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A Comparison of the Use of Artificial Neural Networks, Fractal Time Series and Fractal Neural Networks in Financial Forecasts

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by

Beverly A. Swisshelm

A dissertation submitted in partial fulfillment of the requirements
for the degree of Doctor of Philosophy

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Effective prediction of future financial states has been a major quest for groups ranging from national governments to individual investors. The size, diversity and complexity of financial markets make traditional statistical methods ineffective in predicting beyond a very short time frame.

Alternative models using artificial neural networks and fractal time series have had better results in long-term predictions, but still do not work in all situations. This dissertation combined features of artificial neural networks and fractal time series to create a fractal neural network. Fractals exhibit repetitive patterns when a unit is broken down into its components. This similarity property was used to create a fractal neural network that could be broken out into separate, smaller neural networks. The recurring nature of the fractal pattern indicates that phenomena exhibiting repetitive patterns may be effectively modeled with fractal neural networks.

Computer models of fractal time series, artificial neural networks and fractal neural networks were constructed and used to analyze and predict the exchange rate between the Deutschemark and the US Dollar and between the US dollar and the British Pound. Results confirmed that the exchange rates for 1994 to 1995 exhibit fractal patterns. Three layer artificial neural networks and fractal neural networks were constructed, trained on the 1994 data, and used to predict exchange rates for the first half of 1995.

The number of correct predictions of the direction of change of the exchange rates calculated by the fractal neural network exceeded those produced by the artificial neural network for weekly Deutschemark and daily and weekly Pound exchange rates. When the predicted values were compared to actual values and used to form an investment strategy, the fractal network consistently produced a profit that exceeded that of the artificial neural network.

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Chapter 1

Introduction

Over the past thirty years, there have been many new approaches to creating predictive modeling systems. As Connelly pointed out (1996), older models often work with clearly defined linear models that tend to move towards equilibrium states. However, many systems do not tend toward equilibrium, but behave in nonlinear, even chaotic, ways. New techniques were developed, as it became clear that simple models were inadequate to describe systems such as capital markets, blood flow through the human body, branch formation in plants and the windings of a ball of string. In particular, with the potential for high payoffs, the business and financial arenas engendered much demand for accurate models. Interest has been strong for new modeling techniques that utilize features such as non-linear factors, randomness, minimal data, "fuzzy" parameters, chaotic behavior and fractal analysis (Gately, 1996; Mandelbrot, 1983; Peters, 1994).

One approach that has attracted great interest for modeling financial systems is that of artificial neural networks (ANN). While originally developed to simulate and foster understanding of the actions of the human mind, ANN's have been applied to many financial areas. The situations to be modeled often exhibit non-linear relationships that may also be random or chaotic (Saad, Prokhorov & Wunsch, 1998; Beale & Jackson, 2001, Ellacott & Bose, 1996). Results have been mixed, but Jain and Nag (1995) have found that neural networks improve the prediction of prices for IPO's (Initial Public

Offerings) and anticipate successful application to other areas, such as put and call options and futures contracts. Similarly, Desai and Bharati (1998) found that asset returns for large stocks and corporate bonds can be predicted with ANN's. Short-term trends in stock prices have also been effectively modeled with neural networks (Saad, *et al.*, 1998).

The ability of ANN's to utilize seemingly unrelated data sets and model systems where precise analytic equations are not known seems to give them an edge in financial forecasting (Freedman, 1991; Filho, Cabral & Soares, 1998; Goonatilake, 1995; Jain & Nag, 1995; Jamal & Sundar, 1997). These results emphasize that ANN's are especially effective in situations where there are interrelations among complex factors and those relationships are unclear (Jain & Nag, 1995).

One technique for dealing with chaotic or noisy events is to view them in a different framework. In chaotic systems, especially those utilizing time sequences, changing from an Euclidean environment to a fractal framework can better describe the systems (Hall, 1998; Li & McLeod, 1986; Mandelbrot, 1999; Peters, 1989, 1994; Pickover, 1988). "Fractal geometry provides a means of describing the organizing structures underlying irregular shapes or series generated by non-linear dynamic systems by identifying the consistent patterns that operate over scales of size or time" (Peters, 1989, p. 33). In the financial arena, Mandelbrot, in a series of works dating from 1960 through 1972, utilized fractal approaches to describe market activity (Mandelbrot, 1999; Mirowski, 1990, 1995). Peters (1989, 1994) has also successfully applied fractals through Rescaled Range Analysis to capital market returns. His findings indicate that the process is especially relevant to systems that have volatility and act over a long time frame.

Fractals have also been applied to the organization of biological networks of neurons. The human brain, itself, has a hierarchical organization with a fractal-like structure (Chakraborty, Sawada & Chakraborty, 1997). Kim, Sano and Sawada (1993) point out that the human brain cannot be fully represented either as a fully or randomly connected network and instead advocate a fractal connection.

This view of biological fractal connections has been extended to ANN's. Fractal neural networks (FNN's) have been used to examine diverse problems. For example, Chakraborty *et al.* (1997) and Chakraborty and Sawada (1999) used a fractal neural network to study classification of sonar signals. Prevost, Isambert, Depeyre, Donadille & Perisse (1994) found that FNN's can effectively model steel time - temperature - composition transition curves. Several Japanese researchers (Morita, 1993, 1996a, 1996b; Widjaja, 2000; Ieshima & Tokosumi, 1999) have successfully applied FNN's to pattern recognition problems. As early as 1992, Business Week, in a brief report on Hitachi, Ltd., provided a tantalizing hint that fractals and neural networks could be combined to predict stock market behavior. The article indicated that Hitachi would market a fractal neural network workstation, although this author could find no further mention of such a system.

Problem Statement and Goal

More effective techniques for predicting future financial positions from past and current data remain in demand. This dissertation examined the effectiveness of incorporating fractal models in financial system modeling using ANN's. The goal of the dissertation was to determine whether fractal neural networks can be effectively employed in financial systems predictions, whether predictions match reality and whether predictions arising from FNN's match or exceed those of ANN's and fractal time series (FTS). In particular, this research tested the effectiveness of FNN's in predicting Deutschemark/US Dollar (Mark) and the US Dollar/British Pound (Pound) exchange rates and compared the results to predictions made with separate ANN's and FTS models utilizing the same data set.

The FNN was similar to that used by Prevost *et al.* (1994). For this research, a fractal time series model was used to create projections from the set of Deutschemark/US Dollar exchange rates, since Fisher, Calvet and Mandelbrot (1997) have demonstrated that, over time, the exchange rate exhibits fractal behavior. The same data set was used by both an ANN with back propagation and by an FNN with back propagation. The results were compared with those arising from the fractal time series. The results were analyzed and, as predicted, the FNN performed better than either the Fractal Time Series or the ANN.

Relevance and Significance

As with most processes of interest in the real world, variations in financial prices and markets are difficult to predict. But accurate predictions of future states would be of enormous benefit. For example, the U. S. Federal Reserve Board examines trends and tries to predict future economic states. Then, by manipulating interest rates, the Federal Reserve attempts to keep the economy on an even keel, avoiding both recessions and inflation. The more accurate the forecasts, the better the adjustments that can be made.

The managers of mutual and pension funds attempt to forecast future market positions to guide purchases and sales with the intent of increasing their portfolio values. And individual investors are always interested in systems that will effectively guide their stock and bond purchases.

While neural networks have had success in predicting some market aspects, they are not uniformly successful nor do they explain the underlying mechanisms of the systems that they model (Desai & Bharati, 1998; Freedman, 1991; Jain & Nag, 1995, Saad, *et al.,* 1998; Wong, Wang, Goh & Quek, 1992). As Bender (1996) pointed out, one of the major strengths of neural networks is "associate" memory, where associate memory is the capability to use sets of incomplete information about a system to develop a complete representation that system.

Peters (1989, p. 32) posited, "the much-touted randomness of stock and bond market returns masks an underlying fractal structure." And in 1999, Mandelbrot stated that fractal time series "create a more realistic picture of market risks" (p. 71). However, Mandelbrot also noted that the fractal techniques do not always provide an adequate forecast for small time periods.

Barriers and Issues

Financial predictions have long been of interest in both the business and academic worlds. While many financial modeling systems have been available, effective employment of both neural networks and fractals in financial arenas is relatively new. The development of ANN's began as an attempt to model human thought processes, but was soon recognized as potentially valuable for financial predictions. (Gately, 1996) However, functional applications were delayed until the early 1980s, while computer hardware was developed with sufficient power and availability to allow research to proceed. (Eberhart & Dobbins, 1990)

Mirowski (1995) also pointed out that testing fractal time series data requires significant computing power that was not available in the 1970's. To attempt to circumvent the lack of computing resources, calculations testing the FTS approach were often made using index prices, which tended to yield less than satisfactory results.

Along similar lines, fractals were not defined well enough to be effectively employed until Mandelbrot's seminal work codified the new branch of mathematics (1983). More time was needed for a coterie of researchers to develop that understood enough about fractal mathematics to utilize the concepts.

Mirowski (1990, 1995) painted a gloomy historical view of how Mandelbrot's work was received in the late 1960s and early 1970s. Mandelbrot is a mathematician, not an economist and, as an IBM researcher, an academic outsider. Moreover, he placed emphasis on geometry and visualization rather than the definite, continuous functions favored by economists.

"Mandelbrot essentially proposed to relinquish all hope of determinism by renouncing the quest for any mechanistic dynamics in favor of a thoroughgoing stochastic approach in economics, but since this inherently contradicted neoclassical theory, it was rejected by the majority of economists" (Mirowski, 1990, p. 300). Mandelbrot (1997) confirmed this conjecture in the preface to his compendium book on finance in which he thanks IBM for providing "a unique haven for a variety of investigations that science needed, but

Academia neither welcomed nor rewarded" (p. 11). By the mid-1970's, Mandelbrot shifted his studies away from economics into fields in which his work was more readily accepted. With no champion, minimal application of fractals was seen in economics.

Considering the problems with limited computing capacities and the lack of acceptance of fractal models, it was not surprising to find no serious studies on fractal neural networks in financial computing.

Limitations of the Study

While current use of ANN's has shown promise in financial predictions, the results are not consistent. For example, Desai and Bharati (1998) found that ANN's provide no significant improvement over traditional models for predicting performance for small stocks and some government bonds.

Another difficulty with ANN's is their "black-box" nature. Wong *et al.* (1992) discussed the inability of ANN's to explain their predictions. In some cases, the internal processes of ANN's may be intractable or may not be useful in explaining the derivation of the results from the input. For neural networks, the "popularity continues in spite of the fact that the predictions of neural networks cannot be explained or verified." (Pantazopoulos, Tsoukalas, Bourbakis, Brün & Houstis, 1998, p. 520)

Successful applications of ANN's for financial forecasting have used multilayer feedforward networks (MFN) with back propagation. However, the initial construction of these networks is often dependent more on trial and error and on the experience of the user than on a clear formulation for the determination of the number of neurons and/or hidden layers. Jain and Nag (1995) indicated that they chose to utilize a single hidden layer simply because the addition of more layers did not produce better results, although it may decrease the training time. Desai and Bharati (1998) pointed out that there is no consistent approach to determining the number of neurons in the hidden layer and while larger numbers of neurons provide greater flexibility, the network may come to mirror the error in the training set. Also, Prevost *et al.* (1994, p. 1157) indicated that neural networks are most successful when the conditions are ideal, that is:

1) a quantitatively sufficient example database,
2) an ideal distribution of examples in the chosen input parameters space,
3) a nearly nonexistent noise,
4) the chosen parameters are always defined for every example.

In other words, best results occur when there are sufficient observations of good quality to use for training and testing.

This dissertation was limited to predictions of the Deutschemark/US Dollar and US Dollar/British Pound exchange rates. Many other financial systems are also amenable to multiple-approach simulation, but the Mark exchange rate was chosen because the multifractal analysis by Fisher *et al.* (1997) had been done and was used to provide a validation check for the fractal simulation and the work of Walczak examined both the Mark and Pound exchange rates. Also, data was readily and inexpensively available from several sources, including the U. S. Federal Reserve Board.

Summary

Fractal neural networks, which integrate artificial neural networks and fractal time series, were expected to yield a simulation system that can effectively model financial systems. Since ANN's work well with systems comprised of many complex factors, but with relationships that are not clearly defined, and fractal time series effectively describe volatile systems operating over long time frames, yet exhibiting repetitive patterns, FNN's were expected to be useful in modeling financial systems that often exhibit the above features.

Chapter 2

Review of the Literature

This chapter provides an overview of the literature on artificial neural networks, fractal time series and fractal neural networks, echoing the rather erratic progress that has been a hallmark for the field of artificial intelligence. From its initial description by psychological researchers through current research into areas such as fuzzy neural networks, chaos theory and genetic algorithms, the field of artificial intelligence research has followed a sporadic path, moving forward in leaps and sitting quiescent for years. This pathway is particularly true for artificial neural networks.

Historical Overview

Artificial Neural Networks

Initial investigations and nomenclature originated with the psychologists and physiologists. (Nelson & Illingworth, 1991; Kartalopoulos, 1996; Eberhart & Dobbins, 1990). As the computer models were developed, the research and orientation shifted to computer scientists. However, the nomenclature remained that of psychology. The development of ANN's can be visualized through the time-line shown in Figure 1.

To better understand artificial neural networks, it is useful to visualize a natural neural network. The human brain is constructed from cells called neurons. While neurons may vary somewhat, depending on function, they hold to the basic structure that is shown in Figure 2. Within the brain, information flows from neuron to neuron by transmission of

Present	late 80s to now	Interest explodes with conferences, articles, simulations, new companies, government funded research.
Late Infancy	1982	Hopfield at National Academy of Sciences
Stunted Growth	1969	Some research continues
		Minsky & Papert's critique, *Perceptrons*
Early Infancy	late 50s, 60s	Excessive hype
		Research efforts expand
Birth	1956	AI & Neural Computing Fields launched
		Dartmouth Summer Research Project
Gestation	1950s	Age of computer simulation
	1949	Hebb, *The Organization of Behavior*
	1943	McCulloch & Pitts paper on neurons
	1936	Turing uses brain as computing paradigm
Conception	1890	James, *Psychology (Briefer Course)*

Figure 1. A Brief History of Neural Networks. From *A Practical Guide to Neural Nets* (p. 27), by M. M. Nelson and W. T. Illingworth, 1991, New York: Addison-Wesley Publishing Company. Copyright 1991 by Addison-Wesley Publishing Company. Reprinted with permission.

electrochemical impulses. When a neuron receives a signal, it builds an electrochemical impulse that is sent down the axon. At the axonic end, if the impulse is strong enough, a threshold is reached and membrane depolarizes, changing its polarity distribution. In effect, a charge is sent across the synapse. Dendrites from the neurons in the next layer pick up the charge and continue the procedure.

Neurons rarely act alone; instead they form multilayer networks. For example, visual

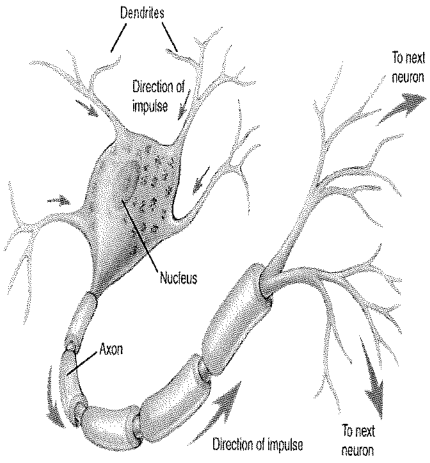

Figure 2. Biological neuron. From *Neuron Image*, McGraw-Hill Companies, Introductory Psychology Image Bank: http://mhhe.com/socscience/intro/ibank/set1.htm. Reprinted with permission.

neurons initially pick up signals from receptor cells in the eye. When the signals pass to the next set of neurons, the signals from each neuron are passed to several neurons and become mixed. After several layers, one image emerges from the individual inputs.

Artificial neural networks were initially developed as a tool to unravel how the human mind worked (Eberhart & Dobbins, 1990). Indeed, much of the terminology used in ANN's refers to anatomical and physiological features of the brain. As a generalization, brain cells known as neurons receive a signal. This signal is passed on to one or more neurons across synaptic gaps by connections made between axons of the instigator and the dendrites of the receptor (Eberhart and Dobbins, Nelson & Illingworth, 1991).

ANN's are organized along similar lines to the brain model. ANN neurons (also known as nodes, processing points or perceptrons) are organized into layers, with the top or initial layer known as the input layer and the final layer as the output layer. Any layers in between are designated as hidden layers. Each of the different layers consists of one or more neurons. The ANN's input layer receives external input values. The input values are weighted and processed, and then directed outward, either to another layer or to a final output. Data from one neuron may be passed to one, some or all neurons in the next layer.

As data enters a neuron of the next layer the input is weighted and, depending on the number of neurons and their weighting factors, combined with input from other neurons. The composite value then is acted upon by a transfer function that adjusts output to lie within a designated range and is passed on, either to the next layer or to the final output.

Each upper neuron may transfer data to more than one neuron in the next layer. If there are multiple nodes in a layer, the weightings of the input from each upper neuron to each of the lower neurons may not all be the same.

For this work, only feed-forward, back propagation ANN's were used. Feed forward ANN's are unidirectional, with data flowing in the forward direction only, going from the input layer, through the hidden layers, to the output layer. No data passes between neurons in the same layer nor does data flow backward to a previous layer. A simplified model of a 3 layer feed-forward ANN resembles that shown in Figure 3.

