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The Prediction of Industry Stock Index Using Artificial Neural Networks

: Cases of Construction Industry and Banking

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Abstract

Previous studies as to the stock return and price volatility descriptors have advocated that industry effects exist over entire industry. We employed the MFM(Multiple Factor Model) paradigm to scrutinize the underlying relationships among the influencing factors such as macroeconomic factors, industry factors, and Intermarket factors, to enhance the understanding on the stock price behavior in the manner that predicts the directions of ISI(Industry Stock Index). Despite the unknown impact size and timing of the industry effects, they offer the benefits to interpret the complex pricing process in stock market. Moreover, the magnitudes of these industry effects usually rely on the industrial structure and features, and national characteristics. In addition to capturing the market timing, the prediction result of stock index can be used as a indicator and a surrogate in the process of portfolio formation. Ranking by different stock risk and return on the basis of industry can serve as a foundation for constructing such a desired portfolio as index fund, tilted fund.

Advances in Artificial Intelligence and Neural Network suggest the feasibility of a valuable prediction system for market direction discovery and profitable trading. With the robustness of Artificial Neural Network, we predicted the directions of the particular ISI(Industry Stock Index) corresponding to the Construction industry and Banking in one month advance.

To this end, we attempted to incorporate the industry effects on the next month's Stock Index movements by adding several variables related to the specific industry. This paper gives rise to the promising factors in predicting the anticipated directions of particular ISI, and the size of anticipated movements. To manage the drawbacks in traditional approaches, versatile techniques in the context of Artificial Neural Networks are used to assist the ISI prediction.

KEY WORDS:
Industry Effects & Factor, Industry Stock Index(ISI) Prediction,
Composite Factor Model, Neural Networks

MOTIVATION and BACKGROUND

Providing the arguments against Sharpe's market model, many studies have remarked the existence of industry effects on the price behavior in stock market *King[66], Fertuck.L [76] Fabozzi and Francis [83].* A couple of domestic studies involved in the industry factors and effects led the empirical tests similar with the King's research framework to apply the Korean stock market *Park[89]Kim,H.K [91].* Moreover, the extended study implemented by *Yoon [94]* addressed that Korean stock market represents the different degree of industry effects according to the industry sectors. Neural Networks attempt to mimic the way in which the human brain processes information and data Hecht-Nielsen [90], Wasserman[89]. Traditional quantitative methods used for predicting the behavior of financial markets often produce unsatisfactory if not dismal results given the complex interactions between a given market's movement and other economic phenomena.. Neural Networks have found an important niche in financial market application, especially stock market prediction, and have recently been applied to portfolio formation and investment engineering.

In the past, many studies as to ANN applications in stock market focus on predicting the direction of global market based- index such as KOSPI, S&P 500. *Kimoto et al [90], Jang et al [91] Chinetti; Gardin, and Rossignoli[93].* By employing the Modular Neural Network, some researches also performed to predict the following month directions of KOSPI, which is just global market index, in Korea market and abroad *Park, J.Y &I. Han [95] Yoda.M [94]*.

Experience with ANN applications in stock market, especially since the early 1990, stock market participants have required the more decomposed sectors predictions to manage the market variability. Moreover, the results of many empirical tests also provided the meaningful evidences that assured the existence of industry effect on the stock price behavior. More specifically, on the basis of inter-industry, some ISIs(Industry Stock Index) tend to move differently with KOSPI which gives the insufficient explanations on the movements of the specific stock groups, subsequently more real market-oriented index prediction have required to describe the extra-market components which represent the real market mechanism *Jung& Kim [95].* At best, making a zoom-in the scope of the securities from attainable basket provides desirable substate in decision making by individual investors and security analysts. Furthermore, more accurate ISI prediction will facilitate the effective stock selection procedure and the diversified investments.

DOMAIN DESCRIPTION

In general, Investors take advantage of the versatile indicators to predict the market conditions. While KOSPI is useful for judging the current market trends and status, it is insufficient to express the characteristics of specific market sectors such as the size and pricing procedure spring from the particular industry. To resolve these drawbacks of KOSPI, ISI(Industry Stock Index) representing the averaged performance of all stocks listed within a industry against the market, serves as well a surrogate indicator for an acute industry analysis as for an actual trading by target portfolio.

