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An investigation into the use of neural networks for the prediction of the stock exchange of Thailand

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AN INVESTIGATION INTO THE USE OF NEURAL NETWORKS FOR THE PREDICTION OF THE STOCK EXCHANGE OF THAILAND

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ABSTRACT

Stock markets are affected by many interrelated factors such as economics and politics at both national and international levels. Predicting stock indices and determining the set of relevant factors for making accurate predictions are complicated tasks. Neural networks are one of the popular approaches used for research on stock market forecast.

This study developed neural networks to predict the movement direction of the next trading day of the Stock Exchange of Thailand (SET) index. The SET has yet to be studied extensively and research focused on the SET will contribute to understanding its unique characteristics and will lead to identifying relevant information to assist investment in this stock market. Experiments were carried out to determine the best network architecture, training method, and input data to use for this task. With regards network architecture, feedforward networks with three layers were used - an input layer, a hidden layer and an output layer - and networks with different numbers of nodes in the hidden layers were tested and compared. With regards training method, neural networks were trained with back-propagation and with genetic algorithms. With regards input data, three set of inputs, namely internal indicators, external indicators and a combination of both were used. The internal indicators are based on calculations derived from the SET while the external indicators are deemed to be factors beyond the control of the Thailand such as the Down Jones Index.

In terms of comparing the performance of neural network trained via back-propagation against those trained via genetic algorithms for SET prediction, the results from this study found no significant performance difference. With regards to only the number of hidden nodes, using categories of small, medium and large, these three groups of neural networks when trained by back-propagation or genetic algorithm, have also shown that there are no statistical differences in their prediction performances.

For the three sets of indicators, the study found there are statistical differences in the prediction performances of the neural networks for the prediction of the movements of the SET index. The neural networks trained using the set of external indicators shows the best average prediction performances among the three sets of indicators and these

include the Dow Jones index, the Hang Seng index, Nikkei index, Minimum Loan Rate (MLR), gold price, exchange rate of the Thai baht and the US dollar and the previous SET index.

Unlike most existing work that used single neural networks for predicting the SET, this study developed a gating network which combines the results of the three best neural networks for predicting the movement of the SET index. This gating network is to be used as an ensemble mechanism. It is composed of two layers with voting and dynamic gates in the first layer and an adaptive gate in the second layer. The study found that the gating network is a better predictor of the directions of the movement of the SET index than any single neural network used in this study.

LIST OF PUBLISHED PAPERS

Chaigusin, S., Chirathamjaree, C., & Clayden, J. (2008). Soft computing in the forecasting of the Stock Exchange of Thailand. *Proceedings of the Fourth IEEE International Conference on Management of Innovation and Technology* (pp. 1277-1281). Bangkok: Thailand.

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DECLARATION

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LIST OF ACRONYMS

ASE	American Stock Exchange
ASX	Australian Stock Exchange
BOA	Bayesian Optimization Algorithm
BPN	Back-Propagation Neural network
BUX	Budapest Stock Exchange Index
DAX	Deutscher Aktien Index
ECGA	Extended Compact Genetic Algorithm
EMA	Exponential Moving Average
EMH	Efficient Market Hypothesis
ES	Evolution Strategy
FTSE-100	United Kingdom for Financial Times Stock Exchange 100.
GA-BPN	Genetic Algorithm based Back-Propagation Neural network
GDP	Gross Domestic Product
GNP-AC	Genetic Network Programming with Actor-Critic
GRNNs	Generalized Regression Neural Networks
HMM	Hidden Markov Models
HRBFN	Hybrid Radial Basis-Function recurrent Network
ISE	Istanbul Stock Exchange
KLCI	Kuala Lumpur Composite Index
KLSE	Kuala Lumpur Stock Exchange
KOSPI	Korea Composite Stock Price Index
KSPI	Korea Stock Price Index
LSD	Least Significant Difference
MAE	Mean Absolute Error
MAI	Market of Alternative Investment
MAPE	Mean Absolute Percentage Error
MLR	Minimum Loan Rate
MOGA	Mutation Only Genetic Algorithm
MOGP	Multi-Objective Genetic Programming
MRE	Mean Relative Error
MSE	Mean Square Error
MSPE	Mean Square Percentage Error
NASDAQ	the National Association of Securities Dealers Automated Quotations
NNs	Neural Networks
NYSE	New York Stock Exchange
PPO	Percentage Price Oscillator
PX-50	Prague Stock Exchange 50 Index
RMSE	Root Mean Square Error
ROC	Rate of Change
RSI	Relative Strength Index
RWH	Random Walk Hypothesis

SET	Stock Exchange of Thailand
SMA	Simple Moving Average
SSE	Sum Square Error
SVM	Support Vector Machine
S&P	Standard & Poor's
TAIFEX	Taiwan Futures Exchange
TAIEX	Taiwan stock Exchange
TDNN	Time Delay Neural Networks
WIG	Warszawski Indeks Gieldowy
WMA	Weighted Moving Average

CHAPTER 1
INTRODUCTION

This chapter is comprised of five sections. The first section introduces the background information and the following section includes the ideas which led to this research. The purpose of this study and explication of the research question will be found in the third section, while the fourth clarifies the contribution made to the field. The final section outlines the manner in which this thesis is organized.

1.1 Introduction

Predicting the performance of a stock market has been an ongoing research area of much interest since the 1990s. A symposium on neural networks and fuzzy logic for financial managers was arranged by Guido J. Deboeck in 1990 and John Loofbourrow presented evidence that these techniques were used in several financial institutes on Wall Street in that period (Deboeck, 1994). Recent work in stock market prediction include those of Fang and Ma (2009) where a Levenberg-Marquardt back-propagation algorithm was used to create a predictive model for short-term prediction of the Shanghai stock exchange market; and Tilakaratne, Mammadov and Morris (2007) described modified neural network algorithms to predict trading signals, whether it was best to buy, hold, or sell shares, of the Australian All Ordinaries Index. Martinez, da Hora, Palotti, Meira, and Pappa (2009) also developed a day-trading system that provides business decisions based on the outputs of an artificial neural network.

However, the issue of whether stock markets can be predicted still remains an ongoing debate. The group who believes that it is possible to predict includes Dr. Paul Werbos, a program director at the National Science Foundation and a past president of the International Neural Network Society, who stated by accounting for a variety of information, many patterns, time frames, and the thinking and behaviours of market traders, there is a possibility to trade in financial markets more wisely (Werbos, 1994, p. xii).

This is contrary to the opinions of those who subscribe to the Random Walk Hypothesis (RWH), believing that, at best, today's price is the most accurate predictor for tomorrow's. RWH states that stock market prices are not affected by their historical prices, they wander in a random manner and thus cannot be predicted. This group argues that it is pointless to apply techniques such as fundamental analysis or machine learning for finding profitable stock or for predicting trends in the market.

Another controversial paradigm in a similar vein is the Efficient Market Hypothesis (EMH) introduced by Eugene Fama in his research (Haugen, 2002). In fact, there is a consensus that RWH is explained by the EMH. The essence of the EMH is that the prices of securities are precisely reflected and determined by all relevant information (Bailey, 2005, p.64) and thus no undervalued stock exists. This hypothesis implies that buying securities is a game of chance and traders cannot beat markets that are efficient and current. However, this hypothesis contains questionable implicit assumptions, and, specifically, establishing which information is relevant for determining security prices is challenging (Bailey, 2005, p.64). Moreover, traders may be biased and may not access and analyse available information with equal efficiency (Haugen, 2002). Despite doubts raised by this hypothesis, progress in stock market predictions has been made in many research publications (Tilakaratne, 2004).

Prediction of stock indices has been an interesting, commercially significant and challenging issue for traders and academics. Techniques to predict stock markets have been widely developed, these relying on the quality of information used in different models; however, many uncertain and interrelated factors affect stock prices and their importance may change through time. Overall, stock markets are complicated and not fully understood. What is certain of all stock markets, however, is the unpredictability of returns. Much research has been carried out in terms of analysing their characteristics: complexity, non-linearity, non-stationary and chaotic, with the aim of better stock market predictions.

Methods for predicting stock markets can be categorised into four groups, namely fundamental analysis, technical analysis, time series analysis and machine learning. Economists may use fundamental and technical analyses. Fundamental analysis involves using leading economic indicators such as the gross domestic product

(GDP), consumer price index, interest rates and exchange rates ("The Stock Exchange of Thailand", 2007). However, each of these economists may interpret the significance of information quite differently.

Technical analysis involves plotting past data to identify trends and recurring patterns of stock prices to assist with future predictions. The data used are generally past open, closed, highest, and lowest prices and trading volume (Yao, Tan & Poh, 1999). Technical analysts basically use trading rules such as single moving trend, composite moving trend, and channel breakout (Deboeck, 1994). The channel breakout can be used as a guide for buying or selling. By using a price channel composing of a price line, a high price line and a low price line, the channel breakout occurs when the price line crosses the high or low price lines ("Price channels," 2009). However, the outcomes from technical analyses may not be robust as their statistical validity has not been confirmed (Yao et al., 1999). In addition, this approach may also be seen to be subjective as charts can be interpreted differently.

Owing to an ability to learn non-linear mappings between inputs and outputs, artificial neural networks (NNs) are one of the more popular machine learning methods used for predicting stock market prices (Egeli, Ozturan & Badur, 2003). Other techniques employed in predicting stock markets include fuzzy logic (Hiemstra, 1994), genetic algorithms (Lin, Cao, Wang, & Zhang, 2004) and Markov models (Hassan & Nath, 2005). Normally, a training set consisting of different types of historical data is used to obtain a predictive model which is then used for future prediction.

1.2 Problem in Context

Although no consensus has yet been reached for the controversial issue as to whether a stock market can be predicted, there are some well-known professional investors who have been very successful stock market traders. Examples include Warren Buffett, Peter Lynch and Bill Miller, who have succeeded in beating average stock market returns for long periods (Yan, 2007). It is hard to believe that their successes should only be credited to pure luck (Yan, 2007) and a common perception is that their success is due to their expertise in finding, understanding and analysing relevant investment information. Some investors believe that they too could reduce investment risks and outperform stock market returns, if they had similar skills to these professional investors. In addition, researchers are curious to find relevant patterns of information for analysing stock markets and for predicting the stock markets' behaviour. This has led to a significant increase in the number of studies in computational finance and/or intelligent finance.

Many techniques are employed to predict stock prices in stock markets worldwide, with researchers now applying artificial intelligence approaches to forecasting. For example, Wang (2003) applied a fuzzy stochastic method to predict stock prices; Lee (2004) used a hybrid radial basis-function recurrent network (HRBFN) for online stock forecasting; Pan, Zhang and Szeto (2005) applied a mutation only genetic algorithm (MOGA) to search for trading rules that would maximize profits. NNs are also regarded by many as one of the more suitable techniques for stock market forecasting (Hulme & Xu, 2001; Yao & Tan, 2001a), resulting in a significant number of studies since the 1980's (such as work of the following authors; Chen (1994); Komo, Chang, & Ko (1994); Pantazopoulos, Tsoukalas, Bourbakis, Brun, & Houstis, (1998); Resta (2000); Narain, & Narain (2002); Weckman, & Lakshminarayanan, (2003); Agarwala, Mclauchlan, & Weckman, (2004); Weckman, & Agarwala, (2004); Lakshminarayanan, Weckman, Snow, & Marvel, (2006); Nenortaite, & Simutis (2006)). Analysis of these published works showed that these are mainly focused on the US, and European international stock markets.

An increasing number of studies recently have focused on other stock markets. For example, Fang and Ma (2009) created a model for short-term prediction of the Shanghai stock exchange market; Tilakaratne, Mammadov and Morris (2007) described a study involving modified neural network algorithms to predict trading of the Australian All Ordinaries Index; Yao et al. (1999) analysed the Kuala Lumpur Stock Exchange (KLSE); Panda and Narasimhan (2006) carried out a study involving the Indian Stock Market; Wang (2009) evaluated his algorithm on the Taiwan Futures Exchange (TAIFEX) and Egeli et al. (2003) used NNs to predict the market index value of the Istanbul Stock Exchange. Hassan and Nath (2005) predicted the stock prices of Southwest Airlines, an American airline; Kim and Lee (2004) focused on prediction of the Korea Composite Stock Price Index (KOSPI); Meng (2008) carried out a project to detect trends of the Straits Times Index of the Singapore Stock Exchange; Chiu and Xu

(2002) focused their attention on the Hong Kong stock market; Kohara (2003) researched the prediction of Tokyo stock prices.

It may be seen from these studies that each stock market possessed unique characteristics. While information gained from other international stock markets may be useful in terms of forecasting returns in a specific market, it is equally important that studies are carried out to understand the unique characteristics of a stock market of interest and how it then relates to other international stock markets. The Stock Exchange of Thailand (SET) has yet to be studied extensively and research focused on the SET will contribute to understanding its unique characteristics and will lead to identifying relevant information to assist investment in this stock market.

While NNs have been demonstrated to be an effective technique for capturing dynamic non-linear relationships in stock markets, employing them for stock market prediction is a still challenging task (Tilakaratne, 2004) as it involves iterative processes of discovering and re-engineering knowledge, theoretical and data-driven modelling, data mining, and trial and error experimentation (Pan, Tilakaratne & Yearwood, 2003). Moreover, knowledge of appropriate neural network configurations for individual stock markets is very limited (Hulme & Xu, 2001). As mentioned earlier, stock markets have different characteristics, depending on the economies they are related to, and, varying from time to time, a number of non-trivial tasks have to be dealt with when developing NNs for predicting exchanges such as the SET. Given the decision to investigate the use of NNs, challenges include finding an appropriate neural network architecture, the selection of representative input vectors of features from the time series data of the market and the availability of sufficient data for training.

From the literature, multi-layer feed-forward NN with back-propagation is the most commonly used architecture in this area; however, the problem of determining the number of optimal hidden layers as well as the number of hidden nodes for each layer for the SET still needs to be addressed. Knowledge of appropriate neural network configurations for SET would be valuable: this also needs to be investigated and documented in order to increase the understanding of developing countries' stock markets and how to apply NNs to such stock markets. Such documented experiences can aid future applications of NNs in stock market prediction as definitive guidelines for deploying NNs have not yet been achieved. Erenshteyn, Foulds and Galuska (1994) stated that the application of NNs requires not only theoretical knowledge but also practical experience. They stated that the designing of suitable NNs is closely connected to the researcher's experience. In addition, stock market prediction has also involved the use of other algorithms such as genetic algorithms and recurrent networks: an important question one may ask is, Which approach will be more effective in terms of the SET?

In terms of understanding the unique characteristics of SET and how it relates to other international stock markets, appropriate indicators and input data to be used for training also need to be investigated. The input data could be raw data such as daily price or volume of stock and it can also consist of fundamental indicators and technical indicators. Kim and Han (2000) used 12 technical indicators, including momentum, rate of change, price oscillator and the direction of change in the daily stock price index. Vanstone, Finnie and Tan (2004) used 14 raw data inputs: price/earnings ratio, book value per share, return of shareholder equity, payout ratio, dividend yield, price to book ratio, total current assets, total gross debt, weighted average number of shares, current ratio, earnings per share, year end share price, ASX200 indicator (the indicator of the Australian Securities Exchange with an index of top 200 Australian companies listed by capitalisation) and AAA return proxy, when AAA refers to credit rating however, the authors did not provide detail about this input. Panda and Narasimhan (2006) used NNs to predict the Bombay Stock Exchange Sensitive Index returns. The authors used input nodes ranging from one to twenty with lagging values of a dependent variable of daily stock return. They found that the averages of root mean square errors (RMSE) mostly declined when the numbers of input nodes increase. In addition, they found that NNs outperformed linear autoregressive and random walk models in both training and testing data sets. NNs were also used to predict the Istanbul Stock Exchange (ISE) index (Egeli et al., 2003). The authors used data from the previous day of ISE national 100 index value, Turkish lira/US dollar exchange rate, simple interest rate weighted average overnight and five dummy variables to represent the five working days, Monday to Friday. They found that NNs provided better prediction than moving averages. Hassan and Nath (2005) predicted the stock prices of Southwest Airlines, an American airline, using a hidden Markov models (HMM) approach. Their investigation used opening, high, low, and closing prices as inputs. They found the results confirmed that there was potential in using HMM in time series forecasting. Lin et al. (2004) investigated the Australian Stock Exchange (ASX), using a trading rule with four parameters. They used a genetic algorithm to find sub-domains of each parameter. Then this algorithm was also used to find a near optimal combination of each stock. There is no consensus as to whether raw values or derived values such as changes in values of variables work better in terms of training NNs. In addition, no definitive rules as to the choice of inputs and outputs to be used for generating NNs for prediction are given in the literature. Zekic (1998) surveyed research and applications of NNs in a total of 184 articles and found that the number of input variables described in these articles ranged from 3 to 88 (Table 2, Zekic, 1998).

1.3 The Purpose of the Study

The main objective of this research is to develop approaches to predict the up or down movements of the next trading day of the SET index using an ensemble of NNs with a gating network. This research also aims to determine a set of the most influential and interrelated factors for the prediction of the SET, by investigating the use of international/external factors, internal factors and combinations of both of these groups in the training of NNs. In addition, this study explores appropriate neural network configurations, using the back-propagation method and genetic algorithm to train the NNs and to compare the performances of the resulting NNs in predicting the SET. An additional requirement is to investigate and compare the prediction performances of using only NNs to using an ensemble of NNs with a gating network. This gating network is used to combine the final prediction outcomes from the NNs. In summary, the project aims to address the following objectives:

- To investigate the process of generating NNs that can be used to predict the direction of movements of the SET index.
- To compare and to evaluate the performances of a neural network trained using a genetic algorithm with one trained using a back-propagation algorithm for predicting the direction of movements of the SET index
- To investigate using only international/external indicators, only internal indicators or both sets to train NNs and to evaluate and compare the resulting NNs in terms of their ability to predict the direction of movements of the SET index.

- To investigate and to develop an ensemble system for prediction of the direction of movements of the SET index and to compare the performance of this ensemble system with the performance of a back-propagation NN.

1.4 Contribution of this Study

Recently, a number of researchers have explored artificial intelligence techniques such as NNs to solve financial problems; these explorations appear to be promising for stock market predictions (Disorntetiwat, 2001). However, further research is needed to optimize the design and information associated with NNs for stock market forecasting, as any application of NNs to predict stock prices relies heavily on the unique characteristics of each stock market. A great deal of research on many different aspects of stock markets, including the application of NNs, has been carried out, but most has targeted the United States market (Pan et al., 2003). There have been limited attempts to research stock markets of developing economies such as Thailand (will be seen from the literature review chapter). Specifically, there is little evidence of existing artificial intelligence approaches which integrate NNs, with a synchronous gating network, to predict the movements of the SET index.

This study makes contributions in terms of the application of artificial intelligence techniques for SET prediction: first, the design of appropriate neural network architectures for the SET; second, the development of an ensemble system of NNs for prediction of the movements of the SET index and third, the list of interrelated indicators associated with the unique characteristics of the SET that can be used for its prediction. This study enhances the understanding of the Thai stock market.

This study extends the knowledge about appropriate neural network configurations for capturing information associated with predicting the SET. It investigated the use of different neural network architectures for predicting the SET, resulting in an increased knowledge about neural network configurations specifically addressing the characteristics of the SET. The outcomes of this study provide a guide to addressing issues such as the number of hidden layers and the number of hidden nodes as well as the activation function that can be used. Work in this study is important to other researchers working with the SET as only rules of thumb exist in the literature for determining suitable neural network configurations. The study also investigated the use of two training methods for NNs, back-propagation and genetic algorithms, and found that there is no significance differences in the performances of NNs trained via either methods. Given that training via genetic algorithm is a much slower process that training via back-propagation, it may be appropriate that training via back-propagation be a preferred option in future investigations.

In contrast to most existing work in predicting the SET using single neural networks, this study also developed a gating network to be used as an ensemble mechanism which combines the results of the three best neural networks for predicting the movement of the SET index. The gating network is composed of two layers with voting and dynamic gates in the first layer and an adaptive gate in the last layer. Experiments and analysis showed that the gating network is a better predictor of the directions of the movement of the SET index than any single neural network. The study provided insights as to the suitability of such gating system for predicting the movements of the SET index. The results and documented approach can be used as guidelines to future applications of neural networks for stock market prediction generally and the Thai stock market specifically.

This study also investigated the differing influences of three groups of factors, namely external factors, internal factors, and a combination of both, on the SET. One of the outcomes from this study is a list of factors influencing prediction of the SET. Analysis from this study demonstrated the effectiveness of different sets of indicators, combined as described above, for SET prediction. Existing studies (Khumyoo, 2000; Krabuansaeng 2003) have either only used some external factors or a combination of some external and technical factors for predicting the SET. To the knowledge of this author, this study is the first attempt to study the SET prediction in this manner, attempting to examine the influence of factors external to the SET versus those that are intrinsic of the SET. The results showed that the set of external/international factors, consisting of the Dow Jones index, the Hang Seng index, the Nikkei index, the minimum loan rate, the gold price and the exchange rate of the Thai baht and the US dollar; were better at predicting the SET in comparison with the set of internal factors which consisted of indicators derived from data associated with only the SET. This finding is interesting as it seems to confirm the practice of investors in developing countries such as the SET where often, their decisions in the stock market are very much influenced by the Dow Jones index, the Hang Seng index and the Nikkei index. Generally, investment involves risks; in order to make decisions in investment, investors have to select and analyse many investment-associated variables. Outcomes from this research may assist investors in SET. The information from this study may be used as a guideline for selecting relevant indicators associated with the SET, which in turn may help to lessen the degree of risks when making decisions about their investments.

All the elements mentioned above will contribute to the embryonic knowledge and the confidence of prospective researchers when approaching the general topic of stock market forecasting in developing countries. This study is but one step along the path towards applying NNs to the SET in order to clarify, explain and predict stock performances. Information may be accumulated, thereby enhancing the use of NNs in financial areas and research areas, and contributing incrementally to the slowly growing knowledge base of this experimental field. Additionally, this forecasting field will, in general, benefit from the further knowledge gained about the various strengths and weaknesses of particular NNs when specific training strategies and gating are applied.

1.5 Organisation of the Thesis

This thesis is composed of seven chapters. An introduction, the contribution to knowledge, the purposes of this thesis and the consequent research questions are contained in this chapter. The remainder of this thesis is structured thus:

- A review of the relevant literature, including the research areas of financial forecasting, genetic algorithms, NNs, and approaches which combine genetic algorithms and NNs, begins Chapter 2. Then follows a review of the techniques used in this study. A review of the application domain, the SET, is in the final section.

- Chapter 3 outlines the process to be employed, discusses the various factors which have the potential to influence the SET and their sources; including descriptions of calculation methods for the factors internal to the SET. A discussion of the pre-processing of data in terms of transforming and scaling as well as descriptions of the training, validating and testing data sets that will used are provided.

- Chapter 4 details neural network concepts and the different configurations to be investigated. The training algorithms, back-propagation and genetic algorithms, are described. Combinations of parameters and choices of the various associated values, for both the back-propagation algorithm and genetic algorithm as well as the results of parameter tuning are also provided.

- Chapter 5 consists of the details of investigations that involve comparing and evaluating the performance of NNs trained using genetic algorithms versus those using back-propagation algorithms. This chapter also describes the impact of number of hidden nodes on the performance of NNs to predict the SET index. In addition, it details the investigation of using only international/external indicators, only internal indicators or both sets of indicators to train NNs and to evaluate and compare the resulting NNs in terms of their ability to predict the SET index.

- Chapter 6 focuses on developing an ensemble system to combine three NNs to work together. An ensemble system which composed of three gates; the ranking gate, genetic gate and adaptive gate is described. Experimentation results, discussions and a summary are also provided.

- Chapter 7 provides the conclusion of the research findings which corresponds to the research objectives and suggestions for future works, which should be carried out to improve and strengthen the results of this research.

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CHAPTER 2
REVIEW OF LITERATURE

When individuals or organisations lack sufficient knowledge or information to enable them to plan future activities, analyses of expectations or forecasting are frequently involved. When it comes to financial matters, investors must develop plans in the face of several uncertainty factors, so that accuracy in forecasting becomes a very important issue. This chapter reviews relevant literature in the financial forecasting area and classifies it according to the forecasting techniques used: genetic algorithms, neural networks and the combination of genetic algorithms and neural networks. Related information about the SET, the application domain of this study, is examined.

2.1 Financial Forecasting

Financial forecasting models have become more sophisticated since Wuthrich et al. (1998) presented a study on daily stock market forecasting through the use of textual web data. They used a variety of sources of financial information such as *The Wall Street Journal*, *The Financial Times*, *Reuters*, *Dow Jones* and *Bloomberg*. These textual information sources contain news, financial analysis reports, and information about the situation in the world's stock, currency and bond markets. This textual information was weighted for use of specific keywords, the weights being used to generate probabilistic rules for a prediction model. These authors predicted five stock market indices but the results were inaccurate.

Other researchers have also used qualitative data for forecasting market trends. Peramunetilleke and Wong (2002) forecast intra-day currency exchange rate movements by weighting keywords in money market news headlines. Their prediction rules, when applied to the weighted data, produced a better outcome than random guessing. However, the data processing was challenging as not all sources were reliable and the meaning of text sections, containing the same keywords, may have differrences. The authors suggested that their technique might be incorporated into other numeric time series analyses to improve the accuracy of predictions.

Many authors have also used artificial intelligence techniques to analyse quantitative data for forecasting purposes, particularly in the financial intelligence field. Examples include Allen and Karjalainen (1999), Iba and Sasaki (1999), Pan et al. (2003), Phua et al. (2003), Rimcharoen, Sutivong and Chongstitvatana (2005). Hellstrom and Holmstrom (2000) developed a technique based on k-nearest-neighbours algorithms to predict trends of stock returns on the Swedish stock market. They found patterns for prediction in the real stock indices and, while the predictions were rather inaccurate, they could be improved if real rather than synthetic data were used. Wang (2003) forecast stock prices in real-time by applying a fuzzy stochastic prediction technique to the Taiwan stock exchange data. Over a one year period, the fuzzy stochastic technique produced more accurate prediction than the gray prediction technique (Wang, 2003).

