Neural Networks and Traditional Time Series Methods: A Synergistic Combination in State Economic Forecasts

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Abstract— **Ever since the initial planning for the 1997 Utah legislative session, neural-network forecasting techniques have provided valuable insights for analysts forecasting tax revenues. These revenue estimates are critically important since agency budgets, support for education, and improvements to infrastructure all depend on their accuracy. Underforecasting generates windfalls that concern taxpayers, whereas overforecasting produces budget shortfalls that cause inadequately funded commitments. The pattern finding ability of neural networks gives insightful and alternative views of the seasonal and cyclical components commonly found in economic time series data. Two applications of neural networks to revenue forecasting clearly demonstrate how these models complement traditional time series techniques. In the first, preoccupation with a potential downturn in the economy distracts analysis based on traditional time series methods so that it overlooks an emerging new phenomenon in the data. In this case, neural networks identify the new pattern that then allows modification of the time series models and finally gives more accurate forecasts. In the second application, data structure found by traditional statistical tools allows analysts to provide neural networks with important information that the networks then use to create more accurate models. In summary, for the Utah revenue outlook, the insights that result from a portfolio of forecasts that include neural networks exceeds the understanding generated from strictly statistical forecasting techniques. In this case, the synergy clearly results in the whole of the portfolio of forecasts being more accurate than the sum of the individual parts.**

Index Terms—**Adaptive expectations, forecasting, genetic algorithms, neural networks, statistical models, time series.**

I. Introduction

STATE TAX revenue forecasts impact the entire state government policy agenda and influence each step of the budgeting process. In the first step of this process, state agencies receive guidelines from the executive branch that are based on initial estimated revenues and expenditures. The agencies then respond to the governor with budget requests. At the conclusion of the first step, the governor and staff submit the budget to the legislature. In the second step, the legislature uses its independent revenue forecasts and then adopts the budget. Finally in the third step, the agency administers the budget in order to make expenditures and revenues match. Revenue projections by the legislature are especially important in the second and third phases of the budgeting process.

Manuscript received November 12, 1996; revised March 5, 1997.

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Publisher Item Identifier S 1045-9227(97)04802-9.

Like most economic time series, tax revenues usually have four different components: trend, cycle, season, and irregular. The challenge is to identify, model, extrapolate, and recombine these patterns to give revenue forecasts. Because of the proficiency and potential of neural networks (NN's) in pattern recognition, initial forecasts based on NN's occurred during the planning stages for the 1997 Utah legislative session. Since this initial implementation, in the Utah budgeting process NN's continue to complement the traditional forecasting approaches that include exponential smoothing, autoregressive integrated moving average (ARIMA), decomposition, and causal models.

Diversity is purposely designed into the revenue estimation process in the State of Utah. The executive and legislative branches independently give separate economic and revenue outlooks. Similar diversity in methodology is equally important because a portfolio of forecasts often reduces the variance and improves the accuracy of predictions. Unfortunately, consideration and evaluation of different forecasting techniques often occurs as though one true and superior method exists. Such a narrow focus forgoes the insights and solutions to very complex problems that result from analyzing the same data from a variety of views. Quests for a single "holy grail" forecasting technique ignore the complementary nature of combinations of forecasts. Different techniques give alternative perspectives and thus increase the chances of discovering structures that are valuable for anticipating the future. The addition of NN's to Utah's forecasting toolkit during this past year will undoubtedly continue to yield important synergy and insights that will contribute better revenue forecasts to the budgeting process.

This paper describes the application of NN's in an important economic time series forecasting situation and details the application of NN's to revenue forecasts for the Office of the Legislative Analyst in the State of Utah. This discussion first addresses the current budgeting and economic situation in Utah and includes a brief overview of two time series, the rate of nonagricultural jobs growth and taxable sales, that play a major role in the development of revenue forecasts. Second, the basic components of time series are defined and a brief overview of NN's, exponential smoothing, and ARIMA methodologies are given. This background with its accompanying references should prove useful for those who might not be familiar with current forecasting procedures and who desire to contribute new NN-based forecasting solutions. Finally, the application of NN's in the current economic situation are shared and

TABLE I
PHASES OF THE BUDGETING CYCLE

	Phase I	**Phase II**	**Phase III**
Function	Propose Budget	Adopt Budget	Execute Budget
Government Branch	Executive	Legislature	Agency
Forecasting Horizon	Long term	Intermediate term	Short term
Quantitative Methodology	Causal	Causal	Neural Networks ARIMA Exponential Smoothing Decomposition Methods Causal Models

compared to statistical time series forecasts. This discussion evidences the importance and potential of NN's for revenue forecasting. It highlights both the successes and limitations of using NN's to make revenue projections.

II. Tax Revenue Forecasting Situation

As mentioned and shown in Table I, the financial management of public programs entails three budgeting steps. Because of the length of the forecasting horizon for Phase I, managers or analysts, under the direction of the executive branch, use systems of equations complete with endogenous and predetermined variables in causal models to forecast expected revenues and expenditures. In Phase II, the legislative body adopts a budget for the coming fiscal year based on similar long-term forecasting techniques. Finally, in Phase III, individual agencies execute their budgets. The shorter horizon of Phase III makes NN's, exponential smoothing, ARIMA, and decomposition methods appropriate for this phase. This paper focuses on monitoring and forecasting in Phase III.

The illustration of the use of NN time series forecasts occurs within the context of the economic and revenue analysis completed in October 1996 as analysts and consultants prepared for the February 1997 legislative session. The 1997 budget was initially passed during the February 1996 legislative session. At the time of the forecasts, the fiscal year was in its fourth month. This paper compares the economic forecasts conditioned on October 1996 information and then judges them against data that subsequently became available in February 1997 during the session.

