A Comparative Study of ARIMA and Neural Network Models:
Case Study in Korean Corporate Bond Yields

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ABSTRACT

A traditional approach to the prediction of economic and financial variables takes the form of statistical models to summarize past observations and to project them into the envisioned future. Over the past decade, an increasing number of organizations has turned to the use of neural networks. To date, however, many spheres of interest still lack a systematic evaluation of the statistical and neural approaches. One of these lies in the prediction of corporate bond yields for Korea.

This paper reports on a comparative evaluation of ARIMA models and neural networks in the context of interest rate prediction. An additional experiment relates to an integration of the two methods. More specifically, the statistical model serves as a filter by providing estimates which are then used as input into the neural network models.

KEY WORDS:
ARIMA, Neural Network, Interest Rate, Prediction.

PURPOSE

The prediction of economic and financial variables is a critical task for many decision makers in both industry and government. A traditional approach to assist in this task has been the development of statistical models to summarize past observations and to project them into the envisioned future. Over the past decade, an increasing number of organizations has turned to the use of neural networks. To date, however, many markets still lack a systematic evaluation of the statistical and neural approaches. One of these lies in the prediction of corporate bond yields for Korea.

This paper reports on a comparative evaluation of ARIMA models and neural networks (NN) in the context of interest rate prediction. In addition, a separate experiment involves an integration of the two methods. More specifically, the statistical model serves as a filter by producing estimates which were then used as input into the neural network models.

In most countries, interest rates are determined largely by the government rather than freely exposed to market forces. This has been especially true of Korea. After 1980, however, the government has relaxed somewhat its tight grip on interest rates. Consequently, the trajectory of interest rates has been partly determined to a meaningful extent by market forces. In this setting, a multivariate model which employs macroeconomic data would appear to hold promise as a predictive methodology (Azoff, 1994; etc.).

In this study, the exemplar of interest rates is the yield for corporate bonds having a maturity of 3 years. This interest rate is predicted using 3 types of approaches: ARIMA models, neural networks, and an integrated structure using both types of methods.

METHODOLOGY

ARIMA model. A popular forecasting technique lies in Autoregressive Integrated Moving Average (ARIMA) models (Box and Jenkins, 1976). ARIMA models assume that the variable used in the model includes all the information. That is, an ARIMA model uses only the previous values of the target variable plus the current and previous values of an external shock. A general form of the model ARIMA(p,d,q) is as follows:

$$\varphi(B)z_t = \phi(B)\nabla^d z_t = \theta_0 + \theta(B)a_t$$

where,

$$\phi(B) = 1 - \phi_1 B - \phi_2 B^2 - \cdots - \phi_p B^p$$

$$\theta(B) = 1 - \theta_1 B - \theta_2 B^2 - \cdots - \theta_q B^q$$

Moreover, $B^m Z_t = Z_{t-m}$ and a_t is white noise.

This general ARIMA model was tailored for the prediction of the target interest rate using the MINITAB program.

Neural Network model. The study employed a multi-layer perceptron neural network using the backpropagation algorithm. The first layer is the input layer, consisting of several nodes. Each input node represents the time-delayed data vector of the target variable (y_t); that is, $y_{t-1}, y_{t-2}, \ldots, y_{t-p}$.

The general architecture is given in Figure 1. This neural network model was implemented by using the program *NeuroShell 2* (Ward, 1993).

Integrated methods. The unit root test was used in the preprocessing stage to check for stationarity (Dickey, 1979). If the data was non-stationary, it was transformed into a stationary series.

In the integrated method, the estimated value from an ARIMA model was used as the input into a neural network. In this way, the ARIMA model served as a filter to attenuate the noise in the input variable.

RESULTS

The case study involved the prediction of month-end yields of Korean corporate bonds having 3 years' maturity. The data series, denoted in this paper as "IR", covers the period from Jan. 1980 to Aug. 1995.

Figure 2 is a time series plot of the data. As suggested by the figure, the series was not stationary. The unit root test confirmed this suspicion, as shown in Table 1.

An approach to selecting the proper ARIMA model is to employ information criteria such as the Final Prediction Error (Akaike, 1969), the Akaike Information Criterion (Akaike, 1974), the Bayesian Information Criterion (Akaike, 1977; Schwarz, 1978; Rissanen, 1978), or Hannan & Quinn's Criterion (Hannan & Quinn, 1979). The ARIMA model is chosen as the one that minimizes any of these statistics. As shown in Table 2, the statistic for ARIMA(1,1,0) is lower than those of the other models for each criterion. Consequently ARIMA(1,1,0) was selected as the statistical model.