2.2 Genetic Algorithms

Genetic algorithms are problem-solving techniques that can be applied to a wide range of problems including financial challenges such as portfolio optimization, bankruptcy prediction and stock forecasting. Allen and Karjalainen (1999) used them to evaluate different combinations of technical trading rules for predicting efficiency. They employed a genetic algorithm to identify trading rules evident in the daily prices of the Standard & Poor's 500 index (S&P 500 index) from 1928 to 1995, but these rules did not consistently lead to higher returns than a simple buy-and-hold strategy in out-of-sample test periods. However, the research stimulated work on improving research pathways within this field. In the same year, Iba and Sasaki (1999) applied genetic programming, a branch of genetic algorithms, to predict stock prices in the Japanese stock market. They attempted to make investments in the best stocks and to decide when to buy or sell. The authors concluded that decision rules derived by genetic programming yielded higher profits within this market simulation than a free neural network program from *Neural Networks at your Fingertips* developed by Karsten Kutza in 1996. However, the quality of the neural network program may have an influence on this comparison.

Similar to Allen and Karjalainen (1999), Badawy, Abdelazim and Darwish (2005) used genetic algorithms to select trading strategies from nine technical trading rules to maximise trading profit for the Egyptian stock market. The authors used data for the period from May 1999 to May 2005 from the Egyptian stock market. They reported that the genetic algorithm showed better results than the Sharpe Ratio technique, which was also called *Modern Portfolio Theory* (Badawy et al., 2005).

Pan et al. (2005) applied a mutation only genetic algorithm (MOGA) to Microsoft, Intel and Dell data from NASDAQ to search for trading rules that would maximize profits. They found that investment rules involving buying, selling, holding and swapping between two stocks outperformed investment rules involving a single stock. Moreover, MOGA was a more efficient tool than the traditional methods such as random walk, buy and hold or exhaustive search (Pan et al., 2005). Similarly, Rimcharoen et al. (2005) applied an adaptive evolution strategy method, which is an integration of genetic algorithms and evolution strategies, to assess whether the functional forms of five potential driving indicators (the Dow Jones index, Nikkei index, Hang Seng index, gold price, and minimum loan rate (MLR)) differed in their predictive value for the SET index. The authors also found their proposed method to be more efficient than a multiple regression method and that the best prediction strategy used both the Hang Seng index and the MLR.

In an analysis of construction stock trading, Lipinski (2007) also applied two evolutionary algorithms with a set of trading rules. He compared the use of the extended compact genetic algorithm (ECGA) with that of the Bayesian optimization algorithm (BOA) by conducting an experiment using real stock data from the Paris Stock Exchange over the period of July 28, 2000 to January 16, 2001. ECGA provided the best results when compared with the BOA and buy and hold strategies (Lipinski, 2007). However, the ECGA was time-consuming (Lipinski, 2007). Although the results from the BOA were marginally poorer, the author recommended it to be more suitable for real-time application than the ECGA.

In investigating stock trading rules, similar to works by Allen and Karjalainen (1999) and Badawy et al. (2005), Mabu, Chen, Hirasawa and Hu (2007) applied genetic network programming with actor-critic (GNP-AC) to the Tokyo Stock Market. The genetic network programming was regarded as an evolutionary algorithm and extended from genetic algorithm and genetic programming (Mabu et al., 2007). The genetic network programming represents solutions or individuals in graphs (Mabu et al., 2007). The actor-critic was a method combined to reinforce the learning processes of the genetic network programming (Mabu et al., 2007). The authors used data from 20 stocks over the period 2001-2004 to experiment with a stock trading model. The authors concluded that trading with their model was more profitable than employing the buy and hold strategy.

Focusing on expected return and risk of investment, Hassan (2008) used multi-objective genetic programming (MOGP) techniques for portfolio optimisation on United Kingdom for Financial Times Stock Exchange 100 (FTSE-100) stocks over the period January 2002 to December 2005. He found the solutions of MOGP to be non-linear models of financial indicators. The two conflicting goals of MOGP were to maximise return, which was the annualised average return, and to minimise risk which was the standard deviation of return (Hassan, 2008). He suggested that the MOGP was a suitable tool for evaluating the trade-off between risk and return from investments.

To find good strategies for portfolio management, Chang, Tsaur and Huang (2008) applied a genetic algorithm to create a model to allocate weights of investment on stocks to maximise investment return. By using data from 2006 and 2007, the authors reported that the yearly return from their model was better than that of the Taiwan stock exchange (TAIEX). Although the authors did not provide the comparisons of weekly returns from their model with that of the TAIEX, they claimed that a higher return could be obtained from their model.

In finding good combinations of inputs and parameter values for a support vector regression to explore stock market environments, Chiu and Chian (2010) combined a genetic algorithm together with support vector regression to explore the dynamics of stock markets from the United State of America, Singapore, Taiwan and Indonesia. A genetic algorithm was used to select technical indicators to be inputs for the support vector regression. In addition, this algorithm also chose parameter values for a kernel function of the support vector regression. They found that the dynamics of stock markets from Singapore, Taiwan and Indonesia were easier to inspect than those from the United State of America. They concluded from their empirical results that immature economic development countries shown less efficient markets.

2.3 Neural Networks

Neural networks are computer programs consisting of computing nodes and interconnections between nodes (Yao et al., 1999). They are recognised as effective tools for financial forecasting (Yao & Tan, 2001a) and can 'learn' from experience as do humans, cope with non-linear data, and deal with partially understood application domains, such as stock market behaviours. Moreover, the fundamental stock market indicators, gross domestic product, interest rate, gold prices and exchange rates and technical indicators, including closing prices, opening prices, highest prices and lowest prices, can be incorporated into neural networks to help improve predictive outputs (Yao et al., 1999).

2.3.1 Non-integrated Networks

Yao et al. (1999) applied a neural network model to relate technical indicators to future trends in the Kuala Lumpur Composite Index (KLCI) of Malaysian stocks. These authors attempted predictions without the use of extensive market data or knowledge. The technical indicators used as inputs for the neural network model included moving average, momentum and relative strength index (RSI) (Yao et al., 1999). Their experiment used many neural networks with the training method of back-propagation. However, they did not train the neural networks sufficiently nor use fundamental factors for their predictions. Therefore, the robustness of their model for prediction involving other time periods was found to be poor.

In working towards online stock forecasting, Lee (2004) introduced the iJADE stock advisor system which incorporated hybrid radial basis-function recurrent network (HRBFN). The author used prices for 33 major Hong Kong stocks over a ten year period for testing the iJADE stock advisor and structured the HRBFN into three layers; input, hidden, and output. The input layer comprised of two portions with the first being past network outputs, fed back into the network and governed by a decay factor, and the second involved factors related to the prediction problems (Lee, 2004). The author added a structural learning technique as a “forgetting” factor in the back-propagation algorithm and a “time different decay” facility within the network. When compared with other stock prediction models, the iJADE stock advisor produced promising results in terms of efficiency, accuracy and mobility (Lee, 2004).

Similarly, Pan et al. (2003) used neural networks to predict a stock market successfully. They employed neural networks to predict the Australian stock market index (AORD) and attempted to optimize the design as adaptive neural networks. The inputs were relative returns derived from basic factors of the Australian stock market, and inter-market influences on the Australian stock market. They found that a neural network with a hidden layer of two nodes achieved 80% accuracy for directional prediction. Tilakaratne (2004) had discovered a 6-day cycle in the Australian stock market. She also applied neural networks trained with a back-propagation algorithm to discover the optimal neural network architecture and the relative returns series of the open, high, low and closed prices in the Australian stock market. Her optimal neural network architecture comprised three layers; an input layer with 33 nodes, a hidden layer with 3 nodes and an output layer with 4 nodes. The best neural network developed in this study achieved accuracy of at least 81% when predicting the next-day direction of relative returns of open, low, high, and closed prices for the Australian stock market (Tilakaratne, 2004).

Jaruszewicz and Mandziuk (2004) attempted to predict the next day opening value of the Japanese NIKKEI index by developing a multilayered neural network which was structured into separate modules according to input data types. Technical data collected from Japanese, American and German stock markets were pre-processed to prepare them as inputs into the neural network. They found that, for a relatively stable period in the Japanese market (average NIKKEI index volatility of 0.96%) predictive efficiency was very high, with a prediction error of only 0.27%.

Based on companies listed on the Australian Stock Exchange during 2000-2004, Luu and Kennedy (2006) predicted performance using back-propagation neural networks. They measured company performance by using beta, market capitalisation, book to market ratio and standard deviation, finding that approximately sixty percent of companies were classified correctly. The authors also compared the performance of the back-propagation neural network with a support vector machine (SVM); however, the results from these two techniques were not significantly different.

To lessen risks, investors usually spread their investment over stocks in different sectors or industries. Abdelmouez, Hashem, Atiya and El-Gamal (2007) applied back-propagation neural networks and linear models, Box-Jenkins methods and multiple regression for stock sector predictions. They used data collected during the period January 1988 to July 2001 from American stock markets such as New York Stock Exchange (NYSE), American Stock Exchange (ASE), the National Association of Securities Dealers Automated Quotations (NASDAQ) and S&P500. They reported that the best results were achieved from back-propagation neural networks.

Focusing on central Europe stock markets, Barunik (2008) proposed an application to predict stock returns by using neural networks in the prediction tasks and using the Jarque-Bera, a statistical method, to test how the daily and weekly returns vary from the normal distribution. Data from Czech, Hungarian, German and Polish stock markets during the period from 1999 to 2006 were used (Barunik, 2008). He found the prediction accuracy achieved for the Prague Stock Exchange 50 Index (PX-50), Budapest Stock Exchange Index (BUX) and Deutscher Aktien Index (DAX) to be 60 percent for both daily and weekly analysis. However, the author reported that the prediction of the Warszawski Indeks Gieldowy (WIG) was not successful for the economic aspect.

To forecast stock prices of Iran Tractor Manufacturing Company, Omidi, Nourani and Jalili (2011) also used neural networks with a back-propagation algorithm. They designed special returns to be used as inputs. The return was computed by dividing price of day t by price of day t-1. By using a sliding window approach with a window size of 30 to the stock prices to be compute inputs, they fixed a neural network topology to 30-8-8-1. However, the authors did not provided detailed explanation of their result but they claimed that in analysing neural network simulation by using regression, their model was appropriate. In addition, Yixin and Zhang (2010) used three-layer neural networks to predict trends of the prices of 6 stocks trading in China's stock market. They assigned 21 inputs, three hidden nodes at a single hidden layer and one output node. Their experiment found that the trends of future prices of the 6 sample stocks were well predicted.

2.3.2 Integrated Networks (Committee machine)

To improve prediction performance of neural networks, several of their outputs can be used in an integrated manner to produce more accurate outputs (Jimenez, 1998). Derived from the concept of divide and conquer, complex problems can be divided into sub-problems, with each of these then being solved by a neural network (Sospedra, Espinosa & Redondo, 2006, pp.616-625). The group of neural networks is known as an ensemble or committee machine. The mechanisms for combining outputs of a group of neural networks can be of static or dynamic structure. Static structure does not involve input data to adjust outputs from individual neural networks in the combining process, while dynamic structure involves input data in that process (Tang, Lyu & King, 2003).

Su and Basu (2001) designed a committee machine to address the problem of image blurring. This was divided into sub-problems, each solved by an individual neural network. They developed a dynamic gating structure to combine outputs from neural networks. In comparison with a committee machine which has a static structure, the results from the committee machine with a dynamic gating structure, were found to be better.

The results from the Collopy and Armstrong's (1992) study showed that the concept of combining predictions to improve accuracy is supported by 83% of expert forecasters. The use of committee machines is a powerful application of this concept. Schwaerzel and Rosen (1997) used ensemble neural networks to forecast the exchange rates of the British pound, German mark, Japanese yen, and Swiss franc against the U.S. dollar. They reported that their ensemble neural network design resulted in a prediction error with a lower variance than those obtained from individual neural networks. Supporting the use of ensemble neural networks in forecasting stock markets, Disorntetiwat (2001) also published a dissertation on the utility and the effectiveness of ensemble neural networks in accurately forecasting ten global stock indices. He introduced a neural network model, which is comprised of multiple generalized regression neural networks (GRNNs) and a gating network to forecast the stock market indices of 10 countries. He concluded that the proposed model had shown promising results in forecasting the indices in all ten countries.

2.4 Combining Neural Networks and Genetic Algorithms

Genetic algorithms can be incorporated in neural networks for three different purposes: to handle the number of input variables needed for the problem at hand, to find the optimum network topology; and to train neural networks. Genetic algorithms can also be used to eliminate irrelevant input variables for neural networks. Kwon, Choi and Moon (2005) proposed a system called “a neural-genetic stock prediction system”, based on financial correlation between companies to forecast prices of 91 companies. The authors used genetic algorithms to select input variables for recurrent neural networks. They represented a chromosome in genetic algorithms in a one dimensional binary vector. The offspring created by genetic algorithms is a set of inputs for a recurrent neural network (Kwon et al., 2005). The investigation showed that this neural-genetic stock prediction system outperformed both the “buy-and-hold” strategy and a recurrent neural network (Kwon et al., 2005).

To develop optimum network architecture, Andreou, Georgopoulos and Likothanassis (2002) proposed a technique for combined genetic algorithms to evolve network structures which included the number of input nodes and the number of hidden nodes. This enabled irrelevant input variables to be eliminated during this process. Their technique was created to forecast the Greek Foreign Exchange-Rate Market for four major currencies: the U.S. dollar, the Deutsche mark, the French franc, and the British pound against the Greek drachma. They evaluated the performance of the mean relative error (MRE) and the size of the network, their strategy being quite successful in predicting the exchange rate one week ahead (Andreou et al., 2002). Kim, Shin and Park (2005) also applied genetic algorithms with the time delay neural networks to predict the Korea Stock Price Index200. They used genetic algorithms to find an optimum set of network architectural factors and time delays simultaneously. Compared with standard time delay neural networks and a recurrent neural network, this combined approach yielded more accurate predictions.

Instead of predicting of stock market indexes, Khan, Bandopadhyaya and Sharma (2008) investigated only stocks of the Tata Power Company trading on the Indian National Stock Exchange market. The authors applied a back-propagation neural network (BPN) and a genetic algorithm based back-propagation neural network (GA-BPN) to predict the stock prices each day. The authors used data from January 2004 to

December 2006 for the training data set and data from January 2007 to March 2007 for the testing data set. They claimed that the GA-BPN outperformed the BPN. However, little detailed technical insight into the combination of genetic algorithms and back-propagation neural networks was provided.

2.5 Issues in neural network construction

In applying neural networks, the essential background theory in mathematics was provided by Hornik, Stinchcombe and White's work (1989). The authors concluded that multilayer feed-forward neural networks were universal approximators. The authors also made a positive contribution by publishing other works related to the theory of universal approximation using multilayer feed-forward neural networks (Hornik, Stinchcombe, & White, 1990). Barunik (2008, p.361) inferred a conclusion from the theory of the universal approximation that "neural networks can approximate any function with finitely many discontinuities to arbitrary precision".

Since multilayer feed-forward neural networks are able to approximate any measurable function, Hornik et al. (1989) also suggested that the degree of success in neural network applications depended on the learning processes, the number of hidden nodes and relationships between inputs and targets.

In forecasting with neural networks, Yao and Tan (2001a) provided a guideline with seven steps: data pre-processing, input and output selection, sensitivity analysis to find more sensitive indicators on output, data organization, model construction, post analysis and model recommendation. Since designing neural networks is close to being an art (Erenshteyn et al., 1994), the training processes of neural networks also approximate to an art (Yao, 2002), there being no definitive guidelines for designing neural networks. The issues to consider when applying neural networks could be classified as in the following sections.

2.5.1 Input and output selection

Traditionally, changes in predicted targets have been major considerations for investment managers (Yao & Tan, 2001a), because changes in stock prices or stock indices affect the profits or returns on their portfolios.

In terms of inputs, Kaastra and Boyd (1996) suggested that choices of fundamental and technical factors from a single or several stock markets should be taken into researchers' considerations. Target or output may be sensitive to many inputs or factors, so the higher the sensitivity of inputs to output the better for neural network forecasting models (Yao & Tan, 2001a). Simply using all available data as inputs may not improve forecasting results (Yao & Tan, 2001a). Chaigusin, Chirathamjaree and Clayden (2008a) analysed factors influencing their targeted stock market, the SET. They then used those factors as the inputs for their neural network forecasting models in subsequent research (Chaigusin, Chirathamjaree & Clayden, 2008b). Promising forecasting results were achieved from their study. Therefore, the selection of inputs is seen to be related to the degree of success or failure of neural network models as recommended above in Hornik et al.'s (1989) study.

2.5.2 Data pre-processing

Generally, data are screened for missing attributes or outliers before their use. Theoretically, as universal approximators, multilayer feed-forward neural networks are able to find mappings or patterns between inputs and outputs without any pre-processing of the data used (Virili & Freisleben, 2000). Moreover, Kulahci, Ozer and Dogru (2006) also reported neural networks as being suitable for tasks with incomplete, insufficient or fuzzy data.

However, in the real world use of neural network applications, data pre-processing is recommended to enhance the performance of the applications (Virili & Freisleben, 2000), this notion being supported in the works of many other researchers (Kaastra & Boyd, 1996; Yao et al., 1999; Yao & Tan, 2001a; Yusof, 2005; Tsang et al., 2007; Abdelmouez et al., 2007; Chaigusin et al., 2008b). Basically, Deboeck and Cader (1994) recommended scaling all data before it is applied to neural network models.

2.5.3 Model construction

Apart from variable selection (see section 2.5.1), Kaastra and Boyd (1996) and Yao and Tan (2001a) identified certain issues in the neural networks paradigm. These included the number of hidden layers, the number of hidden nodes, the number of output nodes and the transfer functions. The numbers of output nodes can be determined by the target or output required. The following sub-sections will review the numbers of hidden layers, the number of hidden nodes and the transfer functions.

2.5.3.1 The number of hidden layers

Since no theoretical guidelines exist for designing the number of layers in neural network models, experience and trial and error techniques are usually applied. Yao and Tan (2001a) argued that bigger neural networks, in terms of the number of hidden layers and the number of hidden nodes, would not necessarily outperform smaller ones. On the other hand, Kaastra and Boyd (1996) recommended researchers to begin with a single hidden layer or two hidden layers.

Tan and Witting (1993) also applied neural networks with one hidden layer in their stock price prediction model. Yao et al. (1999) constructed both one hidden layer and two hidden layers neural networks to experiment with finding relationships between technical factors and the Kuala Lumpur Composite Index (KLCI). The two best neural network models they found were both of the two hidden layer neural network models (Yao et al., 1999). Kulahci et al. (2006) also applied neural networks with a single hidden layer to predict radioactivity in Hazar Lake. Similarly Tsang et al. (2007) applied a single hidden layer to the initial design of neural network models for the predictions of Hong Kong stock prices. Chaigusin et al. (2008b) applied neural network models with one, two and three hidden layers, finding that a neural network model with three hidden layers gave the best performance. However, comparing the performance between neural network models with two and three hidden layers respectively resulted in only slight differences. In this study, when computational resources are considered, the smaller neural network model may be preferable since it is computationally less expensive.

In addition, Fang and Ma (2009) concluded, in their stock market prediction study, that a three-layer back-propagation neural network model established had high prediction accuracy and good convergence speed. (Recall that a three-layer back-propagation neural network is composed of one input layer, one hidden layer and one output layer.) Apart from Fang and Ma (2009), Ahmad, Mat-Isa and Hussain (2010) used a genetic algorithm to select inputs for neural networks with a single hidden layer for the prediction of the sunspot index from the solar physics research department of the Royal Observatory of Belgium. In addition, for the forecasting of incidences of salmonellosis in humans, Permanasari, Rambli and Dominic (2010) designed a neural network model using a single hidden layer and reported that the results for the forecasting was highly accurate.

In summary, based on the literature, the number of hidden layers should begin with an initial neural network model having a single hidden layer (Kaastra & Boyd, 1996; Yao & Tan, 2001a). Then any number of hidden layers may be added in order to achieve the best or the most acceptable performance (Yao & Tan, 2001a). By this means, experimental processes were involved by adding the numbers of hidden layers and appraising the performance. These processes may not be satisfactory to the critics who want to know the reason why the numbers of hidden layers alter the performance. Similarly Yao and Tan (2001a, p.761) argued that, “A major disadvantage of NNs is that their forecasts seem to come from a black box. One cannot explain why the model made good predictions by examining the model parameters and structure.” However, by achieving their acceptable performance levels, neural networks seem to qualify for their utility and stand firm for their value in real-world applications (Berry & Linoff, 1997, p.288).

2.5.3.2 The number of hidden nodes

Designing the numbers of hidden nodes is also commonly based on trial and error techniques. Mjalli, Al-Asheh and Alfadala (2006, p.333) reported that “there is no way to determine the best number of hidden units without training several networks and estimating the generalisation error of each”. For example, Tan and Witting (1993) applied back-propagation neural networks with the initial numbers of nodes of 5-2-1, 5-5-1, 5-10-1, 10-5-1, 10-10-1 and 10-15-1. The first number in each configuration is the number of nodes in an input layer, the second and the third numbers are the number of nodes in a hidden layer and the number of nodes in an output layer respectively. In addition, Tsang et al. (2007) constructed a neural application called “NN5”. Their neural networks started with three layers: one input layer, one hidden layer and one output layer. There were eight input nodes and one output node with k number of hidden nodes when k was calculated from the product of the number of input nodes multiplied by a natural number, then minus that amount by one. Additional discussion on the number of hidden nodes required for this study is included in Chapter 3.

To organise their experiment, researchers may develop their process by altering the numbers of hidden nodes systematically, but there are insufficient explanations for the reason why altering the numbers of hidden nodes affects neural network performance. This may be one of the reasons for criticism of neural networks as black boxes. Basing their research on their experiences, trial and error, learning by doing, and the lack of formal guidelines, researchers have rarely focused on explaining why their neural network model works; rather they have focused on which models deliver the best performance to be used to solve the real-world problems. Kulahci et al. (2006), Abdelmouez et al. (2007), Chaigusin et al. (2008b) and Khan et al. (2008) reported mainly on the neural network models that they had used or that they found to be the best in their application domains.

2.5.3.3 Transfer functions

Transfer functions are also called activation functions. Neural networks have been applied in many instances. With learning by doing and the lack of guidelines to identify suitable transfer functions, researchers have mainly reported on the transfer functions they used. For example, Adya and Collopy (1998) reported that 18 out of 26 selected articles for their study used a sigmoid function. Yao and Tan (2001a) selected a hyperbolic tangent function as a transfer function in their study. Some studies may use different transfer functions in the different layers of the neural networks. For example, Tilakaratne, Mammadov and Morris (2007) applied a tan-sigmoid function to a hidden layer and used the linear transformation function on an output layer in a feed-forward neural network. Demut, Beale, and Hagan (2008), who wrote the *Neural network toolbox 6 user’s guide* for *Matlab*, used the tan-sigmoid or tansig as a default transfer function for hidden layers and used a linear transfer function as a default transfer function for an output layer.

To summarise, in the construction of neural network applications, researchers have been found to apply neural networks based on previous literature, experience, learning by doing and trial and error. Insights into neural network explanations, as provided in this literature review, may or may not satisfy some critics. However, one paper reviewed concluded with the argument that:

> Neural networks are best approached as black boxes with mysterious internal workings, as mysterious as the origins of our own consciousness. Like the Oracle at Delphi worshipped by the Greeks, the answers produced by neural networks are often correct. They have business value, in many cases a more important feature than explainability (Berry & Linoff, 1997, p.287).

2.5.4 Neural network validation

Liu and Yang (2005) advised that validation issues were generally related to the capability of neural network models to deal with data outside the training data set and the production of an acceptable forecasting performance. Their idea of the validating neural network models related to the generalisation from Kaastra and Boyd (1996). This generalisation is defined as "the idea that a model based on a sample of the data is suitable for forecasting the general population" (Kaastra & Boyd 1996, p.229). This appears to be the goal of using neural network models in real-world applications.

Researchers have sought guidelines for generalisation from neural network models. Two words, underfitting and overfitting, were used to describe two conditions of neural network models. Mjalli et al. (2006, p.333) defined underfitting as "the condition when a neural network that is not sufficiently complex fails to fully detect the signal in a complicated data set"; and overfitting as "the condition occurs when a network that is too complex may fit noise, in addition to signal" (p.333). Both underfitted and overfitted neural network models have lesser degrees of generalisation.

To achieve good performance or a higher degree of generalisation on neural network models, many researchers have sub-divided the data into three sets: training set, validation set and testing set. Such researchers have included Kaastra and Boyd (1996), Zhang, Patuwo, and Hu (1998), Yao and Tan (2001a), Yao and Tan (2001b), Kwon et al. (2005), Yusof (2005), Mjalli et al. (2006), Palmer, Montano and Sese (2006), Sospedra et al. (2006), Mabu et al. (2007), Abdelmouez et al. (2007) and Barunik (2008). The training set is used to create neural network models; the validation set is used to evaluate the models and then the models delivering the best performance are selected to be used, and the testing set to evaluate the true accuracy of predictions (Sarle, 2002). This method is also known as the hold out method (Bishop, 1995, as cited in Sarle, 2002). However, no precise rule has been found in the literature in terms of the sizes of training, validation and testing data sets that should be used (Kaastra, & Boyd, 1996; Zhang et al., 1998).

Since the main goal of prediction tasks is to gain results close to the target, there being no definitive rule for the construction of forecasting models, researchers have tried to adapt some methods facilitated by software or tools they have used or some ideas they have developed in their research. For example, the neural network toolbox in *Matlab* provides the number of epochs to be configured for the stopping of neural networks. This may permit experiments without a requirement for a validation data set. Some researchers have divided data into two sets, a training data set and a testing data set. They held the testing data set as unseen data for their models. They trained the models with the training data set and tested with the testing data set. Gan and Danai (1999), Jaruszewicz and Mandziuk (2004), Chaigusin et al. (2008b) and Khan et al. (2008) have used this approach. Some researchers divided data into more than two sets and sub-divided each set into a training set and a testing set. For example, Kim and Han (2000) divided a ten year data set of the Korea stock price index (KSPI) into ten sets before sub-dividing each set by two, a training data set and a hold out data set which was for testing. Generally the relevant economic information for the stock prices are provided every three or four months by governments and companies, so training using the incomplete full-year data set may cause the model to miss learning some patterns, even though the models have been generated via learning from ten data sets.

Besides the hold out method, other methods such as window-moving and cross validation have also been adapted to be used by some researchers. Kim et al. (2005) used the window-moving method in time delay neural networks (TDNN). The performances of their neural network models were not entirely successful and they recommended further research should be done for gaining more knowledge on the limitations of TDNN. Tsang et al. (2007) and Tilakaratne et al. (2007) also used the window-moving method in their studies. For these three studies, the authors did not compare the window-moving method with the other methods, as the performances of their models were influenced by many factors, such as the various selections of inputs in their domain applications, the numbers of hidden layers and the numbers of hidden nodes.