Utah derives most of its revenue for its general and uniform school funds from sales and income taxes. The revenue forecasts for these two funds are strongly influenced by two economic measurements that reveal significant information about Utah's economy. The first is the growth rate for nonagricultural employment because of its effect on personal income. The graph in Fig. 1 shows the cyclical patterns for the period 1981 through March 1996. The solid line results from a locally weighted regression (LOESS) using cross-validation to choose the smoothing span. Even though this represents monthly data, little seasonal or recurrent calendar year patterns occur because the data are monthly year-over-growth rates. Subtracting corresponding months, January 1995 from January 1996, for example, has the tendency to deseasonalize or remove the seasonal pattern from the data. While the rate of job growth has slowed slightly since the peak in 1994, the information available in October suggests that the rate of job growth for Utah is the second highest state in the United States. The key question that analysts face is whether the moderate downward trend will accelerate into the patterns shown for previous cycles or whether job growth will plateau and continue at approximately 5% per year. It is critical that forecasting methods indicate and detect any acceleration of the downward trend as such a move will strongly impact sales and income tax receipts.

Almost all of the revenue for Utah's general fund comes from sales taxes. This makes total taxable sales the second economic variable of great significance. The smoothed line in the trend panel in Fig. 2, resulting from the SABL procedure as explained by Cleveland *et al.* [7], shows the strength of this economic variable. A quarterly seasonal pattern occurs during each calendar year because of such events as summer construction and Christmas retail sales. In the past, this strong exponential growth has generated a series of budget surpluses. Analysts now optimistically build this type of growth into revenue expectations. Should the rate of growth slow, then very large deficits will result. For this reason, forecasting techniques must warn of any impending slowdown in a very timely way. As mentioned, subsequent analysis compares the forecasts of these patterns against actual data that became available after the initial October planning that resulted in forecasted trends.

III. Time Series Components and Patterns

The data graphed in Fig. 1 and Fig. 2 illustrate that economic and business time series often have four main components. The general approach to time series analysis is to consider that the series $x(t)$ is composed of four factors: trend $T(t)$, cycle $C(t)$, season $S(t)$, and irregular $I(t)$. These are often combined in either additive or multiplicative forms

$$\begin{aligned} x(t) &= T(t) + C(t) + S(t) + I(t) \\ x(t) &= T(t) \cdot C(t) \cdot S(t) \cdot I(t). \end{aligned} \quad (1)$$

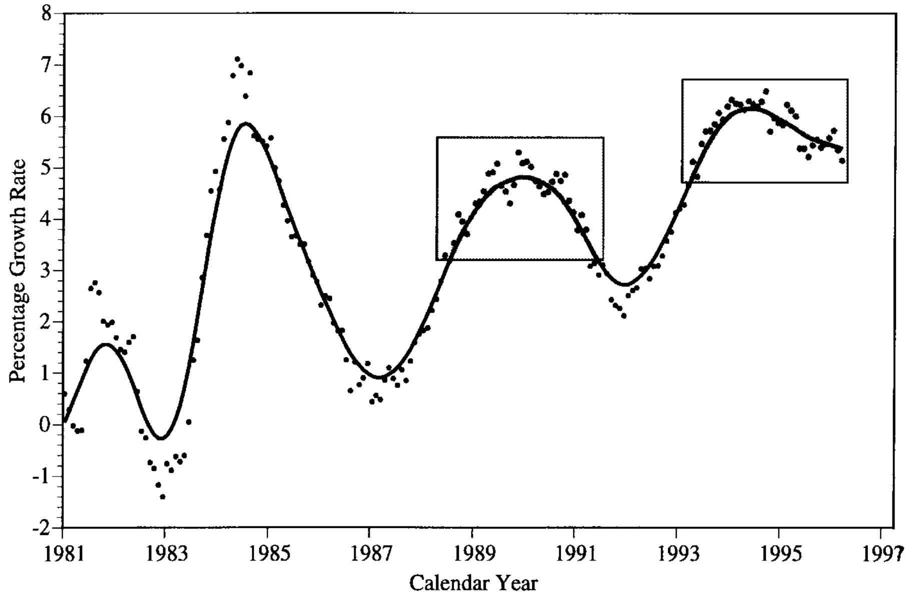

Fig. 1. Utah monthly nonagricultural year-over rate of change 1981–March 1996.

Some such as Newbold and Bos [18] prefer to combine trend and cycle into a single component represented by local rather than global trends. Global trends are those that remain fixed over the entire span of time for which the series is observed. This contrasts with local trends, where nonconstant growth rates evolve smoothly over time.

The problem with attempting to identify cycle is that it does not have a constant period. As shown in Fig. 1, the cyclical historical patterns are extremely important in the jobs growth rate. The ability of NN's to find nonlinear patterns in data make them a good candidate to deal with this type of behavior. Prediction of the turning points is especially important in economic forecasts. Not only is the overall forecasting accuracy important, but it is also critical to know how well techniques predict turning points.

The taxable sales data provide a difficult forecasting challenge. In order to understand some of the difficulties in forecasting this time series, consider the SABL decomposition of the total taxable sales as implemented in the statistical software S-Plus and as shown in Fig. 2. Using a methodology with a similar objective to engineering techniques that separate signals into their component frequencies, classical decomposition algorithms like SABL as explained by Cleveland *et al.* [7] and STL as detailed by Cleveland *et al.* [4] isolate the trend-cycle and seasonal components from a time series by filtering out the irregular or noise factor. Successful identification of trend, cycle, and season then allow forecasts. The identification of the cycle component, because of its irregular period, is much more difficult. Usually a forecast based on decomposition requires a subjective estimate of the cycle component.

Because of the heteroscedasticity or nonconstant variance of the data, the analysis summarized in Fig. 2 is done using the natural logarithm. The Cleveland and Devlin [5] LOESS procedure filters the seasonal and irregular factors from the data to reveal a smoothed nonlinear trend component. This may be appropriately considered as a series of local trends. The exponential growth found in the most recent data provides a significant challenge. The seasonal pattern also shows cause for concern since it is not global and is evolving. Notice the highlighted seasonal factors for the second and third quarters for 1978 versus 1996. The seasonal factor for the second quarter in 1978 is larger than the third quarter, whereas the opposite is true in 1996. The local trend and seasonal patterns along with the heteroscedastic nature of the data make this situation difficult to analyze.

IV. Neural Networks Applied to Time Series

In other problem domains, Lapedes and Farber [15] and Weigand *et al.* [21] successfully apply time-delay NN's (TDNN's) to time series prediction. This section briefly summarizes the application of genetic algorithms to optimize important aspects of the design of the TDNN that are used in the present discussion.

