Are neural networks a better forecaster?

In some cases, neural nets prove to be superior to their regression counterparts — if they're applied correctly. Here's a representative comparison of a neural net for forecasting electricity demand with a well-designed regression model.

By Stephan Kudyba

Despite the technical analysis influx futures trading has experienced in the past decade, statistical models of markets' fundamental underpinnings continue to enjoy a strong following. Thus, deciding how to go about building a model remains a key decision for many traders and analysts. Complicating this is the continuous evolution of modeling techniques. Early this century, the question was whether a statistical approach to economic theory was an appropriate analytical method. The acceptance of this procedure then led to the sophisticated forms of regression and econometric applications.

The increased availability of economic data sources in today's information age as well as ongoing enhancements in computer technology have enabled a constant "pushing of the envelope" of forecasting techniques. The stages of the process range from single equation regression and univariate or sole time series applications to sophisticated systems of equations and finally to state-of-the-art "artificial intelligence" or neural network technology.

Here, we will analyze this quantitative modeling technology by running a comparison of forecast accuracy between a sophisticated Semtsa (structural econometric model time series analysis) and a neural net-based computer algorithm, looking at predictive accuracy between the two approaches. This experiment offers some insight into where model builders should focus their efforts.

A closer look We often refer to neural nets as artificial intelligence because they are computer algorithms that attempt to reproduce human thought and reasoning. A simple neural net comprises a number of processing elements called neurons that are connected to other neurons that form layers of neurons.

The connectors or "synapses" have a weight that is assigned to them during the optimization process. This structure mirrors the neural net of a human brain where the neurons, in conjunction with their synapses, process input impulses during the human learning stage. The optimization process of neural nets resembles the minimizing of the error term in that of least squared standard regression. The difference lies in that neural nets consider linear, non-linear and pattern recognition relationships in the input data and conduct the optimization process automatically.

Standard regression models require the analyst to apply different functional forms to the data, such as deciding on exponential powers of the explanatory variables. By including the functional form as part of the optimization process, neural nets claim to better predict trending relationships among model variables and identify crucial turning points. Also, neural nets use a unique algorithm approach in such a way the technology does not have a problem with collinearity, a strong

INSIDE THE MODELS

SEMTSA: Below are the forms for the Semtsa model expressed as functions. The actual model is far too complex to reproduce here. See the referenced journal article for the whole model.

$KWH_t = f(a, KWH_{t-1}, GNP_t, PEL_t)$

$GNP_t = f(a, GNP_{t-1}, PFO_t, PFO_{t-1}, T, D_{74}, ART)$

$PEL_t = f(a, GNP_{t-1}, PFO_t, PFO_{t-1}, PEL_{t-1}, T^{-1}, ART)$

$PFO(t) = f(a, PFO_{t-1}, D_s)$

a is an intercept term,
KWH is total sales (demand) of electricity,
GNP is gross national product,
PEL is the real price of electricity,
PFO is the real price of fuel oil,
D_{74} is a dummy variable beginning in 1974,
D_s indicates dummy variables used for various subperiods,
T is time trend,
ART indicates an autoregressive term.

NEURAL NET: Here are the final variables and their t- and t^2-statistics for the neural net. The $\bar{R}^2$ and F-statistics for each model also are listed.

ELECTRICITY DEMAND MODEL

Explanatory variable	Effective T	T^2-statistic
Electricity demand $_{t-1}$	4,163	4,125
Price of fuel oil $_t$	-50	110

$\bar{R}^2$: 93.19 F- statistic: 13,581

OIL PRICE MODEL

Explanatory variable	Effective T	T^2-statistic
Price of fuel oil $_{t-1}$	78.34	69.94
Price of fuel oil $_{t-2}$	-19.10	19.25

$\bar{R}^2$: 83.65 F- statistic: 180

Source: "Oil Shocks And The Demand For Electricity," *The Energy Journal*, vol. 14, no. 2, for the Semtsa equation; Cognos Corp. for the neural net.

relationship between two of the predictor variables, which can cause major errors in standard regression analysis models.