Neural networks also need to be trained, in this case by back propagation. In back propagation, a training set of data with known outcomes is used. The ANN processes the data and the output is compared to the actual value. The difference or error is used to adjust the weighting of the data passed from layer to layer. The ANN, using the adjusted weightings again processes the training sets. The cycle is repeated until a minimum error value is reached or a maximum number of cycles are processed, at which time the ANN is considered to be trained. After training, the ANN uses the final weight values to make

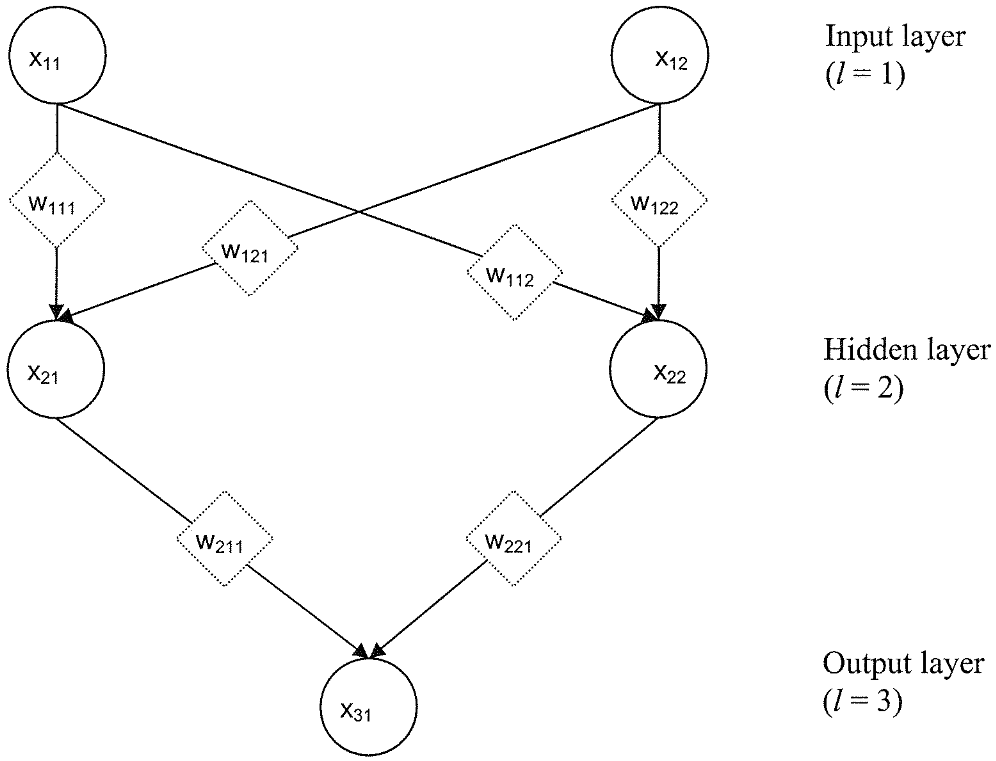

Figure 3. Three layer artificial neural network.

predictive calculations.

Fractal Time Series

"A fractal is a geometric shape that can be separated into parts, each of which is a reduced-scale version of the whole." (Mandelbrot, 1999, p. 71) Mandelbrot codified and expanded on this concept in his formulation of the new mathematical field of fractal geometry. Of the foundation concepts, self-similarity, the property by which a part can be transformed into the whole by utilizing a transforming ratio (Mandelbrot, 1999) is the starting point for fractal applications to finance.

A self-similar figure (Mandelbrot, 1983) is one in which no dimension or direction has more importance than another does. For example, a head of cauliflower can be uniformly scaled to reveal clumps and further to reveal flowerets. "The fine details seen under a microscope are the same (scale aside) as the gross features seen by the naked eye." (Mandelbrot, 1999, p. 152) In self-similar figures, the scales of each coordinate position are tightly bound to the other.

As an example of self-similarity, consider a narrow corridor that runs between two large mirrors. When a person stands in the corridor facing one of the mirrors, the observer will see the expected self-reflection but also the reflection of the observer's back seen as the image of the second mirror reflected in the first. But the second mirror image also shows a reflection of the first and that secondary image of the first again shows the second, but in a smaller size. These images continue to provide ever-smaller cascading images, each showing the entire scene.

In other situations, dimensions exist that have a unique importance and are independent of the value of other dimensions, with time being a prime example of a unique dimension. For example, a graph of stock prices over time could be constructed in many forms, with differing units for both time and prices. Constructs with a unique dimension are denoted as self-affine, a generalization of self-similar.

Irregularity is the hallmark of these self-affine structures and is quantified by the scale factor and the Hurst-Hölder exponent, H, which represents the fractal co-dimension. Unlike Euclidean dimensions, fractal dimensions are not required to be integers.

In arenas such as finance, self-affine structures can be extended. Many seemingly random factors exhibit fractal structure that may enter into the determination of values such as stock prices. Such structures are then referred to as multifractals. When a portion of a system is recognized as a fractal, the self-affine nature of the part can be used to predict the nature of the system as a whole.

Fractal Neural Networks

The application of fractals to neural networks would seem a reasonable union, but there are few references to FNN's in the literature. Widjaja (2000) noted that he had not "found any paper on formal and thorough analysis of the properties of Fractal Neural Network." Murthy and Pittman (1998) have made a rigorous connection of fractal structure to neural networks by demonstrating that the convergence of the gradient descent technique in ANN's can be proved with fractal theory. The FNN techniques employed by Prevost *et al.* (1994) provide a first approach to the application of FNN's to actual problems. Ieshima and Tokosumi (1999) and Widjaja (2000) have begun to apply FNN's to cognitive applications such as pattern recognition.

Prevost *et al.* (1994) contend that an FNN is especially useful in situations where the input values are sparse or incomplete or where the data relationships are complex and non-linear. Within the network, after the first hidden layer, the weighting factor for each input value directly depends not only on the output of the layer immediately above it, but also on the output from the neurons in the layer above the immediate predecessor layer. Such a structure exhibits self-similarity (Prevost *et al.*, 1994). The approach to correction of the weighting values is also more complex and must take into consideration the weighting values of both the previous and the preceding layers.

Theory and Research Literature Specific to the Topic

Artificial Neural Networks

As Gately (1996, p. 12) points out, "neural networks are best applied to problems that require pattern matching, complex interrelationships, or selective use of data." Financial forecasts, with the myriad of factors, fit well into this scenario.

An examination of the literature indicates that neural networks can provide an effective tool in financial predictions, but no single approach can be clearly designated as optimal. Many techniques are shown in the literature, including variations in the types of input data, the neural network architecture and the approaches utilized in training and post-processing.

Gately (1996) also reviews general considerations needed to construct a financial neural network. He notes that the training set must contain the samples of the desired result such as stock prices or exchange rates and the related time frame. Additionally, two classes of factors, fundamental and technical, are often included in the data. Fundamental factors, such as benchmark stock indices, trading volume, the price of gold, the prime interest rate and the inflation rate, may be thought of as quasi-independent factors, while technical factors, such as money flow index, volatility and the relative strength index (RSI), are considered dependent, since they are derived from the stock price and/or volume information. Gately observes that neural network simulations that use only fundamental indicators can be effective, but ANN's relying solely on technical factors rarely are. However, the addition of technical factors to fundamental indicator-based ANN's can improve performance.

The input data sets may consist of minimal data types such as stock prices, stock price changes or index prices and either the date or the time (Saad, *et al.,* 1998; Schierholt & Dagli, 1996; Ornes & Sklansky, 1997). These minimal data sets are often utilized when the project attempts to compare results from different neural network approaches.

When more input types are added, predictions tend to improve. Lowe (1994) used the stock prices of seven component stocks to predict the future FTSE-100 Index price. Chen (1994) uses four daily market prices - opening, high, low and closing - to predict market prices. Brauner, Dayhoff, Sun and Hormby (1997) used from eight to fifteen inputs of factors such as the price of gold and the Dow Jones Industrial Average to predict stock prices.

When specific stock prices are to be predicted, the addition of corporate data, in addition to market indicators, can significantly improve network performance. Mani, Quah, Mahfoud and Barr (1995) and Atiya, Talaat and Shaheen (1997) used such corporate data as earnings and cash flow, in addition to market indicators. Falas, Charitou and Charalambous (1994) used corporate data in the form of ratios or changes in values. Regardless of the type of neural network architecture, addition of corporate factors resulted in more accurate predictions.

Selective acquisition of training data and preprocessing of input data also improved prediction results. Tsaih, Hsu and Lai (1998) utilized a rule-based system to filter training data and to activate triggers for neural network calculations. Ornes and Sklansky (1997) used a dual network approach in their S & P 100 predictions. In training, outlying and anomalous values were used to train a second neural network. The data points used in the actual predictions were routed to the appropriate network, based on the match with the standard or anomalous data.

Much of the literature focuses on comparisons of different neural network architectures. Chen (1994) compared the results of predicting currency market prices and the Dow Jones Industrial Average using standard feed-forward propagation, general regression, class-sensitive and conjugate gradient trained neural networks. Hobbs and Bourbakis (1995) used a fuzzy neural network to predict stock prices. Tsaih, Hsu and Lai (1998) used recurrent, back-propagation and probabilistic neural networks to predict the S & P 500 Index. Schierholt and Dagli (1996) calculated the S & P 500 Index and the currency Index using both feed-forward and probabilistic neural networks. In each of these cases, at least one of the networks outperformed the feed-forward neural network. However, the differences in input data, time periods used and the output results prevent any direct comparison among the studies.

Gately (1996) examined multiple architectures, including back-propagation, recurrent, jump-connection, Ward, Kohonen, probabilistic and general regression, and made calculations using the same data sets. He suggests that factors such as training and input data density, processing power and speed, ability to preprocess data, selection of activation functions and the time available for training have major impacts on the predictions of each of the architectures.

Fractal Time Series

Mandelbrot (1997) has applied fractals to finance in many situations. In the early 1960's he used fractals to work with income maximization and commodity prices. After a lengthy gap, Mandelbrot returned to financial modeling, asserting that "variations in financial prices can be accounted for by a model derived from my work in fractal geometry. Fractals – or their later elaboration, called multifractals – do not purport to predict the future with certainty. But they do create a more realistic picture of market risks" (p. 71).

Mandelbrot, along with Fisher and Calvet, further expanded upon the multifractal concept by creating the multifractal model of asset returns (MMAR) (Mandelbrot, Fisher & Calvet, 1997) and further refining the model to focus on local behavior over short time intervals (Calvet, Fisher & Mandelbrot, 1997). They then applied the MMAR model to the simulation of the Deutschemark/U. S. Dollar exchange rates (Fisher *et al.,* 1997).

Peters (1998) applied fractals to stock and bond returns through a systems denoted rescaled range analysis (R/A). In particular, he notes that prices exhibit strong bias from prior history and that the effect of the bias can be described through fractal modeling. He further refined his approach (1994) with the Fractal Market Hypothesis, a model that proposes the appearance of the distribution of returns has the same structure regardless of investment time periods. He also states "the shorter the term of the investment horizon, the more important technical factors, trading activity, and liquidity become" (p. 48).

However, Ambrose, Ancel and Griffiths (1993) dispute the applicability of R/A, noting that results can be unduly influenced by short-term biases.

Lux (1999) applied the multifractal model of Mandelbrot, Calvet and Fisher to four different financial arenas, the German and U. S. stock market indices (DAX and NYSE Composite Indices), the Deutschemark/U.S. Dollar exchange rate and the price of gold on the London Precious Metals Exchange. He found the multifractal model to outperform standard predictive models.

Fractal Neural Networks

Studies (Merrill and Port, 1991; Kim, Sano & Sawada, 1993) have shown that biological neural systems exhibit a fractal structure. The introduction of fractal analysis would seem to be a reasonable extension of artificial neural networks. Indeed, Prevost, *et al.* (1994) used a fractal neural network to predict steel transformation curves. Their results showed improved results over non-fractal ANN predictions. Hitachi Ltd. (Business Week,1992) is reported to have developed a fractal neural network system to model the financial markets. However, no further mention of this system can be found. It appears that other than the Hitachi system, fractal neural networks have not been applied to financial predictions.

Summary

Both ANN's and fractal time series have been separately employed, with some success, in financial predictions. Fractals have been applied to ANN's in a non-financial situation and should be extensible to financial modeling.

Chapter 3

Methodology

Research Method Employed

This dissertation required the creation of two related modeling systems, each of which ran on a microcomputer. The first was a modular feed forward, back propagation artificial neural network system and the second was a modular feed forward fractal neural network system with back propagation. The programming was done in Microsoft Visual Basic® 6.0. To facilitate ease of testing of each of the different systems and to follow common programming practices, the programs utilized easily replaced modules and/or functions.

The first stage involved creation of the system to create an MFN system using a hyperbolic tangent transfer function, starting from the computer programs listed by Masters (1993), Gately (1996), and Rao and Rao (1995). In the computer code, particular attention was paid to maintaining naming and indexing conventions that promoted ease of understanding that could be converted, with minimal effort, into code for the FNN. Training was conducted by back propagation of errors.

The FNN was constructed by modifying the MFN system, using the network system described by Prevost *et al.* (1994) as a guide. The output layer incorporated data from both the input and first hidden layer and the training process, as described below, was modified to accommodate the additional connections.

In order to provide ease of operation, few factors were "hard-coded". For both simulation systems a parameter file, *SETUP.DAT* (Appendices G and H), and an input data file, *INPUT.DAT*, were used. The simulation program was set to read in the parameters, display the parametric values, allow the user to change the values and finally proceed to process the data. Both files were simple ASCII text files.

Multiple output files were created for each data set. Each run created a file that reiterated the parameters, listed the processing time, and stored the final Least Mean Square (LMS) error. Other files contained the starting weights, the final calculated output values, and the final weights.

To facilitate the analysis of all runs for the set, additional files were generated, an errors file (*ERRORS.DAT*) containing the final LMS error for each set and one file of the calculated values for each output node for each testing point in each set, along with the actual value. Again, these were ASCII files that could be directly printed or imported into a spreadsheet.

The same data used by the MFN and fractal time series were tested and the results compared. The results were examined and an analysis of the finding created. The results were analyzed and inferences made about causes of success or failure of fractal neural networks to successfully predict financial values.

Data Selection

Testing was done to predict both the Deutschemark/US Dollar Exchange rate and the US Dollar/British Pound. While data is available for many years, only exchange rates after 1972 were used, since the exchange rates were not allowed to float until after the Bretton Woods Agreement was signed in 1972 (Peters, 1994). Similarly, the analysis terminated with the 1998 data, when concerns about the effects of the rise of the Euro overshadowing individual currencies such as the Deutschemark and Pound become important.

Data was downloaded from the US Federal Reserve Board Internet site (www.frbchi.org/econinfo/finance/for-exchange/welcome.html). These files contained the "noon buying rates in New York City certified by the Federal Reserve Bank of New York for customs purposes for cable transfers payable in foreign currencies." (US Federal Reserve Board, 2000) In particular, the text files *FOREX_H.TXT* and *FOREX_C.TXT*, that contained data from January 1, 1971 to December 31, 1993 and from January 1, 1994 to July 5, 2000, respectively, were used.

The data files were downloaded from their respective sources and imported into a Microsoft Excel® 2002 spreadsheet. Exchange rates with zero values were removed. In general, zero values corresponded to weekends (Saturdays and Sundays) and to holidays when governments and/or markets were closed. Also, over the test period, holidays changed. For example, the early dates had separate holidays for Washington's and Lincoln's birthdays, while later years had closed markets for Presidents' Day. No attempt was made to directly correlate the dates from year to year. As a time series, all values with non-zero rates were considered to be "work days" with no attempt made to compensate for missing calendar days. In keeping with the presentation of data by the Federal Reserve, the two sets of currency values were inverted to one another, with the Mark data given as Deutschemarks to US Dollars and the Pound data as US Dollars to British Pounds. The exchange rates then show mirror trends as can be seen in the graphs in Appendix K.

In order to focus this work on the effects of converting from an Euclidean to a fractal approach, the data range was narrowed to use only the exchange rates from January 1994 through June 1995. This date range matches that suggested by Walczak (2001). He states that adequate and, at times, better predictions can be made using a limited data set instead of a much larger set. The data were further manipulated so that all analyses were performed on the differences between the exchange rates of successive date ranges. For both Pound and Mark calculations, data from the prior year, 1994, were used to predict the next day exchange rates for the first six months of 1995. Both daily and weekly differences were employed. For each date, the difference between the rate one day in the future (tomorrow) and that date (today) was used as the outcome value (future lag). Three sets were used for daily calculations, a three day set, a skewed three day set and a five day set. The three day set (D3) consisted of the future lag and three lags for the difference between today and yesterday (one day lag), today and two days past (two day lag), and today and three days past (three day lag). Similarly the skewed three day set (D3S) consisted of the future lag, the one day lag, the two day lag, and the five day lag. The five day set (D5) had the future lag and all the lags between one and five.

The weekly set (W) required first extracting one day each week. Where possible, Wednesdays were chosen, since pre- and post-weekend fluctuations tend to appear on Fridays and Mondays and fewer "holiday" closures occur midweek. If the Wednesday in the week was a holiday, the following Thursday was used. The weekly set comprised the one week future lag, usually the difference between Wednesday of next week and Wednesday of this week, and the one to five weekly lags. The final sizes of the sets are shown in Table 2.