Industry Selection criteria

One of the most effective ways in selecting an appropriate industry is to assess the level of interactive activities in a industry in question. By using this selection strategy, it can take the key advantage to look into the degree of coherence between real economy and stock market. As the first step, it may be recommended to collect the possible outstanding criteria referred from the related previous studies. After screening by the applicability to the actual system and the interview with industry analysts, the criteria outlined like the below have been determined. The table below illustrate the overall criteria for selecting the target industry.

[Table 1] Industry selection criterion

Industry selection criterion
Non- service and Service industry
Homogeneous movement to exogenous factors on stock market
The number of stocks in KOSPI(Construction = 51 , Banking=21)
Relevance to real economic conditions
Troika stocks- Construction, Finance(bank), Wholesale & Distribution
Independence or dependency against KOSPI fluctuation

Consequently, the prediction system includes the two candidate industries for ISI prediction. The selected correspond to the Construction and Banking industry.

Industry Factors and Effects

It is a extremely challenging task to find out the influencing factors and their effects on the stock market. There has not been empirically tested whether which or how many factors describe the stock price movements. Furthermore, these factors spread out not only from quantitative to qualitative indicators but also from macro to micro context factors. To identify the sources related to the price movements from the selected industry, the prediction system employs the general types of securities analysis. First, it make a classification by dividing the chosen candidates into technical and fundamental indicators to extract the meaningful factors, and then these indicators are grouped by the four sectors such as macroeconomic, InterMarket, Industry, and technical factors.

GENERAL FRAMEWORK

Forecasting time horizon

A proper prediction point will be affected by many factors, including the accuracy of the model, the amount of noise in the data, the frequency of trading and the underlying dynamics of the problem itself. Although industry analysis is a useful tool in implementing the long term investment strategies, it is also required to predict the short term horizon for the traders who often prefer to take a buying or selling positions. Given that a training set is composed of monthly data, at least in our case, a prediction point will be appropriate on the monthly basis. As a result, the presented system will predict the rising or falling of the selected Industry Stock Index on coming month.

Variables Mining & Selection

Picking up the appropriate input variables is critical in generating the effective Neural Network prediction system. Despite various techniques have been suggested for variable selection, most of them failed to produce the best possible results. These kinds of linear correlation-based technique have been criticized and debated due to their masking effects for other variables during selection process. In noisy data set, these techniques are poor to find out the subtle and powerful linear and non-linear interactions among variables *NeuralWork Predict Reference manual [95]*. In the global market analysis, investors and financial analysts need to analyze the InterMarket relationship, the industrial relationship, and the level of the adaptability against external environment impacts. To meet the security analysis challenges of the 1990s, the new method benefited from technical analysis, *Synergistic Market Analysis*, was presented by *Lou Mendelsohn [91]*. This method reorganized the inter-relatedness, the non-linearity in the financial market and made use of synergy effects among the technical and fundamental analysis.

For our research model, several items, for instance data availability, market condition, and set separation strategies, were considered to explore the effective variables on the prediction model. In terms of efficiency, the former two steps; the literature review and field expert interview , are used to collect the potential significant variables. The last step, correlation analysis, allows the system to check the existence of consistent linear correlation between the actual outputs and candidate variables. A key advantages of this step is that consistent correlation during within-sample period provides a more comprehensive understanding about the target output's movements to be occur. This analysis was operated by sliding 4 years time window within training and testing set.

Factors identification

The stock market factors influencing the ISI movements can be categorized as four provinces according to the common economic context. Stock market interacts typically with macroeconomic factors, industry factors, and market factors in the boundaries of global investment scope. In the past studies, the majority of conventional approach were used to reduce the size of input variable to reasonable level. Our research applies the pilot test to a rather large group of raw variables set with *NueralWork Predict* window version. After tremendous trials and errors, the prediction system determined the significant variable sets by combining the results of the other steps mentioned from the above. The following [Table 2] briefly displays the potential factors in accordance with stock return generating process.