But neural nets do have limitations. One potential shortcoming is the notion of overfitting or over-optimization (see, for example, "The Amateur Scientist," *Scientific American*, September 1992). This common problem occurs during training. The neural net's performance in linking dependent to independent variables generally will improve the longer the weight adjustment process continues. However, when out-of-sample data are introduced to the system, the net's performance often breaks down. The reason is the neural net learned too many anomalies of the given input data, which it attempted to apply to the new data. Such overfitting results from the improper design of the network structure.

The representative neural net in this article was built with a program that includes certain algorithms that limit the negative overfitting aspects of neural nets. The model uses a multilayer perceptive neural net with a hidden layer. (See "In the library" for sources for more detailed explanations of neural nets and regression analysis.) To test the predictive performance of this technology, we obtained data from an econometric-based model and compared the results.

An econometric approach This econometric model was built with the goal of improving forecasts for the U.S. demand of electricity, a strong growth segment for the futures industry recently. The model uses the Semtsa approach, which combines traditional econometric techniques with modern time series methods. That is, a system of equations was used to project the right-hand-side variables in an electricity demand equation and incorporate an independent variable into the model, namely, the price of oil, to enhance its predictive capability through the oil shock years of the 1970s. The system of equations developed was estimated via non-linear three-stage least squares and involved the general form (see "Inside the models," below, left). The equation was developed by E. Kokkelenberg and T. Mount and presented in "Oil Shocks and the Demand for Electricity," *The Energy Journal*, vol. 14, no. 2. 1993.

The model treats the price of oil as an explanatory variable and sales of electricity, GNP and the price of electricity as dependent variables. The price of oil is used to project future prices of electricity and GNP, which in turn are the explanatory variables in the electricity demand equation.

Generally, the dependent variables are treated as an interdependent system, and the price of oil is specified as a univariate Arima model with step functions to account for major swings in oil prices. The model uses data that begin in the mid-1940s and forecasts several periods over the given range, attempting to provide accurate predictions for the demand for electricity. But can a neural net improve upon these predictions?

Comparative study A comparative neural net was built for the Semtsa model by using all the information used by the developers of the Semtsa model from the ➠

HOW CLOSE COUNTS?

The neural net was consistently more significant than the Semtsa model for forecasting electricity demand.

	Neural net	Semtsa
ERMS		
Elec. demand	0.057	0.187
Price of oil	0.956	0.940
MAPE		
Elec. demand	1.81%	5.94%
Price of oil	23.67%	23.15%

How models are made

The methodology of model building often incorporates the study of econometrics, which generally means "economic measurement." Econometrics combines economic theory, mathematical economics, economic statistics and mathematical statistics. Constructing an econometric model generally involves following specific analytic stages.

Initially, you should establish a statement of theory or hypothesis. For example, income is determined by money supply, investment expenditure and government expenditure. This hypothesis then needs to be specified into a precise functional relationship, incorporating the variables involved. It can take the form of a single or multi-equation model. Given the above hypothesis, the econometric model could take the form of a multi-equation system, such as:

$$Y_1 = B10 + B11Y_2(t) + A11X_1(t) + A2X_2(t) + u_1(t)$$
$$Y_2 = B20 + B21Y_1(t) + u_2(t)$$

Y_1 is income
Y_2 is money supply
X_1 is investment
X_2 is government spending
u_1, u_2 are residuals

X_1 and X_2 are the only variables determined outside the system. The regression coefficients (B11, B21, A11, A12) illustrate the influence the explanatory variables exert on the output variables.

The next stage of model development estimates the functional form. This involves collecting the relevant available data on all the stated variables and applying the tools of regression analysis.

Having obtained parameter estimates, you then must develop suitable criteria to determine whether the estimates generated conform to the expectations of the theory tested. For example, we would expect B11 in the above model to be positive, illustrating the positive relationship between money supply and income. You must also determine whether the parameters are merely a function of accidental outcome of the sampling process or statistically significant. This requires statistical inference or hypothesis testing (for example, examining t-statistic values).