Efficient functioning of the neural network required data values scaled to fit within the range of -1 to +1. The range was further narrowed to -0.9 to +0.9 to permit calculated output to exceed the input values. Since the actual lag values are not evenly distributed between positive and negative values, the conversion process was shifted to produce values that directly correspond to the sign of the lag. This permitted rapid preliminary analysis of the data.

Several sources (Fisher, *et* al., 1997; Peters, 1994; Schmitt, *et* al., 1999) have determined that exchange rates exhibit fractal properties. In particular, the Hurst-Hölder exponent, *H*, gives a measure of the fractal nature of a series. For purely independent series such as true Brownian motion, *H* equals 0.50. Time series with values of *H* greater than 0.5 indicate a fractal influence, in particular, situations where early values influence later instances. These processes may also be known as persistent time series or characterized as having long memory effects. Schmitt *et al.* (1999, p. 41) show the values for the exchange rates of the Swiss Franc (CHF), Deutschemark (DEM), US Dollar (USD), British Pound (GBP) and Japanese Yen (JPY) with the French Franc to have *H* significantly greater than 0.50 (Table 1). Similarly, Peters (1994) consistently finds *H* to be greater than 0.60 for Japanese Yen/US Dollar, Deutschemark/US Dollar and British Pound/US Dollar exchange rates.

Series	CHF	DEM	GBP	JPY	USD
H	0.56 ± 0.03	0.63 ± 0.03	0.60 ± 0.03	0.60 ± 0.03	0.58 ± 0.03

Table 1. Estimates of Hurst Exponent. From Multifractal analysis of foreign exchange data. *Applied Stochastic Models and Data Analysis,* (p. 41), by F. Schmitt, D. Schertzer, and S.M. Lovejoy, M. Nelson and W. T. Illingworth, 1999. Copyright 1999 by John Wiley & Sons. Used with permission.

Procedures

Fractal Time Series

The fractal time series calculations relied heavily on the formulation put forth by Peters (1994) and his clarification of some typographical errors through an email exchange with this author. Other variations may be seen in the work done by Fisher *et al.* (1997) and Schmitt, Schertzer and Lovejoy (1999).

Peters' Rescaled Range Analysis system (1994) works with time dependent systems. The process utilizes the self-affine feature of fractal systems by successively dividing a series into smaller steps and examining the underlying common structure of the system.

A time series with *M* points was successively divided into smaller and smaller units. At each step, an analysis will be preformed and the rescaled range of that step was calculated. From the set of rescaled ranges, factors such as the Hurst-Hölder exponent were extracted and used to predict future values.

The time series with M points, $z_1, \ldots, z_M$, was transformed into a new series with $N = (M - 1)$ points by creating a set of stepped logarithmic ratios $x_i = \ln(z_{(i+1)} / z_i)$, where $i = 1, 2, \ldots, (M-1)$. The time period was then divided in P contiguous sets, each with n points; such that $P * n = N$.

For each set a, an average of the points in each individual set were calculated by letting

$\overline{x_a} = (1/n) * \sum_{k=1}^{n} x_{k,a}$ where $a = 1, 2, \ldots, P$. These averages can be used to calculate the

accumulated difference from the mean, $X_{k,a}$, for each of the subsets, a,

$X_{k,a} = \sum_{i=1}^{k} (x_{i,a} - \overline{x_a})$, where $k = 1, 2, \ldots,$ n.

Once the accumulated difference is obtained, the range, R_a, and the standard deviation, S_a, for each subset a are calculated by $R_a = \max(X_{k,a}) - \min(X_{k,a})$ and

$S_a = (\frac{1}{n} * \sum_{k=1}^{n} (x_{k,a} - \overline{x_a})^2)^{0.5}$, with $1 \le k \le n$, respectively. Finally, the range is normalized

by dividing by the corresponding standard deviation for the subset. For the entire set A with subsets of consisting of n points, the rescaled range then becomes

$(R/S)_n = (1/P) * \sum_{a=1}^{P} (R_a / S_a)$.

The number of points, n, in the subset is increased and the process is then repeated. This continues until $n = (M - 1)/2$. When all steps are completed, the Hurst-Hölder exponent is calculated through a least squares analysis of the equation $\ln(R/S_n) = \ln(c) + H * \ln(n)$.

Peters (1994) notes that n must be greater or equal to 10 and that the number of data points used should be critically considered. The optimum number of points will provide the largest number of modulo zero dividers and must include both the beginning and the ending points. Additionally, the number of points selected will depend on the length of any cycles and on the time period covered by the results. For example, if the data points are taken every 20 working days (approximately representing one working month), a four year cycle of highs and lows would need more than forty eight points to begin to see the pattern emerge. However, if daily values are to be used, the number of points selected would have to be greater than 960 to show the repetition. He suggests that the number of points be increased until convergence appears.

Peters (1994) also determined that the exchange rates are autoregressive. Such processes tie the changes at any point in the series to prior changes. The number of prior steps to which the change is related determines the order of the autoregressive process. Thus, a first order autoregressive process, AR(1), is related only to the prior step. A second order process, AR(2), is related to both the prior and the second prior step. Peters suggests that for trading data observed on a scale of days or weeks, an AR(1) process is sufficient.

To correct for an AR(1) process, the data series is transformed by $Z_t = Y_t - (c + d^* Y_{(t-1)})$. The constants are estimated by a least squares fit to the data. For the Deutschemark/US Dollar data, the initial prices, $P_1, P_2, \ldots, P_t$, at each time period will be transformed by $S_t = \ln(P_t / P_{(t-1)})$. The AR(1) transformation then becomes $x_t = S_t - (c + d^* S_{(t-1)})$.

Artificial Neural Network

Feed forward back propagation artificial neural network calculations are normally performed in two steps – training and prediction. For training, a set of input values with related, known results are processed by the network, generating output values. The calculated output values are compared with the actual results and the difference (error) is used to adjust the network. This process is repeated until the error falls below a minimum acceptable value, a maximum number of training cycles are accomplished, or the system begins to diverge. At that point, the neural network is "trained". The parameters of the trained network are then retained.

The predictive phase requires passing a set of input values through the network using the parameters determined in the training phase. For each input set, output values are calculated. While the first step may require hundreds or thousands of passes through the network to converge to final weights but the predictive calculations using those weights require only a single pass through the network.

A general artificial neural network consists of l layers, with layer 1 the input layer, layer l the output layer and layers 2, 3, . . . , l -1 the hidden layers. The total number of nodes in layer l are $N(l)$. Let x_{ij} be a j^{th} node in the i^{th} layer. In a feed-forward network each node in a layer contributes to all nodes in the next layer, but does not interact with nodes within the same layer. The input values are appropriately weighted, so that

$x_{i+1,k} = \sum_{j=1}^{N(i)} w_{ijk} x_{ij}$ where w_{ijk} is the weight of the value of the node x_{ij} that is passed on to node $x_{i+1,k}$ and $N(i)$ is the number of nodes in layer i.

However, to ensure that values remain bounded, a transfer function is normally used to constrain values to lie within a boundary set. For this work, the commonly used hyperbolic tangent function was employed to ensure that results lay between minus one and plus one (Masters, 1993). The transformed result, $X_{i+1,k}$, then has the form

$$X_{i+1,k} = \frac{e^{x_{i+1,k}} - e^{-x_{i+1,k}}}{(e^{x_{i+1,k}} + e^{-x_{i+1,k}})}.$$

In this work, the network was constructed with three layers ($l = 3$), an input layer, one hidden layer and an output layer. The output layer had only one node, the exchange rate and the hidden layers had either five or ten nodes, depending on the number of input points.

For the first calculation on the data set, nodal transfer weights between –0.3 and +0.3 were randomly generated. Eberhart and Dobbins (1990) suggested this range, noting that it may be appropriate as it lies within the upper and lower bounds. However, they did admit, "there is no better reason than 'it works'" (p. 45).

Following the notation of Prevost *et al.* (1994), the training set, $T_{(r)}$, consisted of R sample points so that $T_r = \{I_{r1}, I_{r2}, \ldots, I_{rN}: O_r\}$ where $1 \leq r \leq R$, N is the number of input points, I_{rn}, $1 \leq n \leq N$, and O_r is the single output point. In the training processes, each sample passed through the network. For each r, the input values, I_{rn}, were used as the initial values with in the network: $x_{1n} = I_{rn}$, $n = 1, 2, \ldots, N$. The final calculated output value, $x_{31}(r)$, for each sample r was then compared to the actual output value O_r.

The differences were then used to correct the weighting factors and the process iteratively rerun until convergence was obtained, a maximum number of iteration cycles reached, or the error began to increase rather than decrease. Swingler (1996) notes that there are two approaches to correction. The first is to correct the weights after each sample. The second is to run through all samples and use the combined difference to calculate a weighting correction. Swingler states that both methods have advantages and drawbacks, but neither has a significant convergence advantage. This work used the combined difference method to save calculation steps and speed ccomputations.

The least mean square error was used to test for convergence: $E = (\sum_{r=1}^{R}(x_{31}(r) - O_r)^2)^{1/2}$.

If neither convergence nor a maximum number of iterations has been reached, the error was used to adjust the nodal weights and the training calculations were rerun. Each weight, w_{ijk}, was adjusted to minimize the error. When a minimum is reached, the first derivative of the function should be zero. Since the hyperbolic tangent function,

$f(x) = \dfrac{e^x - e^{-x}}{e^x + e^{-x}}$, has a first derivative of $f'(x) = \left(\dfrac{2}{e^x + e^{-x}}\right)^2$, the iterative processes

attempted to find the network weights that made $\left(\dfrac{2}{e^x + e^{-x}}\right)^2 = 0$. For each interim step,

new weights were calculated by $w_{ijk}(\text{new}) = w_{ijk}(\text{old}) + E * X_{ij}' * X_{ij}$.

It should be noted that MFN's may not always converge or may converge to a false minimum (Eberhart & Dobbins, 1990; Gately, 1996; Swingler, 1996). To help avoid this, a learning rate, α, is used to slow the movement to convergence. The modified correction equation then becomes $w_{ijk}(\text{new}) = w_{ijk}(\text{old}) + \alpha * E * X_{ij}' * X_{ij}$, with α significantly less than 1. The network had to be carefully watched. If it did not show a tendency to converge, the starting weights and the learning rate were adjusted and the process rerun. On the other hand, if a network is over trained, it may memorize values and incorrectly predict new values (Gately, 1996).

For this work, eight sets of calculations were made, four each for the Mark/Dollar exchange rate and the Dollar/Pound exchange rate (See Table 2). In both cases three sets of runs were made using daily lag values: 1, 2, and 3 day lags (Set D3); 1, 2, and 5 day lags (Set D3S); and 1, 2, 3, 4, and 5 day lags (Set D5). A fourth set of runs used the five previous weekly lags (Set W). In the training sessions, values from 1994 were used to set the initial parameters and the data points corresponding to values for the first half of 1995 were predicted. Walczak (2001) and Zhang and Hu (1998) have noted that such small data sets can give reasonable results.

Data Set	**Lag Period**	**Lags (Input)**	**Training Set**	**Results**	**Hidden Layer Nodes**
D3	Days	1, 2, 3	251	126	5
D3S	Days	1, 2, 5	251	126	5
D5	Days	1, 2, 3, 4, 5	251	126	5
W	Weeks	1, 2, 3, 4, 5	52	25	10

Table 2: Data Set Parameters

Approximately 250 initial tests were performed using five sets and 500 cycles (epodes) to determine optimal values for number of nodes for the hidden layer and the learning parameter. The preliminary tests suggested that the use of 5 hidden nodes for the daily trials and 10 hidden nodes for the weekly sets would be effective. In all cases, a value of 0.2 for the learning value led to a reasonable balance of convergence and speed.

For the reported results, each set consisted of 100 runs, each with its own randomly generated initial values and a learning parameter of 0.2. A maximum of 30,000 epodes were permitted for each run within the set, regardless of the LMS. If the LMS error became less than 0.002, or if ten successive epodes had an LMS error that was larger than the previous value, the training was terminated. If the error was larger than that of the previous epode, the learning parameter was halved and the smaller value used in the next epode. For every set of calculations, the initial parameters were saved to a file to permit later usage by the FNN (see below). All final training output values, the predicted values, and error values were saved to separate disk files for later analysis.

Fractal Neural Network

The fractal neural network computations were based on the work of Prevost *et al.* (1994). They describe a neural network that has, after the first set of computations, nodal weights that are no longer constants, but variables that depend on the values of the second prior layer. These weights can be expressed as pseudo-networks of their own, as shown in Figure 4. As each nodal value is determined by weighted values from both the previous layer and the second previous layer, an echoing, self-similar pattern develops, describing a fractal system.

The model describing the traditional MFN was expanded for the fractal system. The three-layer network was again used, with an input (first) layer, a single node as the output (fourth) layer and one hidden layer. Where possible, notation that was the same or similar to that of the MFN was used.

The left side of Figure 4 shows that the FNN resembles the MFN, with nodal values weighted and passed to the nodes of the next layer. However, in the FNN, the nodal

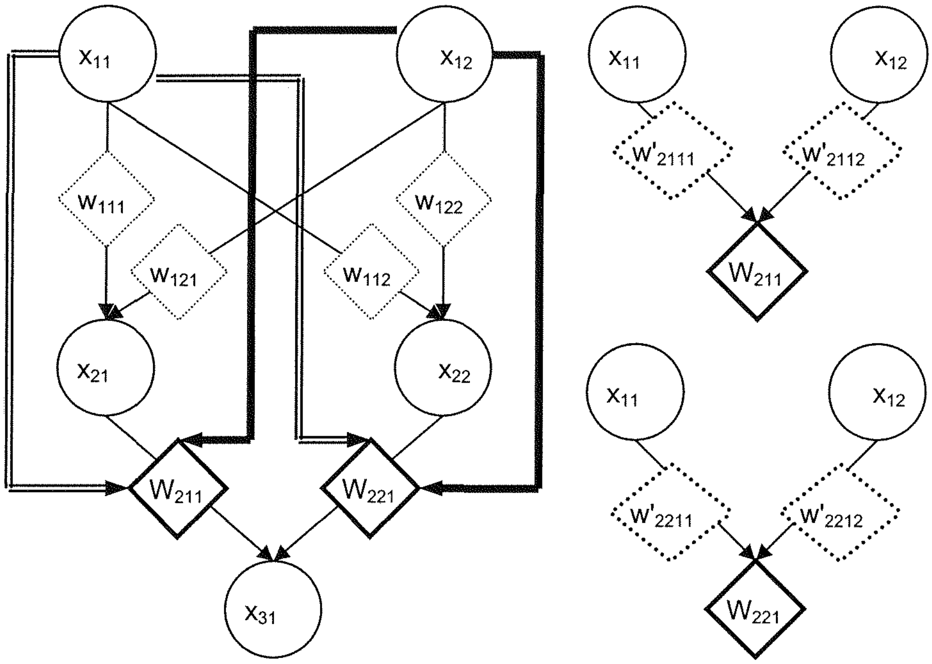

Figure 4. Three layer fractal neural network.

weights can then be expanded into "mini" networks arising from the second prior layer, as shown on the right side of Figure 4.

Since there is no layer above the input layer, the computations for the values of the nodes of the first hidden layer are the same as those of the MFN. For any node $x_{2,k}$ of the second layer (first hidden layer) having $N(1)$ nodes in layer 1, $x_{2,k} = \sum_{j=1}^{N(1)} w_{1jk} x_{1j}$ where w_{1jk} is the weight of the value of the node x_{1j} that is passed on to node x_{2k}. This weight is independent of the individual nodal values for layer 1. For the remainder of the FNN, the layers after the second, hidden or output, are represented as $x_{i+1,k} = \sum_{j=1}^{N(i)} W_{ijk} x_{ij}$ where i is greater than 2 and W_{ijk} is the pseudo-weight. This portion of the network, which has the structure of an MFN, is referred to as the "core" network.

As noted above, the pseudo-weight can be described as the output of another network, so that $W_{ijk} = \sum_{l=1}^{N(i-1)} w'_{i-1,jkl} x_{i-1,l}$, where $N(i-1)$ is the number of nodes in the second prior layer (two layers higher). The new weight, $w'_{i-1,jkl}$, is a different weight from that used in the "core" terms. For notational clarity, these weights are referred to as fractal weights. Each sample point has a set of pseudo-weights associated with it that vary for each sample point.

The training portion of the network process was also an extension of the training process for an MFN. To more closely correlate the FNN with the MFN, the FNN used as the initial set of weights for the first to second layer (input to first hidden) the initial weight file from the same run of the MFN, along with the same learning parameter of 0.2. The initial values for all fractal weights were randomly assigned within the range –0.3 to +0.3 and a separate fractal learning parameter was assigned to the fractal portion of the network. The output values were computed and, as with the MFN, an error value determined. The computations were made for all points in the input set. Then, for each layer, the combined error values were used to calculate new values for the pseudo-weights, W_{ijk}, in the core network, just as was done with the MFN.

The differences between the original and the new pseudo-weights were used as correction terms to the subordinate networks. By using a technique similar to the MFN process, the fractal weights were recalculated for every training point. Since the pseudo-weights are directly dependent on the nodal values, rather than calculating a single new value for fractal weight, each point in the training set required that the fractal weights be recalculated for every point. A simple average was then calculated for every fractal weight and the average then became the new weight. The iterative process continued until convergence was reached. The trained network was then used in predictive computations.