[Table 2] Input variables by factors grouping

Factor name	Variable candidates
Economy Factors	Price Index, Exchange Rate, M2, CBI, Raw material Price index, BILEAD
Industry Factors	-Construction-
	Contract amount, Area Permitted, Wage, Dividend, PER
	- Bank-
	TAS, YAEDAE, Dividend, PER, TLOAN, Exchange rate(US, Yen)
Market Factors	Trading Volume, Deposit, KOSPI
Derived Factors (Technical indicators)	Moving Average, Regression Coefficient, Disparity, Relative Strength Index

For concreteness of input variable selection, the correlation analysis is especially performed on the macroeconomic and industry variables within Banking industry. In this additional procedure, the prediction system produced the new variable set reduced such as industry variables as BPER, EXUS, EXYEN CBR, TLOAN, TAS for banking industry. As a result of selection process, we got by the input variable sets for the composite models of each industry.

Model development

Many factors sprung from economy events influence the volatility of stock market in various ways. To scrutinize these factor's influences on the stock market, some different models based on the factors determined from the previous section mentioned are considered to enhance the capability of encapsulating the industry effects and factors. Each model may contain one or more factor groups such as time series and macroeconomic factors. The following [Table 3] shows the definition and the components of the derived models based on factor categories.

[Table 3] Experiment Model Description

Factor \Model	Time-series	InterMarket	Composite
Time-series	ISI (from t-5)	ISI (t-2), DKOSPI(t-1)	ISI (t-2), DKOSPI (t-1)
InterMarket	-	KDEPOSIT, CVolume	KDEPOSIT, CVolume
Tech'l Factor	-	MA, RSI, DSP, RC	MA, RSI, DSP KRC,KMA
Macro-economic	-	-	M_2, CBR, PI, RPI,BLEAD
Industry Factors	-	-	CAREA,CAMOUNTCPER,CDIV,CWAGE, EX(US,YEN), TAS, BPER,BDIV

ISI Prediction Model

From the simple time series model, we extended the composite model by adding the macroeconomic and industry factors. The superiority of these factor lies in the robustness, in that these are considered as to be significant in forecasting the industry stock index movement with specific sector expressions. These factors are set as additional input matrix to the derived model in the form of their economic aspect. We present the ***Composite Model*** extended from InterMarket model to the network in the order of Macroeconomic, Industry , Stock market and Technical indicator, and Time series data.

ISI Prediction Experiment

In developing the Stock Index prediction system, proper Neural Network design is critical task for generating good forecasts. But there are some tackling problems in deciding the following five key items such as the optimal time window to predict, the set of inputs to be used in the models, the type of indicator, and the duration of prediction.

Input data selection

Raw data matrix consisted of total 186 monthly observations of CISI(Construction Industry Stock Index) from January 1980 to June 1995. In case of the BISI(Banking Industry Stock Index), the prediction system utilize the 126 observations sampled from January 1985 to June 1995 as inputs. After set separation, these raw data sets use for the training, the testing ,and the hold-out phase in research model. Data indices calculated at month 't' are provided to forecast the future trends for the next month 't+1'. The difference is calculated for the price data between the averaged prices of every monthly ISI and for the volume data, which contains valuable information about the price movement. Dealing with the technical indicators and Time-series data , they should also be included to the input data matrix due to the effects that the significant macroeconomic movements reflect their fluctuations on the future prices behavior. On the other hand, network outputs will be the increase or the decrease of next month' price index with magnitude.

Data preprocessing

To support Neural Nets produce accurate forecasts, the selected raw input data must be preprocessed. Two widely used preprocessing methods are known as transformation and normalization. The transformation is fulfilled to each input field to make the information contents obvious to the neural network. As output values to be predicted is the difference of stock index between next month and current month, the system takes the same type of data to be used at the desired output column. Such input variables as macroeconomic variables and industry variables are used as the form of ratio. The system also applies the log transformation to the MA(3m) of ISI($ISI_{(t-1)}/ISI_{(t)}$. It implies that the value derived is the difference of the log $ISI_{(t-1)}$ and log $ISI_{(t)}$ Fortunately, the transformation methods is decided after interview with the modeling experts, and trials and errors.

To train the network, the training data sets are extricated the values of 20(for CISI), 15(for BISI) indicators. To improve the learning efficiency, the pre-processing, called as filtering, procedure such as normalized and scaled applied to make the input indexes to become in the[-1,1] range which is suitable for neural network processing. The proposed system uses the Min/Max table Utility supported by *NeuralWork pro* in conjunction with data I/O which allow automatic scaling and offsetting which map real world features or measurements to values acceptable to a network.