Given observed values of the state of a dynamic system at times less than or equal to t, the forecasting problem is to use the observed data to accurately predict $x(t+p)$, where x represents the state of the dynamic system and p is some prediction time step into the future. Time-series prediction is the essence of the type of processing done by a TDNN. Fig. 3 illustrates how the finite time sequence $\{x(t), x(t-1), x(t-2), \cdots, x(t-n)\}$ is mapped into a single output y. Hassoun [11] shows that this architecture can easily be generalized for the case where x or y are vectors.

The present research considers two alternative models for comparing NN's with statistical forecasting models. The first is the TDNN described by Waibel [20]. This TDNN is a multilayer feedforward network whose hidden and output neurons are replicated in the model. Each connection is set to a specific interval back in time. The first connection is set at the current time, the second connection is set to one period past, a third connection to two periods back, etc.

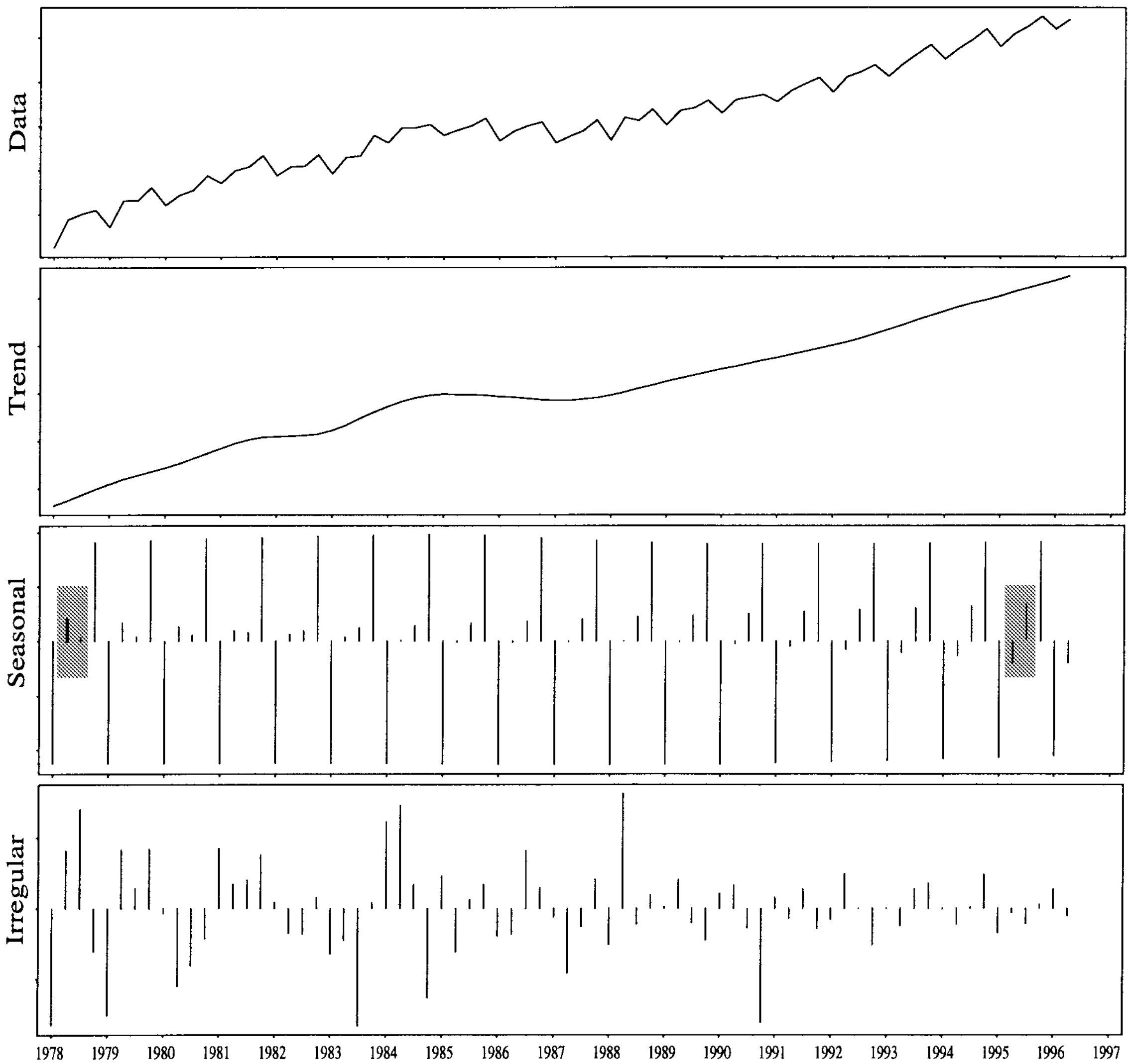

Fig. 2. SABL decomposition of natural logarithm of total taxable sales.

The second variation is the backpropagation network (BP), with prespecified lagged data as inputs. Alternative architectures exist for these NN's, and finding the architecture that performs best can be critical. As an alternative to these conventional heuristic methods, genetic algorithms (GA's) offer more formal and robust methods of designing NN architecture.

Many recent books and articles include material on the use of GA's to assist in determining the NN architecture for a particular problem. Significant developments include the work of Harp *et al.* [9] and Miller *et al.* [16]. They enlist GA's to aid in determining the best connections among network units. Whitley and Hanson [23] select the weights in a relatively fixed architecture. Harp *et al.* [10] evolve appropriate network structures and learning parameters. Chalmers [2] develops learning rules for NN's. Montana and Davis [17] find an effective set of weights for a fixed set of connections in order to classify underwater lofargrams into two classes.

In the present applications, GA's help determine three architectural features: the number of layers (limited to one or two hidden layers), the number of processing units in each hidden layer, and type of activation function for units at each layer. GA's are also used to find the best time delay for the data used in TDNN's. The applications described here use direct encoding after the method of Miller *et al.* [16].

V. Time Series Analysis

Although NN's and traditional time series approaches to forecasting develop independently, White [22] tries to relate NN and statistical methodologies. He suggests a complementary relationship between the two approaches. Traditional time series techniques include classical decomposition and exponential smoothing. Both these techniques develop from practical application as opposed to formal statistical derivation. Among the statistical techniques, ARIMA models achieve extensive use and acceptance. ARIMA development tools are widely available through most commercial statistical software.

