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A "Learning" System as an Economic Forecasting Tool in Mineral and Energy Industry
-Case Study of U. S. Petroleum Resource Appraisal-

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ABSTRACT : This study explores that learning model that has been employed for many years in the description of and projection of system or process performance promises to be very useful in long-term forecasting, especially of technology or related productivity measures, in mineral and energy industries. This study also provides some empirical results on the measurement of the learning curve in U. S. petroleum resource assessment and demonstrates how the learning system can be used as an economic forecasting tool.

INTRODUCTION

The learning curve, sometimes called the experience curve, progressive curve, or improvement curve, has been used for more than a generation as a means of measuring and predicting productivity improvement for processes of manufacturing systems, investigating cost behavioral patterns, cost estimation, and decision making in general. Even though the learning curve concept has received considerable attention in such uses, there has been very little application in the mineral and energy industry, and practically no use whatsoever in economic forecasting in mineral and energy industries.

Pierson (1981) suggested that applying learning-curve theory in mineral and energy industries might be fruitful. In an recent application of learning-curve theory in mineral and energy industry, Harris (1984) demonstrated the learning-curve concept as a means of estimating undiscovered usable resources. He also noted that the quantity-quality models and the estimation by Cargill et al. (1980, 1981) of mercury resources are forms of learning curve analysis.

When learning is considered with regard to the objective of long-term forecasting, the procedure herein described could be used as a means for long range forecasting. One useful way of viewing research on a learning system as a tool for economic forecasting is to distill from it three related propositions :

1. Long-term forecasting may be performed better by working with the integral series rather than its time derivative (annual), because projections reflect more the overall patterns and relations and less the short and intermediate cyclical and erratic variations.
2. There are some "economic", as distinguished from "technologic" relations, that exhibit learning patterns.
3. These learning relations may be linked with other relations to form a learning system with communications and links from price to market determinants, e. g., income.

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GENERAL CONCEPT OF THE LEARNING SYSTEM

Learning is indicated by improvement (learning) in $\tilde{Y}_t$ with an increase in $\tilde{X}_t$:

$$\tilde{Y}_t = \frac{\tilde{Z}_t}{\tilde{X}_t} = \frac{\sum_{i=1}^{t} r_i}{\sum_{i=1}^{t} s_i}$$

where

r = measure of performance of the system
s = level of activity of the system
$\tilde{Y}_t$ = the learning measure

$$\tilde{Y}_t = \frac{\tilde{Z}_t}{\tilde{X}_t} = L(\tilde{X}_t),$$

where $\tilde{X}_t$ = cumulative number of output units and L( )is the learning relation.

When the learning model is to be used to estimate $\tilde{Z}_t$, the following relation is employed : $\tilde{Z}_t = L(\tilde{X}_t)\ \tilde{X}_t$. Furthermore, given either direct projection of $\tilde{X}_t$ or a forecast value for S_{t+1}, the performance level for period t +1 can be forecast by the following :

$$r_{t+1}=\frac{d\tilde{Z}_{t+1}}{d\tilde{X}_{t+1}} = L(\tilde{X}_{t+1})\tilde{X}_{t+1} + L(\tilde{X}_{t+1}),$$

where

$$\tilde{X}_{t+1} = \tilde{X}_t + s_{t+1}$$

CASE STUDY: U. S. PETROLEUM RESOURCE APPRAISAL

The structural form of the forecasting model of U. S. petroleum resource appraisal is represented by the following set of equations.

$$\tilde{Y}_t=\frac{\tilde{Z}_t}{\tilde{X}_t} = A\tilde{X}_t^{\alpha} \quad (1)$$

where

$\tilde{Y}_t$ = average cumulative discovery rate(bbls/ft)

$$\tilde{Z}_t=\sum_{i=1}^{t} r_i$$

where

r = amount of crude oil discoveries

$$\tilde{X}_t=\sum_{i=1}^{t} s_i$$

where

s = footage of exploratory drilling

α = an exponent (parameter to be estimated), or the learning index of the curve

A logarithmic version of equation (1) is

$$\ln\tilde{Y}_t = \ln A + \alpha \ln\tilde{X}_t \quad (2)$$

Data for r_t, annually 1900-1982, were obtained from the American Petroleum Institute. Variable s_t, was obtained from the Departement of Energy and the American Petroleum Institute. In the empirical investigation r_t and s_t were measured in millions of barrels and in millions of feet, respectively. Fig. 1 shows average discoveries of crude oil in the United States from 1938 to 1982. The data on cumulative discoveries with respcet cumulative exploratory drilling shows a strong linear pattern of the learning curve (Fig. 2). First of all, the response variable (Y_t) was regressed on the cumulative drilling variable($\tilde{X}_t$) by the ordinary least squares(OLS) method(1939~1982).