Resources Used

The author provided all appropriate computer hardware and software and all needed computer programming. Calculations were run on several computers, each with 512 MB memory and processor speeds ranging from 850 MHz to 1.8 GHz. These systems used either Windows 2000ME® or Windows XP® as the operating system. No difference, except for speed of completion, was noted in the results of the same calculations run on different computers when started with the same parameters from a file of fixed starting values.

Data for analysis were downloaded from the Internet sites of the US Federal Reserve Board. As noted above, the *FOREX_H.TXT* and *FOREX_C.TXT* files from the US Federal Reserve provided the exchange rate data. The data points and the lags calculated from the data are shown in Appendices C through F.

Reliability and Validity

In order to follow the restrictions of the time series calculations, the input data were divided into two subsets, one with early data (1994 daily exchange rates) that was used to set parameters and then to train the networks and a second set of later data (January through June 1995) was used to predict values. The "predicted" values were then compared to the actual values.

Tests for Validity and Conversion

For the neural networks, initial starting weights were modified by generating a set of random starting weights for each run. These weights are multiples of a pseudo-random number ranging from 0 to +1 that was generated by the program. The "randomness" of these seeds was determined by generating several sets of 10,000 values each within the range of 0 to +1 and sorting them into groups by tenths. The distributions were uniform, with subset counts within the range 950 to 1050, indicating a random distribution.

For each run through the data set, the network calculations were allowed to proceed until the LMS error became less than a predetermined value, a maximum number of cycles was exceeded, or 10 consecutive iterations showed increasing LMS error. Normally, non-convergent results would have been discarded. However, in order to better compare equivalent starting positions in the ANN and FNN calculations, non-convergent values were retained.

Hu, Zhang, Jiang, and Patuwo (1999) note that most neural network research found in the literature uses the approach of dividing the data set into two subsets – one for training and one for testing or validating the results. They also suggest that other techniques of cross-validation, such as moving and rolling validation approaches may produce better forecasts. Reed and Marks (1999) also contend that other cross-validation techniques such as leave-one-out, k-fold cross-validation and bootstrapping may be effective when used with small data sets. However, Walczak has obtained improved predictions using a simple two subset approach and small datasets. For this work's comparison of the effectiveness of ANN's with of FNN's, the simpler two subset structure was used to minimize the difficulty in comparing two complex models.

Both the results of the calculations and the scaled actual results were imported into an Excel® spreadsheet. The change from one period to another was calculated for the observations and for the final value from each run. The directional change, either positive or negative, was calculated and compared with the actual directional change. Agreement with the actual directional change would provide a prediction that would be profitable. The calculated results were also converted back to the exchange rates and compared with the observed rates. From these a total profit or loss for the test period was calculated, based on a fixed value of sales or purchases per transaction.

Summary

Three systems were constructed to model the Mark and Pound exchange rates: a fractal time series; a multilayer, feed-forward neural network; and fractal neural network. These models were used to predict "future" values of the exchange rate and their predictive abilities were compared.

Chapter 4

Results

Data Analysis

The success of the both the ANN and the FNN was determined both by the ability of the networks to predict the direction of change of the exchange rate and the net gain or loss that would be realized by utilizing the predictions. In other words, would tomorrow's exchange rate be higher or lower than today's and, if the predictions were followed and a sale or purchase made, would there be a profit or loss?

Prior to network simulations, FTS calculations were made to verify that the data sets to be tested exhibited fractal values. For the Daily and Weekly data for both the Pound and the Mark systems, the Hurst exponents were calculated.

For both the ANN and the FNN the results are presented as summaries of 100 runs on the same data sets (Appendix I). Each ANN epode exhibits somewhat different output values, iteration cycles, and LMS errors arising from the randomly generated starting weights. The FNN epodes show the similar disparities since they utilize the same starting weights for the first hidden layer as the ANN epodes. The procedure for analyzing of the results was the same for both ANN and FNN calculations.

The first test of the data, the directional change, determined how often the network (either ANN or FNN) matched the change in the direction of the exchange rate, *i. e.* whether the network's prediction of an increase or decrease in the exchange rate was correct. This analysis required subtracting each day's actual rate from the actual rate of the next day to determine whether the rate increased or decreased. Then that day's actual rate was subtracted from the predicted rate for the next day. The predicted change and actual change were considered to match if both increased or both decreased, regardless of whether the amount of change matched. An average of the percentage of correct predictions was found for all of the epodes.

The second test examined the potential for profit or loss based on the predictions of the networks. In accordance with Walczak (2001), standard blocks of currency of 62,500 DEM for the Mark/dollar exchange or 31,500 pounds for the Pound/Dollar exchange were purchased or sold based upon the next day predictions. If the exchange rate was predicted to rise for the next day, the block was purchased at the current day's price. If the exchange rate was predicted to fall, the block was sold at the current day's price. The actual value of the next day price was used to determine whether the transaction outcome was a profit or loss. These amounts were then compared to "forecasts" made using the actual values.

Findings

FTS Calculations

The FTS calculations require sufficient data points to allow their distribution into multiple sets. The initial data must be evenly divisible and provide sufficient subsets so that reasonable values of the exponents may be calculated. For the weekly data, the point sets were expanded to 102 data points (July 21, 1993 through June 28, 1995). Similarly, the daily point sets were increased to 402 data points (November 29, 1993 through June 30, 1995).

As shown in Table 3, the Hurst exponent for these short time frames show values in excess of 0.05. Gately (1994) attributes these values to long memory effects that occur independent of the time scale in use. The similarity in the values between the respective daily and weekly sets indicates the presence of a fractal time series.

	Hurst Exponent	**Standard Error**
Mark		
Daily	0. 716	0.010
Weekly	0.714	0.013
Pound		
Daily	0.717	0.013
Weekly	0.692	0.045

Table 3: Hurst Exponents

Least Mean Square Error

One technique for comparing the effectiveness of neural network results is to look at the final value for the LMS error for each related run for the ANN's and FNN's. As can be seen in Table 4 and Appendix I, the FNN's tend to converge to lower LMS errors than those of the ANN's. Also, the FNN's had fewer non-convergent runs than the ANN's. At several points, (see Appendix I, Mark D5 and W charts and Pound D5 and W charts) the non-convergent ANN points do converge under the related FNN.

	NN		FNN		FNN Error less than NN Error
	Average	Standard Deviation	Average	Standard Deviation	
Mark					
Daily – D3	0.044421	0.000576	0.042757	0.000926	5
Daily – D3S	0.044531	0.000816	0.042732	0.001343	6
Daily – D5	0.045288	0.004268	0.042826	0.002027	17
Weekly - W	0.063010	0.047965	0.048283	0.007117	7
Pound					
Daily – D3	0.027737	0.000325	0.027331	0.000590	11
Daily – D3S	0.027757	0.000479	0.027388	0.001561	11
Daily – D5	0.028325	0.002141	0.026629	0.002375	10
Weekly – W	0.141709	0.120264	0.110004	0.013180	11

Table 4: Least Mean Square Error Summary

Predictive Calculations

The best test of the efficacy of the networks is made through the closeness of predictions to actual values. The summary of the calculations is listed in Tables 5 and Appendix J.

	Correct Direction		Profit/Loss	
	NN	FNN	NN	FNN
Mark				
Daily – D3	48.5%	46.7%	-128.63	2,746.37
Daily – D3S	48.6%	46.7%	1,231.50	5,332.75
Daily – D5	49.6%	49.6%	763.00	5,891.37
Weekly - W	50.0%	57.3%	623.88	3,524.37
Pound				
Daily – D3	50.9%	55.0%	720.31	1,946.63
Daily – D3S	50.7%	56.4%	865.12	2,191.06
Daily – D5	49.4%	54.8%	-113.88	1,931.75
Weekly – W	48.5%	52.5%	-654.58	131.44

Table 5: Results Summary

The simplest predictive test is the determination of the direction of change of the rate over the time period. For the Pound, both daily and weekly, and for the weekly Mark, the FNN predictions were more successful than the ANN predictions. Only the weekly Mark had directional ANN predictions that were better than those of the FNN.

However, when the actual profit or loss was calculated, the FNN provided better results than those of the ANN in all cases. The daily Mark values emphasize the need to examine the profits and losses, rather than rely solely on the directional changes. The differences arise from the FNN losses being less than those of the ANN and/or the gains being better. In actual usage, better results could be expected by removing the non-convergent values.

Summary of Results

For all tests, the FNN consistently attained lower least mean square errors than those from the corresponding ANN. Since each FNN epode began with as much of the starting parameters as possible from the ANN, the FNN can be considered to more closely approach the "actual" values. However, there is a price for the improvement in the LMS error. More iterations are needed to reach a better value. Since more calculations are performed for each cycle in the fractal network, processing time increases significantly.

In both neural network models, only limited efforts were made to improve performance. The efforts to optimize the parameters of the models were directed only to the ANN. The parameters and approaches used for the FNN were not optimized but set to match as closely as possible to those from the ANN. In addition, non-convergent values were not discarded, as would normally be done.

Even within this less than optimal strategy, the FNN's provide better predictions than those of the ANN's. The results of the FNN calculations, along with those of the Fractal Time Series, confirm the existence of fractal patterns in exchange rates.

Chapter 5

Conclusion, Implications, Recommendations, and Summary

Conclusion

Fractal neural networks can be thought of as artificial neural networks that can be deconstructed into smaller neural networks, exhibiting the property of self-similarity. The fractal hybrid of a neural network described herein provides a new technique for modeling complex systems, particularly those that exhibit repetitive, fractal patterns. When directly compared to the result of processing by traditional artificial neural networks, fractal neural networks produced better predictions for foreign exchange rates.

Implications

Fractal neural networks can be expected to improve successful results for systems that use artificial neural networks. FNN's add more complexity and more capacity to factor in long memory features. Systems that show repetitive patterns over time would be good candidates for FNN analysis. Exchange rates, interest rates, and stock and bond markets are some financial systems that could be modeled with FNN's. FNN's may also be applicable to studies of climate, stellar phenomena, animal migrations and linguistic patterns.

Recommendations

The work done with FNN's can be expanded in many ways. The testing procedure can be modified to include other cross-validation approaches, such as k-fold or rolling validation. More hidden layers and/or nodes can be added to the network. With additional layers, more of the fractal processing would be included. For example, in a network with two hidden layers, the weights from hidden layer one to hidden layer two would be calculated from the nodes of the input layer and the weights from the second hidden layer to the output layer would be calculated from the nodes of the first hidden layer.

The fractal pattern can also be expanded to bring in the effects of several higher layers. For example, in a network with two hidden layers, the weights from hidden layer one to hidden layer two would be calculated from the values of the nodes of the input layer. However, the weights from the second hidden layer to the output layer would be calculated from the nodes of the first hidden layer and the nodes of the input layer. Larger scope of treatments would enable the potential development of a set of best practices for FNN analyses.

Summary

Fractal neural networks can expand the flexibility and effectiveness of financial predictions made with neural networks. FNN's can minimize the least mean squared error of the calculations and, as an aggregate, provide better predictions.

Appendix A

Expansion of Nodal Value Calculations

For a simple three layer ANN with no transfer functions, the output value will be

$$y = x_{31} = w_{211} * x_{21} + w_{221} * x_{22}.$$

Since $x_{21} = w_{111} * x_{11} + w_{121} * x_{12}$ and $x_{22} = w_{112} * x_{11} + w_{122} * x_{12}$,

$$y = w_{211} * (w_{111} * x_{11} + w_{121} * x_{12}) + w_{221} * (w_{112} * x_{11} + w_{122} * x_{12})$$

$$= (w_{111} * w_{211} + w_{112} * w_{221}) * x_{11} + (w_{121} * w_{211} + w_{122} * w_{221}) * x_{12}.$$

For a three layer FNN, the output value for the core will be similar to that of the ANN

$$y = x_{31} = W_{211} * x_{21} + W_{221} * x_{22}.$$

Since $x_{21} = w_{111} * x_{11} + w_{121} * x_{12}$ and $x_{22} = w_{112} * x_{11} + w_{122} * x_{12}$,

$$y = W_{211} * (w_{111} * x_{11} + w_{121} * x_{12}) + W_{221} * (w_{112} * x_{11} + w_{122} * x_{12}).$$

The pseudo-weight expansions are

$$W_{211} = w'_{2111} * x_{11} + w'_{2112} * x_{12} \text{ and } W_{221} = w'_{2211} * x_{11} + w'_{2212} * x_{12}.$$

Substituting for the pseudo-weights,

$$y = (w'_{2111} * x_{11} + w'_{2112} * x_{12}) * (w_{111} * x_{11} + w_{121} * x_{12})$$

$$+ (w'_{2211} * x_{11} + w'_{2212} * x_{12}) * (w_{112} * x_{11} + w_{122} * x_{12})$$

$$= [w_{111} * w'_{2111} + w_{112} * w'_{2211}] * x_{11}^2$$

$$+ [w_{121} * w'_{2111} + w_{111} * w'_{2112} + w_{122} * w'_{2211} + w_{112} * w'_{2212}] * x_{11} * x_{12}$$

$$+ [w_{121} * w'_{2112} + w_{122} * w'_{2212}] * x_{12}^2.$$

Even these simple networks show that the ANN is linearly dependent on the input values, while the FNN has higher order dependencies on the input values. It can be expected that the FNN will have more capability to model long-term, persistent effects.

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Date	Mark	Lags 5 Day	4 Day	3 Day	2 Day	1 Day	Future
1/3/1994	1.7420	0.0415	0.0410	0.0240	0.0070	0.0025	-0.0040
1/4/1994	1.7380	0.0370	0.0200	0.0030	-0.0015	-0.0040	0.0030
1/5/1994	1.7410	0.0230	0.0060	0.0015	-0.0010	0.0030	0.0015
1/6/1994	1.7425	0.0075	0.0030	0.0005	0.0045	0.0015	-0.0108
1/7/1994	1.7317	-0.0078	-0.0103	-0.0063	-0.0093	-0.0108	0.0026
1/10/1994	1.7343	-0.0077	-0.0037	-0.0067	-0.0082	0.0026	0.0052
1/11/1994	1.7395	0.0015	-0.0015	-0.0030	0.0078	0.0052	-0.0045
1/12/1994	1.7350	-0.0060	-0.0075	0.0033	0.0007	-0.0045	0.0158
1/13/1994	1.7508	0.0083	0.0191	0.0165	0.0113	0.0158	0.0002
1/14/1994	1.7510	0.0193	0.0167	0.0115	0.0160	0.0002	-0.0045
1/18/1994	1.7465	0.0122	0.0070	0.0115	-0.0043	-0.0045	0.0000
1/19/1994	1.7465	0.0070	0.0115	-0.0043	-0.0045	0.0000	-0.0097
1/20/1994	1.7368	0.0018	-0.0140	-0.0142	-0.0097	-0.0097	0.0102
1/21/1994	1.7470	-0.0038	-0.0040	0.0005	0.0005	0.0102	0.0035
1/24/1994	1.7505	-0.0005	0.0040	0.0040	0.0137	0.0035	0.0033
1/25/1994	1.7538	0.0073	0.0073	0.0170	0.0068	0.0033	-0.0070
1/26/1994	1.7468	0.0003	0.0100	-0.0002	-0.0037	-0.0070	-0.0015
1/27/1994	1.7453	0.0085	-0.0017	-0.0052	-0.0085	-0.0015	-0.0123
1/28/1994	1.7330	-0.0140	-0.0175	-0.0208	-0.0138	-0.0123	0.0069
1/31/1994	1.7399	-0.0106	-0.0139	-0.0069	-0.0054	0.0069	-0.0084
2/1/1994	1.7315	-0.0223	-0.0153	-0.0138	-0.0015	-0.0084	0.0020
2/2/1994	1.7335	-0.0133	-0.0118	0.0005	-0.0064	0.0020	0.0035
2/3/1994	1.7370	-0.0083	0.0040	-0.0029	0.0055	0.0035	0.0145
2/4/1994	1.7515	0.0185	0.0116	0.0200	0.0180	0.0145	0.0090
2/7/1994	1.7605	0.0206	0.0290	0.0270	0.0235	0.0090	0.0022
2/8/1994	1.7627	0.0312	0.0292	0.0257	0.0112	0.0022	-0.0047
2/9/1994	1.7580	0.0245	0.0210	0.0065	-0.0025	-0.0047	-0.0040
2/10/1994	1.7540	0.0170	0.0025	-0.0065	-0.0087	-0.0040	-0.0009
2/11/1994	1.7531	0.0016	-0.0074	-0.0096	-0.0049	-0.0009	-0.0100
2/14/1994	1.7431	-0.0174	-0.0196	-0.0149	-0.0109	-0.0100	-0.0156
2/15/1994	1.7275	-0.0352	-0.0305	-0.0265	-0.0256	-0.0156	-0.0033
2/16/1994	1.7242	-0.0338	-0.0298	-0.0289	-0.0189	-0.0033	0.0067
2/17/1994	1.7309	-0.0231	-0.0222	-0.0122	0.0034	0.0067	-0.0124
2/18/1994	1.7185	-0.0346	-0.0246	-0.0090	-0.0057	-0.0124	0.0070
2/22/1994	1.7255	-0.0176	-0.0020	0.0013	-0.0054	0.0070	0.0037
2/23/1994	1.7292	0.0017	0.0050	-0.0017	0.0107	0.0037	-0.0082
2/24/1994	1.7210	-0.0032	-0.0099	0.0025	-0.0045	-0.0082	-0.0120
2/25/1994	1.7090	-0.0219	-0.0095	-0.0165	-0.0202	-0.0120	-0.0052
2/28/1994	1.7038	-0.0147	-0.0217	-0.0254	-0.0172	-0.0052	0.0082
3/1/1994	1.7120	-0.0135	-0.0172	-0.0090	0.0030	0.0082	-0.0090
3/2/1994	1.7030	-0.0262	-0.0180	-0.0060	-0.0008	-0.0090	0.0045
3/3/1994	1.7075	-0.0135	-0.0015	0.0037	-0.0045	0.0045	0.0105
3/4/1994	1.7180	0.0090	0.0142	0.0060	0.0150	0.0105	-0.0005
3/7/1994	1.7175	0.0137	0.0055	0.0145	0.0100	-0.0005	-0.0010