An outline of these techniques gives a brief background for comparison to NN's as they apply to time series analysis. This summary is intended as an overview with references to sources that can provide more detail. The discussion of

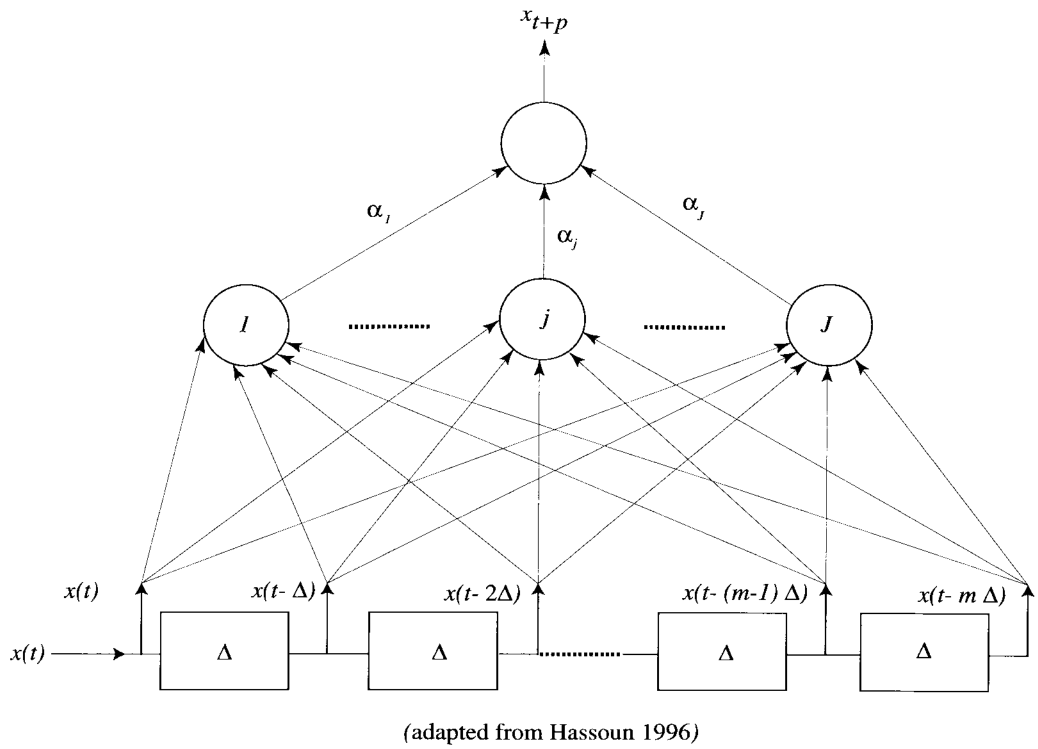

Fig. 3. Time-delay NN's nomenclature.

classical decomposition, exponential smoothing, and ARIMA models follows in that order.

A. Exponential Smoothing

Adaptive expectations or exponential smoothing refers to processes whereby decision makers adjust their expectations as information evolves. As new information appears, decision makers compare their previously held expectations with new data, correcting their expectations or forecasts accordingly. When the expected value exceeds the observed data, decision makers decrease the forecast. Similarly, when the observed data exceeds the expected value, decision makers increase the forecast.

Newbold and Bos [18] give a clear and rigorous explanation of exponential smoothing algorithms. Depending on the components in the data, three different versions of exponential smoothing are often used. The first, simple exponential smoothing, should be used when season or trend do not exist in the data. Simple exponential smoothing occurs through the equation

$$L(t) = \alpha x(t) + (1-\alpha)L(t-1). \tag{2}$$

Upon the receipt of new information $x(t)$, the algorithm updates the previous expectation $L(t-1)$ by taking a linear combination of the new information and previous expectation to give the updated expectation $L(t)$. The α controls the weight given to the new information.

Whenever trend exists in the data, simple exponential smoothing forecasts tend to lag one period behind the actual data. In response to this poor performance of simple exponential smoothing forecasts when trend exists in the data, Holt [14] develops the following procedure:

$$\begin{aligned} L(t) &= \alpha x(t) + (1-\alpha)(L(t-1) + T(t-1)) \\ T(t) &= \beta(L(t) - L(t-1)) + (1-\beta)T(t-1) \\ \hat{x}(p) &= L(t) + pT(t-1). \end{aligned} \tag{3}$$

A comparison shows that Holt's method builds on simple exponential smoothing. With each new observation in the time series $x(t)$, first the level $L(t)$ is updated. Second, the difference between $L(t)$ and $L(t-1)$ provides the information needed to update the previous trend estimate $T(t-1)$. The smoothing parameter β reflects the subjectively determined importance of the new information relative to the previous expectation for the trend. Finally, the third equation gives the forecast for p periods beyond period t.

Because data often exhibit a seasonal pattern in addition to trend, Winters [24] augments Holt's method with an additional equation as shown in the following Holt–Winters algorithm of multiplicative seasonality with s seasons during the year:

$$\begin{aligned} L(t) &= \alpha \frac{x(t)}{S(t-s)} + (1-\alpha)(L(t-1) + T(t-1)) \\ T(t) &= \beta(L(t) - L(t-1)) + (1-\beta)T(t-1) \\ S(t) &= \gamma \frac{x(t)}{L(t)} + (1-\gamma)S(t-s) \\ \hat{x}(p) &= (L(t) + pT(t))S(t+p-s). \end{aligned} \tag{4}$$

After initially deseasonalizing the data using a seasonal index $S(t-s)$, the first two equations are identical to Holt's method. The third equation updates the seasonal index by using γ as a smoothing parameter. The fourth equation uses the seasonal index to adjust Holt's forecasting equation.