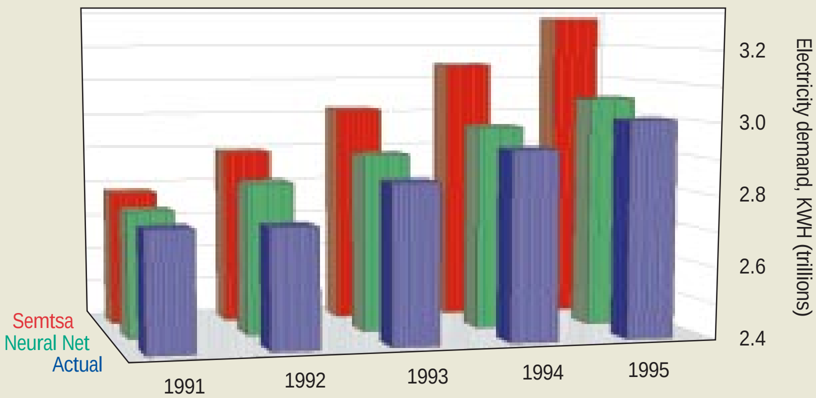
Because our equation is based on the interrelated theory that income is determined by money supply, investment expenditure and government expenditure, while money supply is determined by the level of income, we have a simultaneous equation model. Thus, the estimation process will require more complex applications than ordinary least squares.

When estimating the money supply equation, the ordinary least squares process likely would result in inconsistent estimates because of the probable correlation between Y_1 and the error term u_2. Therefore, the model builder must apply such techniques as two- or three-stage least squares estimations to obtain consistent unbiased estimators of the model. The model then may be used to forecast the relevant output variables accordingly.

For a more detailed description of the above process, see *Basic Econometrics*, 2nd ed., by Damodar N. Gujarati (McGraw-Hill, 1988).

OUT-OF-SAMPLE COMPARISON

The much better forecasts in the out-of-sample period for the neural net suggest the superior goodness-of-fit statistics weren't a result of overfitting.



years 1945-1990. With the neural net, there was no utilization of structural simultaneous equations. That is, if multiple equations were used, they were not optimized concurrently. Rather, all the identical raw data used to build the Semtsa model was pooled as a vast databank for the neural net program to analyze.

The optimization process involved examining the unique statistical report generated by the program and omitting data series that produced little value-added or had weak relationships to the demand for electricity. When finally achieving the best model to forecast electricity demand, an additional model had to be constructed to produce predicted input values of the explanatory oil variable to generate forecasts for the demand of electricity. The models were optimized with this goal in mind: to achieve the highest $\bar{R}^2$ in conjunction with the strongest t-, t^2- and F-statistics. The final model along with these optimized results is listed in "Inside the models" (page 52).

The $\bar{R}^2$ statistic differs from the general R^2 coefficient as it adjusts for the number of independent observations for which the model was tested. The term "adjusted" means the statistic is modified for the degrees of freedom associated with the sums of squares entering into the R^2 equation. (For $k > 1$, the $\bar{R}^2 < R^2$, where k is the number of parameters in the model, including the intercept term.)

Generally, the t-statistic is a statistical inference test that is used to illustrate whether a given input (explanatory) variable is significant in its influence on the output variable. If a variable's t-statistic exceeds a specified value given the amount of input variables in the equation and sample observations (degrees of freedom) for a relevant significance level, then the variable can be accepted as a reliable estimator for the output variable. (The t-statistic used by the neural net differs slightly from the classical method as it incorporates a measurement to address non-linearity.)

The t^2 statistic is unique to the neural net method which, like the t-statistic, measures the importance of an input variable on its influence on the output variable. It addresses non-linear relationships between the two variables and is calculated as:

$$t^2 = \sqrt{(AS)} * \frac{\delta_i}{\delta_r} * \sqrt{n-k}$$

δ_i is input standard deviation,
δ_r is output standard deviation,
n is the number of observations,
k is the number of model inputs,
AS is the average squared slope on the cross-section.