$$\ln Y_t = 6.82538 - 0.374181 n\tilde{X}_t$$

(305.8) (-107.74)

Corrected $R_2 = 0.996$

Then,

$$\tilde{Y}_t = 920.92629\ \tilde{X}_t^{-0.37418}$$
$$\tilde{Z}_t = 920.92629\ \tilde{X}_t^{0.62582} \quad (3)$$

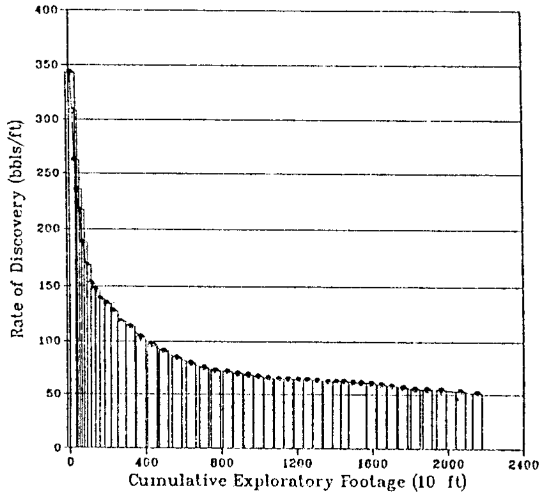

Fig. 1. Average discoveries of crude oil in the United States from 1938 to 1982.

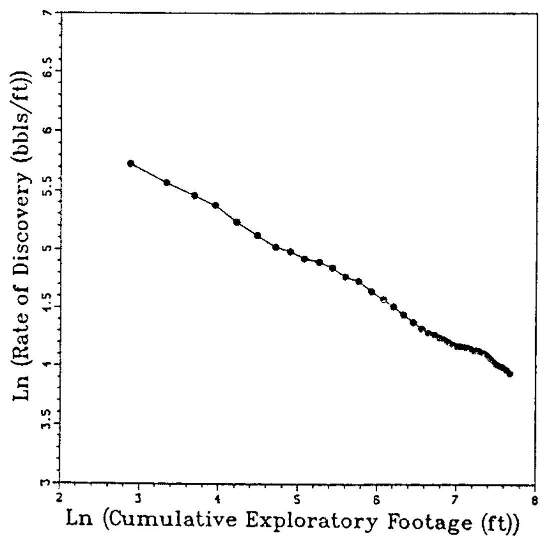

Fig. 2. Learning curve of crude oil discoveries.

Suppose it were desired to predict the average discovery rate ($\frac{r}{s}$). From equation(3),

$$r_t = \frac{d\tilde{Z}_t}{d\tilde{X}_t}\cdot\frac{d\tilde{X}_t}{dt} = (920.92629)(0.62582)\tilde{X}_t^{-0.37418}\ s_t$$

Then,

$$\frac{r_t}{s_t} = (920.92629)(0.62582)\tilde{X}_t^{-0.37418} \quad (4)$$

This result appears satisfactory, for the predicted curve of the annual average discovery rate is also generally successful in tracing the trend of the actual historical values (see Fig. 3). Use of this model to forecast discovery rates requires a forecast of cumulative drilling, $\tilde{X}_t$. The plot of cumulated drilling against time shows a straight line pattern (1946-1982) (Fig. 4). Cumulated drilling, $\tilde{X}_t$, was regressed on time, t, by the OLS method ;

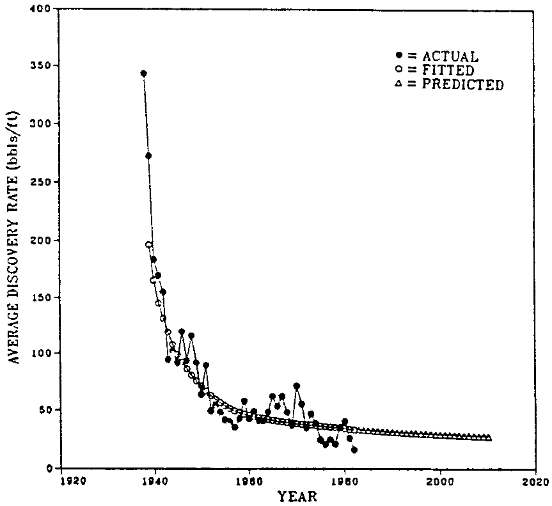

Fig. 3. Forecast of average discovery rate of U. S. crude oil.