B. ARIMA Models

ARIMA models as conceptualized by Box and Jenkins [1] combine autoregression with moving averages terms that are linear in the time series $x(t)$ and white noise terms $\varepsilon(t)$. An autoregressive model of order p or $AR(p)$ is given by

$$\phi(B)x(t) = (1 - \phi_1 B - \cdots - \phi_p B^p)x(t) \tag{5}$$

where B is the backshift operator $B^j x(t) = x(t-j)$ and ϕ_i represent the autoregression parameters. Similarly, a moving average process of order q or $MA(q)$ is

$$\theta(B)\varepsilon(t) = (1 - \theta_1 B - \cdots - \theta_q B^q)\varepsilon(t) \tag{6}$$

where θ_i represent the moving average parameters. Combining the autoregressive and moving average components into an ARMA model gives

$$\phi(B)x(t) = \theta(B)\varepsilon(t). \tag{7}$$

This class of models requires a stationary time series in order to be useful for forecasting. The conditions for weak stationarity are that for all t

$$\begin{aligned} E[x(t)] &= \mu \\ \mathrm{Var}(x(t)) &= E[x(t) - \mu)^2] = \sigma^2 \\ \mathrm{Cov}(x(t), x(t-k)) &= E[x(t) - \mu)(x(t-k) - \mu)] = \gamma_k. \end{aligned} \tag{8}$$

The three conditions correspond, respectively, to a constant mean, variance, and autocovariance structure.

Both trend and heteroscedasticity often compromise the stationarity condition. The solution to this problem is to apply power transformations and differencing before fitting an ARMA model. Regular differencing of order d filters the trend from the data through the following operation:

$$\nabla^d = (1 - B)^d. \tag{9}$$

This gives the general ARIMA (p, d, q) that has the form

$$\phi(B)\nabla^d x(t) = \theta(B)\varepsilon(t). \tag{10}$$

Periodic aspects of time series often require augmentation of the regular ARIMA model with seasonal components. The seasonal ARIMA $(p, d, q)(P, D, Q)^s$ model for such time series is represented by

$$\Phi(B^s)\phi(B)\nabla_s^D \nabla^d x_t = \Theta(B^s)\theta(B)\varepsilon_t. \tag{11}$$

The three additional seasonal components are a seasonal difference, a seasonal AR with parameters Φ_i, and seasonal MA with parameters $\Theta_i$that are, respectively, defined as

$$\begin{aligned} \nabla_s^D &= (1 - B^s)^D \\ \Phi(B^s) &= 1 = \Phi_1 B^s - \cdots - \Phi_p B^{sP} \\ \Theta(B^s) &= 1 - \Theta_1 B^s - \cdots - \Theta_p B^{sQ}. \end{aligned} \tag{12}$$

The ARIMA modeling process first attempts to evaluate the stationarity of the time series. Second identification of the orders for the autoregressive and moving average components occurs through analysis of the autocorrelations and partial autocorrelations. Third, estimation of the autoregression and moving average parameters occurs. After successive iterations through steps two and three converge, the resulting model is used to generate forecasts.

VI. The Role of Neural Nets in Economic Forecasts

Forecasts by the Office of the Legislative Fiscal Analyst in the state of Utah have traditionally been dominated by econometric models based on regression and simultaneous equation models. Approximately five years ago, analysts began using smoothing and ARIMA techniques more extensively in the forecasting process. Because recent academic work that compares NN's with alternative time series methodologies clearly demonstrated NN's advantages relative to traditional techniques, they were added to the group of state revenue estimation procedures at the beginning of the 1997 fiscal year.

A significant reference summarized by Clemen [3] attests to the value of using a portfolio of forecasts rather than relying on a single methodology. A portfolio of forecasts can be superior to any one forecasting methodology even when one clearly outperforms each individual technique. One does not want to eliminate one technique simply because it does not have the best performance. As in a portfolio of stock market holdings, modeling errors from alternative techniques tend to cancel each other out.

Two applications illustrate some of the successes and challenges encountered in using NN's to forecast tax revenues. The first concentrates on the rate of growth in nonagricultural employment and the second analyzes taxable sales.

A. Rate of Growth in Nonagricultural Employment

As mentioned, Utah's growth rate in nonagricultural employment is among the fastest in the nation for the past three years. The graph in Fig. 1 shows a pronounced trend-cycle and Fig. 4, which depicts the historical pattern since 1993, shows that the rate of growth seems to have peaked in late 1994. The rate of growth in the data reaches a plateau that leaves the critical question of how long can jobs expand exponentially before beginning an eventual cyclical decline. The forecasts in Fig. 4 reveal that the NN renders a very different answer to this question than exponential smoothing or ARIMA models. The unexpected NN result helps identify a pattern in the data that traditional forecasts overlook.

The consensus expectation among national and state econometric forecasters is that the growth rate in nonagricultural employment in Utah will slowly decline toward a more sustainable 3–4%. This follows from the natural tendency of regression toward the mean. The ARIMA model matches this sentiment and the linear downward trend of exponential smoothing also indicates slowing. Because of construction in preparation for the 2002 Winter Olympics and because of major state government expenditures on highways and transportation, however, it is anticipated that the downward trend will level off rather than continue declining as suggested by exponential smoothing.

In contrast to the exponential smoothing and ARIMA forecasts, the NN predictions cause a reassessment of expectations. Preoccupation with the apparent beginning of downward move

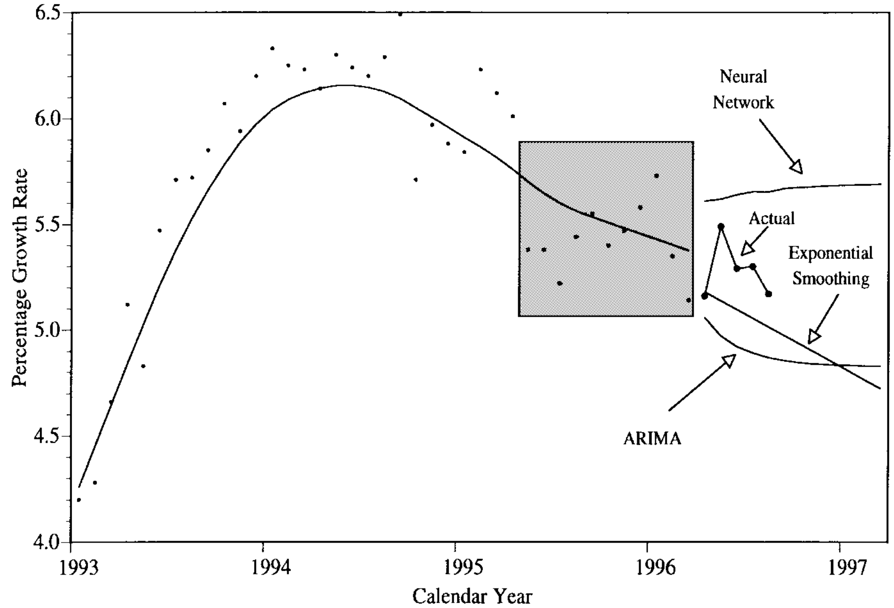

Fig. 4. Utah monthly nonagricultural year-over-rate of change forecasts April 1996 through March 1997.

in the cycle results in a failure to note subtle changes in the data. In response to the highlighted points rather than the smoothed downward trend, the NN model detects more strength in the numbers than previously seen.