In order to identify the appropriate neural model, we varied the number of input nodes from 1 to 5. The learning phase consisted of 142 data points and the testing phase of 40 points. The NN models used in this study may be classified into 3 types. The first type, Model A, was a neural network model with the raw data set (IR) which was non-stationary.

Table 3 shows the result of the NN models tested. As shown in the table, the NN model with four input nodes, representing the lagged variables from y_{t-1} to y_{t-4}, had the lowest value of RMSE during the test phase.

Model B involved the same neural nets but the inputs took the form of the first differenced data (DIR), which was stationary. As shown in Table 3, the NN model with one input node, representing time lag 1, yielded better predictions than the other models. In this fashion, the best Model B structure had the same lag as the best ARIMA model.

Model C embodied the integrated approach using both ARIMA and NN models. In particular, the output of the ARIMA(1,1,0) model was used as input to the NN models. The predictive performance is summarized in Table 4. The results were not precisely as we expected.

Table 4 indicates that the performance of the NN models was better than the performance of ARIMA. Among NN models, the best performance belonged to model B, the network with the first time lagged input variable using stationary data. These results were as expected.

The surprising result is that the integrated model underperforms neural network models working in isolation. It appears that the statistical model eliminates too much information during the filtering stage.

An ANOVA test is shown in Table 5. The results confirm that differences in performance among the ARIMA and NN models were significant. However, a series of t-tests (not shown here) indicates that the three neural models did not differ significantly from each other in terms of their predictive power.

FUTURE WORK

The univariate models utilized in this study implicitly assume that the target variable is the only important factor. In reality, however, many other variables affect the trajectory of interest rates. Future work will investigate more sophisticated models using multivariate inputs and examine alternative configurations for integrating predictive models.

REFERENCES

Akaike, "Fitting autoregressive models for prediction," ***Ann. Inst. Statist. Math.***, vol. 21, pp. 407-419, 1969.

Akaike, "A new look at the statistical model identification," ***IEEE Trans. Automatic Control***, vol. AC-19, pp. 716-723, 1974.

Akaike, "An objective use of Bayesian models," ***Ann. Inst. Statist. Math.***, vol. 29, pp. 9-20, 1977.

Azoff, E.M., ***Neural Network Time Series Forecasting of Financial Markets.*** NY: Wiley & Sons Ltd., 1994.

Box, G.E.P. and G. M. Jenkins, ***Time Series Analysis: forecasting and control.*** San Francisco: Holden-Day, 1976.

Dickey, D.A. and W.A. Fuller, "Distribution of the estimators for autoregressive time series with a unit root.", ***Journal of the American Statistical Association***, vol. 74, pp. 427-431, 1979.

Hannan, E., J. and B. G. Quinn, "The determination of the order of an autoregression," ***J. Roy. Statist. Soc., Ser. B***, vol. 41, pp. 190-195, 1979.

Rissanen, J., "Modeling by shortest data description," ***Automatica***, vol. 14, pp. 465-471, 1978.

Schwarz, G., "Estimating the dimension of a model," ***Ann. Statist.***, vol. 6, pp. 461-464, 1978.

Ward Systems Group, ***Neuro Shell 2.*** MD: Ward Systems Group, 1993.

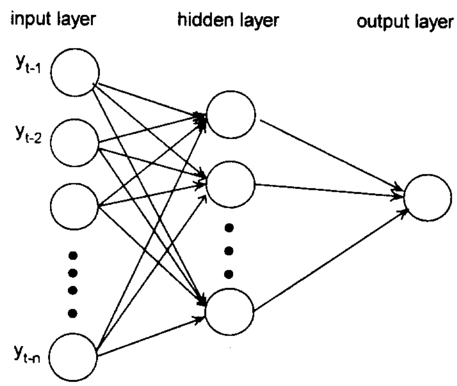

Figure 1. NN architecture.

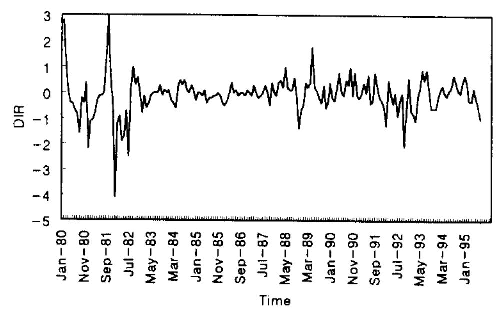

Figure 2-b. 1st differenced series.