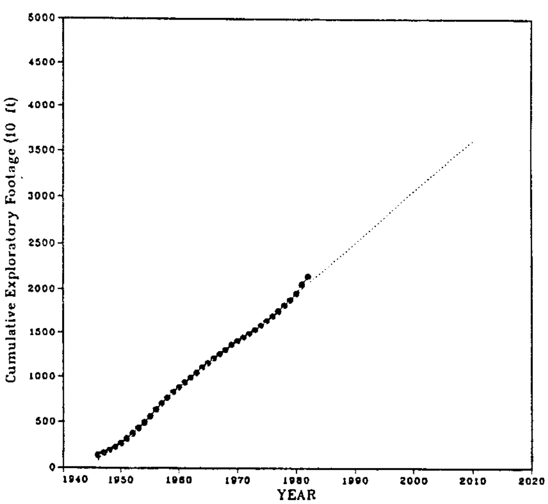

Fig. 4. Forecast of cumulative exploratory footage.

$$X_t = 24.77205 + 55.34116t$$
$$(2.35) \qquad (114.36)$$
$$\text{Corrected } R^2 = 0.997$$

A forecast of the average discovery rate(Fig. 3) was made using equation(4) with the future cumulative drilling forecast(Fig. 4).

Suppose we were interested in forecasting the amount of annual discoveries(r_t).

$$\text{Given } \tilde{Z}_t = \tilde{Y}_t \cdot \tilde{X}_t = 920.92629 \tilde{X}_t^{0.62582}$$

$$\frac{d\tilde{Z}_t}{d\tilde{X}_t} = (920.92629)(0.62582)\ \tilde{X}_t^{-0.37418}$$

$$\text{Since } r_t = \frac{d\tilde{Z}_t}{dt} \frac{d\tilde{Z}_t}{d\tilde{X}_t} \cdot \frac{d\tilde{X}_t}{dt},$$

$$r_t = (920.92629)(0.62582) \tilde{X}_t^{-0.37418}\ s_t$$

Thus, this form the learning model can be used to forecast of annual oil discoveries. Fig. 5 reveals that such an estimate of oil discoveries of crude oil is more optimistic than that made by Hubbert(1974). The basic assumption of the Hubbert model was what the time path of cumulative discoveries could be approximated by a logistic curve. The derivative of the model of cumulative discoveries is an estimate of the time path of annual discoveries. The learning model represents not a simple trend equation,

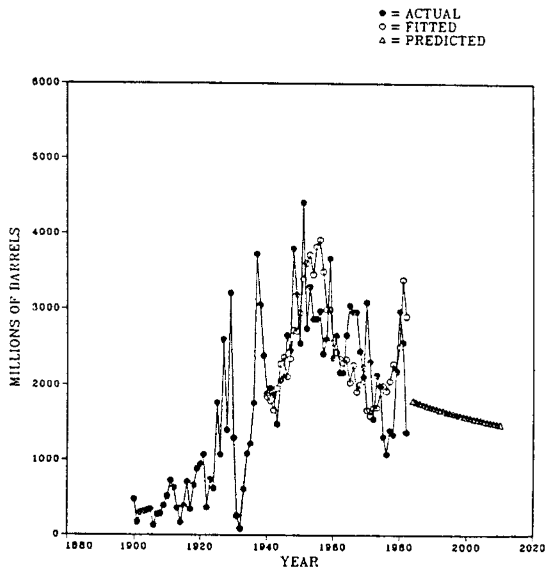

Fig. 5. Forecast of crude oil discoveries in U. S.

but a useful benchmark for technological change. Accumulated experience based on the cumulative output can clearly affect productivity of a technology.

For the purpose of comparing the learning model with life cycle models, the derivative logistic, normal, and cauchy models were fit to discovery data from 1900 to 1982 (Fig. 6). A computer printout of slope characteristics (Fig. 7) of the cumulative plot of crude oil discoveries over time suggested the first derivative logistic as the appropriate model for fitting the data (Jeon, 1989). Forecasts of crude oil discoveries were calculated for each year using the following equation.

$$y_t = \frac{(153752)(0.0827838)(5.01262)e^{-0.0827838t}}{(1+5.01262e^{-0.0827838t})^2}$$

$$AAE = 0.214$$

Interestingly, estimates of the cauchy distribution and the normal distribution from annual discovery data provided better fits than the first derivative logistic curve as measured by AAE (Average absolute error).