The exponential smoothing, ARIMA, and NN forecasts shown in Fig. 4 are based on information available through October 1996. During the February 1997 evaluation of the forecasts in conjunction with the legislative session, however, additional information was available. Comparison of this actual data with the forecasts in Fig. 4 validates the optimism of the NN forecasts since the second and third quarters of 1996 seem to have been much stronger than either exponential smoothing or ARIMA predicted. The NN forecasts are a little too optimistic, however, and average value of the three different methods seemingly gives the most accurate estimates.

Extensive alteration of the smoothing parameters for Holt's method yields a pattern similar to NN's. Conventional methods of choosing these parameters do not discover this combination and miss the pattern found by NN's. This tends to affirm the Reynolds *et al.* [19] proposal to use NN's to find optimal ARIMA models.

Because the anticipation of the eventual downturn in the nonagricultural jobs growth rate is so important in the current budgeting situation in the State of Utah, more information is needed about the ability of alternative techniques to detect transitions in the cycle. The period 1989–92 as highlighted in Fig. 1 provides the historical data for such comparisons. The performance of the different forecasting techniques during this peak period helps assess their value in anticipating a downturn in the current expansion. Consider the comparison shown in Fig. 5 for NN, ARIMA, and two exponential smoothing models. The ARIMA and exponential smoothing models give similar forecasts to those presented and discussed for the current situation. Both detect a downward trend in the data. The exponential smoothing models that have large values for α and β accentuate the strong downward movement in the more recent observations. Large values for Holt's method mean that this technique seldom misses changes in the direction of a time series but also signals many false turns. The exponential smoothing models with smaller values for α and β forecast a more gradual descent. Due to the structure of the ARIMA(3,1,0) model used for the jobs growth rate data, the forecasts gradually decline. This ARIMA model gives this pattern or a similar gradual increase for all different phases of the business cycle. This makes good one-period-ahead forecasts but does not give accurate predictions for longer horizons.

As shown in Fig. 5, NN's forecast the downturn and even though it provides optimistic predictions of the growth rate, it nonetheless correctly determines the direction. This outcome gives credibility to the NN forecast for the current situation. If the NN had failed to detect the downward movement in this test data, then the NN prediction that the high growth rate would continue is questionable. Since it does demonstrate an ability to ascertain a change in direction in the business cycle, this makes the NN forecast more believable.

The process of assessing the accuracy of NN forecasts during the test period 1989–1992 generates interesting findings that spawn hope for even greater NN potential in helping detect turning points in business cycles. Applications to date suggest that the use of GA's to devise different TDNN and BP architectures for time series analysis and prediction seems to provide significant advantages over single architectures devised by convention or rules-of-thumb. Although proving this conjecture is not central to purpose of the present discussion, nonetheless, an example from these applications may be of interest.

Consider Fig. 6 that reports the results of models that were trained on the first 100 instances of the job rate time series. This model is then used to predict the next 19 time periods without the model seeing any further actual data. This is done as a means of observing how the model reacts to the cycle

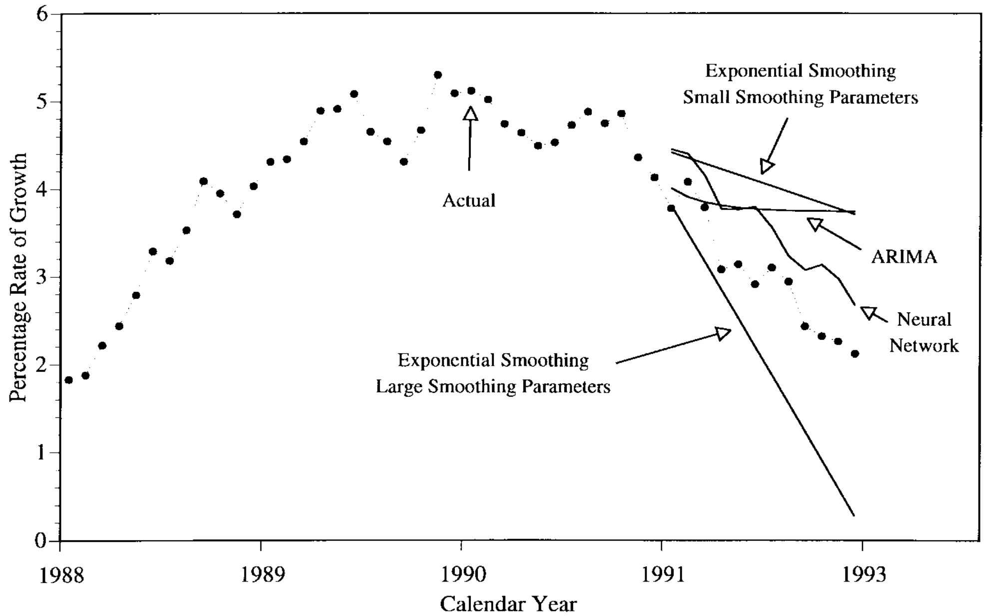

Fig. 5. Utah monthly nonagricultural year-over rate of change alternative forecast comparison.