For the cross validation method, Luu and Kennedy (2006) compared the performances of neural network models with a 10–fold cross validation scheme and with a hold out method in the forecasting of the performances of Australian listed companies. They found that the best neural network model with hold out method achieved 58.7 percent accurate of prediction (Luu & Kennedy, 2006). The best neural network model with 10-fold cross validation delivered the best performance at 50 percent (Luu & Kennedy, 2006).

To summarise, almost all researchers used only one method rather than two or more methods for the validation of the models being employed. The accuracy or performance of the models may be influenced by many factors. It was difficult to decide which method, hold out or cross validation is a better method for prediction tasks. However, Luu & Kennedy (2006) have offered some useful advice for forecasting neural performance; suggesting that the hold out method is a more appropriate method in forecasting.

2.5.5 Training methods

Training is the process to produce, find or set the weights of nodes in a neural network in order to ensure the outputs from the neural network are as close as possible to the desired or actual results or target (Berry & Linoff, 1997, p.303). There are different methods for training neural networks, back-propagation being the most popular (Zhang et al., 1998). The genetic algorithm is also a possible alternative for training neural networks.

2.5.5.1 Back-propagation method

The most common method used for training neural networks is back-propagation, first introduced by John Hopfield (Berry& Linoff, 1997, p.303). The back-propagation concept generally follows three steps:

1. The network gets a training example and, using the existing weights in the network, it calculates the output or outputs for the example.

2. In the Back-propagation algorithm, the errors is then calculated by taking the difference between the calculated result and the expected result (actual result).

3. The error is fed back through the network and the weights adjusted to minimize the error (Berry& Linoff, 1997, p.304).

Neural networks with back-propagation method or back-propagation neural networks provide reasonable speed (Franklin, 2003), are straightforward (Yusof, 2005) and tend to deliver reasonable outputs or results for unseen data (MathWorks, 2009). Many forecasting investigations used neural networks which included back-propagation methods. Examples include Schwaerzel and Rosen (1997), Tkacz (2001), Jaruszewicz and Mandziuk (2004), Luu and Kennedy (2006), Mjalli et al. (2006), Abdelmouez et al. (2007) and Chaigusin et al. (2008b). However the main drawback of back-propagation neural networks is the likelihood of being trap in local optima (Berry& Linoff, 1997, p.305).

2.5.5.2 Genetic algorithm

Appearing in neural network commercial software (Erenshteyn et al., 1994; Berry & Linoff, 1997, p.306), and showing up in some text books such as *Data mining techniques* (Berry& Linoff, 1997) and *Neural network training using genetic algorithms* (Rooij, Jain & Johnson, 1996), the genetic algorithm is a competitive training algorithm for neural networks. Neural networks trained by back-propagation are prone to fall into local optima (Berry& Linoff, 1997, p.305). To prevent this situation and to find the global optima, genetic algorithms have become increasingly popular for training neural networks (Coupelon, n.d.; Berry& Linoff, 1997, p.305). Since genetic algorithms are a global random search technique (Peck & Dhawan, 1995), they provide a wide searching space on problems (Rooij et al., 1996, p.123). Berry and Linoff (1997, p.306) also asserted that neural networks trained by genetic algorithms delivered promising results.

In comparing neural networks, either trained with back-propagation method or with a genetic algorithm, Pendharkar and Rodger (1999) found that a neural network trained with a genetic algorithm delivered better prediction performance and has less tendencies in terms of the over-fitting problem. However, their experiment was conducted on simulation data sets only (Pendharkar & Rodger, 1999). In addition, researchers may adapt genetic algorithm to neural networks in many ways. For example, Kim and Han (2000) proposed SOGANN3 employ a genetic algorithm to optimize multiple factors of neural networks such as weights and the numbers of nodes simultaneously. They reported that the prediction result of the Korea Stock Price Index calculated from SOGANN3 was better than those from a neural network trained with back-propagation, a neural network trained with a genetic algorithm or a neural network with topological factors optimized by a genetic algorithm.

Although Rooij et al. (1996, p.123) confirmed that “there is a definite place for the genetic algorithms in neural network training”, genetic algorithms also have a drawback. When compared with the training process of neural networks using the back-propagation method, the training process of neural networks by using genetic algorithms is inherently slower (Rooij et al., 1996, p.124). However, if the training process operates with advanced computing processors, and not within real-time constraints, the slow speed problem of genetic algorithms in training neural networks may lessen. Additional discussion and design in the use of genetic algorithms to train neural networks will be provided in chapter 5.

2.6 Committee machine construction

The concept of committee machine has been reviewed (see 2.3.2). It is similar to decision making in real world situations by a committee, wherein commonality of opinions from the majority will be decisive in taking actions. To develop this concept within their proposed system of face recognition, Tang et al. (2003) divided the approaches or mechanisms of committee machines into two types: static structure and dynamic structure.

2.6.1 Static structure

In the static structure, once weights are assigned for each input to calculate the overall output, there is no mechanism involved to update the weights for each input dynamically. Schwaerzel and Rosen (1997) used a regression function to assemble their predictors. The most popular empirical mechanisms for this structure are average methods (Kadkhodaie-Ilkhchi, Rahimpour-Bonab & Rezaee, 2009). Generally, the three mechanisms used are as follow:

> **Majority vote**: after post-processing the outputs of the classifiers with the winner-take-all method, a majority vote is used to obtain the results of the ensemble. Ties, in the case of even Ensemble size, are broken arbitrarily using the base class. The base class is the class with the highest apriori probability in the learning set. This algorithm is appropriate for the classification problem.
>
> **Simple average**: $Output(t) \quad = \quad \frac{1}{n}\sum_{i=1}^{n} Output_i(t)$
>
> **Weighted Average**: $Output(t) \quad = \quad \frac{1}{n}\sum_{i=1}^{n} w_i\, Output_i(t)$
>
> where n denotes the size of the ensemble networks and w_i is the weight of each ensemble network output. (Disorntetiwat, 2001, p.36)

Besides the average methods above, Chen and Lin (2006) and Kadkhodaie-Ilkhchi et al. (2009) applied a genetic algorithm to derive weights on a committee machine. The disadvantage of the static structure is that weights for each result are fixed for all situations (Tang et al., 2003).

2.6.2 Dynamic structure

Dynamic structure refers to mechanisms that change the integration of results according to changes in situations. Tang et al. (2003) developed their weighting mechanism in a gating mechanism to assign weights dynamically in face recognition modules. They used the ratios of the numbers of correct recognition and the numbers of trials to dynamically adjust weights. This means the final results changed dynamically according to the performances of each recognition module. Disorntetiwat (2001, p.55) applied an updating weight mechanism dynamically on a gating network module. The gating module ranked fourteen neural network prediction models by sorting the mean square error of 5-day historical predictions. The results from the best three neural network prediction models were selected and the weights of 0.7, 0.2 and 0.1 for the first, second and third on the ranking respectively. These three best prediction results were used in the calculation of weighted average to produce the final results (Disorntetiwat, 2001, p.55).

2.7 Review of the Stock Exchange of Thailand

Every stock market, including the SET, has unique characteristics and positioning in the world economic system. Financial and statistical methods have been used previously to analyse the behaviours of the SET. Using the role model theory, Suwansiri (2002) investigated the relationship between stock returns and liquidity based on the weekly data of common stocks in SET from 1994 to 2001. The author's results showed that absolute stock return and size of the organisations were significant factors for determining liquidity.

To determine factors influencing the SET, Khumyoo (2000) applied regression specification for two periods of stock data; from January 1994 to December 1995 and from January 1997 to December 1999. The study found some differences in significant factors on stock prices between the two periods. However, there were five common significant factors: the Down Jones index, Hang Seng index, Nikkei index, interest rate, and gold price. Krabuansaeng (2003) also investigated factors determining investment in the SET, his findings supporting Khumyoo's (2000) findings in that the Down Jones index and interest rate affected the SET. However, his investigation also found that net purchase volume of foreign investment and the rate of return investment were significantly influential on investment in the SET. Other evidence supporting Khumyoo (2000) is provided by Rimcharoen et al. (2005), who concluded that the SET index could be reasonably predicted by the Hang Seng index and interest rate. Consequently, the common influential factor on the SET index from those studies was the interest rate.

In applying artificial intelligence methods to forecasting, Rimcharoen (2004) proposed adaptive evolution strategies to forecast the Thai baht exchange rate against the U.S. dollar, the bank deposit and the SET index. In his study, prediction functions were randomly generated and evolved via selection and mutation (Rimcharoen, 2004). The study showed the proposed method was able to formulate successfully a prediction function for each case with the resulting predictions yielding errors less than 5% in all cases (Rimcharoen, 2004). Similarly, Rimcharoen et al. (2005) employed an adaptive evolution strategy method, which was a combination of genetic algorithms and evolution strategies, to structure a predictive function for the SET index. The coefficient of the prediction function evolved through the influence of the adaptive evolution strategy method which led to successful prediction results with an error less than 3% (Rimcharoen et al., 2005). Their experiment was based on data over the two year period 2003 to 2004, and they did not provide prediction result for other time periods. Chaigusin et al. (2008a) suggested the six main factors influencing the Thai stock market. There are the Dow Jones index, Nikkei index, Hang Seng index, gold prices, minimum loan rate, and the value of the Thai baht. They then applied back-propagation neural networks to forecast the SET index in order to verify the suggestions of their earlier study (Chaigusin et al., 2008b). They used data over the period of 2003 to 2004, which was similar to the Rimcharoen et al. (2005) study, finding that the results of these experiments supported their proposal that six factors affected the SET index.

In the context of stock forecasting using intelligent techniques, many different studies have been carried out on various stock markets. However, very few studies have focused on the Stock Exchange of Thailand. One study has highlighted the usefulness of genetic algorithms when investigating the structure of a predictive function for the SET index. However, the challenges of predicting stock markets can differ with the years, with national or international crisis events, and simply how far forward predictions are made e.g. real time, next day, or next week. This study will address these challenges by using a new approach for predicting the SET. Specifically, no research has yet been published on using an ensemble of neural networks, with a gating network to predict the closing value of the SET index for the following day.

2.8 Summary

In accordance with techniques used, many empirical financial forecasting investigations have been reviewed in this chapter. Many of the techniques and combinations of techniques used were introduced such as genetic algorithms, neural networks, combinations of these and the committee machine. The Stock Exchange of Thailand (SET), an application domain in this study, has also been reviewed. In light of the literature in neural network constructions, many construction issues such as the numbers of inputs, of hidden layers and nodes, transfer functions, model validation and training methods, have been discussed. Those issues have not been resolved in the literature, and are open for new research into the accumulation and enhancement of information and knowledge in financial forecasting. This chapter showed that there is a place for this study in the use of neural networks with a gating network, or using a committee machine for the forecasting of the SET index, or hands-on, documented experiences in the financial forecasting arena.

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CHAPTER 5

INVESTIGATION INTO THE USE OF NEURAL NETWORKS FOR PREDICTING THE SET

This chapter describes investigations that involved: (1) comparing and evaluating the performance of neural networks trained using genetic algorithms versus those using back-propagation algorithms, (2) exploring the impact of number of hidden nodes on the performance of neural networks to predict the SET index and lastly (3) exploring the use of only international/external indicators, only internal indicators or both sets to train neural networks and to evaluate and compare the resulting neural networks in terms of their ability to predict the SET index. A summary of the results associated with these investigations will also be provided.

5.1 Comparing neural networks trained using a genetic algorithm versus those using a back-propagation algorithm

This section describes the investigation for comparing the performance of NNs trained using a back-propagation (BP) and a genetic algorithm (GA). The associated steps are outlined below. Parameter tuning was carried out for each of the NN architecture and the three best combinations of parameter values associated with the architecture is then selected. Each of these sets of parameters is then used with a training data set to train a NN. Using a set of test data, the trained NN is then used to predict the direction of movement (up or down) of the next trading day of the SET index. The process of training and testing is repeated ten times. Lastly, calculations for various statistics were carried out.

Procedure

For training method (BP or GA)

  For each architecture (total of 9)

    Parameter-tuning

    Select the three best combinations of parameter values associated with the architecture

For each of these 3 sets of parameter values

Repeat 10 times

Evaluate the performance of the corresponding NN on the test set

Record prediction results

End repeat

Calculate Statistics (average predictive performance of NN)

End (For each set of parameter values)

Calculate Statistics (average and Standard Deviation) of each architecture

End (For each architecture)

End (For training method)

t-test carried out for each architecture (2 sample groups: those trained via BP and those trained via GA)

Results

Tables 5.1 and 5.2 record the results associated with the performances of NNs trained using back-propagation and genetic algorithms respectively. For ease of reference, the second column list the top 3 sets of parameter values associated with each NN architecture and the column with the heading "Validation" showed the results obtained, from the parameter tuning phase. The predictive performance of the trained NN on the test data is shown in the column with the heading "Testing". This value is an average of the percentage of correct predictions made by the corresponding NN over 10 runs. The column "Avg prediction result" showed a value calculated for the average performance of each architecture on the test data and the corresponding standard deviation is shown in the column "stdev". Each of these values are calculated from 30 data points respectively.

Table 5.1: Results associated with NNs trained with the back-propagation algorithm

NN Architecture	Best 3 performing NNs based on the average of validation results	Validation (%)	Testing (%)	Avg prediction result	Stdev
7-4-1	learning rate: 0.25 momentum : 0.2 epoch : 1000	56.58	50.26	49.54	3.52

	learning rate: 0.5 momentum : 0. 2 epoch :500	56.07	47.52		
	learning rate: 0. 25 momentum : 0. 1 epoch : 1000	55.3	50.85		
7-7-1	learning rate: 0. 5 momentum : 0.2 epoch : 250	54.79	49.49	51.71	3.48
	learning rate: 0.5 momentum : 0.2 epoch : 500	54.79	53.08		
	learning rate: 0.125 momentum : 0.2 epoch : 250	54.53	52.56		
7-14-1	learning rate: 0. 5 momentum : 0.2 epoch : 1000	56.24	53.76	53.08	3.20
	learning rate: 0.125 momentum : 0.2 epoch : 1000	55.56	53.85		
	learning rate: 0. 25 momentum : 0. 2 epoch :500	55.47	51.62		
10-5-1	learning rate: 0.25 momentum : 0.2 epoch :500	51.88	47.61	47.75	2.74
	learning rate: 0.125 momentum : 0.2 epoch : 250	51.11	47.61		
	learning rate: 0.5 momentum : 0.2 epoch : 500	50.68	48.03		

10-10-1	learning rate: 0.5 momentum : 0.0 epoch : 1000	51.11	47.86	48.74	3.38
	learning rate: 0.5 momentum : 0.2 epoch : 250	51.03	49.57		
	learning rate: 0. 125 momentum : 0.2 epoch : 250	51.03	48.8		
10-20-1	learning rate: 0.25 momentum : 0.0 epoch : 1000	50.94	48.72	49.03	3.08
	learning rate: 0.125 momentum : 0.1 epoch : 500	50.43	48.46		
	learning rate: 0.5 momentum : 0.1 epoch : 250	50.34	49.91		
16-8-1	learning rate: 0.25 momentum : 0.2 epoch : 500	54.87	48.46	47.86	3.62
	learning rate: 0.25 momentum : 0.2 epoch : 250	53.85	48.29		
	learning rate: 0.125 momentum : 0.2 epoch : 1000	53.59	46.84		
16-16-1	learning rate: 0. 125 momentum : 0.2 epoch :500	54.27	47.01	46.13	2.94
	learning rate: 0. 25 momentum : 0.2 epoch : 1000	54.02	44.02		

	learning rate: 0. 5 momentum : 0. 1 epoch : 1000	53.42	47.35		
16-32-1	learning rate: 0.25 momentum : 0.1 epoch : 500	52.99	44.36	45.19	3.80
	learning rate: 0.5 momentum : 0.2 epoch : 500	52.74	45.56		
	learning rate: 0. 25 momentum : 0.2 epoch : 1000	52.56	45.64		

Table 5.2 shows the results from training NNs using genetic algorithms. For ease of reference, headings of columns have the same meaning as the column heading of table 5.1.

Table 5.2: Results associated with Neural Networks trained using a genetic algorithm

NN Architecture	Best 3 performing NNs based on the average of validation results	Validating (%)	Testing (%)	Average prediction result	Stdev
7-4-1	pop x gens:100 x 250 crossover: 0.6 mutation: 0.01	55.21	51.54	52.42	2.11
	pop x gens:50 x 200 crossover: 0.6 mutation: 0.05	53.68	52.91		
	pop x gens:50 x 200 crossover: 0.8 mutation: 0.01	53.25	52.82		
7-7-1	pop x gens:100 x 250 crossover: 0.8 mutation: 0.01	54.10	51.28	51.94	2.48

	pop x gens:100 x 250 crossover: 0.8 mutation: 0.05	53.76	51.97		
	pop x gens:100 x 250 crossover: 0.6 mutation: 0.01	53.59	52.56		
7-14-1	pop x gens:100 x 100 crossover: 0.6 mutation: 0.05	55.21	51.28	52.05	2.28
	pop x gens:50 x 500 crossover: 0.8 mutation: 0.01	54.53	52.48		
	pop x gens:100 x 250 crossover: 0.8 mutation: 0.05	53.76	52.39		
10-5-1	pop x gens:50 x 500 crossover: 0.8 mutation: 0.01	51.37	49.15	49.37	2.85
	pop x gens:25x1000 crossover: 0.6 mutation: 0.01	51.20	49.74		
	pop x gens:25x1000 crossover: 0.6 mutation: 0.05	50.94	49.23		
10-10-1	pop x gens:50 x 500 crossover: 0.6 mutation: 0.01	51.45	49.32	49.97	2.49
	pop x gens:50 x 200 crossover: 0.8 mutation: 0.05	50.94	50.60		
	pop x gens:50 x 500 crossover: 0.6 mutation: 0.05	50.94	50.00		
10-20-1	pop x gens:50 x 200 crossover: 0.8 mutation: 0.01	51.62	51.37	49.83	3.05

	pop x gens:100 x 250 crossover: 0.8 mutation: 0.01	51.20	49.06		
	pop x gens:50 x 500 crossover: 0.8 mutation: 0.01	51.03	49.06		
16-8-1	pop x gens:100 x 250 crossover: 0.8 mutation: 0.05	53.59	46.92	47.61	4.61
	pop x gens:100 x 100 crossover: 0.6 mutation: 0.01	53.42	49.49		
	pop x gens:100 x 100 crossover: 0.6 mutation: 0.05	52.65	46.41		
16-16-1	pop x gens:25x400 crossover: 0.6 mutation: 0.01	54.02	48.80	49	2.93
	pop x gens:100 x 250 crossover: 0.6 mutation: 0.01	53.85	49.06		
	pop x gens:50 x 200 crossover: 0.6, mutation: 0.01	52.82	49.15		
16-32-1	pop x gens:25x400 crossover: 0.8 mutation: 0.05	54.27	49.66	48.06	4.10
	pop x gens:100 x 250 crossover: 0.8 mutation: 0.05	53.33	49.23		
	pop x gens:100 x 100 crossover: 0.8 mutation: 0.05	53.25	45.30		

From Table 5.1 it can be seen that when the training algorithm is BP, the best prediction on the test set is obtained using the 7-14-1 neural network, with an average of 53.08%. The neural networks trained using 10 inputs (i.e. Data set II) and 16 inputs (Data set III) returned prediction results below 50% on the test data set. In terms of those trained using genetic algorithm (in Table 5.2), the 7-4-1 neural networks showed the highest average, 52.42%.

Analysis

The t-test is a common method used to compare the difference of means of two groups (Aczel and Sounderpandian, 2006). According to Sincich (1996) the sample size of 30 seem to be the cutoff point between small and large since the sample size of 30 seem to be smallest number for which the t value approximate the z value reasonably. For the case of large sample size, the z distribution is almost equivalent to the t distribution (Sincich, 1996). In addition, in testing population means, (Aczel and Sounderpandian, 2006) recommended the use of t-tests when the standard deviations are known for two samples and the distributions of both populations are normal.

In this study, an analysis using the t-test was carried out to see if the average performances of neural networks trained via back-propagation versus those trained via genetic algorithm is statistically different. In terms of carrying out the t-test, for each architecture, there are 30 data points associated with neural networks trained via back-propagation as one sample group and 30 data points for neural networks via genetic algorithm as the second sample group. Similar to other statistics, the distribution of the data set for t-test will approach the normal distribution as the sample size increases progressively from 30 upwards (Carroll, 2003; Arjomand, 2009; Waner & Costenoble, 1998; Kaiwan, 2003). While t-test also has the assumption that the variances of the two populations to be compared are approximately equal, empirical studies involving t-test have shown that this assumption maybe violated without substantial effect on the results if the number of data points in the two groups are the same (Smith, Gratz & Bousquet, 2009). Hypotheses to be tested are the following:

Null hypothesis $H_0 : \mu_1 = \mu_2$ (no difference between the means) and

Alternate hypothesis $H_1 : \mu_1 \neq \mu_2$

The standard deviation, σ, estimates from the sample. Two-tailed test for the significant level (alpha) of 0.05 is used to determine if the null hypothesis is to be accepted.

Equations used for t-test are as follow:

$$t = \frac{\overline{x_1} - \overline{x_2}}{\sqrt{s_p^2(\frac{1}{n_1} + \frac{1}{n_2})}}, \; when \;\; t \;\; has \;\; assumption \quad \sigma_1^2 = \sigma_2^2 \qquad 5.1$$

$$when\ s_p^2 = \frac{(n_1-1)s_1^2+(n_2-1)s_2^2}{n_1+n_2-2},\ t\quad has\ \ assumption\quad \sigma_1^2=\sigma_2^2$$
$$and\ df = n_1+n_2-2\ :(df=58\ ,\ t=2.0021)$$

For the 7-4-1 architecture, variances associated with the data set for back-propagation and that associated with the genetic algorithm NN are found to be not homogeneous by using F-test. Equations used for calculation of t-test for the 7-4-1 are as follow:

$$t = \frac{\overline{x_1}-\overline{x_2}}{\sqrt{(\frac{S_1^2}{n_1}+\frac{S_2^2}{n_2})}},\ when\ \ t\quad has\ \ assumption\quad \sigma_1^2 \neq \sigma_2^2 \qquad 5.2$$

$$when\ df = \frac{(\frac{S_1^2}{n_1}+\frac{S_2^2}{n_2})}{(\frac{(\frac{S_1^2}{n_1})^2}{n_1-1}+\frac{(\frac{S_1^2}{n_1})^2}{n_2-1})},\ \ t\quad has\ \ assumption\quad \sigma_1^2 \neq \sigma_2^2$$

Results for the analysis are shown in Table 5.3.

Table 5.3: Results of t-test to evaluate the predictive performance of NNs trained using BP and NNs trained using GA

NN Architecture	Average performance of the best 3 performing NNs trained with BP on the test data set	Standard Deviation BP	Average performance of the best 3 performing NNs trained with GA on the test data set	Standard Deviation GA	t-test	H0 (accept/ reject)
7-4-1	49.54	3.52	52.42	2.11	-3.84	reject
7-7-1	51.71	3.48	51.94	2.48	-0.29	accept
7-14-1	53.08	3.2	52.05	2.28	1.44	accept
10-5-1	47.75	2.74	49.37	2.85	-2.24	reject
10-10-1	48.74	3.38	49.97	2.49	-1.60	accept
10-20-1	49.03	3.08	49.83	3.05	-1.01	accept

16-8-1	47.86	3.62	47.61	4.61	0.23	accept
16-16-1	46.13	2.94	49	2.93	-3.79	reject
16-32-1	45.19	3.8	48.06	4.1	-2.81	reject

Discussion/summary

From Table 5.3, results for five architectures (7-7-1, 7-14-1, 10-10-1, 10-20-1 and 16-8-1) showed that the means is not statistically different when using two different training algorithms (back-propagation and genetic algorithms). However, the other four architectures showed that differences in their means are statistically significant when trained using different algorithms. Thus, there is no clear cut result as to which training algorithm produced neural networks that performed better (statistically – at significant level of 0.05). Out of the 9 architectures, the null hypothesis was rejected in 4 cases (i.e. the means of the 2 groups are considered statistically different) and in 5 cases it was accepted (i.e. the means of the 2 groups are NOT considered statistically different). From this analysis, the decision was to carry out the next two sets of experiments using both back-propagation and genetic algorithm for training the neural networks.

5.2 Investigate the impact of the number of hidden nodes on the performance of neural networks for predicting the SET

This section outlined the investigation to study the impact of the numbers of hidden nodes on the performance of NNs for predicting the SET. As discussed previously in Chapter 4, three configurations of the number of nodes in a hidden layer will be investigated. These categories are:

- Small (S): number of nodes =*floor*(number of inputs/2) + 1;
- Medium (M): number of nodes = number of inputs
- Large (L): number of nodes = 2*(number of inputs)

As seen in the steps outlined below, the training and testing procedures are the same as that described in section 5.1. Only the steps associated with the analysis differs. The prediction results are grouped into three data sets (S, M and L) on the basis of the number of hidden nodes (as shown above). The number of data points in each data set is

90 and on the basis of the Central Limit Theorem, they can be considered to approach a normal distribution (Carroll, 2003; Arjomand, 2009; Waner & Costenoble, 1998; Kaiwan, 2003). To evaluate if the average of correct predictions between the three groups are statistically different, the one-way ANOVA can be used when the variances of three groups are considered homogeneous. Levene's test is used to verify homogeneity of variances between the different groups.

In the case where the variances between different groups are not homogeneous, mathematical transformations of data such as square root and natural logarithm and logarithm based 10 were first applied. Next, the homogeneity of variance between the different groups is again verified before applying the one-way ANOVA. However, if the variances between different groups are still not homogeneous, the Kruskal-Wallis test, a nonparametric test similar to the one-way ANOVA, is then applied.