		Lags					
Date	Mark	5 Day	4 Day	3 Day	2 Day	1 Day	Future
3/8/1994	1.7165	0.0045	0.0135	0.0090	-0.0015	-0.0010	-0.0080
3/9/1994	1.7085	0.0055	0.0010	-0.0095	-0.0090	-0.0080	-0.0210
3/10/1994	1.6875	-0.0200	-0.0305	-0.0300	-0.0290	-0.0210	-0.0108
3/11/1994	1.6767	-0.0413	-0.0408	-0.0398	-0.0318	-0.0108	0.0142
3/14/1994	1.6909	-0.0266	-0.0256	-0.0176	0.0034	0.0142	0.0034
3/15/1994	1.6943	-0.0222	-0.0142	0.0068	0.0176	0.0034	-0.0058
3/16/1994	1.6885	-0.0200	0.0010	0.0118	-0.0024	-0.0058	-0.0040
3/17/1994	1.6845	-0.0030	0.0078	-0.0064	-0.0098	-0.0040	0.0063
3/18/1994	1.6908	0.0141	-0.0001	-0.0035	0.0023	0.0063	0.0070
3/21/1994	1.6978	0.0069	0.0035	0.0093	0.0133	0.0070	-0.0106
3/22/1994	1.6872	-0.0071	-0.0013	0.0027	-0.0036	-0.0106	-0.0014
3/23/1994	1.6858	-0.0027	0.0013	-0.0050	-0.0120	-0.0014	-0.0178
3/24/1994	1.6680	-0.0165	-0.0228	-0.0298	-0.0192	-0.0178	-0.0010
3/25/1994	1.6670	-0.0238	-0.0308	-0.0202	-0.0188	-0.0010	0.0055
3/28/1994	1.6725	-0.0253	-0.0147	-0.0133	0.0045	0.0055	0.0025
3/29/1994	1.6750	-0.0122	-0.0108	0.0070	0.0080	0.0025	-0.0010
3/30/1994	1.6740	-0.0118	0.0060	0.0070	0.0015	-0.0010	-0.0060
3/31/1994	1.6680	0.0000	0.0010	-0.0045	-0.0070	-0.0060	0.0270
4/1/1994	1.6950	0.0280	0.0225	0.0200	0.0210	0.0270	0.0025
4/4/1994	1.6975	0.0250	0.0225	0.0235	0.0295	0.0025	0.0135
4/5/1994	1.7110	0.0360	0.0370	0.0430	0.0160	0.0135	0.0042
4/6/1994	1.7152	0.0412	0.0472	0.0202	0.0177	0.0042	0.0033
4/7/1994	1.7185	0.0505	0.0235	0.0210	0.0075	0.0033	-0.0075
4/8/1994	1.7110	0.0160	0.0135	0.0000	-0.0042	-0.0075	0.0005
4/11/1994	1.7115	0.0140	0.0005	-0.0037	-0.0070	0.0005	0.0083
4/12/1994	1.7198	0.0088	0.0046	0.0013	0.0088	0.0083	-0.0083
4/13/1994	1.7115	-0.0037	-0.0070	0.0005	0.0000	-0.0083	-0.0025
4/14/1994	1.7090	-0.0095	-0.0020	-0.0025	-0.0108	-0.0025	0.0027
4/15/1994	1.7117	0.0007	0.0002	-0.0081	0.0002	0.0027	0.0073
4/18/1994	1.7190	0.0075	-0.0008	0.0075	0.0100	0.0073	-0.0182
4/19/1994	1.7008	-0.0190	-0.0107	-0.0082	-0.0109	-0.0182	-0.0058
4/20/1994	1.6950	-0.0165	-0.0140	-0.0167	-0.0240	-0.0058	-0.0050
4/21/1994	1.6900	-0.0190	-0.0217	-0.0290	-0.0108	-0.0050	0.0035
4/22/1994	1.6935	-0.0182	-0.0255	-0.0073	-0.0015	0.0035	-0.0147
4/25/1994	1.6788	-0.0402	-0.0220	-0.0162	-0.0112	-0.0147	-0.0003
4/26/1994	1.6785	-0.0223	-0.0165	-0.0115	-0.0150	-0.0003	-0.0080
4/27/1994	1.6705	-0.0245	-0.0195	-0.0230	-0.0083	-0.0080	-0.0034
4/28/1994	1.6671	-0.0229	-0.0264	-0.0117	-0.0114	-0.0034	-0.0061
4/29/1994	1.6610	-0.0325	-0.0178	-0.0175	-0.0095	-0.0061	-0.0137
5/2/1994	1.6473	-0.0315	-0.0312	-0.0232	-0.0198	-0.0137	-0.0068
5/3/1994	1.6405	-0.0380	-0.0300	-0.0266	-0.0205	-0.0068	0.0185
5/4/1994	1.6590	-0.0115	-0.0081	-0.0020	0.0117	0.0185	0.0076
5/5/1994	1.6666	-0.0005	0.0056	0.0193	0.0261	0.0076	-0.0036
5/6/1994	1.6630	0.0020	0.0157	0.0225	0.0040	-0.0036	-0.0090
5/9/1994	1.6540	0.0067	0.0135	-0.0050	-0.0126	-0.0090	0.0175
5/10/1994	1.6715	0.0310	0.0125	0.0049	0.0085	0.0175	0.0000
5/11/1994	1.6715	0.0125	0.0049	0.0085	0.0175	0.0000	-0.0033
5/12/1994	1.6682	0.0016	0.0052	0.0142	-0.0033	-0.0033	0.0018
5/13/1994	1.6700	0.0070	0.0160	-0.0015	-0.0015	0.0018	0.0039

Date	Mark	Lags: 5 Day	4 Day	3 Day	2 Day	1 Day	Future
5/16/1994	1.6739	0.0199	0.0024	0.0024	0.0057	0.0039	-0.0084
5/17/1994	1.6655	-0.0060	-0.0060	-0.0027	-0.0045	-0.0084	-0.0085
5/18/1994	1.6570	-0.0145	-0.0112	-0.0130	-0.0169	-0.0085	-0.0022
5/19/1994	1.6548	-0.0134	-0.0152	-0.0191	-0.0107	-0.0022	-0.0078
5/20/1994	1.6470	-0.0230	-0.0269	-0.0185	-0.0100	-0.0078	-0.0015
5/23/1994	1.6455	-0.0284	-0.0200	-0.0115	-0.0093	-0.0015	0.0080
5/24/1994	1.6535	-0.0120	-0.0035	-0.0013	0.0065	0.0080	-0.0085
5/25/1994	1.6450	-0.0120	-0.0098	-0.0020	-0.0005	-0.0085	-0.0015
5/26/1994	1.6435	-0.0113	-0.0035	-0.0020	-0.0100	-0.0015	0.0005
5/27/1994	1.6440	-0.0030	-0.0015	-0.0095	-0.0010	0.0005	0.0008
5/31/1994	1.6448	-0.0007	-0.0087	-0.0002	0.0013	0.0008	-0.0003
6/1/1994	1.6445	-0.0090	-0.0005	0.0010	0.0005	-0.0003	0.0092
6/2/1994	1.6537	0.0087	0.0102	0.0097	0.0089	0.0092	0.0147
6/3/1994	1.6684	0.0249	0.0244	0.0236	0.0239	0.0147	-0.0009
6/6/1994	1.6675	0.0235	0.0227	0.0230	0.0138	-0.0009	-0.0010
6/7/1994	1.6665	0.0217	0.0220	0.0128	-0.0019	-0.0010	0.0045
6/8/1994	1.6710	0.0265	0.0173	0.0026	0.0035	0.0045	0.0040
6/9/1994	1.6750	0.0213	0.0066	0.0075	0.0085	0.0040	-0.0095
6/10/1994	1.6655	-0.0029	-0.0020	-0.0010	-0.0055	-0.0095	-0.0185
6/13/1994	1.6470	-0.0205	-0.0195	-0.0240	-0.0280	-0.0185	-0.0035
6/14/1994	1.6435	-0.0230	-0.0275	-0.0315	-0.0220	-0.0035	-0.0078
6/15/1994	1.6357	-0.0353	-0.0393	-0.0298	-0.0113	-0.0078	-0.0040
6/16/1994	1.6317	-0.0433	-0.0338	-0.0153	-0.0118	-0.0040	-0.0202
6/17/1994	1.6115	-0.0540	-0.0355	-0.0320	-0.0242	-0.0202	-0.0105
6/20/1994	1.6010	-0.0460	-0.0425	-0.0347	-0.0307	-0.0105	-0.0080
6/21/1994	1.5930	-0.0505	-0.0427	-0.0387	-0.0185	-0.0080	0.0130
6/22/1994	1.6060	-0.0297	-0.0257	-0.0055	0.0050	0.0130	-0.0052
6/23/1994	1.6008	-0.0309	-0.0107	-0.0002	0.0078	-0.0052	-0.0143
6/24/1994	1.5865	-0.0250	-0.0145	-0.0065	-0.0195	-0.0143	-0.0085
6/27/1994	1.5780	-0.0230	-0.0150	-0.0280	-0.0228	-0.0085	0.0030
6/28/1994	1.5810	-0.0120	-0.0250	-0.0198	-0.0055	0.0030	0.0027
6/29/1994	1.5837	-0.0223	-0.0171	-0.0028	0.0057	0.0027	0.0013
6/30/1994	1.5850	-0.0158	-0.0015	0.0070	0.0040	0.0013	0.0075
7/1/1994	1.5925	0.0060	0.0145	0.0115	0.0088	0.0075	-0.0090
7/5/1994	1.5835	0.0055	0.0025	-0.0002	-0.0015	-0.0090	-0.0143
7/6/1994	1.5692	-0.0118	-0.0145	-0.0158	-0.0233	-0.0143	0.0048
7/7/1994	1.5740	-0.0097	-0.0110	-0.0185	-0.0095	0.0048	-0.0080
7/8/1994	1.5660	-0.0190	-0.0265	-0.0175	-0.0032	-0.0080	-0.0302
7/11/1994	1.5358	-0.0567	-0.0477	-0.0334	-0.0382	-0.0302	-0.0143
7/12/1994	1.5215	-0.0620	-0.0477	-0.0525	-0.0445	-0.0143	0.0140
7/13/1994	1.5355	-0.0337	-0.0385	-0.0305	-0.0003	0.0140	0.0135
7/14/1994	1.5490	-0.0250	-0.0170	0.0132	0.0275	0.0135	0.0075
7/15/1994	1.5565	-0.0095	0.0207	0.0350	0.0210	0.0075	-0.0105
7/18/1994	1.5460	0.0102	0.0245	0.0105	-0.0030	-0.0105	0.0198
7/19/1994	1.5658	0.0443	0.0303	0.0168	0.0093	0.0198	-0.0038
7/20/1994	1.5620	0.0265	0.0130	0.0055	0.0160	-0.0038	0.0132
7/21/1994	1.5752	0.0262	0.0187	0.0292	0.0094	0.0132	0.0171
7/22/1994	1.5923	0.0358	0.0463	0.0265	0.0303	0.0171	-0.0016

Date	Mark	Lags 5 Day	4 Day	3 Day	2 Day	1 Day	Future
7/25/1994	1.5907	0.0447	0.0249	0.0287	0.0155	-0.0016	-0.0037
7/26/1994	1.5870	0.0212	0.0250	0.0118	-0.0053	-0.0037	-0.0115
7/27/1994	1.5755	0.0135	0.0003	-0.0168	-0.0152	-0.0115	0.0067
7/28/1994	1.5822	0.0070	-0.0101	-0.0085	-0.0048	0.0067	0.0053
7/29/1994	1.5875	-0.0048	-0.0032	0.0005	0.0120	0.0053	-0.0100
8/1/1994	1.5775	-0.0132	-0.0095	0.0020	-0.0047	-0.0100	0.0018
8/2/1994	1.5793	-0.0077	0.0038	-0.0029	-0.0082	0.0018	0.0017
8/3/1994	1.5810	0.0055	-0.0012	-0.0065	0.0035	0.0017	0.0005
8/4/1994	1.5815	-0.0007	-0.0060	0.0040	0.0022	0.0005	-0.0012
8/5/1994	1.5803	-0.0072	0.0028	0.0010	-0.0007	-0.0012	0.0000
8/8/1994	1.5803	0.0028	0.0010	-0.0007	-0.0012	0.0000	0.0017
8/9/1994	1.5820	0.0027	0.0010	0.0005	0.0017	0.0017	-0.0048
8/10/1994	1.5772	-0.0038	-0.0043	-0.0031	-0.0031	-0.0048	0.0003
8/11/1994	1.5775	-0.0040	-0.0028	-0.0028	-0.0045	0.0003	-0.0190
8/12/1994	1.5585	-0.0218	-0.0218	-0.0235	-0.0187	-0.0190	-0.0075
8/15/1994	1.5510	-0.0293	-0.0310	-0.0262	-0.0265	-0.0075	-0.0003
8/16/1994	1.5507	-0.0313	-0.0265	-0.0268	-0.0078	-0.0003	0.0050
8/17/1994	1.5557	-0.0215	-0.0218	-0.0028	0.0047	0.0050	-0.0087
8/18/1994	1.5470	-0.0305	-0.0115	-0.0040	-0.0037	-0.0087	-0.0070
8/19/1994	1.5400	-0.0185	-0.0110	-0.0107	-0.0157	-0.0070	-0.0095
8/22/1994	1.5305	-0.0205	-0.0202	-0.0252	-0.0165	-0.0095	0.0086
8/23/1994	1.5391	-0.0116	-0.0166	-0.0079	-0.0009	0.0086	0.0071
8/24/1994	1.5462	-0.0095	-0.0008	0.0062	0.0157	0.0071	0.0008
8/25/1994	1.5470	0.0000	0.0070	0.0165	0.0079	0.0008	0.0200
8/26/1994	1.5670	0.0270	0.0365	0.0279	0.0208	0.0200	0.0119
8/29/1994	1.5789	0.0484	0.0398	0.0327	0.0319	0.0119	-0.0014
8/30/1994	1.5775	0.0384	0.0313	0.0305	0.0105	-0.0014	0.0020
8/31/1994	1.5795	0.0333	0.0325	0.0125	0.0006	0.0020	-0.0053
9/1/1994	1.5742	0.0272	0.0072	-0.0047	-0.0033	-0.0053	-0.0170
9/2/1994	1.5572	-0.0098	-0.0217	-0.0203	-0.0223	-0.0170	-0.0131
9/6/1994	1.5441	-0.0348	-0.0334	-0.0354	-0.0301	-0.0131	0.0046
9/7/1994	1.5487	-0.0288	-0.0308	-0.0255	-0.0085	0.0046	0.0097
9/8/1994	1.5584	-0.0211	-0.0158	0.0012	0.0143	0.0097	-0.0194
9/9/1994	1.5390	-0.0352	-0.0182	-0.0051	-0.0097	-0.0194	0.0015
9/12/1994	1.5405	-0.0167	-0.0036	-0.0082	-0.0179	0.0015	0.0070
9/13/1994	1.5475	0.0034	-0.0012	-0.0109	0.0085	0.0070	-0.0080
9/14/1994	1.5395	-0.0092	-0.0189	0.0005	-0.0010	-0.0080	0.0082
9/15/1994	1.5477	-0.0107	0.0087	0.0072	0.0002	0.0082	-0.0132
9/16/1994	1.5345	-0.0045	-0.0060	-0.0130	-0.0050	-0.0132	0.0176
9/19/1994	1.5521	0.0116	0.0046	0.0126	0.0044	0.0176	0.0029
9/20/1994	1.5550	0.0075	0.0155	0.0073	0.0205	0.0029	-0.0069
9/21/1994	1.5481	0.0086	0.0004	0.0136	-0.0040	-0.0069	-0.0008
9/22/1994	1.5473	-0.0004	0.0128	-0.0048	-0.0077	-0.0008	-0.0032
9/23/1994	1.5441	0.0096	-0.0080	-0.0109	-0.0040	-0.0032	0.0117
9/26/1994	1.5558	0.0037	0.0008	0.0077	0.0085	0.0117	-0.0065
9/27/1994	1.5493	-0.0057	0.0012	0.0020	0.0052	-0.0065	0.0002
9/28/1994	1.5495	0.0014	0.0022	0.0054	-0.0063	0.0002	-0.0017
9/29/1994	1.5478	0.0005	0.0037	-0.0080	-0.0015	-0.0017	0.0030
9/30/1994	1.5508	0.0067	-0.0050	0.0015	0.0013	0.0030	0.0039