Cauchy Distribution

$$y_t = \frac{1}{0.4611 \cdot 10^{-6} \cdot (t-21.89)^2 + 0.3609 \cdot 10^{-3}}$$

$$t = 1,193$$
$$AAE = 0.190$$

Normal Distribution

$$y_t = \frac{16421.9}{23.5434\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{t-21.822515}{23.5434}\right)^2}$$

$$t = 1,1935$$
$$AAE = 0.199$$

The results of this investigation are reported in Table 1. As can be seen in Table 1, forecasts of the learning model and the cauchy distribution give larger estimates than the first derivative logistic.

Suppose it were desired to predict the ultimate recoverable reserves based upon the learning model :

Givien $r_t = (920.92629)(0.62582)\tilde{X}t^{-3.37418} s_t$,

substitute $\tilde{X}_t = 24.77205 + 55.34116t$ and $s_t = \frac{d\tilde{X}_t}{dt} = 55.34116$ into the above equation.

Then,

$$r_t = 31895(24.77205 + 55.34116t)^{-0.37418}$$

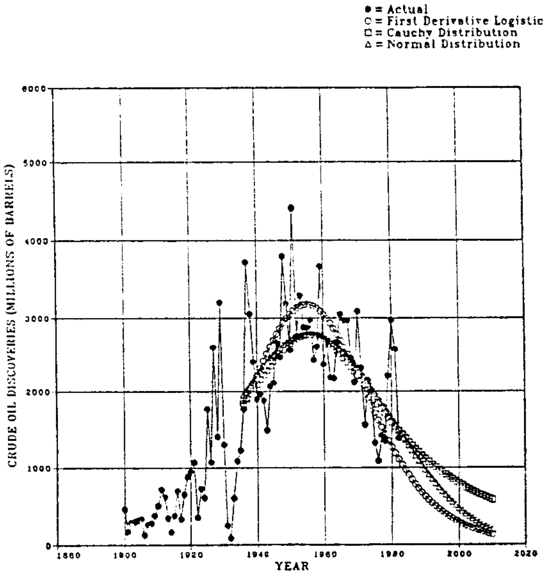

Fig. 6. Projection of crude oil discoveries in U. S.

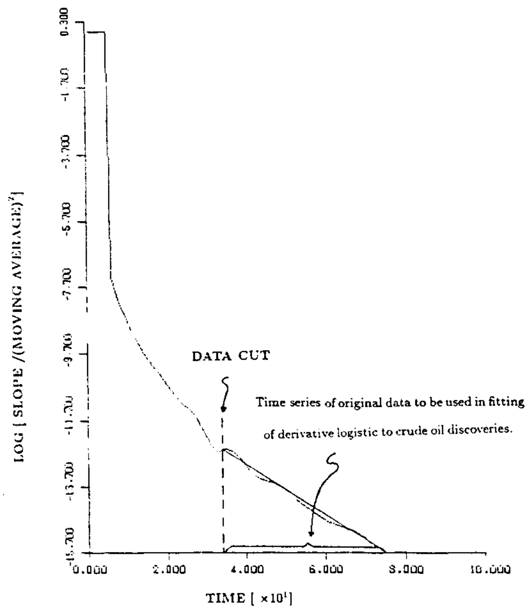

Fig. 7. Best slope characteristic for cumulative data on crude oil discoveries in U. S. with a moving average of 11.

Let $F(\infty)$ represent the potential supply of crude oil, and consider it to consist of known reserves plus cumulative production, $\tilde{Q}_t$, plus future discoveries, which are described by the integral of the above time function.

