FORECASTING KOREAN STOCK PRICE INDEX (KOSPI) USING BACK PROPAGATION NEURAL NETWORK MODEL, BAYESIAN CHIAO'S MODEL, AND SARIMA MODEL

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ABSTRACT

In this study, we forecast Korean Stock Price Index using historical weekly KOSPI data and three forecasting models such as back-propagation neural network model (BPNN), a Bayesian Chiao's model (BC), and a seasonal autoregressive integrated moving average model (SARIMA). KOSPI are forecasted over three different periods. (i.e., short-term, mid-term, & long-term) The performance of the forecasting models is measured by the forecast accuracy metrics such as absolute forecasting errors and square forecasting errors of each model.

The findings are as follows: first, between BPNN and BC, BPNN performs better than BC for mid term and long term forecasting, while BC performs better than BPNN for the short term forecasting. The second, between BPNN and SARIMA, SARIMA performs better than BPNN for mid term and long term forecasting, while BPNN does better than SARIMA the short term forecasting. Between SARIMA and BC, SARIMA performs better than BC for mid term and long term forecasting, while the other way around is true the short term forecasting.

In sum, the SARIMA performs best among the three models tested for mid term and long term forecasting, while BC performs best for the short term forecasting.

2. DATA AND METHODOLOGY

2.1 Index Data

The data used in this study are KOSPI for closing prices from the Korean Stock Exchange (KSE) data base. The data series span from 4th January 1999 to 29th May 2006, totaling 390 weeks (89 months) of observations.

The data are divided into two sub-periods, one for the estimation and the other for the forecasting. We use four different forecasting periods to examine the potential impact of forecasting horizons on the forecasting accuracy. Forecasting horizons used are 20% (long range), 13% and 8% (mid range), and 6% (short range) of the total number of observations. For the long range forecasting, the first 313 weekly data are used for model identification and estimation, while the remaining 77 weekly data (about 20% of 390 weeks) are reserved for evaluating the performance of SARIMA, BC, and the neural network model. Other forecasting periods were defined in the similar way, resulting in mid range (31-50 weeks ahead) and short range (23 weeks ahead) forecasting horizons.

2.2 Neural Network Forecasting

In this study, the back-propagation neural network model (BPNN) is used for time series forecasting. The main reasons for adopting BPNN are twofold. First, BPNN is one of the most popular neural network models in forecasting. Second, BPNN is an efficient way to calculate the partial derivatives of the networks error function with respect to the weights and hence to develop a network model that minimizes the discrepancy between real data and the output of the network model. BPNN can be trained using the historical data of a time series in order to capture the non-linear characteristics of the specific time series.

According to the principle of Ockham's razor, the simplest networks topology yielding satisfactory results is used. The networks are created as '2-1-1': that is, two input layers, one hidden layer, and one output layer. The network is also trained using various other topologies such as 2-X-1, while X = 2, 3, 4, and 5. However, the best results are obtained when there is one hidden layer (i.e., X=1).

2.3 Bayesian Chiao Forecasting

With respect to the sequence of the logistic data having two possible results (i.e. pass, which means "$X_{m-1} < X_m$"; or failure, which means "$X_{m-1} > X_m$), the trends of the central tendency and deviation can be sequentially adjusted. From BC, the posterior distribution X_{m+1} can be calculated.

2.4 Time-series Forecasting

To obtain the KOSPI forecasts from the SARIMA, we adopted the Box and Jenkins' method. Basically, Box and Jenkins' method uses the following three-stage approach to select an appropriate model for the purpose of estimating and forecasting a time-series data.

Identification: we used the SARIMA procedure in SAS statistical software to determine plausible models. The SARIMA procedure uses standard diagnostics such as plots of the series, autocorrelation function (ACF), inverse autocorrelation function, and partial autocorrelation function (PACF).

Estimation: Each of the tentative models is fit and the various coefficient estimates are examined. The estimated models are compared using standard criteria such as Akaike Information Criteria and the significance level of coefficients.

Diagnostic checking: SARIMA procedure is used to check if the residuals from the different models are white noise. The procedure uses diagnostics tests such as ACF, PACF, and Ljung-Box Q-statistics for serial correlation.

Applying these steps, SARIMA (110)(12) for the KOSPI price series, and SARIMA(011)(12) for the KOSPI return series are selected as forecasting models for both weekly and monthly data.