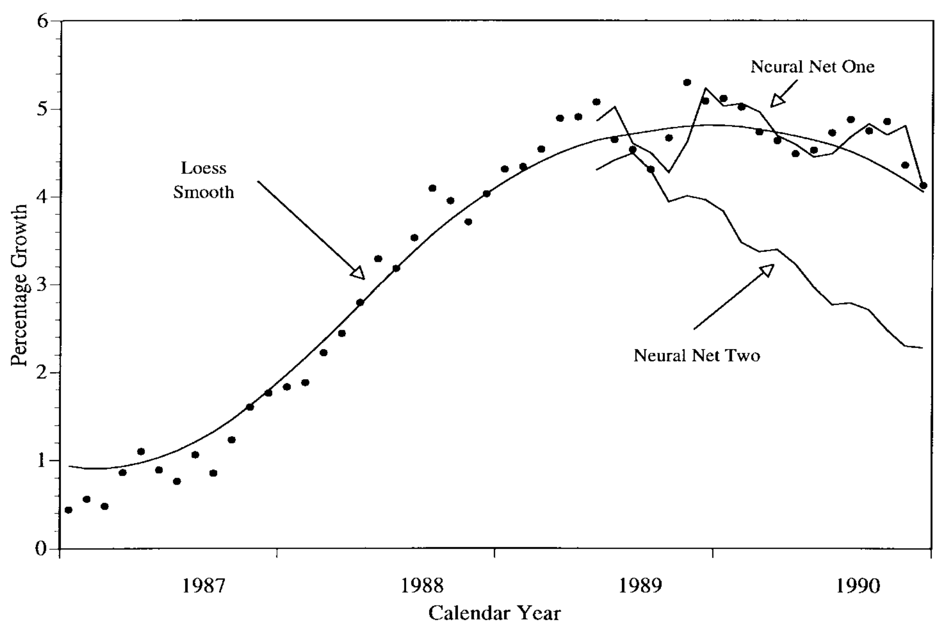

Fig. 6. Utah monthly nonagricultural year-over rate of change alternative NN models.

represented by these time periods. To facilitate exposition, recall that GA's are an integral part of model selection for these applications. Specifically, for any training set, GA's generate a number of candidate architectures for possible application. These candidates are then given a ranking as follows: Given a training set of size $N + K$ instances, the first N instances are used to train a model. Each such model is then tested on the following K instances (usually determined by the desired forecast period, or known or suspected patterns), with the accuracy attained on those K instances used to rank the resulting architectures. This does not, or course, guarantee that performance on other instances not seen by the model will result in the same ranking, but there does appear to be consistency between high-ranking models and low-ranking models in actual prediction performance.

The highest-ranked model developed for the problem described above produces the impressive prediction results labeled as Neural Net One in Fig. 6. An arbitrarily selected lower ranking architecture (two rungs lower) labeled as Neural Net Two in Fig. 6 is given by way of contrast. Although this second NN model yields less accurate results, it does give an early warning of the downturn in the cycle. The difference in performance attained by these two models derived from the same training set, while anecdotal, does suggest that alternative architectures selected by GA's, then ranked, can be an effective method of architecture selection.

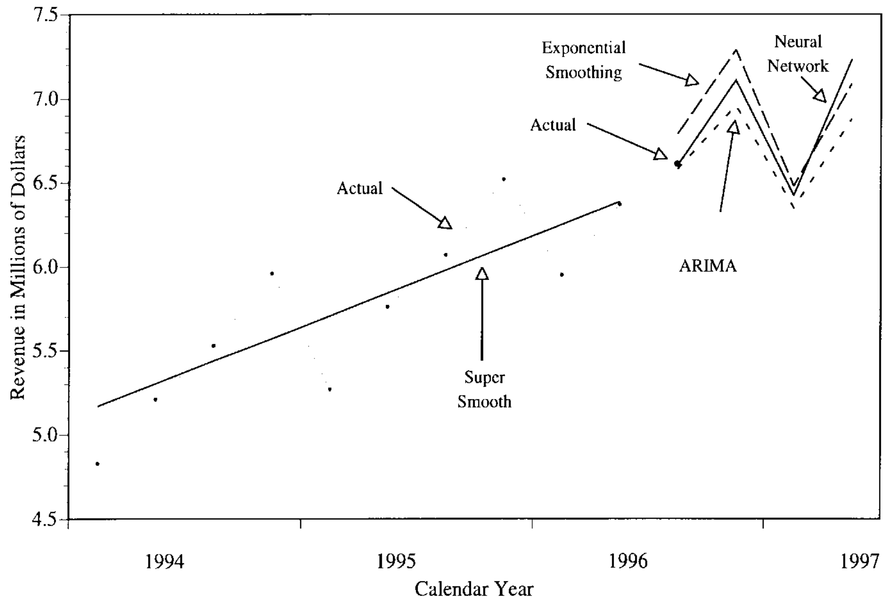

Fig. 7. Utah quarterly total taxable sales third quarter 1996 through second quarter 1997 forecasts.

B. Taxable Sales

Without significant revision, the initial NN model gives valuable insights into the jobs growth data. In contrast, the NN's for taxable sales follow the more typical causal and time series modeling experience that requires many iterations with very puzzling results. The application of NN's to forecasting taxable sales proves more challenging and does not generate the clearly novel information experienced with the nonagricultural employment growth rate.

All three forecasting methods as shown in Fig. 7 suggest that the strong growth trend in taxable sales will continue. Forecasts for the next four quarters clearly continue the trend indicated by the smoothed line and shown in the classical decomposition information in Fig. 2. The exponential smoothing and ARIMA models give very similar patterns in seasonality and differ primarily in the rate of growth that they forecast. As in the case with nonagricultural employment, the forecasts use information available through October 1996. The comparison of these forecasts with the actual third quarter sales that were finalized during February 1997 shows that the NN and ARIMA forecasts turn out to be extremely accurate.

In order for the NN network to give the pattern shown in Fig. 7, it needed help choosing the appropriate training set. With the entire data set, the NN unfortunately encountered difficulty replicating the seasonal pattern found in the last three or four years of the historical data. The probable cause of this difficulty is the NN's apparent attempt to impose global patterns on the data. Because of the evolving seasonality mentioned previously for this data, the NN's struggle with the changing patterns in the second and third quarters. Limiting the training set to the data since 1985 gives the forecasts reported in Fig. 7.