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Date	Mark	5 Day	4 Day	3 Day	2 Day	1 Day	Future
10/3/1994	1.5547	-0.0011	0.0054	0.0052	0.0069	0.0039	-0.0039
10/4/1994	1.5508	0.0015	0.0013	0.0030	0.0000	-0.0039	-0.0083
10/5/1994	1.5425	-0.0070	-0.0053	-0.0083	-0.0122	-0.0083	0.0020
10/6/1994	1.5445	-0.0033	-0.0063	-0.0102	-0.0063	0.0020	0.0008
10/7/1994	1.5453	-0.0055	-0.0094	-0.0055	0.0028	0.0008	0.0027
10/11/1994	1.5480	-0.0067	-0.0028	0.0055	0.0035	0.0027	-0.0055
10/12/1994	1.5425	-0.0083	0.0000	-0.0020	-0.0028	-0.0055	-0.0020
10/13/1994	1.5405	-0.0020	-0.0040	-0.0048	-0.0075	-0.0020	-0.0205
10/14/1994	1.5200	-0.0245	-0.0253	-0.0280	-0.0225	-0.0205	-0.0195
10/17/1994	1.5005	-0.0448	-0.0475	-0.0420	-0.0400	-0.0195	0.0010
10/18/1994	1.5015	-0.0465	-0.0410	-0.0390	-0.0185	0.0010	0.0013
10/19/1994	1.5028	-0.0397	-0.0377	-0.0172	0.0023	0.0013	-0.0013
10/20/1994	1.5015	-0.0390	-0.0185	0.0010	0.0000	-0.0013	-0.0027
10/21/1994	1.4988	-0.0212	-0.0017	-0.0027	-0.0040	-0.0027	-0.0018
10/24/1994	1.4970	-0.0035	-0.0045	-0.0058	-0.0045	-0.0018	-0.0050
10/25/1994	1.4920	-0.0095	-0.0108	-0.0095	-0.0068	-0.0050	0.0035
10/26/1994	1.4955	-0.0073	-0.0060	-0.0033	-0.0015	0.0035	0.0019
10/27/1994	1.4974	-0.0041	-0.0014	0.0004	0.0054	0.0019	0.0123
10/28/1994	1.5097	0.0109	0.0127	0.0177	0.0142	0.0123	-0.0054
10/31/1994	1.5043	0.0073	0.0123	0.0088	0.0069	-0.0054	-0.0078
11/1/1994	1.4965	0.0045	0.0010	-0.0009	-0.0132	-0.0078	0.0075
11/2/1994	1.5040	0.0085	0.0066	-0.0057	-0.0003	0.0075	0.0200
11/3/1994	1.5240	0.0266	0.0143	0.0197	0.0275	0.0200	-0.0025
11/4/1994	1.5215	0.0118	0.0172	0.0250	0.0175	-0.0025	-0.0078
11/7/1994	1.5137	0.0094	0.0172	0.0097	-0.0103	-0.0078	-0.0067
11/8/1994	1.5070	0.0105	0.0030	-0.0170	-0.0145	-0.0067	0.0217
11/9/1994	1.5287	0.0247	0.0047	0.0072	0.0150	0.0217	0.0046
11/10/1994	1.5333	0.0093	0.0118	0.0196	0.0263	0.0046	0.0072
11/14/1994	1.5405	0.0190	0.0268	0.0335	0.0118	0.0072	0.0048
11/15/1994	1.5453	0.0316	0.0383	0.0166	0.0120	0.0048	0.0062
11/16/1994	1.5515	0.0445	0.0228	0.0182	0.0110	0.0062	-0.0057
11/17/1994	1.5458	0.0171	0.0125	0.0053	0.0005	-0.0057	0.0095
11/18/1994	1.5553	0.0220	0.0148	0.0100	0.0038	0.0095	0.0042
11/21/1994	1.5595	0.0190	0.0142	0.0080	0.0137	0.0042	-0.0044
11/22/1994	1.5551	0.0098	0.0036	0.0093	-0.0002	-0.0044	-0.0033
11/23/1994	1.5518	0.0003	0.0060	-0.0035	-0.0077	-0.0033	0.0078
11/25/1994	1.5596	0.0138	0.0043	0.0001	0.0045	0.0078	0.0051
11/28/1994	1.5647	0.0094	0.0052	0.0096	0.0129	0.0051	0.0018
11/29/1994	1.5665	0.0070	0.0114	0.0147	0.0069	0.0018	0.0020
11/30/1994	1.5685	0.0134	0.0167	0.0089	0.0038	0.0020	0.0055
12/1/1994	1.5740	0.0222	0.0144	0.0093	0.0075	0.0055	0.0025
12/2/1994	1.5765	0.0169	0.0118	0.0100	0.0080	0.0025	-0.0042
12/5/1994	1.5723	0.0076	0.0058	0.0038	-0.0017	-0.0042	0.0022
12/6/1994	1.5745	0.0080	0.0060	0.0005	-0.0020	0.0022	-0.0028
12/7/1994	1.5717	0.0032	-0.0023	-0.0048	-0.0006	-0.0028	0.0053
12/8/1994	1.5770	0.0030	0.0005	0.0047	0.0025	0.0053	0.0013
12/9/1994	1.5783	0.0018	0.0060	0.0038	0.0066	0.0013	-0.0048
12/12/1994	1.5735	0.0012	-0.0010	0.0018	-0.0035	-0.0048	-0.0025
12/13/1994	1.5710	-0.0035	-0.0007	-0.0060	-0.0073	-0.0025	0.0000

Date	Mark	Lags 5 Day	4 Day	3 Day	2 Day	1 Day	Future
12/14/1994	1.5710	-0.0007	-0.0060	-0.0073	-0.0025	0.0000	-0.0005
12/15/1994	1.5705	-0.0065	-0.0078	-0.0030	-0.0005	-0.0005	0.0020
12/16/1994	1.5725	-0.0058	-0.0010	0.0015	0.0015	0.0020	0.0010
12/19/1994	1.5735	0.0000	0.0025	0.0025	0.0030	0.0010	-0.0010
12/20/1994	1.5725	0.0015	0.0015	0.0020	0.0000	-0.0010	-0.0018
12/21/1994	1.5707	-0.0003	0.0002	-0.0018	-0.0028	-0.0018	0.0073
12/22/1994	1.5780	0.0075	0.0055	0.0045	0.0055	0.0073	0.0020
12/23/1994	1.5800	0.0075	0.0065	0.0075	0.0093	0.0020	-0.0035
12/27/1994	1.5765	0.0030	0.0040	0.0058	-0.0015	-0.0035	-0.0051
12/28/1994	1.5714	-0.0011	0.0007	-0.0066	-0.0086	-0.0051	-0.0219
12/29/1994	1.5495	-0.0212	-0.0285	-0.0305	-0.0270	-0.0219	0.0000
12/30/1994	1.5495	-0.0285	-0.0305	-0.0270	-0.0219	0.0000	0.0052
1/3/1995	1.5547	-0.0253	-0.0218	-0.0167	0.0052	0.0052	0.0065
1/4/1995	1.5612	-0.0153	-0.0102	0.0117	0.0117	0.0065	-0.0090
1/5/1995	1.5522	-0.0192	0.0027	0.0027	-0.0025	-0.0090	0.0081
1/6/1995	1.5603	0.0108	0.0108	0.0056	-0.0009	0.0081	-0.0148
1/9/1995	1.5455	-0.0040	-0.0092	-0.0157	-0.0067	-0.0148	-0.0060
1/10/1995	1.5395	-0.0152	-0.0217	-0.0127	-0.0208	-0.0060	-0.0040
1/11/1995	1.5355	-0.0257	-0.0167	-0.0248	-0.0100	-0.0040	-0.0085
1/12/1995	1.5270	-0.0252	-0.0333	-0.0185	-0.0125	-0.0085	0.0090
1/13/1995	1.5360	-0.0243	-0.0095	-0.0035	0.0005	0.0090	-0.0049
1/17/1995	1.5311	-0.0144	-0.0084	-0.0044	0.0041	-0.0049	-0.0016
1/18/1995	1.5295	-0.0100	-0.0060	0.0025	-0.0065	-0.0016	-0.0068
1/19/1995	1.5227	-0.0128	-0.0043	-0.0133	-0.0084	-0.0068	-0.0096
1/20/1995	1.5131	-0.0139	-0.0229	-0.0180	-0.0164	-0.0096	-0.0011
1/23/1995	1.5120	-0.0240	-0.0191	-0.0175	-0.0107	-0.0011	0.0005
1/24/1995	1.5125	-0.0186	-0.0170	-0.0102	-0.0006	0.0005	0.0030
1/25/1995	1.5155	-0.0140	-0.0072	0.0024	0.0035	0.0030	-0.0020
1/26/1995	1.5135	-0.0092	0.0004	0.0015	0.0010	-0.0020	0.0020
1/27/1995	1.5155	0.0024	0.0035	0.0030	0.0000	0.0020	-0.0112
1/30/1995	1.5043	-0.0077	-0.0082	-0.0112	-0.0092	-0.0112	0.0189
1/31/1995	1.5232	0.0107	0.0077	0.0097	0.0077	0.0189	0.0003
2/1/1995	1.5235	0.0080	0.0100	0.0080	0.0192	0.0003	-0.0050
2/2/1995	1.5185	0.0050	0.0030	0.0142	-0.0047	-0.0050	0.0070
2/3/1995	1.5255	0.0100	0.0212	0.0023	0.0020	0.0070	0.0050
2/6/1995	1.5305	0.0262	0.0073	0.0070	0.0120	0.0050	0.0057
2/7/1995	1.5362	0.0130	0.0127	0.0177	0.0107	0.0057	-0.0037
2/8/1995	1.5325	0.0090	0.0140	0.0070	0.0020	-0.0037	-0.0043
2/9/1995	1.5282	0.0097	0.0027	-0.0023	-0.0080	-0.0043	-0.0060
2/10/1995	1.5222	-0.0033	-0.0083	-0.0140	-0.0103	-0.0060	-0.0014
2/13/1995	1.5208	-0.0097	-0.0154	-0.0117	-0.0074	-0.0014	-0.0068
2/14/1995	1.5140	-0.0222	-0.0185	-0.0142	-0.0082	-0.0068	-0.0025
2/15/1995	1.5115	-0.0210	-0.0167	-0.0107	-0.0093	-0.0025	-0.0200
2/16/1995	1.4915	-0.0367	-0.0307	-0.0293	-0.0225	-0.0200	-0.0029
2/17/1995	1.4886	-0.0336	-0.0322	-0.0254	-0.0229	-0.0029	-0.0121
2/21/1995	1.4765	-0.0443	-0.0375	-0.0350	-0.0150	-0.0121	-0.0055
2/22/1995	1.4710	-0.0430	-0.0405	-0.0205	-0.0176	-0.0055	-0.0015
2/23/1995	1.4695	-0.0420	-0.0220	-0.0191	-0.0070	-0.0015	-0.0021
2/24/1995	1.4674	-0.0241	-0.0212	-0.0091	-0.0036	-0.0021	-0.0107

		Lags					
Date	Mark	5 Day	4 Day	3 Day	2 Day	1 Day	Future
2/27/1995	1.4567	-0.0319	-0.0198	-0.0143	-0.0128	-0.0107	0.0000
2/28/1995	1.4567	-0.0198	-0.0143	-0.0128	-0.0107	0.0000	0.0080
3/1/1995	1.4647	-0.0063	-0.0048	-0.0027	0.0080	0.0080	-0.0062
3/2/1995	1.4585	-0.0110	-0.0089	0.0018	0.0018	-0.0062	-0.0232
3/3/1995	1.4353	-0.0321	-0.0214	-0.0214	-0.0294	-0.0232	-0.0368
3/6/1995	1.3985	-0.0582	-0.0582	-0.0662	-0.0600	-0.0368	-0.0245
3/7/1995	1.3740	-0.0827	-0.0907	-0.0845	-0.0613	-0.0245	0.0195
3/8/1995	1.3935	-0.0712	-0.0650	-0.0418	-0.0050	0.0195	0.0000
3/9/1995	1.3935	-0.0650	-0.0418	-0.0050	0.0195	0.0000	0.0188
3/10/1995	1.4123	-0.0230	0.0138	0.0383	0.0188	0.0188	-0.0048
3/13/1995	1.4075	0.0090	0.0335	0.0140	0.0140	-0.0048	0.0059
3/14/1995	1.4134	0.0394	0.0199	0.0199	0.0011	0.0059	-0.0279
3/15/1995	1.3855	-0.0080	-0.0080	-0.0268	-0.0220	-0.0279	0.0117
3/16/1995	1.3972	0.0037	-0.0151	-0.0103	-0.0162	0.0117	-0.0117
3/17/1995	1.3855	-0.0268	-0.0220	-0.0279	0.0000	-0.0117	0.0159
3/20/1995	1.4014	-0.0061	-0.0120	0.0159	0.0042	0.0159	0.0151
3/21/1995	1.4165	0.0031	0.0310	0.0193	0.0310	0.0151	-0.0102
3/22/1995	1.4063	0.0208	0.0091	0.0208	0.0049	-0.0102	0.0010
3/23/1995	1.4073	0.0101	0.0218	0.0059	-0.0092	0.0010	0.0112
3/24/1995	1.4185	0.0330	0.0171	0.0020	0.0122	0.0112	-0.0128
3/27/1995	1.4057	0.0043	-0.0108	-0.0006	-0.0016	-0.0128	-0.0142
3/28/1995	1.3915	-0.0250	-0.0148	-0.0158	-0.0270	-0.0142	-0.0075
3/29/1995	1.3840	-0.0223	-0.0233	-0.0345	-0.0217	-0.0075	0.0275
3/30/1995	1.4115	0.0042	-0.0070	0.0058	0.0200	0.0275	-0.0330
3/31/1995	1.3785	-0.0400	-0.0272	-0.0130	-0.0055	-0.0330	-0.0045
4/3/1995	1.3740	-0.0317	-0.0175	-0.0100	-0.0375	-0.0045	0.0101
4/4/1995	1.3841	-0.0074	0.0001	-0.0274	0.0056	0.0101	-0.0036
4/5/1995	1.3805	-0.0035	-0.0310	0.0020	0.0065	-0.0036	-0.0045
4/6/1995	1.3760	-0.0355	-0.0025	0.0020	-0.0081	-0.0045	0.0080
4/7/1995	1.3840	0.0055	0.0100	-0.0001	0.0035	0.0080	0.0255
4/10/1995	1.4095	0.0355	0.0254	0.0290	0.0335	0.0255	-0.0075
4/11/1995	1.4020	0.0179	0.0215	0.0260	0.0180	-0.0075	0.0023
4/12/1995	1.4043	0.0238	0.0283	0.0203	-0.0052	0.0023	-0.0145
4/13/1995	1.3898	0.0138	0.0058	-0.0197	-0.0122	-0.0145	0.0015
4/14/1995	1.3913	0.0073	-0.0182	-0.0107	-0.0130	0.0015	-0.0218
4/17/1995	1.3695	-0.0400	-0.0325	-0.0348	-0.0203	-0.0218	-0.0045
4/18/1995	1.3650	-0.0370	-0.0393	-0.0248	-0.0263	-0.0045	-0.0085
4/19/1995	1.3565	-0.0478	-0.0333	-0.0348	-0.0130	-0.0085	0.0245
4/20/1995	1.3810	-0.0088	-0.0103	0.0115	0.0160	0.0245	-0.0060
4/21/1995	1.3750	-0.0163	0.0055	0.0100	0.0185	-0.0060	-0.0005
4/24/1995	1.3745	0.0050	0.0095	0.0180	-0.0065	-0.0005	-0.0065
4/25/1995	1.3680	0.0030	0.0115	-0.0130	-0.0070	-0.0065	0.0095
4/26/1995	1.3775	0.0210	-0.0035	0.0025	0.0030	0.0095	-0.0015
4/27/1995	1.3760	-0.0050	0.0010	0.0015	0.0080	-0.0015	0.0096
4/28/1995	1.3856	0.0106	0.0111	0.0176	0.0081	0.0096	0.0044
5/1/1995	1.3900	0.0155	0.0220	0.0125	0.0140	0.0044	-0.0110
5/2/1995	1.3790	0.0110	0.0015	0.0030	-0.0066	-0.0110	-0.0048
5/3/1995	1.3742	-0.0033	-0.0018	-0.0114	-0.0158	-0.0048	-0.0054
5/4/1995	1.3688	-0.0072	-0.0168	-0.0212	-0.0102	-0.0054	0.0033

