. In each cycle, the connection weights are modified slightly to better match the example inputs with the corresponding example outputs.



* Usually: “feed-forward” system. Presenting values at the input nodes produces values at the output nodes.
* Each connection has a weight factor, usually determined by “training.”
* May have more than one hidden layer.
* May have feedback (recursion) nodes, wired from successor nodes to earlier layers.



* Linear-weighted sum or other ‘summation’ of inputs and the feedback signal.
* Activation function: The most popular is the sigmoid logistic function:

f(x) = where T is a threshold value



**Training the Network**

Most popular: feed-forward, back-propagation.

1. Randomize the connection weights.
2. Present a randomly-selected training pattern (data instance) to the network.
3. Compare the desired output(s) with the calculated output(s).
4. Test for convergence. If adequate, then goto Step 7 (test performance).
5. Adjust the weights using a “delta rule,” working backward layer-by-layer, to reduce the error.

where *X* is the input vector, *W* is the weight vector,  is the learning constant, and E is the error (a scalar).
6. Loop back to Step 2 (iterate, next pattern).
7. Check the network performance with a separate test data set.
8. Adjust the network or training if needed, and repeat.

Applications of Neural Networks

* Data filtering
* Pattern recognition
	+ Vision systems
	+ Function generator
	+ Failure detection
* Trend analysis
* Process control
* Optimization (traveling salesman problem)

**OILFIELD APPLICATIONS OF NEURAL NETWORKS**

##### Estimating PVT Properties

SPE 38099
“Universal Neural Network Based Model for Estimating the PVT Properties of Crude Oil”
by Ridha B. Gharbi and Adel M. Elsharkawy, Kuwait University, 1997

* 5200 Experimental PVT data sets from all over the world + 254 more for a test set.
* Output and input data, and ranges:

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| --- | --- |
| Bubble-point pressure, psia,  | 79 to 7130 |
| Bubble-point formation volume factor, rb/stb,  | 1.02 to 2.92 |
| Solution gas-oil-ratio, scf/stb,  | 9 to 3370 |
| Gas relative density (air=1),  | 0.50 to 1.67 |
| Stock-tank oil gravity, °API | 14.3 to 59 |
| Reservoir Temperature, °F, T | 74 to 342 |

* Network:
	+ 4 input nodes
	+ 5 neurons in hidden layer
	+ 2 output nodes
* The paper shows the connection weights and biases for the resulting model.

5200 data sets boiled down to the NN structure plus 35 parameters.
* The overall performance was better than any of the published correlations cited.
	+ Correlation coefficient = .9891 for
	+ Correlation coefficient = .9875 for

**Predicting Bit Life**

SPE 51082
“A New Approach to Predict Bit Life Based on Tooth or Bearing Failures” 1998
by H. I. Bilgesu, et al., West Virginia U.,

* Two outputs (third NN):
	+ Bit bearing wear
	+ Bit tooth wear
* And inputs:
	+ Bit type
	+ Bit size
	+ Formation type (1-9, drillability and abrasiveness)
	+ Mud Pump rate
	+ Rotating time
	+ Interval drilled
	+ Weight on bit
	+ Rotary speed
	+ Rotary torque
	+ Rate of penetration

**Forecasting Production**

SPE 30202
“Predicting Production Using a Neural Network
(Artifical Intelligence Beats Human Intelligence)”
by Robert Boomer, Texaco, 1995

* Predicting production of infill wells, Vacuum Field, New Mexico
* San Andres, cyclical evaporites and carbonates, waterflood
* 58 inputs, 46 hidden, 4 output nodes
* Initial, 3, 6 & 12 month average oil production
* Comparison
	+ Professionals’ forecasts:
		- average error: 39 BOPD
		- mean absolute error: 99 BOPD
	+ Neural network forecast
		- average error: –19 BOPD
		- mean absolute error: 27 BOPD
* Screening for all possible locations over eight square miles. Generated production profiles in a couple of hours with a NN what would have taken a professional perhaps months.