Set separation

Ultimate aim for data pre-processing is to generate three sets of data: the training, testing and hold- out set. For this paper, the data matrix is seized into the three sets by the generalized method rather than systematic way. Considering the fact that test set measures how well the model interpolates, test pass assure that the network has not just memorized the training data. For this purpose, the set is randomly selected the 12(month) observations from 1980.5~1992.12 for Construction and 1985.1~1993.12 for Banking.

In the training mode, the network modifies the values of interconnection weights between neurons to adapt its internal representation to improve the mapping of inputs to outputs. The criteria of set separation should be mutually exclusive, that is to say, no containing same data in a subset[*Mendelsohn, 95]* The observations of training set selected for each industry correspond to 140(Construction:1980.5~1992.12),96 (Banking:1985.3~1993.12) in this research.

Validation set is used to estimate model performance in a deployment environment. It is usually the continuous data taken at the beginnings or end of the train and test set. The prediction system selects the observations from January 1993 to June 1995 for construction(30 observations) and from 1994 to June 1995 for Banking(18 observations).

Neural Network Design

While several methods have been proposed to get around the problems of slow convergence and optimal network architecture, these techniques differ in complexity, convergence speed, most importantly, in their generalization performance. Throughout this research, we enumerate the generalized and the well known methodologies to design the effective prediction system.

The proposed system in this paper attempts to configure the near optimum network through various advices such as empirical evidences and commercial package's manual recommendation.

Network Architecture

In designing the BP network, it is necessary to make decisions on the number and the size of network layers. The proposed system is based on three layers feed forward network, which equipped a BP(Back-Propagation) algorithm for learning phase. The number of hidden layers in a BP network may be generally between one or two, as more than two layers do not increase the network's ability to learn *Wasserman[89]*. To preserve the design simplicity and generality, the our prediction system constructs the networks that start with about 5 hidden PEs in one layer. It uses the testing module to find the best performance, and then changes the number of hidden PEs up or down to improve performance. A number of experiments have done with various configurations by increasing the number of hidden nodes from 5 to 15 in 2 steps.

Learning Strategies

The system is trained with changing the learning parameters written down in a specific learning schedule tableau with many different patterns, allowing us to discard the right low-performance networks. Next, it brings up the different learning coefficient schemes to the network training according to Global Learning Schedule filled out by the researcher. To get to stable state, The proposed system is focused on adjusting the three coefficients on schedule with the different rates appropriately: learning coefficients, momentum, and training tolerance. The following initial learning schedule is used to optimize the network for CISI & BISI prediction

[Table 4] Global Learning Schedule

Parameters \Count	5000	10000	30000	50000	100000
Learning Rate	0.3	0.1	0.05	0.0025	0.0001
Momentum	0.6	0.4	0.3	0.1	0.05
Tolerance(RMS)	0.00001	-	-	-	-

The proposed networks also utilized the different learning coefficient schemes. More specifically, as learning progress, the network makes the learning rate lower and the momentum higher to make the network reach a stable state quickly. To prevent the network from being clamped at the local minimum, the Jog Weight Tool was employed to specify a range for a random value to be added to all the variable weights going into the destination layer from the source PE.

Design considerations for neural network learning is dedicated to the choice of transfer function for the PEs. The network produces the network outputs as a type of negative(-) or positive(+), and then they are interpreted as the signal for falling or rising of market. The network simply uses MinMax Table Utility to descale the network output into the real world value's increase or decrease. As a result, we employed the Hyperbolic Tangent as a output transfer function.

Generalization is to measure the ability of a network to recognize the patterns outside the training set. A network having the structure more complicated than necessary 'overfits' in that it leads to good fit for the training set but performing poorly on unseen patterns.

To preserve the generality of model in our paper, the independent test set is constructed by sampling randomly the 12 observations (for Construction), 12 observations (for Banking) within the in-sample period.

ANALYSIS OF EXPERIMENT RESULTS

The different models are evaluated by the accuracy and reliability of the forecasts on training, test, and hold-out sample. It is possible to appraise the relative superiority within the proposed models by the RMS and the %CT (Accuracy), which is the percentage of successful price index trend prediction. This statistics implies that the network is able to predict the trends of a correct averaged index for the coming month. The RMS is used to select the best network and the hit ratio of directions for accuracy in terms of profitability.

In a practical view, the buying and selling simulation is fulfilled to evaluate the system performance. As a initial step, the network with same architecture but three different models is run. Only the hidden nodes are changed by the two steps. If the best node is found, next step is continue to search for a near number of nodes.