Procedure

For training method (BP or GA)

For each architecture (total of 9)

Parameter-tuning

Select the three best combinations of parameter values associated with the architecture

For each of these 3 sets of parameter values

Repeat 10 times

Evaluate the performance of the corresponding NN with on the test set

Record prediction results

End repeat

End (For each set of parameter values)

End (For each architecture)

Group data on the basis of the categories associated with the hidden nodes (S, M, L)

Calculate Statistics (average and Standard Deviation for each of the three categories)

Test for Homogeneity of Variance between the three groups

Carried out one way ANOVA or Kruskal-Wallis test

End (For training method)

Results of neural networks with small, medium, and large number of hidden nodes and trained via back-propagation

Based on information in section 5.1, it's hard to make a conclusion as to differences in performance of neural networks trained using back-propagation and those using genetic algorithms. Thus, this section shows results obtained from neural networks trained using those via back-propagation (BPNN) and those via genetic algorithms (GANN). Table 5.4 shows the performance of back-propagation NNs grouped on the basis of small, medium and large number of hidden nodes. For example, SBP1 consists of neural networks where the number of hidden nodes is approximately half the number of inputs. It can be seen that the averages of prediction performance of MBP2 and LBP3 are a bit better but further analysis needs to be conducted. In a similar way, Table 5.6 shows the performance of neural networks trained using a genetic algorithm and grouped in the same way.

Table 5.4: The performance of BPNNs with small, medium, and large category of hidden nodes

Group	NN Architecture	Average	Standard Deviation
SBP1	7-4-1	48.39	3.38
	10-5-1		
	16-8-1		
MBP2	7-7-1	48.86	3.97
	10-10-1		
	16-16-1		
LBP3	7-14-1	49.10	4.65
	10-20-1		
	16-32-1		

Analysis

The variances of the three groups (SBP1, MBP2, and LBP3) are found not to be homogeneous via the Levene's test that showed the p-value of 0.003 which is less than level significant of 0.05. Then mathematical transformations (square root, and natural logarithm and logarithm base 10) are applied to the 90 data points (averages) of each group; however variances between different groups after applying these mathematical transformations are still not homogeneous. Consequently, the one-way ANOVA should not be used. Then the Kruskas-Wallis test is used to test whether the samples of these three groups are from the same population at significant level of 0.05 using the hypotheses below.

In the Kruskas-Wallis test, the three sets of data points are assembled into a single set of size M and then each of the data points are ranked ordered from the smallest value (given a rank of one) to the highest (a rank of M and in this case M= 270). These resulting ranks are returned into their sample groups that they originally belong to. The Mean Rank of each group is then calculated and is shown in Table 5.5. The test statistic for the Kruskal-Wallis test is H statistic. The Kruskas-Wallis test has been described as an "analysis of variance by rank" and test whether the medians of the three groups are statistically different (did not come from the same population) at a significant level of 0.05.

Null Hypothesis $H_0 : all\ samples\ come\ from\ the\ same\ population$ and

Alternate Hypothesis $H_1 : all\ samples\ do\ not\ come\ from\ the\ same\ population$

SPSS was used to carry out the Kruskas-Wallis test and in SPSS, the H score is converted to a chi-square to obtain a *P* value. The test shows $\chi^2(2, N = 270) = 1.45$ and the p-value for H statistic is **0.49** which is larger than significant level of 0.05. The null hypothesis is accepted: all data from the three groups are from the same population. Consequently, there are no statistical differences in the prediction results from neural networks with either category of small, medium or large numbers of hidden nodes and trained using the back-propagation algorithm.

Table 5.5: The Mean Rank for each group associated with the Kruskas-Wallis test for BPNNs with categories of small, medium, and large number of hidden nodes

Group	N	Mean Rank
SBP1	90	127.93
MBP2	90	136.86

LBP3	90	141.71

Results for Neural networks with small, medium, and large number of hidden nodes and trained via Genetic Algorithm

In a similar way, NNs trained using a genetic algorithm are grouped into SGA1, MGA2 and LGA3 according the numbers of hidden nodes. Table 5.6 shows the performance of these NNs on the test data.

Table 5.6: The performance of GANNs with small, medium, and large category of hidden nodes

Group	NN Architecture	Average	Standard Deviation
SGA1	7-4-1	49.80	3.87
	10-5-1		
	16-8-1		
MGA2	7-7-1	50.30	2.88
	10-10-1		
	16-16-1		
LGA3	7-14-1	49.98	3.59
	10-20-1		
	16-32-1		

Analysis

Again, the homogeneity of the variances are tested using Levene's test, showing a p-value of 0.02 which is less than 0.05, consequently the one-way ANOVA should not be used. The Kruskal-Wallis test is used for determining if the samples are from the identical population at the significant level (alpha) of 0.05. This analysis has hypotheses as follow:

Null Hypothesis $H_0 : all\ samples\ come\ from\ the\ same\ population$ and

Alternate Hypothesis $H_1 : all\ samples\ do\ not\ come\ from\ the\ same\ population$

It was found that the p-value is **0.89** ($\chi^2(2, N=270)=0.22$) which is larger than 0.05. Thus, the null hypothesis is accepted. Consequently, all samples from three groups are from the identical population, implying that the medians of the three groups are not statistically different. The Mean Rank of each group is also shown in table 5.7.

Table 5.7: The Mean Rank for each group associated with the Kruskal-Wallis test for GANNs with categories of small, medium, and large number of hidden nodes

Group	N	Mean Rank
SGA1	90	133.38
MGA2	90	138.59
LGA3	90	134.52

Since the Kruskal-Wallis test does not make a distributional assumption, it is not as powerful as the ANOVA. The decision to use this test is due to the fact that the 3 groups do not have equal variances. However, in the literature, it is has been stated that the ANOVA is robust to violations of the equal-variance when the groups are of equal size (which is the case here, as each group has 90 data points). A decision was then made to also carry out the one way ANOVA on the 3 groups trained via back-propagation and via genetic algorithm respectively. The results associated with this analysis are shown below:

Null hypothesis $H_0 : \mu_1 = \mu_2 = \mu_3$ (no difference between the means) and

Alternate Hypothesis: $H_1 : H_0$ *is not true* .

Two-tailed test for significance and the significant level (alpha) of 0.05 is used to determine if the null hypothesis is to be accepted.

Table 5.8: The One-way ANOVA of the BPNNs with small, medium, and large sizes

Source of Variance(SOV)	degree of freedom	Sum Square (SS)	Mean Square (MS)	F-ratio
Between Groups (SBP1, MBP2 and LBP3)	2	23.69	11.85	0.73

The results from the One-way ANOVA associated with NNs trained via back-propagation are shown in the table 5.8. The F-ratio is found to be 0.73. Based on a significant level of 0.05, the number of degree of freedom for numerator is two and degree of freedom of denominator 267, the value of $F_{0.05\ (2,\ 267)}$ is 3.0333 which is more than 0.73. The hypothesis, $H_{0,}$ is true, and thus the means of the three groups are not statically different.

In terms of the one way ANOVA for NNs trained via genetic algorithm, Table 5.9 showed the results.The F-ratio is 0.48. However, the value of $F_{0.05(2,267)}$ is 3.0333, which is more than 0.48. Consequently, the hypothesis H_0 is true. Therefore, the means of the three groups are not statistically different.

Table 5.9: The One-way ANOVA of the GANNs with small, medium, and large sizes

Source of Variance(SOV)	degree of freedom	Sum Square (SS)	Mean Square (MS)	F-ratio
Between Groups (SGA1, MGA2 and LGA3)	2	11.70	5.85	0.48
Within Groups	267	3222.40	12.07	
Total	269	3234.10		

Further analysis involving the ANOVA confirmed the results obtained from the Kruskal-Wallis test.

Discussion/summary

Based on the results in this section, it can be seen that the results between NNs trained via back-propagation and those via genetic algorithm are consistent, namely, the categories of hidden nodes as determined in this study appear to have no impact on the predictive performance of NNs with these groups of hidden nodes respectively. As shown from the test results all sample from the three groups of NNs (and independent of the training algorithms) on the test data were found to be from the same population, in other words, the medians of these three groups are not statistically different. In the next section, the influences of inputs factors for training NNs for predicting the SET will be investigated.

5.3 Investigate the influence of different indicators for training Neural Networks and to evaluate and compare the resulting Neural Networks in terms of their ability to predict the SET index

This section outlined an investigation addressing one of the aims of this study, which is to examine the use of different groups of indicators to train NNs and then to evaluate and compare these resulting NNs in terms of their ability to predict the SET index. As described previously in Chapter 3, the set of 7 inputs are considered the set of 6 external factors (e.g. Dow Jones index, gold price) and the SET whereas the set of 10 inputs are calculated from attributes intrinsic to the SET. The set of 16 inputs comprised of the group of external and internal factors, i.e. a combination of the previous two sets.

The procedure used is very similar to that outlined in Section 5.2, except that the data associated with the predictive performance of the NNs on the test data is grouped differently. As shown in Table 5.10, results associated with all NNs trained using 7 inputs and back propagation are considered as belonging to one data set (BP1), similarly those trained with 10 inputs and 16 inputs are also grouped into their respective groups (BP2 and BP3). The analysis is then carried out using these three data sets. In the same way, NNs trained using a genetic algorithm and the different groups of indicators are categorised into GA1, GA2 and GA3 on the basis of the number of input factors, namely 7, 10 and 16 factors respectively.

Similar to the previous section, the one-way ANOVA is used to evaluate if the means of the predictive performance of the three groups on the test data are statistically different when the variances of the three groups are homogeneous, otherwise, the Kruskal-Wallis test is to be applied. Since there are 90 data points in each group, the data set can be considered to approach a normal distribution on the basis of the Central limit Theorem (Carroll, 2003; Arjomand, 2009; Waner & Costenoble, 1998; Kaiwan, 2003). However, the homogeneity of variances still needs to be tested using the Levene's test.

Results associated with back-propagation neural networks

Based on the three sets of inputs, the performances of the back-propagation NNs on test data are shown in table 5.10. The averages and standard deviation of each group are calculated from 90 data points. The value in the “Average” column is an average of the percentage of correct predictions made by the NNs trained using a specific set of inputs on the test data. For example, 51.44 is the average of the percentage of correct predictions made by the NNs trained using the set of 7 inputs (Data Set 1) on the test data. The results showed that the average performance of the group of NNs trained using the set of 7 inputs performed better than the other 2 groups of NNs.

Table 5.10: The predictive performance on the test data of BPNNs trained using each of the three sets of inputs

Group	NN Architecture	Average	Standard Deviation
BP1	7-4-1	51.44	3.67
	7-7-1		
	7-14-1		
BP2	10-5-1	48.51	3.09
	10-10-1		
	10-20-1		
BP3	16-8-1	46.39	3.61
	16-16-1		
	16-32-1		

The Levene's test is used to test for the homogeneity of variance and the results showed that the variances of three groups (BP1, BP2 and BP3) are homogenous with p-value = 0.85. The one-way ANOVA is then used to test if the means of three groups are statistically different using the hypotheses below:

Null Hypothesis: $H_0 : \mu_1 = \mu_2 = \mu_3$

Alternate Hypothesis: $H_1 : \mu_i \neq \mu_j \ ; \exists i \neq j$

Two-tailed test for significance and the significant level (alpha) of 0.05 is used to determine if the null hypothesis is to be accepted. The results from the one-way ANOVA are shown in a following table.

Table 5.11: The One-way ANOVA results of BPNNs associated with the three sets of inputs

Source of Variance(SOV)	Degree of Freedom	Sum Square (SS)	Mean Square (MS)	F-ratio
Between Groups (BP1, BP2 and BP3)	2	1159.02	579.51	48.19
Within Groups	267	3210.50	12.02	
Total	269			

The value of $F_{0.05(2,267)}$ is 3.03. From the results as shown in the table 5.11, the F-ratio is 48.19, more than 3.03. Consequently, H_0 is rejected, so there is at least one of means from the three groups of NNs which is statistically different from the others. After that the Least Significant Difference (LSD) and Tukey HSD are used for multiple comparisons of each pairs of the means of these three groups and the results shows each mean is statistically different from each other. The implication then is that the three groups of inputs have different impact in the SET index and the BP1 with 7 inputs is the best group of indicators to predict the movements of the SET index.

Results associated with neural networks trained via genetic algorithm

Similar to the previous section, NNs trained using a genetic algorithm and the different groups of indicators are categorised on the basis of the number of input factors into three groups, namely, GA1, GA2 and GA3. The performances of these 3 groups on the test data are shown in Table 5.12. Consistent with the results from NNs trained via back-propagation, the results here showed that the average performance of the group of NNs trained using the set of 7 inputs, with 52.14%, outperformed the other 2 groups of NNs.

Each of the group has 90 data points. To determine whether the one-way ANOVA or the Kruskal-Wallis test should be used to analyse, the homogeneity of variances between groups is tested via the Levene's test which results p-value of 0.00 (less than level significant of 0.05), consequently, the variances of GA1, GA2 and GA3 are not statistically homogenous. Thus, the Kruskal-Wallis test should be used in this analysis.

Table 5.12: The performance of GANN associated with the three sets of inputs

Group	NN Architecture	Average	Standard Deviation
GA1	7-4-1	52.14	2.28
	7-7-1		
	7-14-1		
GA2	10-5-1	49.72	2.78
	10-10-1		
	10-20-1		
GA3	16-8-1	48.22	3.94
	16-16-1		
	16-32-1		

The results from the Kruskal-Wallis test are shown in Table 5.13. The test for a significant level (alpha) of 0.05 is used to determine if the null hypothesis is to be accepted.

Null Hypothesis $H_0: all\ samples\ come\ from\ the\ same\ population$ and

Alternate Hypothesis $H_1: all\ samples\ do\ not\ come\ from\ the\ same\ population$

It was found that the p-value is **0.00** ($\chi^2(2, N=270) = 59.48$) which is less than 0.05. Thus, the null hypothesis is rejected and this implication is that at least one of the medians of three groups are statistically different from others.

Table 5.13: The Mean Rank from the Kruskal-Wallis test for GANNs associated with the three sets of inputs

Group	N	Mean Rank
GA1	90	184.93
GA2	90	123.82
GA3	90	97.76

Discussion/summary

From the results above, it can be seen that the group of NNs trained using the 7 inputs (group of 6 external factors and the SET) outperforms those trained using the set of 10 (internal factors) and the group of 16 (external and internal factors). This result is consistent for NNs trained using back-propagation and genetic algorithm and showed that the average predictive performances on the test data across the three groups of NNs are statistically different. The implication is that the group of 7 factors, namely,

x_1: the SET index

x_2: the Dow Jones index

x_3: the Hang Seng index

x_4: the Nikkei index

x_5: the Minimum Loan Rate (MLR)

x_6: the gold price

x_7: the exchange rate of the Thai baht and the US dollar

when used in training NNs, produced NNs that are better at predicting the SET.

The above analysis demonstrated the effectiveness of different sets of indicators, for SET prediction. Many existing studies (e.g. Khumyoo, 2000; Krabuansaeng 2003) have either only used some external factors or a combination of some external and technical factors for predicting the SET. However, this study has attempted to examine the influence of factors external to the SET versus those that are intrinsic of the SET, to ascertain which set can be used to train NNs that has a better performance in SET prediction.

The results also showed that NNs trained using 10 inputs outperformed those trained using 16 inputs. The expectation would have been the reverse as the latter consisted of the internal and external factors. It would be expected that if the group of 7 was" good" for training NNs then when it is included with the group of 10 inputs, the combination would have produced NNs that would be able to predict better than those trained with 10 inputs only. One possible explanation for this might be related to the process of parameter tuning. The process used in the study was to find a "*global*" set of parameters which as applied to all 9 architectures. Given that NNs with 16 inputs are more complex, the same set of parameter values might not work as well. Further investigation might be to do parameter tunning for each group (7, 10, 16 inputs) of NNs.

5.4 Summary

This chapter has described the investigations relating to three research questions. Section 5.1 described the study for comparing and evaluating the performance of NNs trained using genetic algorithms versus those using back-propagation algorithms. The experimentations and analysis showed that there is no clear cut result as to which training algorithm will produce NNs that performed better in terms of predicting the direction of movement of the SET. Section 5.2 described the process to explore the impact of number of hidden nodes on the performance of NNs to predict the SET index and the analysis indicated that there were no significant differences in terms of the three categories defined in the study. Lastly Section 5.3 outlined the study that looked at exploring the use of three sets of input factors (external indicators, only internal indicators or both) to train NNs and to evaluate and compare these resulting NNs in terms of their ability to predict the SET index. The analysis showed that NNs trained using the set of external indicators outperforms the others. The investigation involving the use of an ensemble system for predicting the movement of the SET index and the comparison of its performance with that of a single NN will be described in Chapter 6.

CHAPTER 7

CONCLUSION AND FUTURE WORKS

This chapter is comprised of two sections. The first section is the conclusion of the research findings which are corresponding to the research objectives. Some suggestions of further works, that should be carried out to improve and strengthen the results of this research, are also provided in the last section.

7.1 Conclusion

Prediction of stock markets has been an interesting and challenging issue. Neural networks have been used in many research attempts to predict the performance of stock markets. While neural networks have shown to be a good technique for stock market prediction, the understanding of the unique characteristic of the stock market of interest also influences the performances of the prediction. Moreover, the configurations of neural networks are significant in developing prediction approach, especially to each individual stock market. Besides single neural networks being used for predictions, the ensemble mechanism to combine prediction results from neural networks has been involving in the stock market prediction.

This research investigated the use of neural networks to predict the movement direction (up or down) of the next trading day of the SET index. The investigation involved experimenting with different neural network configurations for the SET, employed two training algorithms (back-propagation and genetic algorithms) and compared and analyse results from these experiments. To understand the unique characteristic of the SET, this study partitions selected indicators into groups; one group that consists of only international/external factors (deem to be factors beyond the control of the Thailand); a group consisting of only internal factors (based on calculations derived from the SET) and a combination of both groups. Lastly, this study also investigated the use of a gating network as an ensemble mechanism which combines the results of the three best neural networks for predicting the movement of the SET index.

This study has addressed the following aims:

- To investigate the process of generating NNs that can be used to predict the direction of movements of the SET index.
- To compare and to evaluate the performances of a neural network trained using a genetic algorithm with one trained using a back-propagation algorithm for predicting the direction of movements of the SET index
- To investigate using only international/external indicators, only internal indicators or both sets to train NNs and to evaluate and compare the resulting NNs in terms of their ability to predict the the direction of movements of the SET index.
- To investigate and to develop an ensemble system for prediction of the direction of movements of the SET index and to compare the performance of this ensemble system with the performance of a back-propagation NN.

To investigate the process of generating neural networks to predict the direction of movements of the SET index, the understanding of the SET and configurations of neural network have been carried out using relevant literature as the basis. The sixteen factors (the previous day SET index, the Dow Jones index, the Hang Seng index, the Nikkei index, the Minimum Loan Rate (MLR), the gold price, the exchange rate of the Thai baht and the US dollar, the volume of buying /selling of foreign investment, the Exponential Moving Average (EMA) over 20 days, the 5-daylag of the SET index, the Relative Strength Index (RSI), the Percentage Price Oscillator (PPO), the 5-day Disparity, the 10-day Disparity, the 20-day Standard deviation and the 15-day Rate of Change (ROC)) which influence the SET have been selected to be investigated. These factors are then grouped into three data sets, international/external indicators, only internal indicators or both sets, to study how they affect the SET. The investigation of these factors and gathering data to be used has been described in Chapter 3. The three sets of factors have been used to set the configurations of neural networks in terms of number of input nodes and hidden nodes. The numbers of hidden nodes are categorised into 3 groups, namely small (approximately half the number of input), medium (equal to the number of input) and large (double the number of input) respect to the numbers of input nodes. This leads to using nine neural network architectures as candidates in this study. Parameter tuning was then carried out so that comparisons made in experiments can be carried out in a "fair manner".

In parameter tuning, back-propagation and genetic algorithm have been used to train neural networks. With training via the back-propagation algorithm, the "tuned" parameters are learning rate with the observation values of 0.5 and 0.25 and 0.125, momentum of 0, 0.1 and 0.2 and epoch of 250, 500 and 1000. These are used to train the nine neural network architectures, resulting in 27 combinations to train neural network. For genetic algorithm training, main parameters (number of evaluations - population x generation, crossover rate and mutation rate) are tuned with their observation values (number of evaluations: 25x400=10000, 25x1000=25000, 50x200=10000, 50x500=25000, 100x100 = 10000 and 100x250=25000, crossover rate: 0.6 and 0.8, mutation rate: 0.01 and 0.05). These combine with nine neural network architectures to become 24 combinations for training neural network with genetic algorithm. This procedure has been described in Chapter 4.

In achieving the second and third aims, the nine neural network architectures with the two training algorithms along with their combinations from parameter tunning have been investigated in terms of the impact of training algorithms, categories of hidden nodes and three sets of inputs (only international/external indicators, only internal indicators, or both). The results of these investigations are described in Chapter 5.

To address the fourth aim of investigating and developing an ensemble system for prediction of the movements of the SET index and comparing the performance of this ensemble system with the performance of an individual neural network, the gating network has been described in Chapter 6. This gating network is used as an ensemble, incorporating the three best selected neural networks from experiments described in Chapter 5. The gating network composed of two layers with voting and dynamic gates in the first layer and an adaptive gate in the last layer. The outputs of the three best neural networks are passed forward from the first layer to the last layer to produce the outcome of predictions.

The research has presented the process of generating neural networks to predict the movement of the SET index. By means of generating nine architecture neural networks and with the aim of comparing and evaluating the performances of neural networks trained via back-propagation versus genetic algorithms, the results indicated that four out of nine architectures showed statistical differences in their prediction performances. However, the remaining five architectures showed that there are no statistical differences. These findings may not strengthen the assertion of Berry and Linoff (1997, p.306) in getting promising results of using genetic algorithm to train neural networks but it can be one evidence to support Rooij et al. (1996, p.123) in their confirming that the genetic algorithm is able to use as a training algorithm for neural networks.

With regards to only the number of hidden nodes, using categories of small, medium and large, these three groups of neural networks when trained by back-propagation, have shown that there are no statistical differences in their prediction performances. Similarly, the three groups of neural networks trained via genetic algorithm have also shown no statistical differences in performances between the three categories of hidden nodes. While on the basis of the proposed categories used in this study, there appears to have no impact, experiments involving finer granularity in terms of the number of hidden nodes may shed more information in terms of the influence of the numbers of hidden nodes in the use of neural networks. A limitation of this research is the use of only one hidden layer and only varying the number of hidden nodes in this layer. Increasing the number of hidden layers in a Neural Network may produce different results and as indicated in point 2 of section 7.2, further investigations should be carried out.

With regards to the influence of using different indicators for the prediction of the movements of the SET index, the neural networks are grouped according to indicators (external indicators, internal indicators and the combination of both internal/external indicators) used as input to the training. One of the aims is to examine the influence of the set consisting of only external factors versus the set consisting of only internal factors as well as a combination of both. With back-propagation, the three groups of neural networks show statistical differences of their prediction performances. Similarly, three groups of neural networks trained via genetic algorithm also show statistical differences in their prediction performances. The result shows that the indicators used in the prediction of the movements of the SET index influence the prediction performances and supports the findings of Khumyoo (2000), Rimcharoen et al. (2005) and Chaigusin et al. (2008a) in showing that some combinations of these external indicators influence the movements of the SET index. On the data set used in this study (2 years duration), neural networks trained using the set of external factors appears to perform better in predicting the SET in comparison to those trained using the other two sets of indicators. This set of external indicators consists of the Dow Jones index, the Hang Seng index, Nikkei index, Minimum Loan Rate (MLR), gold price, exchange rate of the Thai baht and the US dollar and the previous day SET index.

In real prediction tasks, more than one predictor can be used. With using ensemble neural networks, three neural networks are assembled to make predictions of the movements of the SET index. In comparing with using a single neural network, the ensemble neural network (by using a gating network as assembling manner) is better in the predictions. This finding supports Jimenez (1998)'s suggestion that to improve prediction performance of neural networks, several of their outputs can be used in an integrated manner to produce more accurate outputs. In addition, the finding of this research is similar to the finding of Schwaerzel and Rosen (1997) in getting better results when using ensemble neural networks to forecast the exchange rates of the British Pound, German Mark, Japanese Yen, and Swiss Franc against the US Dollar when comparing with using individual neural network. In addition, both the results of Disorntetiwat (2001)'s study in using ensemble neural networks for forecasting ten stock indices (e.g. S & P 500 index); and the results of this study in using ensemble neural network for predicting the SET index show support for the use of ensemble neural networks. These studies reinforce and promote the use of ensemble neural networks.

7.2 Future Works

This work is only one attempt of using neural network in the prediction of the movements of the SET index. More attempts should be carried out leading to improvements and reinforcements for the results of this research. Some points that possibly lead to further works include:

1. Stock markets are changing from time to time. This study use daily data from January 2003 to February 2005, composing of 780 data points which use the earliest 70% for training, the next 15% for validating and the latest 15% for testing as seen in Chapter 3. To strengthen the set of indicators influencing the SET index, applying the different time periods should be investigated. In addition, applying different sizes of the data points in training, validating and testing should be taken place.

2. Finding from section 5.3 suggests that the group of external factors (7 factors) is better in the prediction of the movement of the SET index, the group of internal factors, a group of 10 factors, did not perform as well as the group of 7 factors. The group of 16 factors performed the worst. Further investigation should be carried out to explore why the group of 16 factors did not do so well. If the reason for it not doing so well is "bad data", this group has the "good data" (the group of external factors) incorporated with "not so good data" (group of 10 internal factors) and so it should perform better than the group of 10 factors. However, it is not the case. Neural network with 16 inputs is also bigger, further work might be to investigate if the effect is due to the training as this study has carry out only one process of parameter tuning for all 3 groups (7, 10, 16 factors). Investigation of parameter tunning for each subgroup might be another venue of exploration. Further investigations should also be carried out to study the impact of increasing the number of hidden layers in a systematic manner to understand its impact on the performances of these neural networks for predicting the direction of movement of the SET.

3. Findings for the SET is that the group of external factors seems to be better for prediction the movements of the SET index, further work might be to look at other "developing market" like the SET to see whether/if they are also more influenced by external factors (rather than internal factors). Another thing might also do a study to compare a "mature market" against "developing market" using the same approach to see whether the mature market less influenced by external factors or not.

4. From parameter tunning in Chapter 4, this study use 24 sets of combinations of parameters values associated with the number of evaluations (population x generations), crossover rate and mutation rate for finding optimal values for training neural networks via genetic algorithm. These parameters could be assigned in different values to investigate how they may affect the performances of the resulting neural networks. In a similar way, the 27 sets of combinations of parameter values associated with momentums, learning rate, epoch of back-propagation neural networks could be investigated using

different values. This study has investigated the tuning of a subset of all parameters associated with back-propagation and genetic algorithm. Further exploration to improve the performance of neural networks in SET prediction may involve tuning those parameters that have not been investigated previously.