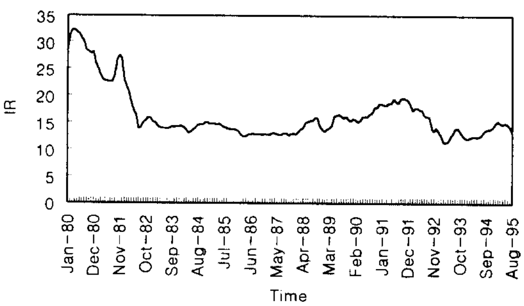

Figure 2-a. Korean corporate bond yield with 3 years' maturity.

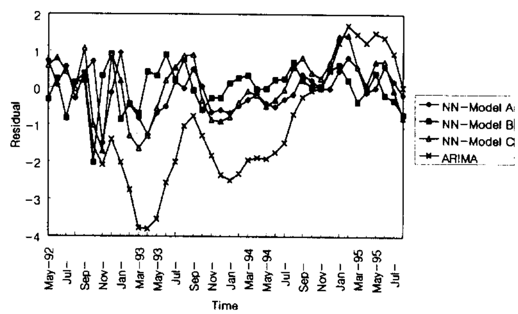

Figure 3. Plot of Residuals.

Table 1. Augmented Dickey-Fuller Unit Root Test on Interest Rate (IR).

Variable	Critical Value		ADF Test Statistic	Comments**
IR	1%	- 4.0109	- 3.264195	Accept at p = 0.05
	5%	- 3.4352		
	10%	- 3.1413		
DIR*	1%	- 4.0111	- 5.917628	Reject at p = 0.01
	5%	- 3.4353		
	10%	- 3.1414		

* : $DIR_t = IR_t - IR_{t-1}$
** : Null hypothesis of a unit root.

Table 2. The information criteria estimates for ARIMA identification.

MODEL	MSE	AIC	FPE	BIC	HQ
ARIMA(1,1,0)	**0.3929**	**- 0.91147**	**0.40183**	**- 0.87544**	**- 0.89686**
ARIMA(2,1,0)	0.3948	- 0.89529	0.40826	- 0.84124	- 0.87970
ARIMA(0,1,1)	0.3997	- 0.89431	0.40878	- 0.85829	- 0.87970
ARIMA(0,1,2)	0.3970	- 0.88973	0.41053	- 0.83569	- 0.86781
ARIMA(1,1,1)	0.3947	- 0.89554	0.40816	- 0.84150	- 0.87362
ARIMA(2,1,1)	0.3967	- 0.87912	0.41473	- 0.80706	- 0.84989
ARIMA(1,1,2)	0.4029	- 0.86361	0.42121	- 0.79156	- 0.83439

Note: MSE denotes the Mean Square Error; AIC the Akaike Information Criterion; FPE the Final Prediction Error; and HQ the criterion by Hannan & Quinn.

Table 3. RMSE of forecasts by several types of neural network models
(test period covers May 92 - Aug. 95).

Input layer	NN - Model A	NN - Model B	NN - Model C
Time Lag (1)	0.601931	**0.549891**	**0.806655**
Time Lags (1) - (2)	0.559010	0.552606	0.845731
Time Lags (1) - (3)	0.563978	0.561493	0.862840
Time Lags (1) - (4)	**0.556437**	0.556890	0.807751
Time Lags (1) - (5)	0.57052	0.562173	0.810724
Recommended Model	Time Lags (1) - (4)	Time Lag (1)	Time Lag (1)

Table 4. Comparison of prediction performance for ARIMA and NN models.

Model	NN - Model A	NN - Model B	NN- Model C	ARIMA(1,1,0)
RMSE	0.556437	0.549891	0.806655	1.851802

Table 5. 1-way ANOVA for the results in Table 4.

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                       - - -  O N E W A Y  - - - - -

         Variable B (forecasting error)
   By    Variable A (model type)

                             Analysis of Variance

                                 Sum of          Mean        F         F
Source                  D.F.     Squares         Squares     Ratio     Prob.

Between Groups            3       28.1221        9.3740     10.3000    .0000
Within Groups           153      139.2448         .9101
Total                   156      167.3669
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