Models Performance Comparison

The [Table 5] lists the correlation coefficient and the accuracy of hit the directions. After preliminary experiments, the best performed network is chosen on the basis of %CT from each models within a industry. The following table shows the performance of the resulting network which extracted from the best networks within three models for Construction and Banking industry.

[Table 5] Results of CISI prediction

Models	# of Hidden nodes	RMS	Corr.	Up/Down	%CT	AVG.
Time-series	8	26.87	0.26	(15/7)/30	73.33	66.67%
InterMkt	5	25.52	0.39	(14/9)/30	76.67	66.67%
Composite	5	22.33	0.61	(15/9)/30	80.00	76.67%

The table above indicates that the prediction results of composite model added with the industry and several economic variables is better than those of other models in almost performance measures. The ***Composite Model*** predicts the average CISI of coming month as a 80% accuracy. It is a fairly good result. In other words, the network has the ability of predicting the correct index trends of next month about 80 out of 100 times. These results imply that some industry factors improve the explanatory power for ISI(Industry Stock Index)'s movements in future.

The [Figure A-1] also illustrates the fitting capability of composite model. Regardless of error in magnitude, the directions of emerging month is quite exactly predicted in our prediction model. In a large sense, this means that ***Composite model*** is better profitable than the other models.

[Table 6] Results of BISI Prediction

Model	# of Hidden nodes	RMS.	Corr.	Up/Down	CT%	AVG.
Time-series	11	38.66	0.247	(5/7)/18	66.67	52.38%
InterMkt	3	37.56	0.237	(1/9)/18	55.56	38.89%
Composite	8	37.44	0.299	(5/7)/18	66.67	56.25%

As listed in the [Table 6] results of BISI prediction, It doesn't virtually shows a significant difference between. the best performed network of Time series and that of Composite model . Time series model produces a 66% accuracy, and Composite model also shows the same 66% accuracy. On the other hand, it is able to assess ***Composite Model*** better in the eyes of average network performance. Unfortunately, we didn't get the good performance in forecasting the BISI compared with that of Construction by Neural Network relatively.

Appendix [figure A-2] depicts the results of BISI composite model with actual outputs at the below. However, as shown from the above, It just shows the level of normal performance in the financial market. In this case, a large fitting error between the actual and the predicted value causes the great RMS, lower r and R^2.

Comparison between NN & MLR

To justify the comparative advantages between the methodologies, our research is also forced to compare the MLR with NN. In many previous studies, MLR was selected as the counter measure for the performance comparison *Jang et all [91]Refines et all[93]*. Because of similarities such as multivariate data analysis and analogue outputs which our research model holds, MLR are chosen. Owing to multi-colinearity of ISI data, the step-wise method is applied to the initial input vectors. From the outputs of step-wise regression, significant variables are obtained three for construction and two for banking. Interestingly, these variables belong to the industry factor categories. For Construction, the selected correspond to CPER, CDIV, and DKOSOI (Difference of KOSPI(t-1). On the other hand, Banking has two significant variables such as EXUS and BPER .

With these variables, the experiment is performed to predict the coming month's ISI(Industry Stock Index). The [Table 7] shows the results of prediction and comparison with Neural Network.

[Table 7] Comparison between MLR and NN

Industry	Models	Learning(r)	Up/Down	CT%
Banking	NN(Composite)	0.96786	(5/7)/18	66.67
	ML Regression	0.41601	(8/1)/18	50.00
Constr'n	NN(Composite)	0.94889	(15/9)/30	80.00
	ML Regression	0.48288	(10/9)/30	63.33

The table above implies that NNs outperform the MLRs with fairly good performance in both learning and prediction phase.

Taken a correlation coefficient as the evaluation measure of learning capability, NNs present the high ***r*** (correlation coefficient) value such as 96% and 94% in learning phase, and 29% and 61% in hold-out set. In contrast, MLRs show lower performance than those of NNs in both industries and experimental phase.

Buying and Selling simulation

To translate the produced results into a more valuable form is meaningful in that verifies the effectiveness of the prediction model and the system. Having the recommendations produced from system, the proposed system iterates the simulation of a buying and a selling the index in the Korea Stock Exchange.