5. Findings in Chapter 6 are the results of using simple gating rules, further investigation might focus on the use complex rules as well as to explore other strategies such as using a combination of some rules and genetic algorithm for improving the performance of ensemble neural networks in SET prediction.

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Appendix A: The Best 5 for NNs trained by genetic algorithm

Architecture	Best combination	Training (%)	Validation (%)
7 - 4 - 1	pop x gens:100 x 250, crossover: 0.6, mutation: 0.01	61.81	55.21
	pop x gens:50 x 200, crossover: 0.6, mutation: 0.05	61.21	53.68
	pop x gens:50 x 200, crossover: 0.8, mutation: 0.01	61.32	53.25
	pop x gens:50 x 500, crossover: 0.8, mutation: 0.05	61.54	53.25
	pop x gens:25 x 400, crossover: 0.6, mutation: 0.05	60.95	53.16
7 - 7 - 1	pop x gens:100 x 250, crossover: 0.8, mutation: 0.01	61.69	54.10
	pop x gens:100 x 250, crossover: 0.8, mutation: 0.05	61.81	53.76
	pop x gens:100 x 250, crossover: 0.6, mutation: 0.01	61.74	53.59
	pop x gens:25 x 1000, crossover: 0.8, mutation: 0.01	60.79	53.42
	pop x gens:25 x 400, crossover: 0.6, mutation: 0.01	61.14	53.16
7 - 14 - 1	pop x gens:100 x 100, crossover: 0.6, mutation: 0.05	62.33	55.21
	pop x gens:50 x 500, crossover: 0.8, mutation: 0.01	61.76	54.53
	pop x gens:100 x 250, crossover: 0.8, mutation: 0.05	62.03	53.76
	pop x gens:50 x 200, crossover: 0.6, mutation: 0.05	61.69	53.25

	pop x gens:50 x 500, crossover: 0.6, mutation: 0.05	61.63	53.08
10 - 5 - 1	pop x gens:50 x 500, crossover: 0.8, mutation: 0.01	62.55	51.37
	pop x gens:25 x 1000, crossover: 0.6, mutation: 0.01	62.53	51.20
	pop x gens:25 x 1000, crossover: 0.6, mutation: 0.05	62.51	50.94
	pop x gens:25 x 400, crossover: 0.6, mutation: 0.01	62.09	50.77
	pop x gens:50 x 200, crossover: 0.6, mutation: 0.01	62.56	50.68
10 - 10 - 1	pop x gens:50 x 500, crossover: 0.6, mutation: 0.01	62.84	51.45
	pop x gens:50 x 200, crossover: 0.8, mutation: 0.05	63.57	50.94
	pop x gens:50 x 500, crossover: 0.6, mutation: 0.05	63.5	50.94
	pop x gens:50 x 200, crossover: 0.6, mutation: 0.05	63.13	50.85
	pop x gens:25 x 1000, crossover: 0.8, mutation: 0.05	62.95	50.68
10 - 20 - 1	pop x gens:50 x 200, crossover: 0.8, mutation: 0.01	63.42	51.62
	pop x gens:100 x 250, crossover: 0.8, mutation: 0.01	63.61	51.20
	pop x gens:50 x 500, crossover: 0.8, mutation: 0.01	62.99	51.03
	pop x gens:100 x 250, crossover: 0.6, mutation: 0.05	63.63	50.68
	pop x gens:25 x 400, crossover: 0.8, mutation: 0.05	63.08	50.51
16 - 8 - 1	pop x gens:100x250, crossover: 0.8, mutation: 0.05	64.58	53.59

	pop x gens:100x100, crossover: 0.6, mutation: 0.01	64.56	53.42
	pop x gens:100x100, crossover: 0.6, mutation: 0.05	65.09	52.65
	pop x gens:100x250, crossover: 0.6, mutation: 0.01	64.40	52.31
	pop x gens:100x250, crossover: 0.8, mutation: 0.01	65.06	52.31
16 - 16 - 1	pop x gens:25 x 400, crossover: 0.6, mutation: 0.01	63.35	54.02
	pop x gens:100 x 250, crossover: 0.6, mutation: 0.01	64.76	53.85
	pop x gens:50 x 200, crossover: 0.6, mutation: 0.01	64.38	52.82
	pop x gens:25 x 1000, crossover: 0.6, mutation: 0.05	64.27	52.56
	pop x gens:50 x 500, crossover: 0.6, mutation: 0.01	63.79	52.48
16 - 32 - 1	pop x gens:25x400, crossover: 0.8, mutation: 0.05	64.31	54.27
	pop x gens:100x250, crossover: 0.8, mutation: 0.05	65.99	53.33
	pop x gens:100x100, crossover: 0.8, mutation: 0.05	66.32	53.25
	pop x gens:100x250, crossover: 0.8, mutation: 0.01	65.35	52.65
	pop x gens:100x250, crossover: 0.8, mutation: 0.01	65.17	52.31

Appendix B: The Best 5 for NNs trained by a back-propagation algorithm

Architecture	Best combination	Training (%)	Validation (%)
7 - 4 - 1	learning rate: 0.25 , momentum : 0.2 epoch : 1000	59.71	56.58
	learning rate: 0.5 , momentum : 0.2 epoch : 500	56.96	56.07
	learning rate: 0.25 , momentum : 0.1 epoch : 1000	56.65	55.30
	learning rate: 0.125 , momentum : 0.2 epoch : 1000	58.39	55.13
	learning rate: 0.125 , momentum : 0.2 epoch : 500	54.49	54.87
7 - 7 - 1	learning rate: 0.5 , momentum : 0.2 epoch: 250	57.45	54.79
	learning rate: 0.5 , momentum : 0.2 epoch: 500	59.76	54.79
	learning rate: 0.125 , momentum : 0.2 epoch: 250	59.08	54.53
	learning rate: 0.25 , momentum : 0.2 epoch: 1000	59.74	54.02
	learning rate: 0.25 , momentum : 0.1 epoch: 1000	55.02	53.85
7 - 14 - 1	learning rate: 0.5 , momentum : 0.2 epoch: 1000	61.81	56.24
	learning rate: 0.125 , momentum : 0.2 epoch: 1000	62.25	55.56
	learning rate: 0.25 , momentum : 0.2 epoch: 500	59.63	55.47
	learning rate: 0.5 , momentum : 0.2 epoch: 500	60.04	55.21

	learning rate: 0.25 , momentum : 0.2 epoch: 1000	60.48	54.87
10 - 5 - 1	learning rate: 0.25 , momentum : 0.2 epoch: 500	62.01	51.88
	learning rate: 0.125 , momentum : 0.2 epoch: 250	57	51.11
	learning rate: 0.5 , momentum : 0.2 epoch: 500	62.25	50.68
	learning rate: 0.125 , momentum : 0.1 epoch: 500	58.99	50.43
	learning rate: 0.5 , momentum : 0.0 epoch: 1000	59.32	50.34
10 - 10 - 1	learning rate: 0.5 , momentum : 0.0 epoch: 1000	62.14	51.11
	learning rate: 0.5 , momentum : 0.2 epoch: 250	61.74	51.03
	learning rate: 0.125 , momentum : 0.2 epoch: 250	61.17	51.03
	learning rate: 0.25 , momentum : 0.1 epoch: 1000	63.19	50.77
	learning rate: 0.5 , momentum : 0.1 epoch: 1000	62.55	50.09
10 - 20 - 1	learning rate: 0.25 , momentum : 0.0 epoch: 1000	60.75	50.94
	learning rate: 0.125 , momentum : 0.1 epoch: 500	59.08	50.43
	learning rate: 0.5 , momentum : 0.1 epoch: 250	59.95	50.34
	learning rate: 0.5 , momentum : 0.0 epoch: 500	57.58	50.09
	learning rate: 0.25 , momentum : 0.2 epoch: 500	61.30	50.00
16 - 8 - 1	learning rate: 0.25, momentum : 0.2, epoch: 500	65.11	54.87

	learning rate: 0.25, momentum : 0.2, epoch: 250	64.10	53.85
	learning rate: 0.125, momentum : 0.2, epoch: 1000	68.00	53.59
	learning rate: 0.5, momentum : 0.1, epoch: 250	56.83	53.50
	learning rate: 0.5, momentum : 0.2, epoch: 250	62.62	53.50
16 - 16 - 1	learning rate: 0.125, momentum : 0.2, epoch: 500	66.04	54.27
	learning rate: 0.25, momentum : 0.2, epoch: 1000	69.91	54.02
	learning rate: 0.5, momentum : 0.1, epoch: 1000	64.82	53.42
	learning rate: 0.25, momentum : 0.0, epoch: 250	61.47	53.42
	learning rate: 0.5, momentum : 0.0, epoch: 500	61.47	53.16
16 - 32 - 1	learning rate: 0.25, momentum : 0.1, epoch: 500	62.66	52.99
	learning rate: 0.5, momentum : 0.2, epoch: 500	64.27	52.74
	learning rate: 0.25, momentum : 0.2, epoch: 500	68.42	52.56
	learning rate: 0.5, momentum : 0.0, epoch: 500	61.48	52.39
	learning rate: 0.125, momentum : 0.0, epoch: 500	63.75	52.22

Appendix C: Daily Data

Date	SET	Move DJ (previous day)	Hang Seng	Nikkei	MLR	Gold Price	Exchange (Baht/USD)	Volume (buy/sell)
2 Jan 03	351.52	8601.6900	9365.5200	8578.9500	6.7500	7050.0000	43.2599	0.6100
3 Jan 03	357.23	8773.5700	9583.8500	8578.9500	6.7500	7050.0000	43.1860	1.0500
6 Jan 03	364.15	8740.5900	9665.9600	8713.3300	6.7500	7050.0000	42.9835	1.3700
7 Jan 03	365.51	8595.3100	9652.4000	8656.5000	6.7500	7000.0000	42.9104	1.7700
8 Jan 03	360.41	8776.1800	9688.2100	8517.8000	6.7500	6950.0000	42.9615	1.2100
9 Jan 03	358.76	8776.1800	9675.4100	8497.9300	6.7500	7050.0000	42.7878	0.9200
10 Jan 03	360.37	8785.9800	9675.4100	8497.9300	6.7500	7050.0000	42.8692	0.9600
13 Jan 03	364.05	8842.6200	9834.0800	8470.4500	6.7500	7050.0000	42.8859	0.8600
14 Jan 03	373.33	8723.1800	9796.3100	8553.0600	6.7500	7050.0000	42.8122	1.1300
15 Jan 03	371.82	8697.8700	9873.4900	8611.7500	6.7500	7050.0000	42.7326	1.4200
16 Jan 03	370.48	8586.7400	9743.2300	8609.1700	6.7500	7000.0000	42.7842	0.9400
17 Jan 03	367.16	8586.7400	9614.5900	8690.2500	6.7500	7100.0000	42.8358	1.3100
20 Jan 03	371.45	8442.9000	9552.0200	8558.8200	6.7500	7100.0000	42.9213	1.4100
21 Jan 03	375.91	8318.7300	9568.4700	8708.5800	6.7500	7100.0000	42.8965	1.7400
22 Jan 03	373.17	8369.4700	9560.2900	8611.0400	6.7500	7150.0000	42.8738	1.6400
23 Jan 03	376.56	8131.0100	9584.7000	8790.9200	6.7500	7250.0000	42.8545	1.1100
24 Jan 03	376.30	7989.5600	9460.6000	8731.6500	6.7500	7250.0000	42.7739	1.3900
27 Jan 03	370.80	8088.8400	9298.6700	8609.4700	6.7500	7300.0000	42.7378	1.1600
28 Jan 03	374.76	8110.7100	9325.6000	8525.3900	6.7500	7300.0000	42.7932	1.0700
29 Jan 03	369.69	7945.1300	9240.7900	8331.0800	6.7500	7300.0000	42.7230	1.2900
30 Jan 03	370.30	8053.8100	9240.7900	8316.8100	6.7500	7250.0000	42.8174	1.1100
31 Jan 03	370.01	8109.8198	9240.7900	8339.9400	6.7500	7350.0000	42.8626	0.8600
3 Feb 03	372.40	8013.2900	9240.7900	8500.7900	6.7500	7350.0000	42.8996	1.3300
4 Feb 03	373.37	7985.1802	9252.7100	8484.9004	6.7500	7450.0000	42.8617	1.2800
5 Feb 03	373.28	7929.2998	9180.4697	8549.8496	6.7500	7550.0000	42.7933	1.1200
6 Feb 03	379.10	7864.2300	9126.1504	8484.1904	6.7500	7400.0000	42.8683	0.9900
7 Feb 03	378.95	7920.1099	9150.9502	8448.1602	6.7500	7400.0000	42.9236	1.1600
10 Feb 03	375.48	7843.1099	9232.1396	8484.9297	6.7500	7450.0000	43.0870	1.0300
11 Feb 03	379.14	7758.1699	9194.9102	8484.9297	6.7500	7350.0000	43.1984	0.9300
12 Feb 03	380.26	7749.8701	9314.9004	8664.1699	6.7500	7300.0000	43.1255	1.2300
13 Feb 03	370.25	7908.7998	9173.4297	8599.6602	6.7500	7050.0000	43.0883	1.1000
14 Feb 03	368.71	7908.7998	9201.7598	8701.9199	6.7500	7150.0000	43.1049	0.6900
17 Feb 03	368.71	8041.1499	9383.6797	8771.8896	6.7500	7150.0000	43.1049	0.6900
18 Feb 03	370.45	8000.6001	9397.0498	8692.9697	6.7500	7000.0000	43.1943	1.0400
19 Feb 03	371.18	7914.9600	9427.6299	8678.4404	6.7500	6950.0000	43.0984	0.9000
20 Feb 03	364.42	8018.1099	9390.4805	8650.9199	6.7500	7050.0000	43.1011	0.7900
21 Feb 03	359.53	7858.2402	9250.8604	8513.5400	6.7500	7100.0000	42.9235	0.7300
24 Feb 03	362.09	7909.5000	9239.4697	8564.9502	6.7500	7100.0000	42.9507	0.9400
25 Feb 03	356.76	7806.9800	9148.4805	8360.4902	6.7500	7200.0000	42.8750	0.6900
26 Feb 03	356.02	7884.9902	9116.2803	8356.8096	6.7500	7100.0000	42.8447	0.7100
27 Feb 03	358.89	7891.0801	9134.2402	8359.3799	6.7500	7150.0000	42.7985	0.9300
28 Feb 03	361.32	7837.8599	9122.6602	8363.0400	6.7500	6950.0000	42.7668	0.7800
3 Mar 03	367.67	7704.8701	9268.7695	8490.4004	6.7500	7000.0000	42.8407	1.2400
4 Mar 03	364.55	7775.6001	9181.8896	8480.2197	6.7500	7000.0000	42.7509	0.9300
5 Mar 03	359.90	7673.9902	9109.1797	8472.6201	6.7500	7100.0000	42.6390	0.7100

6 Mar 03	358.96	7740.0298	8962.2598	8369.1504	6.7500	7100.0000	42.7488	0.8600
7 Mar 03	358.48	7568.1802	8907.0996	8144.1201	6.7500	7100.0000	42.7065	0.6800
10 Mar 03	353.29	7524.0601	8861.8701	8042.2598	6.5000	7050.0000	42.5726	0.6400
11 Mar 03	350.98	7552.0698	8859.9297	7862.4302	6.5000	7050.0000	42.5703	0.3600
12 Mar 03	352.44	7821.7500	8874.9902	7943.0400	6.5000	7000.0000	42.7007	0.7300
13 Mar 03	353.48	7859.7100	8787.4502	7868.5601	6.5000	6900.0000	42.8431	0.7700
14 Mar 03	358.24	8141.9199	8956.1699	8002.6899	6.5000	6700.0000	42.8625	1.2100
17 Mar 03	354.61	8194.2305	8804.1602	7871.6401	6.5000	6900.0000	42.7433	0.8200
18 Mar 03	362.85	8265.4502	9041.5098	7954.4600	6.5000	6800.0000	42.9379	1.0700
19 Mar 03	361.13	8286.5996	9158.5898	8051.0400	6.5000	6850.0000	43.0575	1.1700
20 Mar 03	364.24	8521.9697	9194.5596	8195.0498	6.5000	6750.0000	43.0874	1.1600
21 Mar 03	363.62	8214.6797	9179.1904	8195.0498	6.5000	6750.0000	43.0473	1.0100
24 Mar 03	361.28	8280.2305	9108.4502	8435.0703	6.5000	6650.0000	43.0999	1.1500
25 Mar 03	363.74	8229.8799	9062.1504	8238.7598	6.5000	6700.0000	42.9434	1.3900
26 Mar 03	368.14	8201.4502	9047.0898	8351.9199	6.5000	6650.0000	42.9884	1.1400
27 Mar 03	368.94	8145.7700	8872.3203	8368.6699	6.5000	6700.0000	42.9921	1.0300
28 Mar 03	369.53	7992.1300	8863.3600	8280.1600	6.5000	6650.0000	43.0566	0.8000
31 Mar 03	364.55	8069.8600	8634.4500	7972.7100	6.5000	6750.0000	43.0100	0.6500
1 Apr 03	362.22	8285.0600	8596.8900	7986.7200	6.5000	6800.0000	42.9617	0.6100
2 Apr 03	363.02	8240.3800	8706.1900	8069.8500	6.5000	6700.0000	42.9666	1.0600
3 Apr 03	365.12	8277.1500	8648.1600	8017.7500	6.5000	6650.0000	43.0464	0.9600
4 Apr 03	371.93	8300.4100	8822.4500	8074.1200	6.5000	6600.0000	43.2019	1.0800
7 Apr 03	371.93	8298.9200	8962.2100	8249.9800	6.5000	6550.0000	43.2019	1.0800
8 Apr 03	375.82	8197.9400	8806.6600	8131.4100	6.5000	6500.0000	43.2110	0.9700
9 Apr 03	376.20	8221.3300	8636.8500	8057.6100	6.5000	6550.0000	43.1078	0.8200
10 Apr 03	375.02	8203.4100	8625.7200	7980.1200	6.5000	6600.0000	43.0388	0.7700
11 Apr 03	383.36	8351.1000	8645.6500	7816.4900	6.5000	6600.0000	42.9656	0.8400
14 Apr 03	383.36	8402.3600	8533.5500	7752.1000	6.5000	6600.0000	42.9656	0.8400
15 Apr 03	383.36	8257.6100	8632.1000	7838.8300	6.5000	6600.0000	42.9656	0.8400
16 Apr 03	386.54	8337.6500	8675.1400	7879.4900	6.5000	6550.0000	43.0103	1.2200
17 Apr 03	384.63	8337.6500	8675.1400	7821.9000	6.5000	6550.0000	42.8513	0.8300
18 Apr 03	384.50	8328.9000	8675.1400	7874.5100	6.5000	6600.0000	42.8658	0.9400
21 Apr 03	385.50	8484.9900	8675.1400	7969.0800	6.5000	6600.0000	42.8173	0.9800
22 Apr 03	378.97	8515.6600	8571.9100	7790.4600	6.5000	6700.0000	42.8636	0.7500
23 Apr 03	375.39	8440.0400	8519.6000	7793.3800	6.5000	6700.0000	42.8321	0.6900
24 Apr 03	369.71	8306.3500	8442.1100	7854.5700	6.5000	6700.0000	42.8899	0.6400
25 Apr 03	368.53	8471.6100	8409.0100	7699.5000	6.5000	6700.0000	43.0005	0.5800
28 Apr 03	368.85	8502.9900	8435.0400	7699.5000	6.5000	6700.0000	43.0686	0.6700
29 Apr 03	372.92	8480.0898	8744.2200	7607.8800	6.5000	6700.0000	42.9661	1.1100
30 Apr 03	374.63	8454.2500	8717.2197	7831.4199	6.5000	6700.0000	42.9558	1.5900
1 May 03	374.63	8582.6800	8717.2197	7863.2900	6.5000	6700.0000	42.9558	1.5900
2 May 03	375.24	8531.5700	8808.1800	7907.1900	6.5000	6850.0000	42.8841	0.7200
5 May 03	375.24	8588.3600	8916.4900	7907.1900	6.5000	6850.0000	42.8841	0.7200
6 May 03	380.05	8560.6300	8889.2200	8083.5600	6.5000	6800.0000	42.7301	1.0800
7 May 03	379.45	8491.2200	8901.0500	8109.7700	6.5000	6850.0000	42.5985	1.0600
8 May 03	378.20	8604.6000	8901.0500	8031.5500	6.5000	6800.0000	42.5270	1.2500
9 May 03	384.32	8726.7300	9084.1600	8152.1600	6.5000	6900.0000	42.6565	0.9200
12 May 03	383.49	8679.2500	9155.5700	8221.1200	6.5000	6900.0000	42.4878	1.7000
13 May 03	386.79	8647.8200	9119.0400	8190.2600	6.5000	6950.0000	42.5201	1.4000
14 May 03	385.22	8713.1400	9103.6900	8244.9100	6.5000	6900.0000	42.4298	1.0000
15 May 03	385.22	8678.9700	9126.0700	8123.4000	6.5000	6900.0000	42.4298	1.0000
16 May 03	383.00	8493.3900	9093.1800	8117.2900	6.5000	6950.0000	42.2282	1.2000

19 May 03	379.03	8491.3600	9087.3700	8039.1300	6.5000	7050.0000	42.0820	0.8700
20 May 03	382.97	8516.4300	9050.4000	8059.4800	6.5000	7150.0000	42.1770	0.9600
21 May 03	387.37	8594.0200	9059.8000	8018.5100	6.5000	7200.0000	42.0052	1.6000
22 May 03	388.62	8601.3800	9131.4900	8051.6600	6.5000	7250.0000	42.1910	1.3700
23 May 03	395.52	8601.3800	9303.7300	8184.7600	6.5000	7200.0000	42.0419	1.4600
26 May 03	396.88	8781.3500	9492.7100	8227.3200	6.5000	7200.0000	41.8912	1.3500
27 May 03	400.69	8793.1200	9420.8100	8120.2400	6.5000	7200.0000	41.7749	1.2200
28 May 03	402.98	8711.1800	9510.6200	8234.1800	6.5000	7150.0000	41.8239	1.1400
29 May 03	403.40	8850.2600	9508.5500	8375.3600	6.5000	7100.0000	41.9189	1.5100
30 May 03	403.82	8897.8100	9487.3800	8424.5100	6.5000	7150.0000	41.8119	1.1000
2 Jun 03	404.78	8922.9500	9637.5300	8547.1700	6.5000	7100.0000	41.8573	1.3300
3 Jun 03	403.69	9038.9800	9662.8200	8564.4900	6.5000	7100.0000	41.6674	1.2500
4 Jun 03	412.68	9041.3000	9662.8200	8557.8600	6.5000	7100.0000	41.7469	1.4300
5 Jun 03	415.63	9062.7900	9639.0100	8657.2300	6.5000	7100.0000	41.7105	1.5200
6 Jun 03	418.21	8980.0000	9694.6300	8785.8700	6.5000	7100.0000	41.6346	1.0500
9 Jun 03	419.28	9054.8900	9733.5100	8822.7300	6.5000	7100.0000	41.8100	0.9400
10 Jun 03	424.05	9183.2200	9703.7200	8789.0900	6.5000	7050.0000	41.8100	1.0300
11 Jun 03	422.60	9196.5500	9662.0600	8890.3000	6.5000	6950.0000	41.9362	1.2100
12 Jun 03	431.73	9117.1200	9736.8400	8918.6000	6.5000	6950.0000	41.9035	1.5200
13 Jun 03	427.97	9318.9600	9855.6400	8980.6400	6.2500	6950.0000	41.7800	1.4800
16 Jun 03	429.75	9323.0200	9862.2800	8839.8300	6.2500	6950.0000	41.6464	1.0700
17 Jun 03	442.30	9293.7998	10030.3701	9033.0000	6.2500	7000.0000	41.6182	1.4000
18 Jun 03	446.20	9179.5300	9970.2998	9092.9697	6.2500	7050.0000	41.6345	1.6800
19 Jun 03	454.19	9200.7500	9980.1100	9110.5100	6.2500	7000.0000	41.7219	1.7000
20 Jun 03	452.66	9072.9500	9930.3100	9120.3900	6.2500	7000.0000	41.6759	1.1900
23 Jun 03	458.79	9109.8496	9734.2900	9137.1400	6.2500	7000.0000	41.6943	1.2300
24 Jun 03	450.02	9011.5300	9629.3496	8919.2598	5.7500	6900.0000	41.6715	0.9600
25 Jun 03	453.89	9079.0400	9628.9900	8932.2600	5.7500	6800.0000	41.6619	1.2600
26 Jun 03	459.34	8989.0500	9606.1100	8923.4100	5.7500	6800.0000	41.6188	1.2700
27 Jun 03	457.51	8985.4404	9657.2100	9104.0600	5.7500	6750.0000	41.8160	1.2800
30 Jun 03	461.82	9040.9502	9577.1201	9083.1104	5.7500	6800.0000	42.1177	0.9700
1 Jul 03	461.82	9142.8398	9577.1201	9278.4902	5.7500	6850.0000	42.1177	0.9700
2 Jul 03	477.73	9070.2100	9602.6201	9592.2402	5.7500	6900.0000	42.0499	1.3700
3 Jul 03	489.80	9070.2100	9646.1000	9624.8000	5.7500	6900.0000	41.9075	1.2900
4 Jul 03	495.72	9216.7900	9636.8100	9547.7300	5.7500	6900.0000	41.7699	0.9700
7 Jul 03	489.33	9223.0900	9892.4000	9795.1600	5.5000	6900.0000	41.6991	1.1000
8 Jul 03	496.64	9156.2100	9992.8700	9898.7200	5.5000	6800.0000	41.7345	1.0600
9 Jul 03	482.52	9036.0400	10027.4100	9990.9500	5.5000	6750.0000	41.7738	0.8200
10 Jul 03	474.28	9119.5898	9983.3100	9955.6200	5.5000	6750.0000	41.7695	1.1400
11 Jul 03	484.39	9177.1500	9911.5000	9635.3496	5.5000	6750.0000	41.7904	1.0400
14 Jul 03	484.39	9128.9700	10122.4000	9755.6300	5.5000	6750.0000	41.7904	1.0400
15 Jul 03	494.20	9094.5900	10135.5500	9751.0000	5.5000	6800.0000	41.6737	1.1600
16 Jul 03	503.19	9050.8203	10207.1700	9735.9700	5.5000	6700.0000	41.7461	1.0900
17 Jul 03	495.08	9188.1500	10096.7197	9498.8604	5.5000	6750.0000	41.7077	1.1000
18 Jul 03	493.04	9096.6900	10140.8400	9527.7305	5.5000	6750.0000	41.8042	0.7500
21 Jul 03	487.44	9158.4500	10102.8600	9527.7305	5.5000	6800.0000	41.7785	0.9900
22 Jul 03	488.58	9194.2402	10008.7100	9485.9700	5.5000	6900.0000	41.9070	0.8500
23 Jul 03	480.44	9112.5100	9900.5596	9615.3398	5.5000	6900.0000	41.9408	0.7900
24 Jul 03	478.90	9284.5700	9923.1400	9671.0000	5.5000	7050.0000	42.0288	0.6100
25 Jul 03	484.86	9266.5100	9939.2000	9648.0100	5.5000	7050.0000	42.0251	0.8800
28 Jul 03	480.48	9204.4600	10134.8800	9839.9100	5.5000	7050.0000	42.0200	1.1900
29 Jul 03	478.29	9200.0500	10198.6000	9834.3100	5.5000	7100.0000	42.1205	0.8000