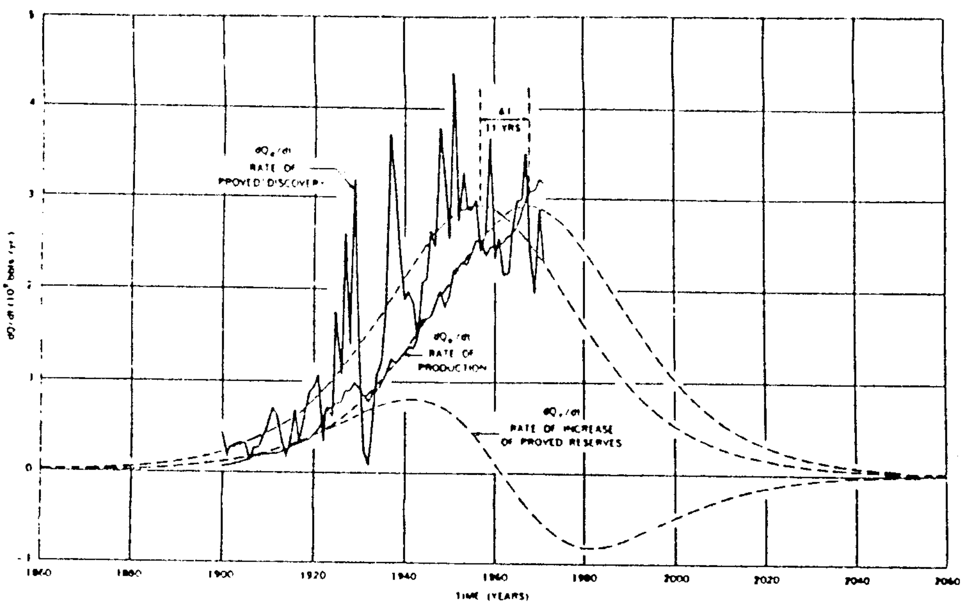

Fig. 8. Annual production and proved discoveries of crude oil in the conterminous United States from 1900 to 1971 superposed on the theoretical curves (dashed) derived from Hubbert's logistic curves (from Harris, 1984).

$$F(\infty) = \tilde{Q}_t + \int_{t^*}^{\infty}(920.92629)(0.62582)(55.34116)(24.77205 + 55.34116t)^{-0.37418}dt$$

where,

$\tilde{Q}_t$ = known discovered reserves

$t^* = 37$ for 1982

Consider the equation,

$$F(\infty) = \tilde{Q}_t + \int_{t^*}^{\infty} AB\,\beta(\alpha + \beta t)^{-\Psi}dt$$
$$= \tilde{Q}_t + \frac{AB}{1-\Psi}(\alpha + \beta t)^{1-\Psi}\Big|_{t^*}^{\infty}$$
$$= \tilde{Q}_t + \frac{AB}{1-\Psi}(\alpha + \beta \cdot \infty)^{1-\Psi} - \frac{AB}{1-\Psi}(\alpha + \beta \cdot t^*)^{1-\Psi} \qquad (5)$$

Let us evaluate F for $t = 115$ (year 2060), the terminal year used by Hubbert(see Fig. 8), instead of $t = \infty$.

From Eq. 5, we obtain

$$F(115) = 145860 + 1471.55(24.77205 + 55.3411 \cdot 115)^{0.62582} - (24.77205 + 55.3411 \cdot 37)^{0.62582}$$
$$= 324993 \cdot 10^6 (\text{bbls})$$
$$= 325.10^9 (\text{bbls})$$

Thus, the learning model estimate of potential supply at year 2060 is about 325 billion bbls, nearly twice the estimate made by Hubbert.

Table 1. Forecasts of Annual Discoveries (In Millions of Barrels).

Model	Year 2000	Year 2010	Peak Year
First Derivative Logistic	292	131	1955
Cauchy Dist.	795	585	1956
Normal Dist.	479	197	1956
Learning Curve	1587	1490	1956

CONCLUSION

This study explores the implications of the learning curve for long term forecasting of mineral and energy industry. This study begins by considering the empirical evidence which applies when a learning curve is present. Then, if a learning pattern is present, the learning model is used to examine an economic measure for specified levels of economic activity.

This study also provides some empirical results on the learning curve in U. S. petroleum resource appraisal and demonstrates how the learning model can be used as an economic forecasting tool.

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광물 및 에너지 분야 경제 예측 방법으로서의 배움모형

전 규 정

요약 : 본문은 기술진보 혹은 생산성 측정과 같은 기술모형에 오랫동안 사용되어진 배움모형의 광물 및 에너지 분야 경제 예측 방법으로서의 유용성을 제시하였다. 또한 사례연구로서 미국 석유자원평가에 배움 모형을 적용하여 미국 석유자원 부존량을 예측하였으며 배움모형이 경제 예측방법에 어떻게 접근하는지를 구체적으로 설명하였다.