The timing for when to buy and sell stocks is given by the network's output: If prediction system produce the negative(positive) signal, take a position for short(long). And then calculate the cumulative rate of return for prediction periods. In this way, the operation gives the chance to uncover whether the Neural Network prediction system outperforms the simple buy-and-hold strategy and MLR, and whether composite model produces the more profits than other proposed models.

Since ISI(Industry Stock Index) is not actually tradable asset in the current stock market, it will be a more practical simulation to assume that an index itself should be a tradable assets in the market and have no transaction cost.

The results of performance by each methodologies are illustrated on the [Figure A-3]. The figure reflects the performances of investment strategies in buy-and -hold, MLR, and NN respectively. Each line implies the performance of the prediction system in terms of cumulative rate of return gained from each trade.

[Table 8] Simulation Results of Methodology basis

Methods basis/ industry	Construction	Banking
MLR	19%	-4%
Buy &Hold	24%	-12%
NN	112%	4%

The buy and hold strategy yields the 24% rate of returns, that is difference between initial and final rate of return, otherwise the neural network composite model yields a rate of returns of about 112% over the same period. In the case of the methodology basis, NNs display the greater rate of returns by the 112% rate of return calculated in cumulative ways.

In the similar way, the results of performance comparison between the methodologies in banking industry also report that NNs yield the greater rate of returns than those of MLR. In spite of the difference between each methodology is small, it is more valuable task to calculate the loss and gains in terms of profitability in practice.

the Figure [A-4] illustrates the simulation results on the basis of methodology in banking. The proposed models of both Construction and Banking also are simulated respectively, and results is displayed with the [Table 9]. As shown from the table below, the rates of return of models don't give any consistent implications to both industries through their outputs.

[Table 9] Simulation Results of Model basis

Models/Industries	Construction	Banking
Time/Series	54%	14%
InterMarket	58%	11%
Composite	112%	8%

In case of Banking, the results show that time series model slightly outperforms the composite model with more rate of return.

CLOSURE

Findings

Regardless of tremendous trials and errors to search for optimal outputs, the results from this research are not the final word in predicting the accurate ISI in this domain. In addition, heavy noisy data in stock market has prevented us from getting to a reliable level as the designed predictive system. However, we intend to present the results discovered from this experiments fro the purpose of enhancing the generality of some findings. First, Judging from the results of this research as to industry effects and factors, Banking industry is less related to the real economy events than Construction. Secondly, according to domain features, adding industry factors or macroeconomic factors may guarantee the better performance for ISI prediction. In summary, one need to pre-analyze the overall trends or the correlation between the prediction input stream and economic phenomena.

Further Research Directions

In a real investment world, a piece of published and quantitative information are insufficient to explain the stock price movements over short-term in Banking. More specifically, the short-term prediction models such as one month ahead prediction, to be effective, should include more technical variables to explain the fluctuations of stock index in future. Because macroeconomic factors can't obtain by the weekly data, the new data manipulations method combining the monthly data with technical indicators need to develop.

Moreover, with non-coincident data sources resulted from data availability and pricing timing, investors need to translate theses data into the informative data which is useful on the short-term investment horizon. To illustrate the variables selection process, It is advisable to invent any effective methods to handle appropriately the different characteristic variables such as a time-lagged or a indirect influencing factor, and factor involving on different economic sectors. For instance, it would be helpful to deal with these domain by employing the dual or multi-network architecture, deriving the common variables within the range that holds the valuable information .

The banking, taken as non-manufacturing industries, is quite sensitive to the qualitative information disclosures such as government policies, big financial accidents. These kinds of industry factors may lead the ISI movements to the unpredictable directions. If possible, a promising preprocess steps need to embed these non-quantitative information into the quantitative input variable set.

The last one is rather intuitive due to the additional problems caused by both redundancy and ambiguity. For the ISI prediction, we utilize the data vectors obtained from forecasting the one month(t+1) and three month(t+3) as the independent variables of the prediction system. If not the problems stated from above, this approach will promise to create the effective variables.

Reference

Ahamdi, H., "Testability of the Arbitrage Pricing Theory by Neural Network," In *Proceedings of the IEEE International Joint Conference on Neural Networks*, (1990), I 385-394.