30 Jul 03	474.90	9233.8000	10121.2200	9632.6600	5.5000	7100.0000	42.0712	0.9200
31 Jul 03	484.11	9153.9700	10134.8300	9563.2100	5.5000	7050.0000	42.0997	0.7700
1 Aug 03	491.54	9186.0400	10248.5996	9611.6699	5.5000	7000.0000	42.0920	1.3600
4 Aug 03	494.84	9036.3200	10183.1396	9452.7900	5.5000	6900.0000	42.0601	0.9900
5 Aug 03	489.99	9061.7402	10177.3800	9382.5800	5.5000	6900.0000	42.0871	0.9400
6 Aug 03	489.77	9126.4500	9987.5400	9323.9102	5.5000	6950.0000	42.1313	0.8700
7 Aug 03	498.38	9191.0900	9958.0500	9265.5600	5.5000	6950.0000	42.1246	1.2000
8 Aug 03	503.20	9217.3496	9945.2200	9327.5300	5.5000	6950.0000	41.9832	1.6100
11 Aug 03	513.19	9310.0600	10093.5400	9487.7998	5.5000	7000.0000	41.9614	1.4100
12 Aug 03	513.19	9271.7600	10184.1700	9564.8100	5.5000	7000.0000	41.9614	1.4100
13 Aug 03	525.15	9310.5600	10301.4700	9752.7500	5.5000	7000.0000	41.9277	1.3000
14 Aug 03	518.83	9321.6900	10374.0200	9913.4700	5.5000	7050.0000	41.8200	1.2000
15 Aug 03	519.04	9412.4500	10424.5596	9863.4697	5.5000	7100.0000	41.7349	1.0900
18 Aug 03	520.51	9428.9004	10525.0400	10032.9700	5.5000	7050.0000	41.7248	1.5400
19 Aug 03	525.94	9397.5100	10564.0596	10170.2305	5.5000	7000.0000	41.7097	1.2200
20 Aug 03	521.10	9423.6800	10475.3300	10292.0600	5.5000	7050.0000	41.7381	0.9800
21 Aug 03	530.21	9348.8700	10643.6300	10362.6900	5.5000	7100.0000	41.6828	1.1600
22 Aug 03	534.81	9317.6400	10760.7300	10281.1700	5.5000	7050.0000	41.6118	1.0700
25 Aug 03	529.53	9340.4500	10764.2200	10276.6400	5.5000	7050.0000	41.4668	0.7600
26 Aug 03	531.06	9333.7900	10753.9300	10332.5700	5.5000	7050.0000	41.4689	0.5700
27 Aug 03	525.82	9374.2100	10678.5498	10308.9902	5.5000	7050.0000	41.4188	0.7400
28 Aug 03	535.91	9415.8203	10760.1201	10225.2197	5.5000	7100.0000	41.2577	1.0100
29 Aug 03	537.71	9415.8203	10908.9902	10343.5498	5.5000	7100.0000	41.2875	1.1800
1 Sep 03	545.23	9523.2695	10903.4004	10670.1797	5.5000	7200.0000	41.1504	0.9700
2 Sep 03	541.90	9568.4600	10939.9404	10690.0801	5.5000	7200.0000	41.0892	1.1400
3 Sep 03	539.88	9587.9000	11102.3600	10715.6900	5.5000	7100.0000	41.0012	0.8600
4 Sep 03	545.43	9503.3398	11138.6200	10646.9500	5.5000	7100.0000	40.8943	1.0900
5 Sep 03	557.81	9586.2900	11170.6104	10650.7695	5.5000	7150.0000	40.9618	1.1700
8 Sep 03	564.41	9507.2000	11165.2800	10683.7600	5.5000	7150.0000	40.8990	1.0100
9 Sep 03	557.55	9420.4600	11046.8200	10922.0400	5.5000	7150.0000	40.6878	1.0800
10 Sep 03	560.57	9459.7600	10810.3100	10856.3200	5.5000	7200.0000	40.5013	0.7200
11 Sep 03	561.66	9471.5498	10883.5195	10546.3301	5.5000	7200.0000	40.6175	0.7700
12 Sep 03	568.37	9448.8100	10883.5195	10712.8096	5.5000	7200.0000	40.9656	0.8900
15 Sep 03	566.54	9567.3398	10992.7305	10712.8096	5.5000	7150.0000	40.7554	1.0500
16 Sep 03	568.83	9545.6500	11071.3799	10887.0303	5.5000	7150.0000	40.6691	1.0100
17 Sep 03	558.70	9659.1300	11140.0500	10990.1100	5.5000	7100.0000	40.5746	1.1300
18 Sep 03	553.32	9644.8200	11069.2200	11033.3200	5.5000	7150.0000	40.7089	0.6300
19 Sep 03	567.21	9535.4100	10968.4200	10938.4200	5.5000	7150.0000	40.6223	0.7800
22 Sep 03	562.19	9576.0400	10873.2700	10475.1000	5.5000	7200.0000	40.1294	0.9900
23 Sep 03	566.13	9425.5100	10944.3600	10475.1000	5.5000	7250.0000	40.1575	0.7800
24 Sep 03	575.55	9343.9600	11295.8900	10502.2900	5.5000	7200.0000	40.1877	1.2600
25 Sep 03	576.68	9313.0800	11286.5200	10310.0400	5.5000	7250.0000	40.1925	0.9600
26 Sep 03	580.87	9380.2400	11290.1500	10318.4400	5.5000	7200.0000	40.2243	0.8800
29 Sep 03	580.93	9275.0600	11141.2800	10229.5700	5.5000	7150.0000	40.1499	0.6700
30 Sep 03	578.98	9469.2000	11229.8700	10219.0500	5.5000	7150.0000	40.0964	0.8700
1 Oct 03	569.75	9487.8000	11229.8700	10361.2400	5.5000	7200.0000	40.0032	0.7800
2 Oct 03	567.02	9572.3100	11546.1200	10593.5300	5.5000	7200.0000	39.8194	0.7400
3 Oct 03	558.34	9594.9800	11608.7200	10709.2900	5.5000	7200.0000	39.6512	0.8100
6 Oct 03	544.36	9654.6100	11734.4800	10740.1400	5.5000	6950.0000	39.7097	0.7400
7 Oct 03	544.39	9630.9000	11723.9200	10820.3300	5.5000	7000.0000	39.6654	0.9500
8 Oct 03	560.74	9680.0100	11720.8000	10542.2000	5.5000	7000.0000	39.3234	1.2600
9 Oct 03	573.63	9674.6800	11800.3700	10531.4400	5.5000	7000.0000	39.3838	1.1800

10 Oct 03	582.15	9764.3800	11935.8300	10786.0400	5.5000	6900.0000	39.3827	1.2400
13 Oct 03	578.59	9812.9800	11961.9700	10786.0400	5.5000	6900.0000	39.1729	0.8200
14 Oct 03	568.47	9803.0500	11856.0200	10966.4300	5.5000	6950.0000	39.7427	0.8400
15 Oct 03	576.10	9791.7200	12056.1800	10899.9500	5.5000	7050.0000	40.1290	0.7500
16 Oct 03	583.61	9721.7900	12027.5700	11025.1500	5.5000	7050.0000	39.9829	0.7600
17 Oct 03	588.60	9777.9400	12044.4900	11037.8900	5.5000	7000.0000	40.0124	0.8000
20 Oct 03	592.78	9747.6400	12147.8900	11161.7100	5.5000	7000.0000	39.9974	1.1600
21 Oct 03	593.02	9598.2400	12250.6900	11031.5200	5.5000	7000.0000	40.0585	0.9200
22 Oct 03	604.77	9613.1300	12238.6300	10889.6200	5.5000	7100.0000	40.0465	0.9000
23 Oct 03	604.77	9582.4600	11737.1800	10335.1600	5.5000	7100.0000	40.0465	0.9000
24 Oct 03	609.25	9608.1600	11736.3700	10335.7000	5.5000	7150.0000	39.9078	0.7000
27 Oct 03	615.68	9748.3100	11749.7200	10454.1200	5.5000	7200.0000	40.0136	0.9300
28 Oct 03	615.39	9774.5300	12091.8800	10561.0100	5.5000	7200.0000	40.0468	0.8400
29 Oct 03	624.06	9786.6100	12130.5100	10739.2200	5.5000	7150.0000	40.0579	0.9400
30 Oct 03	624.37	9801.1200	12143.3500	10695.5600	5.5000	7200.0000	40.0377	0.7600
31 Oct 03	639.45	9858.4600	12190.1000	10559.5900	5.5000	7200.0000	40.0217	0.9300
3 Nov 03	659.96	9838.8300	12386.8100	10559.5900	5.5000	7200.0000	40.0397	1.8500
4 Nov 03	665.06	9820.8300	12440.7200	10847.9700	5.5000	7100.0000	40.0286	1.1800
5 Nov 03	673.70	9856.9700	12438.9200	10837.5400	5.5000	7150.0000	39.9841	1.0700
6 Nov 03	667.54	9809.7900	12150.0900	10552.3000	5.5000	7150.0000	39.9726	0.6700
7 Nov 03	671.00	9756.5300	12215.1700	10628.9800	5.5000	7150.0000	40.0067	0.9000
10 Nov 03	664.36	9737.7900	12156.6800	10504.5400	5.5000	7150.0000	39.9882	0.5300
11 Nov 03	647.55	9848.8300	12003.6200	10207.0400	5.5000	7200.0000	39.9881	0.6500
12 Nov 03	653.49	9837.9400	11971.4800	10226.2200	5.5000	7250.0000	40.0182	0.6900
13 Nov 03	658.15	9768.6800	12227.5700	10337.6700	5.5000	7300.0000	40.0333	0.9700
14 Nov 03	657.38	9710.8300	12203.5300	10167.0600	5.5000	7300.0000	39.9979	0.7100
17 Nov 03	640.84	9624.1600	11997.0200	9786.8300	5.5000	7350.0000	39.9956	0.7000
18 Nov 03	636.75	9690.4600	12027.2600	9897.0500	5.5000	7350.0000	39.9973	0.3900
19 Nov 03	619.03	9619.4200	11872.9900	9614.6000	5.5000	7400.0000	40.0024	0.5400
20 Nov 03	614.23	9628.5300	11845.4100	9865.7000	5.5000	7350.0000	40.0070	0.4900
21 Nov 03	613.43	9747.7900	11839.8000	9852.8300	5.5000	7350.0000	40.0039	0.8300
24 Nov 03	605.29	9763.9400	11848.5600	9852.8300	5.5000	7400.0000	39.9871	0.9300
25 Nov 03	605.03	9779.5700	12008.0700	9960.2000	5.5000	7300.0000	39.9926	0.8300
26 Nov 03	630.82	9779.5700	12086.6700	10144.8300	5.5000	7300.0000	40.0199	0.8900
27 Nov 03	635.25	9782.4600	12075.9900	10163.3800	5.5000	7400.0000	39.9985	1.1900
28 Nov 03	646.03	9899.0500	12317.4700	10100.5700	5.5000	7350.0000	40.0256	1.2600
1 Dec 03	641.15	9853.6400	12456.9900	10403.2700	5.5000	7400.0000	40.0291	1.2100
2 Dec 03	646.64	9873.4200	12412.2300	10410.1500	5.5000	7450.0000	40.0120	1.2400
3 Dec 03	659.43	9930.8200	12361.1800	10326.3900	5.5000	7500.0000	40.0031	0.9200
4 Dec 03	659.29	9862.6800	12342.6500	10429.9900	5.5000	7500.0000	39.9983	0.9700
5 Dec 03	659.29	9965.2700	12314.7300	10373.4600	5.5000	7500.0000	39.9983	0.9700
8 Dec 03	664.36	9923.4200	12177.4400	10045.3400	5.5000	7550.0000	39.9840	0.8100
9 Dec 03	667.08	9921.8600	12393.6400	10124.2800	5.5000	7550.0000	39.9601	0.8800
10 Dec 03	667.08	10008.1600	12398.3800	9910.5600	5.5000	7600.0000	39.9601	0.8800
11 Dec 03	674.00	10042.1600	12554.5800	10075.1400	5.5000	7550.0000	39.8899	0.9600
12 Dec 03	674.45	10022.8200	12594.4200	10169.6600	5.5000	7550.0000	39.7900	0.9900
15 Dec 03	689.05	10129.5600	12520.1700	10490.7700	5.5000	7500.0000	39.7389	0.9800
16 Dec 03	691.88	10145.2600	12260.3300	10271.6000	5.5000	7550.0000	39.7513	0.9300
17 Dec 03	687.88	10248.0800	12193.1200	10092.6400	5.5000	7550.0000	39.7468	1.0100
18 Dec 03	700.93	10278.2200	12240.2500	10104.0000	5.5000	7600.0000	39.7653	0.9900
19 Dec 03	709.15	10338.0000	12371.7500	10284.5400	5.5000	7600.0000	39.7417	1.1200
22 Dec 03	718.33	10341.2600	12487.9900	10284.5400	5.5000	7600.0000	39.7451	0.9300

23 Dec 03	718.47	10305.1900	12420.5100	10284.5400	5.5000	7600.0000	39.7380	1.0600
24 Dec 03	723.39	10305.1900	12456.7000	10371.2700	5.5000	7600.0000	39.7389	0.9200
25 Dec 03	721.65	10324.6700	12456.7000	10365.3500	5.5000	7650.0000	39.6850	1.0700
26 Dec 03	734.89	10450.0000	12456.7000	10417.4100	5.5000	7650.0000	39.6676	1.1700
29 Dec 03	746.81	10425.0400	12464.2900	10500.6200	5.5000	7650.0000	39.6759	1.0400
30 Dec 03	764.23	10453.9200	12526.7400	10676.4600	5.5000	7700.0000	39.7043	1.0800
31 Dec 03	772.15	10409.8500	12575.9400	10676.4600	5.5000	7700.0000	39.7378	1.2400
2 Jan 04	772.15	10544.0700	12801.4800	10676.4600	5.5000	7700.0000	39.7378	1.2400
5 Jan 04	790.93	10538.6600	13005.3300	10825.1700	5.5000	7700.0000	39.4946	1.5300
6 Jan 04	769.68	10529.0300	13036.3200	10813.9900	5.5000	7750.0000	39.3230	0.9900
7 Jan 04	750.97	10592.4400	13157.6800	10757.8200	5.5000	7750.0000	39.1834	0.9500
8 Jan 04	773.55	10458.8900	13203.5900	10837.6500	5.5000	7700.0000	39.1226	1.4500
9 Jan 04	783.44	10485.1800	13385.8000	10965.0500	5.5000	7750.0000	39.1125	1.8900
12 Jan 04	794.01	10427.1800	13352.2200	10965.0500	5.5000	7800.0000	39.0420	1.0500
13 Jan 04	792.23	10538.3700	13396.6500	10849.6800	5.5000	7750.0000	38.9963	1.2800
14 Jan 04	790.84	10553.8500	13320.8800	10863.0000	5.5000	7750.0000	39.0352	0.9500
15 Jan 04	767.39	10600.5100	13249.8100	10665.1500	5.5000	7700.0000	39.1166	0.7000
16 Jan 04	778.44	10600.5100	13167.7600	10857.2000	5.5000	7500.0000	39.1066	0.8400
19 Jan 04	774.67	10528.6600	13253.3100	11036.3300	5.5000	7500.0000	39.1333	1.2500
20 Jan 04	771.88	10623.6200	13570.4300	11103.1000	5.5000	7500.0000	39.1589	2.0000
21 Jan 04	766.72	10623.1800	13750.5800	11002.3900	5.5000	7550.0000	39.1253	1.5000
22 Jan 04	760.17	10568.2900	13750.5800	11000.7000	5.5000	7550.0000	39.1249	1.0200
23 Jan 04	754.44	10702.5100	13750.5800	11069.0100	5.5000	7550.0000	39.1343	0.7500
26 Jan 04	725.56	10609.9200	13727.2700	10972.6000	5.5000	7500.0000	39.3293	1.0000
27 Jan 04	739.47	10468.3700	13761.8800	10928.0300	5.5000	7500.0000	39.3880	0.9000
28 Jan 04	722.14	10510.2900	13431.7800	10852.4700	5.5000	7500.0000	39.2214	0.9300
29 Jan 04	714.04	10488.0700	13334.0100	10779.4400	5.5000	7550.0000	39.3111	0.6100
30 Jan 04	698.90	10499.1800	13289.3700	10783.6100	5.5000	7400.0000	39.3765	0.8800
2 Feb 04	667.33	10505.1800	12999.9800	10776.7300	5.5000	7450.0000	39.3201	0.6900
3 Feb 04	699.75	10470.7400	13090.0100	10641.9200	5.5000	7400.0000	39.2924	1.0100
4 Feb 04	718.06	10495.5500	13086.7300	10447.2500	5.5000	7350.0000	39.1717	1.6600
5 Feb 04	734.55	10593.0300	13030.9400	10464.6000	5.5000	7350.0000	39.1438	0.8900
6 Feb 04	711.15	10579.0300	13309.6000	10460.9200	5.5000	7300.0000	39.1923	1.4900
9 Feb 04	732.05	10613.8500	13576.6800	10402.6100	5.5000	7400.0000	39.1305	1.1700
10 Feb 04	739.64	10737.7000	13515.6600	10365.4000	5.5000	7450.0000	39.1005	1.5900
11 Feb 04	753.24	10694.0700	13524.7600	10365.4000	5.5000	7450.0000	39.0295	1.0600
12 Feb 04	748.16	10627.8500	13625.1300	10459.2600	5.5000	7500.0000	38.9796	1.2000
13 Feb 04	755.18	10627.8500	13739.8000	10557.6900	5.5000	7500.0000	39.0385	1.4200
16 Feb 04	738.92	10714.8800	13831.5300	10548.7200	5.5000	7500.0000	39.0057	0.8400
17 Feb 04	748.83	10671.9900	13815.4400	10701.1300	5.5000	7550.0000	39.1207	0.7200
18 Feb 04	742.33	10664.7300	13928.3800	10676.8100	5.5000	7600.0000	39.1305	1.5400
19 Feb 04	732.97	10619.0300	13867.2200	10753.8000	5.5000	7550.0000	39.1893	0.8700
20 Feb 04	728.64	10609.6200	13868.3700	10720.6900	5.5000	7550.0000	39.2535	0.7100
23 Feb 04	724.86	10566.3700	13765.0700	10868.9600	5.5000	7400.0000	39.3693	0.9000
24 Feb 04	720.28	10601.6200	13756.4100	10644.1300	5.5000	7400.0000	39.3687	0.7900
25 Feb 04	704.65	10580.1400	13599.4700	10658.7300	5.5000	7450.0000	39.2924	0.8000
26 Feb 04	697.92	10583.9200	13674.6400	10815.2900	5.5000	7350.0000	39.3652	1.1100
27 Feb 04	716.30	10678.1400	13907.0300	11041.9200	5.5000	7350.0000	39.4223	1.0400
1 Mar 04	705.25	10591.4800	13918.6500	11271.1200	5.5000	7400.0000	39.3523	1.3300
2 Mar 04	701.75	10593.1100	13731.3500	11361.5100	5.5000	7400.0000	39.3728	1.2500
3 Mar 04	696.24	10588.0000	13454.0900	11351.9200	5.5000	7300.0000	39.4935	0.7500
4 Mar 04	700.59	10595.5500	13451.5600	11401.7900	5.5000	7300.0000	39.6078	0.6600

5 Mar 04	700.59	10529.4800	13454.7600	11537.2900	5.5000	7300.0000	39.6078	0.6600
8 Mar 04	704.46	10456.9600	13573.5400	11502.8600	5.5000	7400.0000	39.6166	0.9000
9 Mar 04	710.66	10296.8900	13397.2500	11532.0400	5.5000	7400.0000	39.4305	0.7400
10 Mar 04	705.29	10128.3800	13214.2000	11433.2400	5.5000	7450.0000	39.4815	0.7800
11 Mar 04	707.74	10240.0800	13024.0600	11297.0400	5.5000	7400.0000	39.5104	1.1500
12 Mar 04	695.08	10102.8900	12932.2300	11162.7500	5.5000	7450.0000	39.4945	0.6300
15 Mar 04	678.42	10184.6700	12919.4100	11317.9000	5.5000	7350.0000	39.5431	0.9500
16 Mar 04	669.80	10300.3000	12932.6200	11242.2900	5.5000	7400.0000	39.5901	0.6500
17 Mar 04	674.41	10295.7800	12975.7200	11436.8600	5.5000	7450.0000	39.5155	1.1700
18 Mar 04	687.19	10186.6000	12816.1900	11484.2800	5.5000	7500.0000	39.5418	1.3900
19 Mar 04	681.27	10064.7500	12790.5800	11418.5100	5.5000	7600.0000	39.4922	1.1300
22 Mar 04	681.34	10063.6400	12550.9100	11318.5100	5.5000	7600.0000	39.5858	0.9700
23 Mar 04	679.22	10048.2300	12588.3600	11281.0900	5.5000	7700.0000	39.5606	1.1500
24 Mar 04	677.61	10218.8200	12678.1300	11364.9900	5.5000	7700.0000	39.6020	1.0400
25 Mar 04	664.66	10212.9700	12520.2100	11530.9100	5.5000	7700.0000	39.6332	0.9500
26 Mar 04	665.25	10329.6300	12483.2400	11770.6500	5.5000	7700.0000	39.6667	0.7100
29 Mar 04	645.80	10381.7000	12427.3400	11718.2400	5.5000	7750.0000	39.6264	0.5200
30 Mar 04	649.21	10357.7000	12641.3900	11693.6800	5.5000	7750.0000	39.6617	1.8700
31 Mar 04	647.30	10373.3300	12681.6700	11715.3900	5.5000	7750.0000	39.5485	1.2700
1 Apr 04	671.92	10470.5900	12676.2500	11683.4200	5.5000	7800.0000	39.3085	1.1300
2 Apr 04	693.12	10558.3700	12731.7600	11815.9500	5.5000	7800.0000	39.2882	1.6400
5 Apr 04	709.89	10570.8100	12731.7600	11958.3200	5.5000	7700.0000	39.2246	2.1100
6 Apr 04	709.89	10480.1500	12886.9700	12079.7000	5.5000	7700.0000	39.2246	2.1100
7 Apr 04	698.82	10442.0300	12920.0500	12019.6200	5.5000	7700.0000	39.2374	1.0000
8 Apr 04	691.69	10442.0300	12909.3700	12092.5900	5.5000	7750.0000	39.1778	1.0700
9 Apr 04	691.39	10515.5600	12909.3700	11897.5100	5.5000	7750.0000	39.2511	1.1200
12 Apr 04	701.72	10381.2800	12909.3700	12042.7000	5.5000	7750.0000	39.2598	0.8700
13 Apr 04	701.72	10377.9500	13031.8100	12127.8200	5.5000	7750.0000	39.2598	0.8700
14 Apr 04	701.72	10397.4600	12669.8600	12098.1800	5.5000	7750.0000	39.2598	0.8700
15 Apr 04	701.72	10451.9700	12479.2600	11800.4000	5.5000	7750.0000	39.2598	0.8700
16 Apr 04	712.20	10437.8500	12458.3800	11824.5600	5.5000	7450.0000	39.5663	0.7900
19 Apr 04	704.65	10314.5000	12450.0000	11764.2100	5.5000	7500.0000	39.4231	1.0900
20 Apr 04	713.95	10317.2700	12394.3700	11952.2600	5.5000	7450.0000	39.4755	0.7600
21 Apr 04	706.65	10461.2000	12227.3000	11944.3000	5.5000	7350.0000	39.5849	0.8800
22 Apr 04	690.96	10472.8400	12167.7000	11980.1000	5.5000	7350.0000	39.7035	0.6100
23 Apr 04	681.88	10444.7300	12383.9400	12120.6600	5.5000	7400.0000	39.6988	0.4900
26 Apr 04	667.61	10478.1600	12132.6800	12163.8900	5.5000	7400.0000	39.6859	0.4900
27 Apr 04	680.89	10342.6000	12154.9100	12044.8800	5.5000	7450.0000	39.7221	0.6000
28 Apr 04	672.34	10272.2700	12165.3100	12004.2900	5.5000	7450.0000	39.8378	0.8800
29 Apr 04	656.38	10225.5700	12005.5800	12004.2900	5.5000	7250.0000	40.0128	0.4500
30 Apr 04	648.15	10314.0000	11942.9600	11761.7900	5.5000	7350.0000	40.0993	0.5000
3 May 04	648.15	10317.2000	11950.6200	11761.7900	5.5000	7350.0000	40.0993	0.5000
4 May 04	644.10	10310.9500	12098.3000	11761.7900	5.5000	7350.0000	40.0439	0.5600
5 May 04	644.10	10241.2600	11950.4600	11664.7600	5.5000	7350.0000	40.0439	0.5600
6 May 04	634.01	10117.3400	12010.3100	11571.3400	5.5000	7400.0000	39.8854	0.7700
7 May 04	636.80	9990.0200	11910.7600	11438.8200	5.5000	7350.0000	40.0641	0.3100
10 May 04	605.62	10019.4700	11485.5000	10884.7000	5.5000	7250.0000	40.4833	0.3900
11 May 04	618.10	10045.1600	11508.0900	10907.1800	5.5000	7300.0000	40.6902	0.4800
12 May 04	622.01	10010.7400	11528.1800	11153.5800	5.5000	7300.0000	40.6059	1.2900
13 May 04	611.23	10012.8700	11396.9400	10825.1000	5.5000	7300.0000	40.7438	0.7300
14 May 04	609.72	9906.9100	11276.8600	10849.6300	5.5000	7250.0000	40.9243	0.2900
17 May 04	581.61	9968.5100	10967.6500	10505.0500	5.5000	7300.0000	40.9032	0.5600