The problems experienced in detecting the seasonal patterns pose a possible need for NN algorithms that look specifically for these types of patterns. By design the ARIMA and exponential smoothing both adapt to evolving data patterns. In fact, the very adaptive expectations philosophy of exponential smoothing allows this methodology to explicitly accommodate this evolution. A large value for the seasonal smoothing parameter allows the seasonal index to adapt quickly to the new pattern. Hill, *et al.* [12] use a specially developed NN algorithm based on the Holt–Winters method that they find to be clearly superior to other techniques. The ARIMA and exponential smoothing both benefit from the model builders knowledge that the data may have a natural seasonal pattern. Providing the NN with similar information about potential seasonal and evolving patterns may help it perform better.

Yet giving the NN too much structure could limit its ability to find unusual and unexpected results. Forecasts are fairly easy to make when a strong trend exists in the data. The challenge is detecting when a trend is going to change direction. Practical traditional statistical model building requires substantial effort and iteration to produce reasonable forecasts. Forcing NN's and statistical techniques into expected results is potentially a very dangerous approach. As an example, consider the NN model shown in Fig. 8. The unexpected decline in the growth rate as forecasted by the NN is problematic. As yet no detectable slowing has occurred in revenue collections. If the NN turns out to be correct and the growth rate does moderate in contrast to the ARIMA and exponential smoothing predictions, basing revenue forecasts on the NN could save the State of Utah from the severe budget adjustments inherent in large deficits. Whatever the case, the NN forecast again provides a result that deserves attention within a portfolio of alternative forecasts.

VII. Summary and Conclusions

If Utah's experience extrapolates to other states, those interested in good economic forecasts should consider the synergy of including NN's within their portfolios of forecasting techniques. Two applications clearly establish this

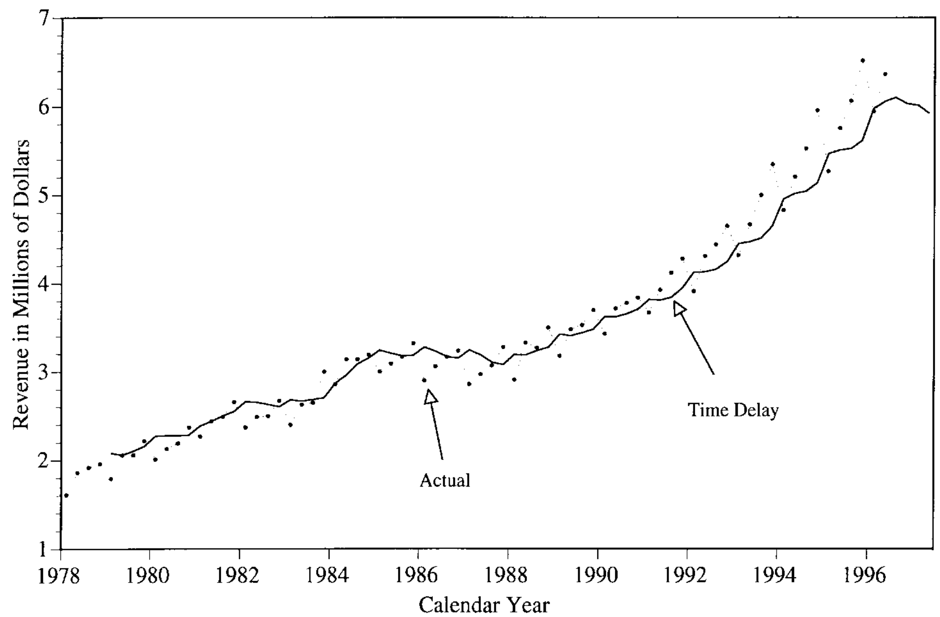

Fig. 8. Utah quarterly total taxable sales example of time delay NN model forecasts.

complementary relationship. In the first, NN's detect a very important strengthening in the nonagricultural employment growth rate that ARIMA and exponential smoothing methods ignore. This discovery strongly influenced the October economic and revenue outlook for Utah. In the second application, the evolving seasonal pattern identified by SABL decomposition guides the selection of the NN training set. In this case, the traditional statistical methods help NN's determine a better model. Although there is not yet a lengthy track record for NN's in forecasting Utah tax revenues, NN's are having an impact that is consistent with studies such Hill *et al.* [12] and Hill *et al.* [13], that find positive evidence of the general time series forecasting value of NN's.

The application of GA's to generate NN architectures aids in constructing robust NN's that are free from the distorting biases often found in the traditional methods used to examine revenue time series. Frequently in forecasting state tax revenues, analysts find what they think that they are looking for and consequently overlook important changes. In this sense, analysts can get caught churning ignorance. NN's prove to be a valuable alternative methodology for pattern discovery and expanded perspective.

Forecasting economic time series will always remain difficult because such variables are so strongly influenced by exogenous political, international, and natural shocks. This means that the irregular component will remain significantly large and extremely difficult to anticipate. NN's, however, with their ability to model nonlinear patterns and learn from the data provide an important forecasting tool to determine the trend-cycle and seasonal components. The applications reported in this paper evidence that NN's can produce significant insights on turning points in business cycles and in revenue patterns. Conversely, the challenges in trying to detect difficult seasonal patterns point to the need for better modeling performance for this time series component.

Experience using NN's to forecast the economy in Utah suggests that the ability of NN's to discover the unexpected vis-a-vis statistical models may be their greatest virtue. Their ability to find new information, however, comes at the cost of being a black box, a significant disadvantage for forecasters who strongly trust their judgement and intuition. In the present applications, however, analysis of NN forecasts yields useful insights that overcome some of the black box problems.

While some who prefer the statistical approach to forecasting may remain skeptical about NN's because of their lack of a rigorous statistical foundation, NN's do fit comfortably with the heterogeneous background of alternative forecasting techniques. Comparisons of forecasting techniques unfortunately often ignore the synergistic nature of techniques from computer science, economics, engineering, and statistics. Everyone involved in making predictions will benefit if NN's continue to progress toward the full realization of their forecasting potential.

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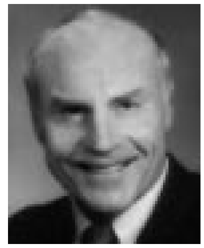

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