		Lags					
Date	Mark	5 Day	4 Day	3 Day	2 Day	1 Day	Future
5/5/1995	1.3721	-0.0135	-0.0179	-0.0069	-0.0021	0.0033	-0.0086
5/8/1995	1.3635	-0.0265	-0.0155	-0.0107	-0.0053	-0.0086	0.0090
5/9/1995	1.3725	-0.0065	-0.0017	0.0037	0.0004	0.0090	0.0190
5/10/1995	1.3915	0.0173	0.0227	0.0194	0.0280	0.0190	0.0375
5/11/1995	1.4290	0.0602	0.0569	0.0655	0.0565	0.0375	0.0175
5/12/1995	1.4465	0.0744	0.0830	0.0740	0.0550	0.0175	-0.0020
5/15/1995	1.4445	0.0810	0.0720	0.0530	0.0155	-0.0020	-0.0085
5/16/1995	1.4360	0.0635	0.0445	0.0070	-0.0105	-0.0085	0.0010
5/17/1995	1.4370	0.0455	0.0080	-0.0095	-0.0075	0.0010	0.0200
5/18/1995	1.4570	0.0280	0.0105	0.0125	0.0210	0.0200	-0.0168
5/19/1995	1.4402	-0.0063	-0.0043	0.0042	0.0032	-0.0168	0.0001
5/22/1995	1.4403	-0.0042	0.0043	0.0033	-0.0167	0.0001	0.0062
5/23/1995	1.4465	0.0105	0.0095	-0.0105	0.0063	0.0062	-0.0080
5/24/1995	1.4385	0.0015	-0.0185	-0.0017	-0.0018	-0.0080	-0.0345
5/25/1995	1.4040	-0.0530	-0.0362	-0.0363	-0.0425	-0.0345	-0.0247
5/26/1995	1.3793	-0.0609	-0.0610	-0.0672	-0.0592	-0.0247	0.0085
5/30/1995	1.3878	-0.0525	-0.0587	-0.0507	-0.0162	0.0085	0.0262
5/31/1995	1.4140	-0.0325	-0.0245	0.0100	0.0347	0.0262	0.0036
6/1/1995	1.4176	-0.0209	0.0136	0.0383	0.0298	0.0036	0.0011
6/2/1995	1.4187	0.0147	0.0394	0.0309	0.0047	0.0011	-0.0137
6/5/1995	1.4050	0.0257	0.0172	-0.0090	-0.0126	-0.0137	0.0112
6/6/1995	1.4162	0.0284	0.0022	-0.0014	-0.0025	0.0112	-0.0112
6/7/1995	1.4050	-0.0090	-0.0126	-0.0137	0.0000	-0.0112	0.0102
6/8/1995	1.4152	-0.0024	-0.0035	0.0102	-0.0010	0.0102	-0.0117
6/9/1995	1.4035	-0.0152	-0.0015	-0.0127	-0.0015	-0.0117	-0.0025
6/12/1995	1.4010	-0.0040	-0.0152	-0.0040	-0.0142	-0.0025	0.0050
6/13/1995	1.4060	-0.0102	0.0010	-0.0092	0.0025	0.0050	-0.0050
6/14/1995	1.4010	-0.0040	-0.0142	-0.0025	0.0000	-0.0050	0.0115
6/15/1995	1.4125	-0.0027	0.0090	0.0115	0.0065	0.0115	-0.0110
6/16/1995	1.4015	-0.0020	0.0005	-0.0045	0.0005	-0.0110	0.0028
6/19/1995	1.4043	0.0033	-0.0017	0.0033	-0.0082	0.0028	-0.0100
6/20/1995	1.3943	-0.0117	-0.0067	-0.0182	-0.0072	-0.0100	-0.0028
6/21/1995	1.3915	-0.0095	-0.0210	-0.0100	-0.0128	-0.0028	0.0076
6/22/1995	1.3991	-0.0134	-0.0024	-0.0052	0.0048	0.0076	-0.0113
6/23/1995	1.3878	-0.0137	-0.0165	-0.0065	-0.0037	-0.0113	0.0049
6/26/1995	1.3927	-0.0116	-0.0016	0.0012	-0.0064	0.0049	-0.0092
6/27/1995	1.3835	-0.0108	-0.0080	-0.0156	-0.0043	-0.0092	0.0180
6/28/1995	1.4015	0.0100	0.0024	0.0137	0.0088	0.0180	-0.0175
6/29/1995	1.3840	-0.0151	-0.0038	-0.0087	0.0005	-0.0175	-0.0005
6/30/1995	1.3835	-0.0043	-0.0092	0.0000	-0.0180	-0.0005	-0.0030

Appendix D

Daily British Pound Data

Date	Pound	Lags					Future
		5 Day	4 Day	3 Day	2 Day	1 Day	
1/3/1994	1.4760	-0.0275	-0.0312	-0.0150	-0.0203	-0.0015	0.0080
1/4/1994	1.4840	-0.0232	-0.0070	-0.0123	0.0065	0.0080	0.0030
1/5/1994	1.4870	-0.0040	-0.0093	0.0095	0.0110	0.0030	-0.0015
1/6/1994	1.4855	-0.0108	0.0080	0.0095	0.0015	-0.0015	0.0045
1/7/1994	1.4900	0.0125	0.0140	0.0060	0.0030	0.0045	0.0023
1/10/1994	1.4923	0.0163	0.0083	0.0053	0.0068	0.0023	-0.0018
1/11/1994	1.4905	0.0065	0.0035	0.0050	0.0005	-0.0018	0.0113
1/12/1994	1.5018	0.0148	0.0163	0.0118	0.0095	0.0113	-0.0061
1/13/1994	1.4957	0.0102	0.0057	0.0034	0.0052	-0.0061	-0.0044
1/14/1994	1.4913	0.0013	-0.0010	0.0008	-0.0105	-0.0044	0.0052
1/18/1994	1.4965	0.0042	0.0060	-0.0053	0.0008	0.0052	-0.0055
1/19/1994	1.4910	0.0005	-0.0108	-0.0047	-0.0003	-0.0055	0.0090
1/20/1994	1.5000	-0.0018	0.0043	0.0087	0.0035	0.0090	-0.0052
1/21/1994	1.4948	-0.0009	0.0035	-0.0017	0.0038	-0.0052	-0.0043
1/24/1994	1.4905	-0.0008	-0.0060	-0.0005	-0.0095	-0.0043	0.0025
1/25/1994	1.4930	-0.0035	0.0020	-0.0070	-0.0018	0.0025	0.0010
1/26/1994	1.4940	0.0030	-0.0060	-0.0008	0.0035	0.0010	-0.0010
1/27/1994	1.4930	-0.0070	-0.0018	0.0025	0.0000	-0.0010	0.0065
1/28/1994	1.4995	0.0047	0.0090	0.0065	0.0055	0.0065	0.0010
1/31/1994	1.5005	0.0100	0.0075	0.0065	0.0075	0.0010	0.0025
2/1/1994	1.5030	0.0100	0.0090	0.0100	0.0035	0.0025	-0.0077
2/2/1994	1.4953	0.0013	0.0023	-0.0042	-0.0052	-0.0077	-0.0023
2/3/1994	1.4930	0.0000	-0.0065	-0.0075	-0.0100	-0.0023	-0.0140
2/4/1994	1.4790	-0.0205	-0.0215	-0.0240	-0.0163	-0.0140	0.0035
2/7/1994	1.4825	-0.0180	-0.0205	-0.0128	-0.0105	0.0035	-0.0107
2/8/1994	1.4718	-0.0312	-0.0235	-0.0212	-0.0072	-0.0107	-0.0103
2/9/1994	1.4615	-0.0338	-0.0315	-0.0175	-0.0210	-0.0103	0.0007
2/10/1994	1.4622	-0.0308	-0.0168	-0.0203	-0.0096	0.0007	0.0026
2/11/1994	1.4648	-0.0142	-0.0177	-0.0070	0.0033	0.0026	0.0060
2/14/1994	1.4708	-0.0117	-0.0010	0.0093	0.0086	0.0060	0.0042
2/15/1994	1.4750	0.0032	0.0135	0.0128	0.0102	0.0042	0.0005
2/16/1994	1.4755	0.0140	0.0133	0.0107	0.0047	0.0005	0.0015
2/17/1994	1.4770	0.0148	0.0122	0.0062	0.0020	0.0015	0.0021
2/18/1994	1.4791	0.0143	0.0083	0.0041	0.0036	0.0021	-0.0007
2/22/1994	1.4784	0.0076	0.0034	0.0029	0.0014	-0.0007	-0.0029
2/23/1994	1.4755	0.0005	0.0000	-0.0015	-0.0036	-0.0029	0.0092
2/24/1994	1.4847	0.0092	0.0077	0.0056	0.0063	0.0092	0.0028
2/25/1994	1.4875	0.0105	0.0084	0.0091	0.0120	0.0028	0.0000
2/28/1994	1.4875	0.0084	0.0091	0.0120	0.0028	0.0000	-0.0021
3/1/1994	1.4854	0.0070	0.0099	0.0007	-0.0021	-0.0021	0.0090
3/2/1994	1.4944	0.0189	0.0097	0.0069	0.0069	0.0090	0.0020
3/3/1994	1.4964	0.0117	0.0089	0.0089	0.0110	0.0020	-0.0069
3/4/1994	1.4895	0.0020	0.0020	0.0041	-0.0049	-0.0069	0.0025
3/7/1994	1.4920	0.0045	0.0066	-0.0024	-0.0044	0.0025	-0.0043

		Lags					
Date	Pound	5 Day	4 Day	3 Day	2 Day	1 Day	Future
3/8/1994	1.4877	0.0023	-0.0067	-0.0087	-0.0018	-0.0043	0.0038
3/9/1994	1.4915	-0.0029	-0.0049	0.0020	-0.0005	0.0038	0.0093
3/10/1994	1.5008	0.0044	0.0113	0.0088	0.0131	0.0093	0.0002
3/11/1994	1.5010	0.0115	0.0090	0.0133	0.0095	0.0002	-0.0067
3/14/1994	1.4943	0.0023	0.0066	0.0028	-0.0065	-0.0067	-0.0018
3/15/1994	1.4925	0.0048	0.0010	-0.0083	-0.0085	-0.0018	0.0002
3/16/1994	1.4927	0.0012	-0.0081	-0.0083	-0.0016	0.0002	0.0020
3/17/1994	1.4947	-0.0061	-0.0063	0.0004	0.0022	0.0020	-0.0022
3/18/1994	1.4925	-0.0085	-0.0018	0.0000	-0.0002	-0.0022	-0.0087
3/21/1994	1.4838	-0.0105	-0.0087	-0.0089	-0.0109	-0.0087	0.0027
3/22/1994	1.4865	-0.0060	-0.0062	-0.0082	-0.0060	0.0027	0.0072
3/23/1994	1.4937	0.0010	-0.0010	0.0012	0.0099	0.0072	0.0011
3/24/1994	1.4948	0.0001	0.0023	0.0110	0.0083	0.0011	0.0027
3/25/1994	1.4975	0.0050	0.0137	0.0110	0.0038	0.0027	-0.0010
3/28/1994	1.4965	0.0127	0.0100	0.0028	0.0017	-0.0010	-0.0115
3/29/1994	1.4850	-0.0015	-0.0087	-0.0098	-0.0125	-0.0115	-0.0027
3/30/1994	1.4823	-0.0114	-0.0125	-0.0152	-0.0142	-0.0027	0.0057
3/31/1994	1.4880	-0.0068	-0.0095	-0.0085	0.0030	0.0057	-0.0145
4/1/1994	1.4735	-0.0240	-0.0230	-0.0115	-0.0088	-0.0145	-0.0055
4/4/1994	1.4680	-0.0285	-0.0170	-0.0143	-0.0200	-0.0055	-0.0059
4/5/1994	1.4621	-0.0229	-0.0202	-0.0259	-0.0114	-0.0059	0.0065
4/6/1994	1.4686	-0.0137	-0.0194	-0.0049	0.0006	0.0065	-0.0002
4/7/1994	1.4684	-0.0196	-0.0051	0.0004	0.0063	-0.0002	0.0079
4/8/1994	1.4763	0.0028	0.0083	0.0142	0.0077	0.0079	-0.0048
4/11/1994	1.4715	0.0035	0.0094	0.0029	0.0031	-0.0048	0.0030
4/12/1994	1.4745	0.0124	0.0059	0.0061	-0.0018	0.0030	0.0025
4/13/1994	1.4770	0.0084	0.0086	0.0007	0.0055	0.0025	-0.0005
4/14/1994	1.4765	0.0081	0.0002	0.0050	0.0020	-0.0005	-0.0036
4/15/1994	1.4729	-0.0034	0.0014	-0.0016	-0.0041	-0.0036	-0.0004
4/18/1994	1.4725	0.0010	-0.0020	-0.0045	-0.0040	-0.0004	0.0050
4/19/1994	1.4775	0.0030	0.0005	0.0010	0.0046	0.0050	0.0083
4/20/1994	1.4858	0.0088	0.0093	0.0129	0.0133	0.0083	0.0090
4/21/1994	1.4948	0.0183	0.0219	0.0223	0.0173	0.0090	-0.0068
4/22/1994	1.4880	0.0151	0.0155	0.0105	0.0022	-0.0068	0.0035
4/25/1994	1.4915	0.0190	0.0140	0.0057	-0.0033	0.0035	0.0122
4/26/1994	1.5037	0.0262	0.0179	0.0089	0.0157	0.0122	0.0018
4/27/1994	1.5055	0.0197	0.0107	0.0175	0.0140	0.0018	0.0020
4/28/1994	1.5075	0.0127	0.0195	0.0160	0.0038	0.0020	0.0043
4/29/1994	1.5118	0.0238	0.0203	0.0081	0.0063	0.0043	0.0069
5/2/1994	1.5187	0.0272	0.0150	0.0132	0.0112	0.0069	-0.0057
5/3/1994	1.5130	0.0093	0.0075	0.0055	0.0012	-0.0057	-0.0135
5/4/1994	1.4995	-0.0060	-0.0080	-0.0123	-0.0192	-0.0135	-0.0015
5/5/1994	1.4980	-0.0095	-0.0138	-0.0207	-0.0150	-0.0015	-0.0045
5/6/1994	1.4935	-0.0183	-0.0252	-0.0195	-0.0060	-0.0045	0.0040
5/9/1994	1.4975	-0.0212	-0.0155	-0.0020	-0.0005	0.0040	-0.0070
5/10/1994	1.4905	-0.0225	-0.0090	-0.0075	-0.0030	-0.0070	0.0006
5/11/1994	1.4911	-0.0084	-0.0069	-0.0024	-0.0064	0.0006	0.0084
5/12/1994	1.4995	0.0015	0.0060	0.0020	0.0090	0.0084	-0.0010
5/13/1994	1.4985	0.0050	0.0010	0.0080	0.0074	-0.0010	0.0040

		Lags					
Date	Pound	5 Day	4 Day	3 Day	2 Day	1 Day	Future
5/16/1994	1.5025	0.0050	0.0120	0.0114	0.0030	0.0040	0.0040
5/17/1994	1.5065	0.0160	0.0154	0.0070	0.0080	0.0040	0.0020
5/18/1994	1.5085	0.0174	0.0090	0.0100	0.0060	0.0020	-0.0005
5/19/1994	1.5080	0.0085	0.0095	0.0055	0.0015	-0.0005	0.0018
5/20/1994	1.5098	0.0113	0.0073	0.0033	0.0013	0.0018	-0.0043
5/23/1994	1.5055	0.0030	-0.0010	-0.0030	-0.0025	-0.0043	0.0003
5/24/1994	1.5058	-0.0007	-0.0027	-0.0022	-0.0040	0.0003	0.0037
5/25/1994	1.5095	0.0010	0.0015	-0.0003	0.0040	0.0037	0.0013
5/26/1994	1.5108	0.0028	0.0010	0.0053	0.0050	0.0013	-0.0013
5/27/1994	1.5095	-0.0003	0.0040	0.0037	0.0000	-0.0013	0.0025
5/31/1994	1.5120	0.0065	0.0062	0.0025	0.0012	0.0025	0.0052
6/1/1994	1.5172	0.0114	0.0077	0.0064	0.0077	0.0052	-0.0090
6/2/1994	1.5082	-0.0013	-0.0026	-0.0013	-0.0038	-0.0090	-0.0027
6/3/1994	1.5055	-0.0053	-0.0040	-0.0065	-0.0117	-0.0027	0.0028
6/6/1994	1.5083	-0.0012	-0.0037	-0.0089	0.0001	0.0028	-0.0003
6/7/1994	1.5080	-0.0040	-0.0092	-0.0002	0.0025	-0.0003	-0.0017
6/8/1994	1.5063	-0.0109	-0.0019	0.0008	-0.0020	-0.0017	0.0004
6/9/1994	1.5067	-0.0015	0.0012	-0.0016	-0.0013	0.0004	0.0017
6/10/1994	1.5084	0.0029	0.0001	0.0004	0.0021	0.0017	0.0118
6/13/1994	1.5202	0.0119	0.0122	0.0139	0.0135	0.0118	-0.0010
6/14/1994	1.5192	0.0112	0.0129	0.0125	0.0108	-0.0010	0.0002
6/15/1994	1.5194	0.0131	0.0127	0.0110	-0.0008	0.0002	0.0006
6/16/1994	1.5200	0.0133	0.0116	-0.0002	0.0008	0.0006	0.0107
6/17/1994	1.5307	0.0223	0.0105	0.0115	0.0113	0.0107	0.0078
6/20/1994	1.5385	0.0183	0.0193	0.0191	0.0185	0.0078	0.0020
6/21/1994	1.5405	0.0213	0.0211	0.0205	0.0098	0.0020	-0.0090
6/22/1994	1.5315	0.0121	0.0115	0.0008	-0.0070	-0.0090	0.0100
6/23/1994	1.5415	0.0215	0.0108	0.0030	0.0010	0.0100	0.0104
6/24/1994	1.5519	0.0212	0.0134	0.0114	0.0204	0.0104	-0.0024
6/27/1994	1.5495	0.0110	0.0090	0.0180	0.0080	-0.0024	0.0017
6/28/1994	1.5512	0.0107	0.0197	0.0097	-0.0007	0.0017	-0.0050
6/29/1994	1.5462	0.0147	0.0047	-0.0057	-0.0033	-0.0050	0.0021
6/30/1994	1.5483	0.0068	-0.0036	-0.0012	-0.0029	0.0021	-0.0093
7/1/1994	1.5390	-0.0129	-0.0105	-0.0122	-0.0072	-0.0093	0.0025
7/5/1994	1.5415	-0.0080	-0.0097	-0.0047	-0.0068	0.0025	0.0090
7/6/1994	1.5505	-0.0007	0.0043	0.0022	0.0115	0.0090	-0.0084
7/7/1994	1.5421	-0.0041	-0.0062	0.0031	0.0006	-0.0084	0.0024
7/8/1994	1.5445	-0.0038	0.0055	0.0030	-0.0060	0.0024	0.0200
7/11/1994	1.5645	0.0255	0.0230	0.0140	0.0224	0.0200	0.0080
7/12/1994	1.5725	0.0310	0.0220	0.0304	0.0280	0.0080	-0.0050
7/13/1994	1.5675	0.0170	0.0254	0.0230	0.0030	-0.0050	-0.0060
7/14/1994	1.5615	0.0194	0.0170	-0.0030	-0.0110	-0.0060	-0.0041
7/15/1994	1.5574	0.0129	-0.0071	-0.0151	-0.0101	-0.0041	0.0048
7/18/1994	1.5622	-0.0023	-0.0103	-0.0053	0.0007	0.0048	-0.0109
7/19/1994	1.5513	-0.0212	-0.0162	-0.0102	-0.0061	-0.0109	-0.0020
7/20/1994	1.5493	-0.0182	-0.0122	-0.0081	-0.0129	-0.0020	-0.0098
7/21/1994	1.5395	-0.0220	-0.0179	-0.0227	-0.0118	-0.0098	-0.0085
7/22/1994	1.5310	-0.0264	-0.0312	-0.0203	-0.0183	-0.0085	0.0010