18 May 04	582.51	9937.7100	11072.3900	10711.0900	5.5000	7300.0000	40.9688	0.3900
19 May 04	614.99	9937.6400	11469.4100	10967.7400	5.5000	7300.0000	40.7972	0.9300
20 May 04	599.88	9966.7400	11339.6200	10862.0400	5.5000	7350.0000	40.8082	0.9600
21 May 04	615.41	9958.4300	11576.0100	11070.2500	5.5000	7350.0000	40.8975	0.9700
24 May 04	608.90	10117.6200	11662.9700	11101.6400	5.5000	7400.0000	40.8284	0.9600
25 May 04	601.51	10109.8900	11692.5600	10962.9300	5.5000	7400.0000	40.9085	0.7600
26 May 04	609.60	10205.2000	11692.5600	11152.0900	5.5000	7450.0000	40.8380	1.8300
27 May 04	630.72	10188.4500	11983.9000	11166.0300	5.5000	7450.0000	40.8258	1.1000
28 May 04	638.59	10188.4500	12116.8700	11309.5700	5.5000	7500.0000	40.6773	1.9200
31 May 04	641.05	10202.6500	12198.2400	11236.3700	5.5000	7450.0000	40.6118	1.1100
1 Jun 04	635.01	10262.9700	12105.5500	11296.7600	5.5000	7450.0000	40.6961	0.9900
2 Jun 04	635.01	10195.9100	12201.7500	11242.3400	5.5000	7450.0000	40.6961	0.9900
3 Jun 04	627.54	10242.8200	11929.9300	11027.0500	5.5000	7450.0000	40.7518	0.9200
4 Jun 04	626.47	10391.0800	12022.6400	11128.0500	5.5000	7400.0000	40.8176	0.6000
7 Jun 04	625.83	10432.5200	12326.8500	11439.9200	5.5000	7450.0000	40.6910	0.8700
8 Jun 04	611.46	10368.4400	12344.1600	11521.9300	5.5000	7500.0000	40.6542	1.0200
9 Jun 04	611.61	10410.1000	12339.9400	11449.7400	5.5000	7350.0000	40.6606	0.7900
10 Jun 04	612.21	10410.1000	12422.8700	11575.9700	5.5000	7350.0000	40.7339	0.7300
11 Jun 04	613.13	10334.7300	12396.3900	11526.8200	5.5000	7350.0000	40.7617	1.0200
14 Jun 04	614.00	10380.4300	12076.5700	11491.6600	5.5000	7400.0000	40.9306	0.3600
15 Jun 04	613.76	10379.5800	12050.6900	11387.7000	5.5000	7400.0000	41.0875	0.5300
16 Jun 04	624.36	10377.5200	12161.7800	11641.7200	5.5000	7450.0000	40.9814	0.4700
17 Jun 04	623.72	10416.4100	12082.8600	11607.9000	5.5000	7400.0000	41.0558	1.0600
18 Jun 04	622.71	10371.4700	11855.5500	11382.0800	5.5000	7450.0000	40.9906	0.8200
21 Jun 04	630.03	10395.0700	11845.5900	11600.1600	5.5000	7500.0000	40.9944	0.6400
22 Jun 04	629.36	10479.5700	11845.5900	11581.2700	5.5000	7500.0000	41.0722	0.6800
23 Jun 04	627.24	10443.8100	11849.7700	11580.5600	5.5000	7550.0000	41.0653	1.0200
24 Jun 04	637.03	10371.8400	12163.6800	11744.1500	5.5000	7550.0000	41.0398	1.1500
25 Jun 04	644.00	10357.0900	12185.5200	11780.4000	5.5000	7600.0000	40.9225	1.5900
28 Jun 04	651.86	10413.4300	12194.6000	11884.0600	5.5000	7600.0000	40.9932	1.0300
29 Jun 04	649.62	10435.4800	12116.3000	11860.8100	5.5000	7600.0000	40.9986	1.6900
30 Jun 04	646.64	10334.1600	12285.7500	11858.8700	5.5000	7500.0000	41.0305	1.4100
1 Jul 04	646.64	10282.8300	12285.7500	11896.0100	5.5000	7550.0000	41.0305	1.4100
2 Jul 04	647.57	10282.8300	12220.1300	11721.4900	5.5000	7550.0000	40.8913	1.2600
5 Jul 04	655.87	10219.3400	12252.1100	11541.7100	5.5000	7550.0000	40.8032	1.1200
6 Jul 04	664.69	10240.2900	12284.0800	11475.2700	5.5000	7550.0000	40.9135	2.1800
7 Jul 04	666.43	10171.5600	12320.2600	11384.8600	5.5000	7550.0000	40.8979	1.1700
8 Jul 04	659.14	10213.2200	12119.7500	11322.2300	5.5000	7600.0000	40.8818	1.0500
9 Jul 04	666.59	10238.2200	12202.2600	11423.5300	5.5000	7700.0000	40.8836	0.7000
12 Jul 04	661.49	10247.5900	12191.0100	11582.2800	5.5000	7700.0000	40.7917	0.9600
13 Jul 04	663.00	10208.8000	12078.3300	11608.6200	5.5000	7650.0000	40.8230	0.8500
14 Jul 04	652.79	10163.1600	11932.8300	11356.6500	5.5000	7650.0000	40.8536	0.9200
15 Jul 04	646.76	10139.7800	11939.4100	11409.1400	5.5000	7650.0000	40.9094	1.1200
16 Jul 04	646.11	10094.0600	12059.2000	11436.0000	5.5000	7650.0000	40.9543	0.7300
19 Jul 04	642.12	10149.0700	12166.9500	11436.0000	5.5000	7700.0000	40.8704	0.8700
20 Jul 04	645.58	10046.1300	12123.6300	11258.3700	5.5000	7700.0000	40.8936	0.7500
21 Jul 04	655.82	10050.3300	12395.1100	11433.8600	5.5000	7650.0000	40.9599	0.6000
22 Jul 04	650.12	9962.2200	12320.2100	11285.0400	5.5000	7650.0000	41.1114	0.4100
23 Jul 04	648.47	9961.9200	12352.9900	11187.3300	5.5000	7600.0000	41.1121	0.6700
26 Jul 04	633.42	10085.1400	12319.8300	11159.5500	5.5000	7550.0000	41.2082	0.6600
27 Jul 04	633.21	10117.0700	12301.3200	11031.5400	5.5000	7600.0000	41.3275	0.5800
28 Jul 04	634.73	10129.2400	12320.2700	11204.3700	5.5000	7550.0000	41.4929	0.7900

29 Jul 04	631.42	10139.7100	12183.1000	11116.8400	5.5000	7600.0000	41.5091	0.6200
30 Jul 04	636.70	10179.1600	12238.0300	11325.7800	5.5000	7550.0000	41.4671	0.7200
2 Aug 04	636.70	10120.2400	12201.3900	11222.2400	5.5000	7550.0000	41.4671	0.7200
3 Aug 04	630.81	10126.5100	12357.1200	11140.5700	5.5000	7600.0000	41.4227	0.7700
4 Aug 04	619.19	9963.0300	12280.2600	11010.0200	5.5000	7650.0000	41.4963	0.6800
5 Aug 04	618.90	9815.3300	12491.9200	11060.8900	5.5000	7650.0000	41.5499	0.6100
6 Aug 04	610.94	9814.6600	12478.6800	10972.5700	5.5000	7650.0000	41.5676	0.6600
9 Aug 04	607.47	9944.6700	12467.4100	10908.7000	5.5000	7700.0000	41.4769	0.2600
10 Aug 04	606.94	9938.3200	12408.0400	10953.5500	5.5000	7700.0000	41.4755	0.6400
11 Aug 04	595.60	9814.5900	12343.1300	11049.4600	5.5000	7700.0000	41.5842	0.9700
12 Aug 04	595.60	9825.3500	12413.4300	11028.0700	5.5000	7700.0000	41.5842	0.9700
13 Aug 04	588.87	9954.5500	12359.8300	10757.2000	5.5000	7700.0000	41.6531	0.8700
16 Aug 04	596.98	9972.8300	12219.7500	10687.8100	5.5000	7800.0000	41.6282	0.7300
17 Aug 04	602.75	10083.1500	12256.1200	10725.9700	5.5000	7800.0000	41.6119	1.0200
18 Aug 04	605.30	10040.8200	12228.5400	10774.2600	5.5000	7850.0000	41.5826	0.9400
19 Aug 04	602.54	10110.1400	12396.6700	10903.5300	5.5000	7850.0000	41.5860	1.0400
20 Aug 04	598.55	10073.0500	12376.9000	10889.1400	5.5000	7850.0000	41.5293	0.8500
23 Aug 04	599.55	10098.6300	12431.7700	10960.9700	5.5000	7900.0000	41.5276	0.7300
24 Aug 04	600.03	10181.7400	12646.4900	10985.3300	5.5000	7900.0000	41.5940	1.1400
25 Aug 04	607.69	10173.4100	12793.0300	11130.0200	5.5000	7850.0000	41.5926	1.2700
26 Aug 04	617.07	10195.0100	12784.3900	11129.3300	5.5000	7900.0000	41.7824	1.3700
27 Aug 04	620.12	10122.5200	12818.4200	11209.5900	5.5000	7900.0000	41.7200	1.7800
30 Aug 04	612.45	10173.9200	12877.7800	11184.5300	5.5000	7850.0000	41.7491	0.9900
31 Aug 04	624.59	10168.4600	12850.2800	11081.7900	5.5000	7900.0000	41.7430	1.2100
1 Sep 04	628.81	10290.2800	13023.8700	11127.3500	5.5000	7950.0000	41.7017	1.4700
2 Sep 04	628.78	10260.2000	12999.0700	11152.7500	5.5000	7950.0000	41.7100	1.6300
3 Sep 04	629.08	10260.2000	12948.1000	11022.4900	5.5000	7900.0000	41.6253	1.1200
6 Sep 04	630.87	10342.7900	13104.3400	11244.3700	5.5000	7850.0000	41.7090	1.5500
7 Sep 04	631.40	10313.3600	13136.0400	11298.9400	5.5000	7850.0000	41.7509	1.0800
8 Sep 04	630.21	10289.1000	13049.9600	11279.1900	5.5000	7800.0000	41.7504	1.4700
9 Sep 04	641.04	10313.0700	12942.2000	11170.9600	5.5000	7850.0000	41.7000	1.2700
10 Sep 04	640.60	10314.7600	13003.9900	11083.2300	5.5000	7850.0000	41.6763	2.0100
13 Sep 04	649.93	10318.1600	13139.5700	11253.1100	5.5000	7850.0000	41.6526	0.9600
14 Sep 04	651.89	10231.3600	13148.0600	11295.5800	5.5000	7850.0000	41.5003	1.5500
15 Sep 04	662.28	10244.4900	13084.4000	11158.5800	5.5000	7850.0000	41.3479	1.4700
16 Sep 04	662.39	10284.4600	13209.8400	11139.3600	5.5000	7850.0000	41.3666	0.9100
17 Sep 04	668.73	10204.8900	13224.9300	11082.4900	5.5000	7850.0000	41.3570	1.1400
20 Sep 04	668.29	10244.9300	13221.3300	11098.1900	5.5000	7850.0000	41.3823	1.2700
21 Sep 04	660.92	10109.1800	13304.4800	11080.8700	5.5000	7850.0000	41.4472	1.3500
22 Sep 04	663.51	10038.9000	13272.2300	11049.4100	5.5000	7900.0000	41.3898	1.4600
23 Sep 04	648.80	10047.2400	13280.4300	11019.4100	5.5000	7900.0000	41.5193	0.7800
24 Sep 04	654.60	9988.5400	13066.8400	10895.1600	5.5000	7950.0000	41.5055	0.8700
27 Sep 04	646.78	10077.4000	13021.9000	10859.3200	5.5000	7950.0000	41.5755	1.0200
28 Sep 04	637.89	10136.2400	12950.8000	10815.5700	5.5000	7950.0000	41.6724	0.5300
29 Sep 04	636.57	10080.2700	12950.8000	10786.1000	5.5000	8000.0000	41.6694	0.9200
30 Sep 04	644.67	10192.6500	13120.0300	10823.5700	5.5000	8000.0000	41.5942	1.4600
1 Oct 04	661.23	10216.5400	13120.0300	10985.1700	5.5000	8100.0000	41.5010	2.3400
4 Oct 04	679.13	10177.6800	13359.2500	11279.6300	5.5000	8100.0000	41.5086	2.0000
5 Oct 04	673.88	10239.9200	13331.1000	11281.8300	5.5000	8050.0000	41.4625	1.3600
6 Oct 04	668.51	10125.4000	13271.5700	11385.3800	5.5000	8100.0000	41.5439	1.2500
7 Oct 04	670.06	10055.2000	13321.7300	11354.5900	5.5000	8100.0000	41.5197	1.6300
8 Oct 04	676.15	10081.9700	13241.4600	11349.3500	5.5000	8100.0000	41.4569	1.1800

11 Oct 04	677.93	10077.1800	13305.1300	11349.3500	5.5000	8150.0000	41.3836	1.0500
12 Oct 04	658.27	10002.3300	13251.5900	11201.8100	5.5000	8150.0000	41.4351	0.6800
13 Oct 04	661.29	9894.4500	13171.5800	11195.9900	5.5000	8100.0000	41.4630	0.7800
14 Oct 04	641.30	9933.3800	13035.3800	11034.2900	5.5000	8100.0000	41.5492	0.7700
15 Oct 04	648.48	9956.3200	13059.4300	10982.9500	5.5000	8150.0000	41.4993	0.7700
18 Oct 04	646.51	9897.6200	13034.7400	10965.6200	5.5000	8150.0000	41.5534	1.4900
19 Oct 04	661.00	9886.9300	13154.5500	11064.8600	5.5000	8100.0000	41.5148	1.2800
20 Oct 04	652.46	9865.7600	12999.1300	10882.1800	5.5000	8150.0000	41.4394	0.7200
21 Oct 04	649.27	9757.8100	13015.2000	10789.2300	5.5000	8250.0000	41.4145	1.6100
22 Oct 04	659.05	9749.9900	13015.2000	10857.1300	5.5000	8200.0000	41.4336	1.8600
25 Oct 04	659.05	9888.4800	12818.1000	10659.1500	5.5000	8300.0000	41.4336	1.8600
26 Oct 04	648.38	10002.0300	12852.3500	10672.4600	5.5000	8250.0000	41.1392	0.9500
27 Oct 04	626.85	10004.5400	12838.7100	10691.9500	5.5000	8250.0000	41.1712	0.6400
28 Oct 04	621.57	10027.4700	13113.1500	10853.1200	5.5000	8200.0000	41.1363	0.9400
29 Oct 04	628.16	10054.3900	13054.6600	10771.4200	5.5000	8200.0000	41.1418	0.8100
1 Nov 04	626.96	10035.7300	13094.2500	10734.7100	5.5000	8300.0000	41.1605	1.1100
2 Nov 04	631.99	10137.0500	13308.7400	10887.8100	5.5000	8250.0000	41.1582	0.7200
3 Nov 04	641.29	10314.7600	13397.6700	10887.8100	5.5000	8150.0000	41.1835	1.3600
4 Nov 04	639.13	10387.5400	13369.0900	10946.2700	5.5000	8250.0000	41.1858	0.7400
5 Nov 04	635.09	10391.3100	13494.9500	11061.7700	5.5000	8250.0000	41.0165	1.0900
8 Nov 04	629.20	10386.3700	13561.4900	10983.8300	5.5000	8300.0000	40.8972	0.8700
9 Nov 04	632.94	10385.4800	13516.6700	10964.8700	5.5000	8300.0000	40.8360	1.1400
10 Nov 04	625.78	10469.8400	13672.3700	10994.9600	5.5000	8300.0000	40.7825	1.6400
11 Nov 04	627.34	10539.0100	13624.5100	10846.9200	5.5000	8300.0000	40.8301	0.9600
12 Nov 04	639.74	10550.2400	13784.4600	11019.9800	5.5000	8300.0000	40.6181	1.2500
15 Nov 04	647.56	10487.6500	13932.2200	11227.5700	5.5000	8300.0000	40.4638	1.4600
16 Nov 04	642.65	10549.5700	13746.0800	11161.7500	5.5000	8300.0000	40.5127	1.5600
17 Nov 04	644.16	10572.5500	13824.9800	11131.2900	5.5000	8350.0000	40.3812	1.6800
18 Nov 04	646.93	10456.9100	13799.8200	11082.4200	5.5000	8400.0000	40.2021	1.5400
19 Nov 04	651.42	10489.4200	13787.6800	11082.8400	5.5000	8400.0000	40.2532	1.6500
22 Nov 04	644.95	10492.6000	13800.6000	10849.3900	5.5000	8400.0000	39.9918	1.2500
23 Nov 04	650.87	10520.3100	14023.2900	10849.3900	5.5000	8400.0000	39.9874	1.5100
24 Nov 04	643.06	10520.3100	13997.0200	10872.3300	5.5000	8400.0000	39.8461	1.4600
25 Nov 04	647.49	10522.2300	13926.6100	10900.3400	5.5000	8400.0000	39.7202	1.8600
26 Nov 04	648.75	10475.9000	13895.0300	10833.7500	5.5000	8400.0000	39.5114	1.2000
29 Nov 04	657.25	10428.0200	14066.9100	10977.8900	5.5000	8400.0000	39.5901	1.1400
30 Nov 04	656.73	10590.2200	14060.0500	10899.2500	5.5000	8400.0000	39.6519	1.3800
1 Dec 04	655.44	10585.1200	14162.8000	10784.2500	5.5000	8400.0000	39.4655	1.0800
2 Dec 04	661.08	10592.2100	14261.7900	10973.0700	5.5000	8400.0000	39.2885	1.6900
3 Dec 04	663.84	10547.0600	14211.8400	11074.8900	5.5000	8350.0000	39.5033	1.6800
6 Dec 04	663.84	10440.5800	14256.8600	10981.9600	5.5000	8350.0000	39.5033	1.6800
7 Dec 04	655.83	10494.2300	14235.7800	10873.6300	5.5000	8400.0000	39.3038	0.9800
8 Dec 04	645.41	10552.8200	14022.3200	10941.3700	5.5000	8300.0000	39.3814	0.6400
9 Dec 04	648.78	10543.2200	14008.8200	10776.6300	5.5000	8200.0000	39.5194	0.6100
10 Dec 04	648.78	10638.3200	13901.8100	10756.8000	5.5000	8200.0000	39.5194	0.6100
13 Dec 04	645.75	10676.4500	13886.1600	10789.2500	5.5000	8150.0000	39.7028	1.0400
14 Dec 04	646.08	10691.4500	14043.5200	10915.5800	5.5000	8150.0000	39.4782	0.3700
15 Dec 04	657.18	10705.6400	14078.5400	10956.4600	5.5000	8150.0000	39.6136	0.8900
16 Dec 04	661.42	10649.9200	14024.6300	10924.3700	5.5000	8200.0000	39.3206	1.2900
17 Dec 04	669.46	10661.6000	13992.4400	11078.3200	5.5000	8150.0000	39.3475	1.5900
20 Dec 04	675.71	10759.4300	14214.0400	11103.4200	5.5000	8200.0000	39.2576	1.2800
21 Dec 04	671.50	10815.8900	14180.7900	11125.9200	5.5000	8200.0000	39.1582	1.8800

22 Dec 04	672.79	10827.1200	14151.0800	11209.4400	5.5000	8150.0000	39.1415	1.3500
23 Dec 04	667.90	10827.1200	14235.3000	11209.4400	5.5000	8150.0000	39.1286	1.3600
24 Dec 04	670.35	10776.1300	14194.9000	11365.4800	5.5000	8150.0000	39.1112	1.0000
27 Dec 04	663.86	10854.5400	14194.9000	11362.3500	5.5000	8200.0000	39.2207	1.3400
28 Dec 04	662.39	10829.1900	14196.9500	11424.1300	5.5000	8200.0000	39.1197	0.7700
29 Dec 04	664.46	10800.3000	14266.3800	11381.5600	5.5000	8200.0000	39.1678	0.9300
30 Dec 04	668.10	10783.0100	14163.5500	11488.7600	5.5000	8100.0000	39.2025	1.6400
31 Dec 04	668.10	10729.4300	14230.1400	11488.7600	5.5000	8100.0000	39.2025	1.6400
3 Jan 05	668.10	10630.7800	14237.4200	11488.7600	5.5000	8050.0000	39.2025	1.6400
4 Jan 05	684.48	10597.8300	14045.9000	11517.7500	5.5000	7950.0000	39.0510	2.3300
5 Jan 05	683.50	10622.8800	13764.3600	11437.5200	5.5000	7950.0000	39.2578	2.0900
6 Jan 05	693.62	10603.9600	13712.0400	11492.2600	5.5000	7950.0000	39.2355	2.1400
7 Jan 05	697.84	10621.0300	13574.8600	11433.2400	5.5000	7850.0000	39.2996	1.8400
10 Jan 05	696.03	10556.2200	13531.3900	11433.2400	5.5000	7800.0000	39.3308	1.1900
11 Jan 05	691.97	10617.7800	13509.2500	11539.9900	5.5000	7800.0000	39.1949	1.0700
12 Jan 05	694.63	10505.8300	13565.3100	11453.3900	5.5000	7800.0000	39.0683	1.0200
13 Jan 05	693.43	10558.0000	13573.2800	11358.2200	5.5000	7850.0000	38.9180	1.3800
14 Jan 05	701.66	10558.0000	13494.7800	11438.3900	5.5000	7800.0000	38.8276	0.9800
17 Jan 05	708.30	10628.7900	13621.6500	11487.1000	5.5000	7750.0000	38.6431	1.6200
18 Jan 05	709.55	10539.9700	13604.2200	11423.2600	5.5000	7750.0000	38.6242	2.0100
19 Jan 05	709.03	10471.4700	13678.6300	11405.3400	5.5000	7750.0000	38.5257	1.6100
20 Jan 05	706.90	10392.9900	13543.5900	11284.7700	5.5000	7750.0000	38.6326	1.1900
21 Jan 05	696.85	10368.6100	13481.0200	11238.3700	5.5000	7750.0000	38.7090	0.9900
24 Jan 05	695.92	10461.5600	13386.9900	11289.4900	5.5000	7800.0000	38.6097	1.0500
25 Jan 05	702.14	10498.5900	13584.0600	11276.9100	5.5000	7800.0000	38.5580	0.8900
26 Jan 05	702.66	10467.4000	13623.6800	11376.5700	5.5000	7750.0000	38.6680	1.2500
27 Jan 05	701.25	10427.2000	13628.9100	11341.3100	5.5000	7800.0000	38.6230	1.4100
28 Jan 05	701.66	10489.9400	13650.0600	11320.5800	5.5000	7800.0000	38.5503	1.4100
31 Jan 05	701.91	10551.9400	13721.6900	11387.5900	5.5000	7750.0000	38.6471	1.6700
1 Feb 05	708.73	10596.7900	13578.2600	11384.4000	5.5000	7750.0000	38.6874	1.3700
2 Feb 05	710.33	10593.1000	13555.8000	11407.1400	5.5000	7750.0000	38.6680	1.7800
3 Feb 05	716.92	10716.1300	13515.3300	11389.3500	5.5000	7750.0000	38.6330	1.6000
4 Feb 05	719.10	10715.7600	13585.1700	11360.4000	5.5000	7650.0000	38.5756	1.5700
7 Feb 05	725.76	10724.6300	13795.0000	11499.8600	5.5000	7600.0000	38.3496	2.5000
8 Feb 05	731.42	10664.1100	13845.6300	11490.4300	5.5000	7550.0000	38.5049	1.5100
9 Feb 05	735.63	10749.6100	13845.6300	11473.3500	5.5000	7550.0000	38.6707	0.9900
10 Feb 05	736.22	10796.0100	13845.6300	11473.3500	5.5000	7600.0000	38.7048	1.7000
11 Feb 05	726.20	10791.1300	13845.6300	11473.3500	5.5000	7700.0000	38.7012	0.9500
14 Feb 05	728.80	10837.3200	14017.2300	11632.2000	5.5000	7700.0000	38.5373	0.8600
15 Feb 05	736.91	10834.8800	13995.8300	11646.4900	5.5000	7700.0000	38.5205	1.0100
16 Feb 05	739.37	10754.2600	14015.4900	11601.6800	5.5000	7700.0000	38.5221	1.1500
17 Feb 05	734.68	10785.2200	13967.8200	11582.7200	5.5000	7750.0000	38.6553	0.8500
18 Feb 05	737.50	10785.2200	14087.8700	11660.1200	5.5000	7750.0000	38.6630	0.7100
21 Feb 05	725.89	10611.2000	14111.6500	11651.0200	5.5000	7800.0000	38.6660	0.9200
22 Feb 05	730.56	10673.7900	14090.5200	11597.7100	5.5000	7800.0000	38.5830	0.5700
23 Feb 05	730.56	10748.7900	13957.9400	11500.1800	5.5000	7850.0000	38.5830	0.5700
24 Feb 05	736.89	10841.6000	14060.9100	11531.1500	5.5000	7900.0000	38.5396	0.7000
25 Feb 05	740.04	10766.2300	14157.0900	11658.2500	5.5000	7900.0000	38.5324	0.8300
28 Feb 05	741.55	10830.0000	14195.3500	11740.6000	5.5000	7900.0000	38.4243	0.8300
1 Mar 05	738.75	10811.9700	14061.1500	11780.5300	5.5000	7900.0000	38.4044	0.5900
2 Mar 05	720.92	10833.0300	13850.7800	11813.7100	5.5000	7850.0000	38.4275	0.7500
3 Mar 05	720.39	10940.5500	13892.3700	11856.4600	5.5000	7850.0000	38.5202	0.8400