Choi JaeHwa and M,Lee, M, Rhee, " Trading S&P 500 Stock Index Futures Using a Neural Network", Proceedings of the Third Annual International Conference on AI Applications on WS, pp.63-71,1995

Davide Chinetti, F.Gardin, C. Rossignoli, " A Neural Network Model for Stock Market Prediction", Proceedings of The Second Annual International Conference on Artificial Application on Wall Street, 1993, pp.64-72.

Deboeck, G. J., *Trading On the Edge*, John Wiley & Sons, Inc., 1994.

Emma Baestaens and W.Max, " Tracking the Amsterdam Stock Index Using Neural Network", Neural Networks in the Capital Market, A Refenes (eds), pp.149-161, 1995

Fabozzi, F.J and J.C.Francis, " Industry Effects and the Determinations of Beta", Quaterly Review of Economics and Business, 1983, pp.61-73.

Fertuck.L, " A Test of Industry Indices Based on SIC Code", Journal of Finacial and Quantitative analysis. Dec, pp 837-848

D. S., Barr, and W. J. Loick, "Artificial Intelligence And Market Analysis," *Technical Analysis of Stock and Commodities*, (1993), 18-29.

Hawley, D. D., J. D. Johnson, and D. Raina, "Artificial Neural Systems: A New Tool for Financial Decision-Making," *Financial Analysts Journal* (Nov.-Dec. 1990), 63-72.

Heston, Steven L and K.G.Rouwnhorst,"Does Industrial structure explain the benefits of international diversification ?", Journal of Financial Economics.,1994

Jacob. Boudoukh, M. Richardson and R.Whitelaw, " Industry Returns and the Fisher Effects", Journal of Finace. Vol.XLIX. No 5. Dec 1994.

____ and ____, "Intelligent Trading of Emerging Market." In G. J. Deboeck (Ed.), *Trading On The Edge*, John Wiley and Sons, Inc., New York, 1994, 80-101.

Jung,H.Y and H.S, Kim," Industry Stock Index differentiation in Stock Market", Monthly Cheil Economic Research, pp 43-58, June,1995

Kamijo, K. and T. Tanigawa, "Stock Price Pattern Recognition -A Reccurent Neural Network Approach-," In *Proceedings of the IEEE International Joint Conference on Neural Networks*, (1990), I 215-221.

King.B.F, " Market and Industry Factors in Stock Price Behavior ", Journal of Business, Jan.1966. pp.139-190

Mendelsohn, L., "Preprocessing Data For Neural Networks," *Technical Analysis of Stock and Commodities*, (Oct 1993), 52-58.

Park, S.J, " A study on Industry effects on Stock Price in Korea stock market", Master thesis, 1989

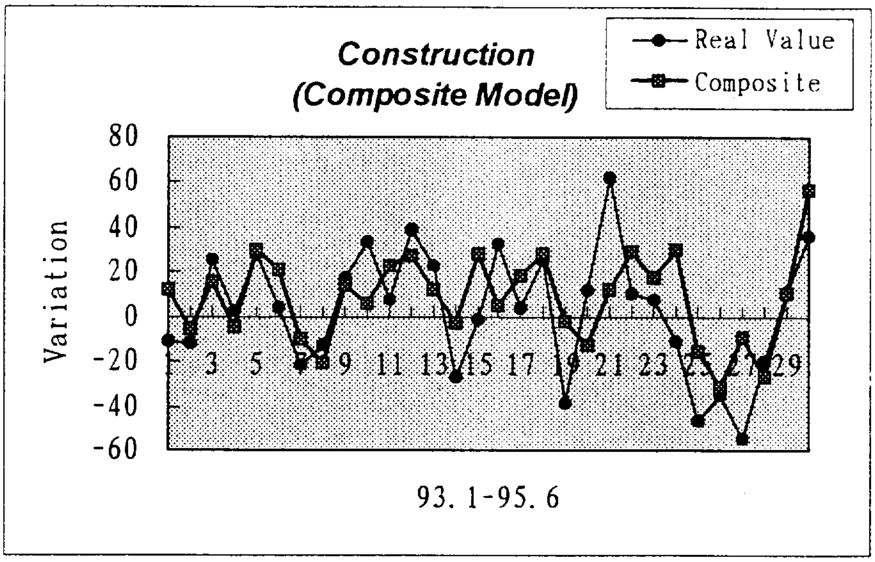
Richard Roll," Industrial Structure and the Comparative Behavior of Interanational Stock Market Indices", The Journal of Finance, Vol. XLVIL, No1. Mar,1992