The F-statistic generally measures the ratio of the explained variance of the model to that of the unexplained or residual variance. It helps to answer the question of whether or not the model estimates are a function of random correlation. For the neural net, a value over two generally indicates a reliable model.

Because many formal statistical measurements between the two approaches are incompatible for strict comparison, we'll use common statistical error measurements to compare the accuracy of each model's output. Specifically, we'll look at the root mean square error and the mean absolute percent error.

The root mean square error is the square root of the mean of the squared errors, defined as:

$$E_{rms} = \sqrt{\frac{\sum_{i=1}^{n} e_i^2}{n}}$$

n is the number of observations,
e_i is the residual error between the actual value and predicted value for observation i.

The mean absolute percent error is the mean of the ratios of errors to their corresponding actual values expressed as a percent.

$$MAPE = \frac{\sum_{i=1}^{n} \frac{|e_i|}{|A_i|}}{n}$$

n is the number of observations,
e_i is observation i's residual error,
A_i is observation i's actual value.

Comparisons of the forecasting accuracy — the root mean square error and mean absolute percent error — for the variables predicted by each model are in "How close counts?" (page 53). "Out-of-sample comparison" (above) gives a graphic representation of each model's forecasts over the out-of-sample period of 1991 through 1995.

For the out-of-sample period, the simple neural net model for electricity demand significantly outperforms the more complex Semtsa. These results appear even more impressive for the artificial intelligence approach when considering the structure of the model. The algorithmic method was able to reduce the issue of predicting the demand of electricity to the two basic variables of a lag on itself and the price of oil, where the latter variable portrayed an inverse relationship to the demand of electricity. But for the Semtsa system of equations, the price of oil is treated as the independent explanatory variable that is used to help predict the dependent variables of GNP and electricity price, which ultimately explains the final level of electricity sales. The neural net has bypassed the intermediate dependent variables of GNP and electricity price and identified a significant relationship between the core independent variable and the ultimate dependent variable.

Further, for the neural net, the model for the price of oil did not use the dummy variables of the Semtsa because of less significant statistical measures. Given the data available from the comparative model, the neural net identified the one- and two-period lags of oil on itself to be the most significant variables. However, given the final model, the variance of forecasts to actual results is noteworthy, which may imply that it could be improved with the introduction of new variables. These additions might include supply and demand factors such as national oil inventory figures, weather forecasts and the availability of existing and new sources of the commodity. Also, because we ended construction of the model for oil in 1990, we make it difficult for ourselves to produce accurate near-term forecasts. The ending observation of 1990 included a mini-shock that lasted for only one period and resembled more of an outlier rather than a systematic shock that should be heavily weighted.

In all fairness to the Semtsa model, it must be mentioned that the regression model used for the demand for electricity attempted to undertake the difficult task of producing a predictive system through the oil shock years of the 1970s as well as the highly volatile period that followed. This type of modeling approach is not only a forecasting but an explanatory mechanism that illustrates the interactions of variables in a system of equations. Yes, the neural net approach did outperform the more traditional model in the selected time period; however, the Semtsa model entailed analysis and forecasts of various sub-periods for which the neural net was not tested. Further analysis could involve applying the neural net approach to the entire Semtsa scenario through the oil-shock years of the 1970s and introducing new variables in an attempt to enhance the forecasting accuracy. FM

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Stephan Kudyba, a Ph.D. candidate in economics at Rensselaer Polytechnic Institute in Troy, N.Y., has developed trading models and managed funds at Citicorp Investment Bank in New York and traded the fixed income markets for Dresdner Bank AG in Frankfurt.

IN THE LIBRARY

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- **"Statistical Analysis of Econometric Models"** by A. Zellner. *The Journal of the American Statistical Association*, 1979, 74.
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