3. RESULTS

Descriptive statistics of forecast errors (FE) from BPNN, BC, and SARIMA using weekly KOSPI price data are presented in Table 1. Those statistics of FE for four different forecasting horizons such as 77 weeks ahead (long), 50 weeks ahead (upper middle), 31 weeks ahead (lower middle), and 23 weeks ahead (short) are presented in Table 1. Mean, standard deviation, minimum, and maximum of FE for four different forecasting horizons are also presented in Table 1. The SARIMA provides smallest mean FE for forecasting horizons of 31 weeks ahead or longer, while BC provides the smallest MFE and SFE.

This may indicate that the, among the three models, SARIMA is the most effective in mid-term and long-term forecasting while BC is the best in short-term forecasting, which is consistent with the findings of Wang et. al. and our prediction.

The mean forecast errors from the above-mentioned three forecasting models, Kruskal-Wallis χ^2 statistics, and the corresponding p-values are presented in Panel A of Table 2. Kruskal-Wallis χ^2 statistics of all four forecasting horizons are statistically significant at 0.001 significance level, indicating that, overall, forecasting errors from the three models are significantly different each other.

Results from pair wise comparisons between BPNN and BC, between BPNN and SARIMA, and between BC and SARIMA are presented in Panel B of Table 2.

Comparisons between BPNN and SARIMA show that SRIMA produce smaller forecasting errors than BPNN for mid-term and long-term forecasting horizons (i.e., 31 weeks, 50 weeks, & 77 weeks), while BPNN produce smaller forecasting errors than SARIMA for short-term forecasting horizon (i.e., 23 weeks). All differences in forecasting errors between BPNN and SARIMA are statistically significant at the significance level of 0.01. This indicates that SARIMA performs better than BPNN in mid-term and long-term forecasting while BPNN performs better than SARIMA in short-term forecasting.

Comparisons between BPNN and BC show that BPNN produce smaller forecasting errors than BC for 77 weeks and 50 weeks forecasting horizons. And the differences in forecasting errors between the two methods are statistically significant at the significance level of 0.01. This indicates that BPNN produce more accurate forecasts than BC for these relatively longer-term forecasting. On the other hand, BC produce smaller forecasting errors than BPNN for 31 weeks and 23 weeks forecasting horizons but the differences in forecasting errors between the two models are statistically significant only for 31 weeks forecasting horizon at the significance level of 0.05. This may indicate that BC performs better than BPNN in 31 weeks ahead forecasting but no meaningful conclusion can be drawn for the 23 weeks ahead forecasting.

Comparisons between BC and SARIMA show that SRIMA produce smaller forecasting errors than BC for mid-term and long-term forecasting horizons (i.e., 31 weeks, 50 weeks, & 77 weeks), while BC produce smaller forecasting errors than SARIMA for short-term forecasting horizon (i.e., 23 weeks). All differences in forecasting errors between BC and SARIMA are statistically significant at the significance level of 0.01. This indicates that SARIMA performs better than BC in mid-term and long-term forecasting while BC performs better than SARIMA in short-term forecasting.

In sum, regarding weekly forecasting, SARIMA is the best forecasting model for mid-term and long-term forecasting, while BC is the best forecasting model for short-term forecasting.

4. CONCLUSIONS

The purpose of this study is to compare the forecasting performance of back-propagation neural network model (BPNN), a BC (BC), and a seasonal autoregressive integrated moving average model (SARIMA) in forecasting Korean Stock Price Index. Forecasting performance is measured by the forecast accuracy metrics such as absolute forecasting errors and square forecasting errors of each model.

KOSPI data over the 390 week (89 month) period extending from January 1999 to May 2006 are analyzed. We find the followings: regarding weekly forecasting of KOSPI, the SARIMA provides most accurate forecasts among the three models tested for mid term and long term forecasting, while BC provides the most accurate forecasts for the short term forecasting. Between BPNN and BC, BPNN provides more accurate forecasts than BC for mid term and long term forecasting, while insignificant difference in forecasting errors exists between the two models for the short term forecasting.

These results are robust across different measures of forecast accuracy. Since the accuracy of forecasting values is dependent on the developing process of forecasting models, the results of this study may also be sensitive to the developing process of the BPNN, BC, and SARIMA.

REFERENCES: Available upon request