Tim Chenoweth and Z. Obradovic, " A Multi-Component Approach to Stock Market Predictions", Proceedings of the Third Annual International Conference on AI Applications on WS, pp.74-79,1995

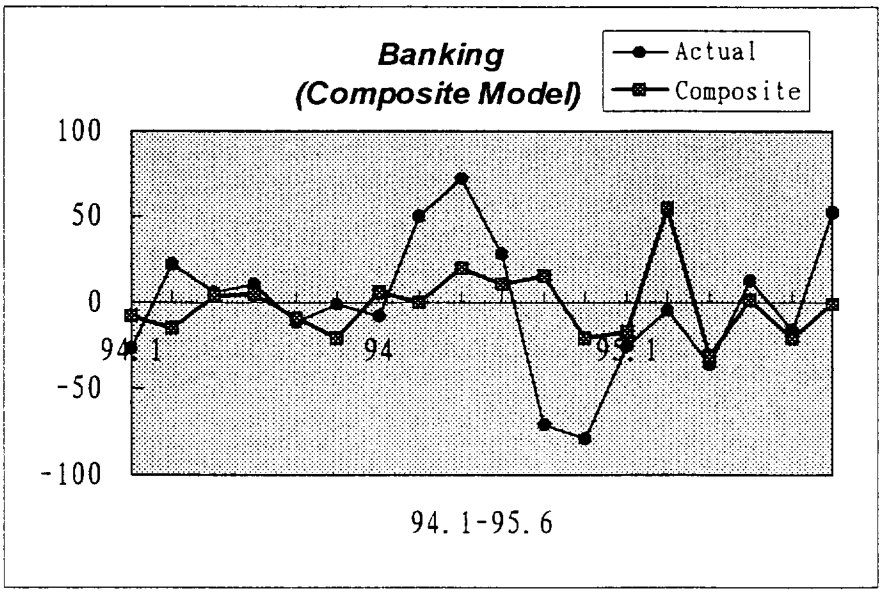
Yoon, Y. and G. Swales, "Predicting Stock Price Performance: A Neural Network Approach," In *Proceedings of the IEEE 24th Annual Conference of Systems Sciences*, (1991), 156-162.

APPENDIX

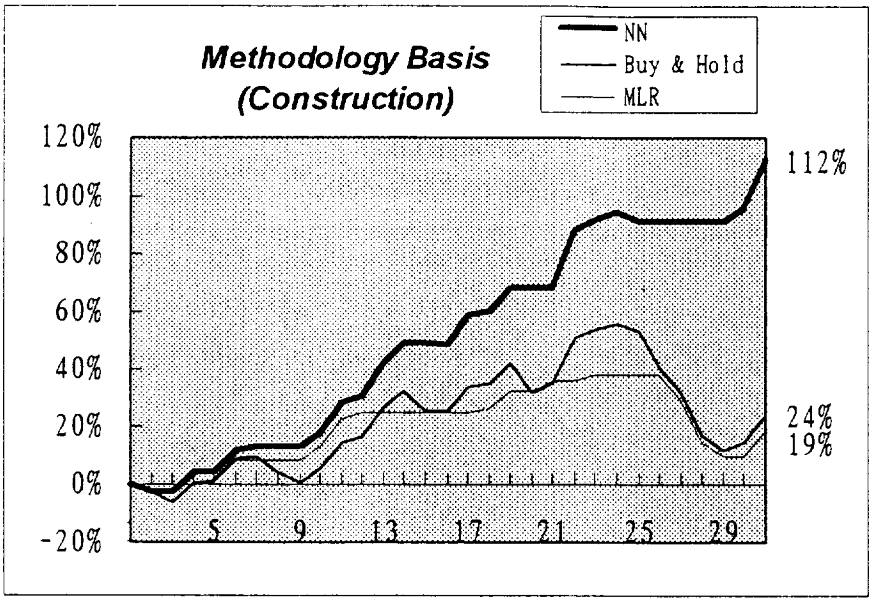
[Figure A-1] Prediction accuracy of Composite model



[Figure A-2] Prediction accuracy of Composite model in Banking



[Figure A-3]   Buying and Selling simulation (construction)



[Figure A-4]   Buying and Selling simulation (Banking)