**Estimating Ultimate Recovery for New Wells**

SPE 39962 (International Student Paper Contest)
“Methods of Neuro-Simulation for Field development,” 1997
by H. Doraisamy, Pennsylvania State U.

SPE 51079
“Key Parameters Controlling the Performance of Neuro-Simulation Applications in Field Development” by H. Doraisamy and T. Ertekin, Pennsylvania State U., 1998

* 4 existing wells, with 1500 days’ production
* 12 additional training wells from reservoir simulation model, positioned to delineate the reservoir
* NN performs non-linear interpolations between the training wells.

SPE 39965
“Practical Use of Neural Networks in Tight Gas Fractured Reservoirs: Application to the San Juan Basin”, 1998
by A. Quenes, et al., Burlington Resources

* Thirteen reservoir properties from three horizons over a 24-township area.
	+ Vertical: pay thickness and resistivity
	+ Horizontal: thickness and resistivity maps; structural property maps
* NN establishes relationships to fracture intensity inferred by the EUR

“Equation-maker” link between fracture drivers and production

Mapped sweet spot areas

**WHEN TO CONSIDER NEURAL NETWORKS**

* An important problem.
* Where a procedural analysis is impractical:
	+ Analysis rules are unknown.
	+ Too many rules would be needed.
	+ The analysis system must be ‘plastic.’
* Have substantial quantity of data, believed related to output variable(s) of interest.
	+ You should have some knowledge of the system and possible dependency (driver) relationships.
	+ You believe those data relationships will continue into the future — to large degree.

**GETTING STARTED AND GUIDELINES**

* Identify a problem of interest.
* Someone with experience and a software tool available?
* Study some of the papers, articles and books.
* Acquire a NN program (free to $400) and experiment with simple examples.
	+ Synthesize data
	+ Replicate demonstration results
* Apply NN to your problem
	+ What variables are likely drivers or related to drivers?
	+ Would the data work better if transformed?
* Experiment with different NN architectures

No. layers, recursive nodes, no. of nodes, learning rules, etc.
* Write a paper for SPE!

**WRAP-UP**

Solar Flare Prediction

* Richard Fozzard, late 1980’s, graduate student, University of Colorado[[1]](#footnote-1)
* The problem: Predicting solar flares for use by the Space Environment Laboratory.
* Other people invested three months to develop an expert system: “THEO”
	+ 700 rules
	+ Outperformed all forecasters except the expert from whom they got the rules.
* Fozzard could set up and train the NN in a couple of evenings, without talking to an expert.
* Inputs: wavelengths of x-rays, pictures of the sun, and the strength of magnetic fields.
* “TheoNet” slightly outperformed THEO.
* The most popular NN application: **Investments and trading**.
	+ One vendor’s software download page had over 17,000 hits in past 30 days (April 1999).
	+ Some vendors sell stock picking and market timing models — and data.
	+ Many people claim to be making money.
* NN’s are increasingly embedded in regular programs:
	+ Programs that learn about your computer use habits.
	+ Combined with expert systems, e.g., airport inspection system

	NN preprocesses the data

	🡪 Hand off to ES for further analysis

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|  | **Neural Networks** | **Expert Systems** |
| Knowledge | More fuzzy, noisyPossibly changing | More concrete |
| Problem-solving | Judgment and intuition | Thinking in rules |
| Knowledge representa­tion | Network pattern and connection weights; don’t know the rules | Rules and frames |

|  |  |  |
| --- | --- | --- |
| Capturing knowledge | Discovery from the data, though domain expertise helpful | Domain expert + knowledge engineer |
| Changing data | Progressive learning (plastic) | Need to revise the knowledge base (brittle) |
| Explanations | Elusive | Common feature |

 **COMMENTS? QUESTIONS?**

1. Sherald, Marge, 1989, “Neural Networks versus Expert Systems: Is There Room for Both?,” *PC AI*, Jul.-Aug., p. 10-15 [↑](#footnote-ref-1)