4 Mar 05	728.42	10936.8600	13730.7800	11873.0500	5.5000	7850.0000	38.6083	1.2800
7 Mar 05	737.42	10912.6200	13771.9500	11925.3600	5.5000	7900.0000	38.5006	1.0600
8 Mar 05	722.60	10805.6200	13881.7100	11886.9100	5.5000	7900.0000	38.4344	1.2700
9 Mar 05	722.58	10851.5100	13941.4700	11966.6900	5.5000	7950.0000	38.4026	0.8400
10 Mar 05	719.53	10774.3600	13856.0200	11864.9100	5.5000	7950.0000	38.3710	0.8000
11 Mar 05	710.98	10804.5100	13890.9300	11923.8900	5.5000	8000.0000	38.4099	1.2100
14 Mar 05	700.22	10745.1000	13906.8500	11850.2500	5.5000	8050.0000	38.3984	0.6500
15 Mar 05	696.84	10633.0700	13816.7500	11821.0900	5.5000	8000.0000	38.4634	0.5200
16 Mar 05	706.64	10626.3500	13832.5200	11873.1800	5.5000	8000.0000	38.5790	0.6300
17 Mar 05	706.53	10629.6700	13817.9900	11775.5000	5.5000	8050.0000	38.5876	1.0600
18 Mar 05	711.40	10565.3900	13828.3700	11879.8100	5.5000	8000.0000	38.6089	1.4200
21 Mar 05	705.03	10470.5100	13834.3500	11879.8100	5.5000	8000.0000	38.6432	0.9200
22 Mar 05	699.53	10456.0200	13776.4700	11841.9700	5.5000	7900.0000	38.7365	0.7500
23 Mar 05	693.26	10442.8700	13603.6100	11739.1200	5.5000	7850.0000	38.7699	0.6600
24 Mar 05	685.06	10442.8700	13597.1000	11745.9700	5.5000	7800.0000	38.8637	0.6000
25 Mar 05	687.32	10485.6500	13597.1000	11761.1000	5.5000	7850.0000	39.0218	1.2400
28 Mar 05	682.98	10405.7000	13597.1000	11792.3000	5.5000	7850.0000	39.2152	0.7800
29 Mar 05	676.91	10405.7000	13411.8800	11599.8200	5.5000	7900.0000	39.3276	0.6300
30 Mar 05	672.82	10503.7600	13425.7500	11565.8800	5.5000	7900.0000	39.4601	0.6600
31 Mar 05	681.49	10404.3000	13516.8800	11668.9500	5.5000	7900.0000	39.2543	0.8800
1 Apr 05	695.83	10421.1400	13491.3500	11723.6300	5.5000	7900.0000	39.3219	0.8800
4 Apr 05	682.52	10458.4600	13513.4100	11667.5400	5.5000	7900.0000	39.5025	0.8000
5 Apr 05	681.66	10486.0200	13513.4100	11774.3100	5.5000	7900.0000	39.6783	0.7000
6 Apr 05	681.66	10546.3200	13562.2600	11827.1600	5.5000	7950.0000	39.6783	0.7000
7 Apr 05	677.97	10461.3400	13602.3500	11810.9900	5.5000	7950.0000	39.7094	0.6100
8 Apr 05	683.76	10448.5600	13666.7200	11874.7500	5.5000	7950.0000	39.7223	0.9600
11 Apr 05	694.34	10507.9700	13659.9300	11745.6400	5.5000	8000.0000	39.7643	0.9700
12 Apr 05	698.28	10403.9300	13658.0500	11670.3000	5.5000	8000.0000	39.7395	1.0900
13 Apr 05	698.28	10278.7500	13799.6200	11637.5200	5.5000	8000.0000	39.7395	1.0900
14 Apr 05	698.28	10087.5100	13772.4000	11563.1700	5.5000	8000.0000	39.7395	1.0900
15 Apr 05	698.28	10071.2500	13638.7500	11370.6900	5.5000	8000.0000	39.7395	1.0900
18 Apr 05	676.90	10127.4100	13355.2300	10938.4400	5.5000	7950.0000	39.7973	0.6800
19 Apr 05	678.37	10012.3600	13444.0900	11065.8600	5.5000	7950.0000	39.6061	0.8000
20 Apr 05	684.19	10218.6000	13501.6300	11088.5800	5.5000	8050.0000	39.4807	0.7700
21 Apr 05	680.60	10157.7100	13597.3100	10984.3900	5.5000	8050.0000	39.5055	0.6200
22 Apr 05	677.25	10242.4700	13693.5500	11045.9500	5.5000	8050.0000	39.6139	0.6500
25 Apr 05	664.47	10151.1300	13750.2300	11073.7700	5.5000	8050.0000	39.5142	0.7700
26 Apr 05	662.13	10198.8000	13859.5800	11035.8300	5.5000	8050.0000	39.5495	0.7600
27 Apr 05	664.63	10070.3700	13839.6400	11005.4200	5.5000	8100.0000	39.6733	0.6800
28 Apr 05	659.24	10192.5100	13909.4200	11008.9000	5.5000	8050.0000	39.6777	1.1400
29 Apr 05	658.88	10251.7000	13908.9700	11008.9000	5.5000	8050.0000	39.7062	1.0200
2 May 05	658.88	10256.9500	13908.9700	11002.1100	5.5000	8050.0000	39.7062	1.0200
3 May 05	669.72	10384.6400	13893.9800	11002.1100	5.5000	8050.0000	39.6673	1.0600
4 May 05	669.72	10340.3800	13945.0500	11002.1100	5.5000	8000.0000	39.5584	1.0600
5 May 05	669.72	10345.4000	14061.7000	11002.1100	5.5000	8000.0000	39.5584	1.0600
6 May 05	689.36	10384.3400	14033.9600	11192.1700	5.5000	8000.0000	39.5485	1.3700
9 May 05	688.21	10281.1100	14085.0900	11171.3200	5.5000	7950.0000	39.6080	1.0500
10 May 05	681.83	10300.2500	14018.3800	11159.4600	5.5000	7950.0000	39.6167	1.0300
11 May 05	684.65	10189.4800	13939.8000	11120.7000	5.5000	7950.0000	39.5626	0.7200
12 May 05	682.12	10140.1200	13968.2800	11077.9400	5.5000	7950.0000	39.5346	0.7800
13 May 05	679.11	10252.2900	13866.8100	11049.1100	5.5000	7850.0000	39.6135	0.8800
16 May 05	670.76	10331.8800	13866.8100	10947.2200	5.5000	7850.0000	39.8151	1.1700

17 May 05	664.61	10464.4500	13667.0300	10825.3900	5.5000	7900.0000	39.9095	0.8800
18 May 05	672.19	10493.1900	13627.0100	10835.4100	5.5000	7900.0000	40.0449	1.2700
19 May 05	676.54	10471.9100	13698.9300	11077.1600	5.5000	7950.0000	39.9396	1.1700
20 May 05	670.65	10523.5600	13717.4200	11037.2900	5.5000	7950.0000	40.0089	0.4000
23 May 05	670.65	10503.6800	13699.1300	11158.6500	5.5000	7950.0000	40.0089	0.4000
24 May 05	663.66	10457.8000	13719.3200	11133.6500	5.5000	7900.0000	40.0772	0.9300
25 May 05	660.18	10537.6000	13562.0600	11014.4300	5.5000	7900.0000	40.0869	1.1300
26 May 05	662.64	10542.5500	13569.9900	11027.9400	5.5000	7950.0000	40.3129	0.9100
27 May 05	663.48	10542.5500	13714.7800	11192.3300	5.5000	7950.0000	40.4983	1.1200
30 May 05	668.20	10467.4800	13845.1000	11266.3300	5.5000	7950.0000	40.4522	1.1300
31 May 05	667.55	10549.8700	13867.0700	11276.5900	5.5000	7950.0000	40.6076	1.0900
1 Jun 05	667.52	10553.4900	13873.0700	11329.6700	5.5000	8000.0000	40.7874	1.0000
2 Jun 05	672.81	10460.9700	13814.5800	11280.0500	5.5000	8000.0000	40.7666	1.0700
3 Jun 05	676.70	10467.0300	13818.4500	11300.0500	5.5000	8050.0000	40.7666	1.0400
6 Jun 05	682.30	10483.0700	13860.5500	11270.6200	5.5000	8100.0000	40.7824	1.4500
7 Jun 05	682.15	10476.8600	13837.2900	11217.4500	5.5000	8100.0000	40.6391	1.2400
8 Jun 05	684.07	10503.0200	13898.5500	11281.0300	5.5000	8100.0000	40.6078	1.6000
9 Jun 05	677.20	10512.6300	13898.3100	11160.8800	5.5000	8100.0000	40.7485	1.0700
10 Jun 05	679.98	10522.5600	13934.7600	11304.2300	5.5000	8100.0000	40.7605	1.2600
13 Jun 05	675.09	10547.5700	13952.0200	11311.5100	5.5000	8100.0000	40.8992	1.3400
14 Jun 05	683.68	10566.3700	13904.8100	11335.9200	5.5000	8150.0000	41.0019	1.5200
15 Jun 05	687.47	10578.6500	13914.3000	11415.8800	5.5000	8150.0000	41.0223	1.6000
16 Jun 05	687.16	10623.0700	13833.5300	11416.3800	5.5000	8200.0000	41.0123	1.4000
17 Jun 05	686.52	10609.1100	13912.0300	11514.0300	5.5000	8350.0000	41.1046	1.6200
20 Jun 05	679.68	10599.6700	13945.7700	11483.3500	5.5000	8400.0000	41.1835	1.7600
21 Jun 05	689.64	10587.9300	13979.3500	11488.7400	5.5000	8400.0000	41.2717	1.1300
22 Jun 05	686.57	10421.4400	14161.0200	11547.2800	5.5000	8400.0000	41.2080	2.0700
23 Jun 05	693.13	10297.8400	14190.4400	11576.7500	5.5000	8400.0000	41.1873	1.5400
24 Jun 05	690.25	10290.7800	14230.2900	11537.0300	5.5000	8450.0000	41.2030	1.7000
27 Jun 05	684.18	10405.6300	14176.0400	11414.2800	5.5000	8450.0000	41.1975	1.0700
28 Jun 05	684.68	10374.4800	14287.4400	11513.8300	5.5000	8450.0000	41.2480	0.6800
29 Jun 05	685.56	10274.9700	14277.2800	11577.4400	5.5000	8400.0000	41.3503	1.2700
30 Jun 05	675.50	10303.4400	14201.0600	11584.0100	5.5000	8450.0000	41.4091	0.9600
1 Jul 05	675.50	10303.4400	14201.0600	11630.1300	5.5000	8400.0000	41.4091	0.9600
4 Jul 05	669.78	10371.8000	14177.8700	11651.5500	5.7500	8350.0000	41.5180	0.7100
5 Jul 05	663.52	10270.6800	14124.8000	11616.7000	5.7500	8350.0000	41.5462	0.7000
6 Jul 05	659.91	10302.2900	14149.9300	11603.5300	5.7500	8300.0000	41.6080	0.7800
7 Jul 05	638.31	10449.1400	14030.8100	11590.1400	5.7500	8300.0000	41.7603	0.7600
8 Jul 05	643.31	10519.7200	13964.4700	11565.9900	5.7500	8350.0000	42.1416	0.7900
11 Jul 05	640.82	10513.8900	14157.2400	11674.7900	5.7500	8400.0000	42.1022	1.0800
12 Jul 05	648.98	10557.3900	14146.9500	11692.1400	5.7500	8400.0000	42.0013	1.2400
13 Jul 05	658.37	10628.8900	14307.3000	11659.8400	5.7500	8400.0000	41.9563	1.3400
14 Jul 05	661.45	10640.8300	14491.5400	11764.2600	5.7500	8350.0000	41.9807	1.2600
15 Jul 05	655.46	10574.9900	14504.2900	11758.6800	5.7500	8300.0000	41.8853	0.8400
18 Jul 05	652.67	10646.5600	14567.0000	11758.6800	5.7500	8300.0000	41.8598	1.0100
19 Jul 05	648.67	10689.1500	14567.7400	11764.8400	5.7500	8300.0000	41.9351	0.9600
20 Jul 05	650.04	10627.7700	14602.7000	11789.3500	5.7500	8300.0000	42.1598	1.3500
21 Jul 05	648.92	10651.1800	14620.1400	11786.7300	5.7500	8350.0000	42.0134	0.8200
22 Jul 05	648.92	10596.4800	14786.4600	11695.0500	5.7500	8300.0000	42.0134	0.8200
25 Jul 05	659.64	10579.7700	14794.0300	11762.6500	5.7500	8300.0000	41.4796	1.6100
26 Jul 05	656.91	10637.0900	14769.9300	11737.9600	5.7500	8300.0000	41.6055	1.3600
27 Jul 05	665.72	10705.5500	14801.8600	11835.0800	5.7500	8300.0000	41.8632	1.1700

28 Jul 05	670.09	10640.9100	14813.3200	11858.3100	5.7500	8350.0000	41.8367	1.5400
29 Jul 05	675.67	10623.1500	14880.9800	11899.6000	5.7500	8400.0000	41.8326	1.8300
1 Aug 05	674.99	10683.7400	14978.8800	11946.9200	5.7500	8450.0000	41.7867	1.2700
2 Aug 05	683.16	10697.5900	15137.0800	11940.2000	5.7500	8450.0000	41.4917	1.0500
3 Aug 05	687.94	10610.1000	15118.5000	11981.8000	5.7500	8400.0000	41.4681	2.3200
4 Aug 05	684.57	10558.0300	15111.5400	11883.3100	5.7500	8450.0000	41.2469	1.8000
5 Aug 05	686.01	10536.9300	15051.3200	11766.4800	5.7500	8450.0000	41.3129	1.1500
8 Aug 05	686.32	10615.6700	15108.9400	11778.9800	5.7500	8500.0000	41.3226	1.0700
9 Aug 05	681.54	10594.4100	15047.8400	11900.3200	5.7500	8450.0000	41.2641	1.4800
10 Aug 05	684.59	10685.8900	15346.4100	12098.0800	5.7500	8450.0000	41.1448	1.1000
11 Aug 05	681.95	10600.3100	15445.2000	12263.3200	5.7500	8450.0000	40.9515	1.1800
12 Aug 05	681.95	10634.3800	15450.9500	12261.6800	5.7500	8550.0000	40.9515	1.1800
15 Aug 05	675.52	10513.4500	15466.0600	12256.5500	5.7500	8550.0000	41.0573	1.2900
16 Aug 05	667.18	10550.7100	15443.6200	12315.6700	5.7500	8550.0000	41.1697	1.0100
17 Aug 05	667.49	10554.9300	15449.5800	12273.1200	5.7500	8650.0000	41.3396	1.0500
18 Aug 05	672.02	10559.2300	15148.0900	12307.3700	5.7500	8550.0000	41.3091	1.1100
19 Aug 05	680.83	10569.8900	15038.6100	12291.7300	5.7500	8550.0000	41.3835	0.9800
22 Aug 05	690.77	10519.5800	15218.6300	12452.5100	5.7500	8500.0000	41.2414	0.9300
23 Aug 05	690.39	10434.8700	14973.8900	12472.9300	5.7500	8500.0000	41.0562	1.1500
24 Aug 05	695.67	10450.6300	14873.8500	12502.2600	5.7500	8500.0000	41.1959	0.9000
25 Aug 05	692.14	10397.2900	14889.1000	12405.1600	5.7500	8500.0000	41.2494	1.5000
26 Aug 05	695.89	10463.0500	14982.8900	12439.4800	5.7500	8500.0000	41.2201	1.1400
29 Aug 05	695.89	10412.8200	14836.9700	12309.8300	5.7500	8550.0000	41.2688	1.1400
30 Aug 05	692.86	10481.6000	14922.2200	12453.1400	5.7500	8550.0000	41.4443	1.0700
31 Aug 05	697.85	10459.6300	14903.5500	12413.6000	5.7500	8450.0000	41.4515	1.0200
1 Sep 05	710.28	10447.3700	15143.7500	12506.9700	5.7500	8500.0000	41.2793	1.0800
2 Sep 05	709.97	10447.3700	15221.8900	12600.0000	5.7500	8600.0000	41.1441	1.2700
5 Sep 05	707.94	10589.2400	15227.8300	12634.8800	5.7500	8600.0000	41.0461	1.0200
6 Sep 05	705.46	10633.5000	15160.7800	12599.4300	5.7500	8600.0000	41.1038	1.4700
7 Sep 05	708.50	10595.9300	15224.5700	12607.5900	5.7500	8600.0000	41.1989	1.2100
8 Sep 05	715.08	10678.5600	15166.1700	12533.8900	5.7500	8600.0000	41.1063	1.1600
9 Sep 05	712.78	10682.9400	15165.7700	12692.0400	5.7500	8600.0000	41.1122	0.9900
12 Sep 05	712.80	10597.4400	15199.7900	12896.4300	5.7500	8650.0000	40.9802	0.8200
13 Sep 05	710.31	10544.9000	15070.5600	12901.9500	5.7500	8650.0000	41.0153	0.9600
14 Sep 05	717.77	10558.7500	15086.6200	12834.2500	5.7500	8650.0000	41.0243	0.8300
15 Sep 05	711.20	10641.9400	15041.0200	12986.7800	6.0000	8650.0000	41.0876	0.9000
16 Sep 05	708.26	10557.6300	14983.2000	12958.6800	6.0000	8800.0000	41.0952	1.2700
19 Sep 05	708.98	10481.5200	14983.2000	12958.6800	6.0000	8850.0000	41.1672	1.3100
20 Sep 05	723.16	10378.0300	15241.8600	13148.5700	6.0000	9050.0000	41.1817	1.3200
21 Sep 05	721.16	10422.0500	15223.6200	13196.5700	6.0000	9050.0000	41.1827	1.2200
22 Sep 05	725.64	10419.5900	15179.9500	13159.3600	6.0000	9150.0000	41.1472	1.3200
23 Sep 05	725.31	10443.6300	15143.9700	13159.3600	6.0000	9050.0000	41.1632	1.3200
26 Sep 05	721.28	10456.2100	15274.3100	13392.6300	6.0000	9000.0000	41.3068	1.5100
27 Sep 05	724.24	10473.0900	15189.8800	13310.0400	6.0000	9050.0000	41.3681	1.0500
28 Sep 05	723.20	10552.7800	15221.4600	13435.9100	6.0000	9050.0000	41.3242	1.1000
29 Sep 05	722.83	10568.7000	15431.2500	13617.2400	6.0000	9100.0000	41.2076	1.2400
30 Sep 05	723.23	10535.4800	15428.5200	13574.3000	6.0000	9150.0000	41.1075	1.0200
3 Oct 05	717.42	10441.1100	15394.3900	13525.2800	6.0000	9050.0000	41.2447	1.1700
4 Oct 05	714.90	10317.3600	15382.2100	13738.8400	6.0000	9050.0000	41.2211	1.0900
5 Oct 05	717.17	10287.1000	15161.0300	13689.8900	6.0000	9050.0000	41.1568	0.9500
6 Oct 05	710.79	10292.3100	14839.3000	13359.5100	6.0000	9050.0000	41.0758	1.0200
7 Oct 05	708.98	10238.7600	14847.7900	13359.5100	6.0000	9100.0000	40.9538	1.3500

10 Oct 05	707.05	10253.1700	14898.7700	13359.5100	6.0000	9150.0000	40.9158	1.0300
11 Oct 05	709.13	10216.9100	14898.7700	13556.7100	6.0000	9200.0000	40.9920	1.2300
12 Oct 05	709.20	10216.5900	14575.0200	13463.7400	6.0000	9200.0000	41.1124	1.1300
13 Oct 05	704.32	10287.3400	14621.8300	13449.2400	6.2500	9150.0000	41.0665	1.2500
14 Oct 05	700.02	10348.1000	14485.8800	13420.5400	6.2500	9150.0000	40.9797	0.8700
17 Oct 05	696.28	10285.2600	14541.3500	13400.2900	6.2500	9100.0000	40.9126	0.7800
18 Oct 05	695.18	10414.1300	14597.4000	13352.2400	6.2500	9150.0000	41.0037	0.9900
19 Oct 05	684.07	10281.1000	14372.7600	13129.4900	6.2500	9100.0000	40.9662	0.8900
20 Oct 05	681.92	10215.2200	14408.9400	13190.4600	6.2500	9000.0000	41.0194	1.0200
21 Oct 05	686.21	10385.0000	14487.8500	13199.9500	6.2500	8950.0000	40.9670	0.8000
24 Oct 05	686.21	10377.8700	14402.3500	13106.1800	6.2500	8950.0000	40.9670	0.8000
25 Oct 05	676.84	10344.9800	14424.8800	13280.6200	6.2500	9050.0000	40.9931	1.0500
26 Oct 05	685.04	10229.9500	14458.1400	13395.0200	6.2500	9100.0000	40.9092	0.9000
27 Oct 05	685.29	10402.7700	14381.0600	13417.0800	6.2500	9100.0000	40.9196	0.8800
28 Oct 05	682.25	10440.0700	14215.8300	13346.5400	6.2500	9100.0000	40.8586	0.6300
31 Oct 05	682.62	10406.7700	14386.3700	13606.5000	6.2500	9100.0000	40.8863	0.8500
1 Nov 05	693.27	10472.7300	14572.2600	13867.8600	6.2500	9000.0000	40.9004	0.9100
2 Nov 05	699.88	10522.5900	14597.4800	13894.7800	6.2500	8950.0000	40.9145	0.9600
3 Nov 05	704.79	10530.7600	14601.5900	13894.7800	6.2500	8950.0000	40.9381	1.4200
4 Nov 05	706.23	10586.2300	14585.7900	14075.9600	6.2500	8950.0000	40.9771	1.1100
7 Nov 05	700.75	10539.7200	14365.7900	14061.6000	6.2500	8900.0000	41.1135	1.2200
8 Nov 05	695.60	10546.2100	14403.2000	14036.7300	6.2500	8900.0000	41.1943	1.0900
9 Nov 05	696.85	10640.1000	14597.5500	14072.2000	6.2500	9000.0000	41.3174	1.1100
10 Nov 05	694.44	10686.0400	14633.3300	14080.8800	6.2500	9100.0000	41.3142	1.0500
11 Nov 05	690.45	10697.1700	14740.6000	14155.0600	6.2500	9050.0000	41.2462	1.0000
14 Nov 05	683.41	10686.4400	14629.4900	14116.0400	6.2500	9100.0000	41.2313	0.7700
15 Nov 05	681.58	10674.7600	14627.4100	14091.7700	6.2500	9100.0000	41.2892	0.9100
16 Nov 05	675.31	10720.2200	14650.5400	14170.8700	6.2500	9100.0000	41.2860	0.8300
17 Nov 05	672.63	10766.3300	14787.9800	14411.7900	6.2500	9100.0000	41.2807	0.7900
18 Nov 05	676.41	10820.2800	14883.3200	14623.1200	6.2500	9300.0000	41.2841	1.4500
21 Nov 05	672.06	10871.4300	14885.5700	14680.4300	6.2500	9300.0000	41.3383	1.5000
22 Nov 05	674.25	10916.0900	14885.6500	14708.3200	6.2500	9450.0000	41.3157	0.9300
23 Nov 05	669.18	10916.0900	15062.3500	14708.3200	6.2500	9450.0000	41.2583	1.0000
24 Nov 05	669.76	10931.6200	15084.3900	14742.5800	6.2500	9450.0000	41.2812	0.9200
25 Nov 05	669.89	10890.7200	15081.4700	14784.2900	6.2500	9500.0000	41.3105	1.8400
28 Nov 05	666.69	10888.1600	15100.0000	14986.9400	6.2500	9550.0000	41.3581	0.7600
29 Nov 05	669.90	10805.8700	15028.7600	14927.7000	6.2500	9650.0000	41.3322	1.0900
30 Nov 05	667.75	10912.5700	14937.1400	14872.1500	6.2500	9600.0000	41.3206	1.4600
1 Dec 05	660.95	10877.5100	15068.0300	15130.5000	6.2500	9600.0000	41.3249	1.1300
2 Dec 05	659.91	10835.0100	15200.3800	15421.6000	6.2500	9750.0000	41.4525	1.2000
5 Dec 05	659.91	10856.8600	15158.8200	15551.3100	6.2500	9750.0000	41.4525	1.2000
6 Dec 05	679.16	10810.9100	14990.6100	15423.3800	6.2500	9850.0000	41.4633	1.0200
7 Dec 05	694.87	10755.1200	15134.9500	15484.6600	6.2500	9900.0000	41.4225	1.6200
8 Dec 05	692.58	10778.5800	14879.1600	15183.3600	6.2500	10050.0000	41.3842	1.8300
9 Dec 05	697.74	10767.7700	14910.5100	15404.0500	6.5000	10100.0000	41.3514	1.4700
12 Dec 05	697.74	10823.7200	14984.4000	15738.7000	6.5000	10450.0000	41.3514	1.4700
13 Dec 05	693.48	10883.5100	14942.6200	15778.8600	6.5000	10150.0000	41.2840	1.6900
14 Dec 05	694.72	10881.6700	14976.2600	15464.5800	6.5000	10000.0000	41.1668	1.5300
15 Dec 05	690.49	10875.5900	15059.0200	15254.4400	6.5000	9750.0000	41.0506	1.3900
16 Dec 05	691.17	10836.5300	15029.8100	15173.0700	6.5000	9600.0000	41.0393	2.1700
19 Dec 05	691.28	10805.5500	15182.8900	15391.4800	6.5000	9750.0000	41.0300	0.6400
20 Dec 05	698.68	10833.7300	15169.1700	15641.2600	6.5000	9800.0000	41.0293	1.0500

21 Dec 05	698.43	10889.4400	15221.4200	15957.5700	6.5000	9500.0000	41.0377	1.2500
22 Dec 05	696.41	10883.2700	15182.5300	15941.3700	6.5000	9600.0000	41.0464	1.1900
23 Dec 05	698.95	10883.2700	15183.5800	15941.3700	6.5000	9700.0000	41.0409	0.8100
26 Dec 05	701.37	10777.7700	15183.5800	16107.6700	6.5000	9750.0000	41.0215	1.2900
27 Dec 05	706.47	10796.2600	15183.5800	15969.4000	6.5000	9750.0000	41.0528	1.0800
28 Dec 05	705.29	10784.8200	15101.5400	16194.6100	6.5000	9850.0000	41.0833	0.9900
29 Dec 05	710.22	10717.5000	15045.5900	16344.2000	6.5000	10000.0000	41.0773	1.1400
30 Dec 05	713.73	10717.5000	14876.4300	16111.4300	6.5000	9950.0000	41.0773	1.1000
02 Jan 06	713.73	10847.4100	14876.4300	16111.4300	6.5000	9950.0000	41.0773	1.1000