Date	Pound	Lags 5 Day	4 Day	3 Day	2 Day	1 Day	Future
7/25/1994	1.5320	-0.0302	-0.0193	-0.0173	-0.0075	0.0010	-0.0076
7/26/1994	1.5244	-0.0269	-0.0249	-0.0151	-0.0066	-0.0076	0.0062
7/27/1994	1.5306	-0.0187	-0.0089	-0.0004	-0.0014	0.0062	0.0011
7/28/1994	1.5317	-0.0078	0.0007	-0.0003	0.0073	0.0011	0.0098
7/29/1994	1.5415	0.0105	0.0095	0.0171	0.0109	0.0098	-0.0047
8/1/1994	1.5368	0.0048	0.0124	0.0062	0.0051	-0.0047	0.0010
8/2/1994	1.5378	0.0134	0.0072	0.0061	-0.0037	0.0010	0.0017
8/3/1994	1.5395	0.0089	0.0078	-0.0020	0.0027	0.0017	-0.0008
8/4/1994	1.5387	0.0070	-0.0028	0.0019	0.0009	-0.0008	0.0038
8/5/1994	1.5425	0.0010	0.0057	0.0047	0.0030	0.0038	-0.0003
8/8/1994	1.5422	0.0054	0.0044	0.0027	0.0035	-0.0003	-0.0037
8/9/1994	1.5385	0.0007	-0.0010	-0.0002	-0.0040	-0.0037	0.0008
8/10/1994	1.5393	-0.0002	0.0006	-0.0032	-0.0029	0.0008	0.0002
8/11/1994	1.5395	0.0008	-0.0030	-0.0027	0.0010	0.0002	0.0055
8/12/1994	1.5450	0.0025	0.0028	0.0065	0.0057	0.0055	-0.0028
8/15/1994	1.5422	0.0000	0.0037	0.0029	0.0027	-0.0028	0.0005
8/16/1994	1.5427	0.0042	0.0034	0.0032	-0.0023	0.0005	-0.0027
8/17/1994	1.5400	0.0007	0.0005	-0.0050	-0.0022	-0.0027	0.0050
8/18/1994	1.5450	0.0055	0.0000	0.0028	0.0023	0.0050	0.0040
8/19/1994	1.5490	0.0040	0.0068	0.0063	0.0090	0.0040	0.0020
8/22/1994	1.5510	0.0088	0.0083	0.0110	0.0060	0.0020	0.0025
8/23/1994	1.5535	0.0108	0.0135	0.0085	0.0045	0.0025	0.0000
8/24/1994	1.5535	0.0135	0.0085	0.0045	0.0025	0.0000	0.0000
8/25/1994	1.5535	0.0085	0.0045	0.0025	0.0000	0.0000	-0.0180
8/26/1994	1.5355	-0.0135	-0.0155	-0.0180	-0.0180	-0.0180	-0.0015
8/29/1994	1.5340	-0.0170	-0.0195	-0.0195	-0.0195	-0.0015	0.0010
8/30/1994	1.5350	-0.0185	-0.0185	-0.0185	-0.0005	0.0010	0.0012
8/31/1994	1.5362	-0.0173	-0.0173	0.0007	0.0022	0.0012	0.0083
9/1/1994	1.5445	-0.0090	0.0090	0.0105	0.0095	0.0083	0.0030
9/2/1994	1.5475	0.0120	0.0135	0.0125	0.0113	0.0030	0.0012
9/6/1994	1.5487	0.0147	0.0137	0.0125	0.0042	0.0012	-0.0025
9/7/1994	1.5462	0.0112	0.0100	0.0017	-0.0013	-0.0025	-0.0026
9/8/1994	1.5436	0.0074	-0.0009	-0.0039	-0.0051	-0.0026	0.0067
9/9/1994	1.5503	0.0058	0.0028	0.0016	0.0041	0.0067	0.0193
9/12/1994	1.5696	0.0221	0.0209	0.0234	0.0260	0.0193	-0.0073
9/13/1994	1.5623	0.0136	0.0161	0.0187	0.0120	-0.0073	0.0050
9/14/1994	1.5673	0.0211	0.0237	0.0170	-0.0023	0.0050	-0.0043
9/15/1994	1.5630	0.0194	0.0127	-0.0066	0.0007	-0.0043	0.0210
9/16/1994	1.5840	0.0337	0.0144	0.0217	0.0167	0.0210	-0.0180
9/19/1994	1.5660	-0.0036	0.0037	-0.0013	0.0030	-0.0180	0.0085
9/20/1994	1.5745	0.0122	0.0072	0.0115	-0.0095	0.0085	0.0035
9/21/1994	1.5780	0.0107	0.0150	-0.0060	0.0120	0.0035	-0.0020
9/22/1994	1.5760	0.0130	-0.0080	0.0100	0.0015	-0.0020	0.0053
9/23/1994	1.5813	-0.0027	0.0153	0.0068	0.0033	0.0053	-0.0068
9/26/1994	1.5745	0.0085	0.0000	-0.0035	-0.0015	-0.0068	0.0030
9/27/1994	1.5775	0.0030	-0.0005	0.0015	-0.0038	0.0030	-0.0015
9/28/1994	1.5760	-0.0020	0.0000	-0.0053	0.0015	-0.0015	0.0040
9/29/1994	1.5800	0.0040	-0.0013	0.0055	0.0025	0.0040	-0.0030
9/30/1994	1.5770	-0.0043	0.0025	-0.0005	0.0010	-0.0030	0.0015

		Lags					
Date	Pound	5 Day	4 Day	3 Day	2 Day	1 Day	Future
10/3/1994	1.5785	0.0040	0.0010	0.0025	-0.0015	0.0015	-0.0002
10/4/1994	1.5783	0.0008	0.0023	-0.0017	0.0013	-0.0002	0.0077
10/5/1994	1.5860	0.0100	0.0060	0.0090	0.0075	0.0077	0.0015
10/6/1994	1.5875	0.0075	0.0105	0.0090	0.0092	0.0015	-0.0010
10/7/1994	1.5865	0.0095	0.0080	0.0082	0.0005	-0.0010	-0.0085
10/11/1994	1.5780	-0.0005	-0.0003	-0.0080	-0.0095	-0.0085	0.0030
10/12/1994	1.5810	0.0027	-0.0050	-0.0065	-0.0055	0.0030	0.0005
10/13/1994	1.5815	-0.0045	-0.0060	-0.0050	0.0035	0.0005	0.0095
10/14/1994	1.5910	0.0035	0.0045	0.0130	0.0100	0.0095	0.0190
10/17/1994	1.6100	0.0235	0.0320	0.0290	0.0285	0.0190	0.0035
10/18/1994	1.6135	0.0355	0.0325	0.0320	0.0225	0.0035	0.0045
10/19/1994	1.6180	0.0370	0.0365	0.0270	0.0080	0.0045	0.0035
10/20/1994	1.6215	0.0400	0.0305	0.0115	0.0080	0.0035	0.0040
10/21/1994	1.6255	0.0345	0.0155	0.0120	0.0075	0.0040	0.0020
10/24/1994	1.6275	0.0175	0.0140	0.0095	0.0060	0.0020	0.0090
10/25/1994	1.6365	0.0230	0.0185	0.0150	0.0110	0.0090	-0.0045
10/26/1994	1.6320	0.0140	0.0105	0.0065	0.0045	-0.0045	0.0048
10/27/1994	1.6368	0.0153	0.0113	0.0093	0.0003	0.0048	-0.0138
10/28/1994	1.6230	-0.0025	-0.0045	-0.0135	-0.0090	-0.0138	0.0120
10/31/1994	1.6350	0.0075	-0.0015	0.0030	-0.0018	0.0120	-0.0030
11/1/1994	1.6320	-0.0045	0.0000	-0.0048	0.0090	-0.0030	0.0025
11/2/1994	1.6345	0.0025	-0.0023	0.0115	-0.0005	0.0025	-0.0220
11/3/1994	1.6125	-0.0243	-0.0105	-0.0225	-0.0195	-0.0220	-0.0020
11/4/1994	1.6105	-0.0125	-0.0245	-0.0215	-0.0240	-0.0020	0.0055
11/7/1994	1.6160	-0.0190	-0.0160	-0.0185	0.0035	0.0055	0.0050
11/8/1994	1.6210	-0.0110	-0.0135	0.0085	0.0105	0.0050	-0.0160
11/9/1994	1.6050	-0.0295	-0.0075	-0.0055	-0.0110	-0.0160	-0.0058
11/10/1994	1.5992	-0.0133	-0.0113	-0.0168	-0.0218	-0.0058	-0.0112
11/14/1994	1.5880	-0.0225	-0.0280	-0.0330	-0.0170	-0.0112	-0.0040
11/15/1994	1.5840	-0.0320	-0.0370	-0.0210	-0.0152	-0.0040	-0.0125
11/16/1994	1.5715	-0.0495	-0.0335	-0.0277	-0.0165	-0.0125	0.0055
11/17/1994	1.5770	-0.0280	-0.0222	-0.0110	-0.0070	0.0055	-0.0090
11/18/1994	1.5680	-0.0312	-0.0200	-0.0160	-0.0035	-0.0090	-0.0020
11/21/1994	1.5660	-0.0220	-0.0180	-0.0055	-0.0110	-0.0020	0.0035
11/22/1994	1.5695	-0.0145	-0.0020	-0.0075	0.0015	0.0035	0.0030
11/23/1994	1.5725	0.0010	-0.0045	0.0045	0.0065	0.0030	-0.0095
11/25/1994	1.5630	-0.0140	-0.0050	-0.0030	-0.0065	-0.0095	0.0000
11/28/1994	1.5630	-0.0050	-0.0030	-0.0065	-0.0095	0.0000	0.0013
11/29/1994	1.5643	-0.0017	-0.0052	-0.0082	0.0013	0.0013	0.0027
11/30/1994	1.5670	-0.0025	-0.0055	0.0040	0.0040	0.0027	-0.0018
12/1/1994	1.5652	-0.0073	0.0022	0.0022	0.0009	-0.0018	-0.0050
12/2/1994	1.5602	-0.0028	-0.0028	-0.0041	-0.0068	-0.0050	-0.0012
12/5/1994	1.5590	-0.0040	-0.0053	-0.0080	-0.0062	-0.0012	0.0020
12/6/1994	1.5610	-0.0033	-0.0060	-0.0042	0.0008	0.0020	0.0031
12/7/1994	1.5641	-0.0029	-0.0011	0.0039	0.0051	0.0031	-0.0009
12/8/1994	1.5632	-0.0020	0.0030	0.0042	0.0022	-0.0009	-0.0030
12/9/1994	1.5602	0.0000	0.0012	-0.0008	-0.0039	-0.0030	0.0035
12/12/1994	1.5637	0.0047	0.0027	-0.0004	0.0005	0.0035	-0.0032
12/13/1994	1.5605	-0.0005	-0.0036	-0.0027	0.0003	-0.0032	0.0007

		Lags					
Date	**Pound**	**5 Day**	**4 Day**	**3 Day**	**2 Day**	**1 Day**	**Future**
12/14/1994	1.5612	-0.0029	-0.0020	0.0010	-0.0025	0.0007	0.0018
12/15/1994	1.5630	-0.0002	0.0028	-0.0007	0.0025	0.0018	0.0000
12/16/1994	1.5630	0.0028	-0.0007	0.0025	0.0018	0.0000	-0.0008
12/19/1994	1.5622	-0.0015	0.0017	0.0010	-0.0008	-0.0008	-0.0022
12/20/1994	1.5600	-0.0005	-0.0012	-0.0030	-0.0030	-0.0022	-0.0005
12/21/1994	1.5595	-0.0017	-0.0035	-0.0035	-0.0027	-0.0005	-0.0133
12/22/1994	1.5462	-0.0168	-0.0168	-0.0160	-0.0138	-0.0133	-0.0017
12/23/1994	1.5445	-0.0185	-0.0177	-0.0155	-0.0150	-0.0017	0.0005
12/27/1994	1.5450	-0.0172	-0.0150	-0.0145	-0.0012	0.0005	-0.0015
12/28/1994	1.5435	-0.0165	-0.0160	-0.0027	-0.0010	-0.0015	0.0167
12/29/1994	1.5602	0.0007	0.0140	0.0157	0.0152	0.0167	0.0063
12/30/1994	1.5665	0.0203	0.0220	0.0215	0.0230	0.0063	-0.0041
1/3/1995	1.5624	0.0179	0.0174	0.0189	0.0022	-0.0041	-0.0019
1/4/1995	1.5605	0.0155	0.0170	0.0003	-0.0060	-0.0019	0.0030
1/5/1995	1.5635	0.0200	0.0033	-0.0030	0.0011	0.0030	-0.0117
1/6/1995	1.5518	-0.0084	-0.0147	-0.0106	-0.0087	-0.0117	0.0055
1/9/1995	1.5573	-0.0092	-0.0051	-0.0032	-0.0062	0.0055	0.0012
1/10/1995	1.5585	-0.0039	-0.0020	-0.0050	0.0067	0.0012	0.0007
1/11/1995	1.5592	-0.0013	-0.0043	0.0074	0.0019	0.0007	0.0123
1/12/1995	1.5715	0.0080	0.0197	0.0142	0.0130	0.0123	-0.0045
1/13/1995	1.5670	0.0152	0.0097	0.0085	0.0078	-0.0045	0.0010
1/17/1995	1.5680	0.0107	0.0095	0.0088	-0.0035	0.0010	0.0027
1/18/1995	1.5707	0.0122	0.0115	-0.0008	0.0037	0.0027	0.0043
1/19/1995	1.5750	0.0158	0.0035	0.0080	0.0070	0.0043	0.0127
1/20/1995	1.5877	0.0162	0.0207	0.0197	0.0170	0.0127	0.0078
1/23/1995	1.5955	0.0285	0.0275	0.0248	0.0205	0.0078	0.0005
1/24/1995	1.5960	0.0280	0.0253	0.0210	0.0083	0.0005	-0.0028
1/25/1995	1.5932	0.0225	0.0182	0.0055	-0.0023	-0.0028	-0.0024
1/26/1995	1.5908	0.0158	0.0031	-0.0047	-0.0052	-0.0024	-0.0023
1/27/1995	1.5885	0.0008	-0.0070	-0.0075	-0.0047	-0.0023	0.0050
1/30/1995	1.5935	-0.0020	-0.0025	0.0003	0.0027	0.0050	-0.0120
1/31/1995	1.5815	-0.0145	-0.0117	-0.0093	-0.0070	-0.0120	-0.0010
2/1/1995	1.5805	-0.0127	-0.0103	-0.0080	-0.0130	-0.0010	0.0025
2/2/1995	1.5830	-0.0078	-0.0055	-0.0105	0.0015	0.0025	-0.0187
2/3/1995	1.5643	-0.0242	-0.0292	-0.0172	-0.0162	-0.0187	-0.0043
2/6/1995	1.5600	-0.0335	-0.0215	-0.0205	-0.0230	-0.0043	-0.0030
2/7/1995	1.5570	-0.0245	-0.0235	-0.0260	-0.0073	-0.0030	-0.0047
2/8/1995	1.5523	-0.0282	-0.0307	-0.0120	-0.0077	-0.0047	0.0042
2/9/1995	1.5565	-0.0265	-0.0078	-0.0035	-0.0005	0.0042	0.0062
2/10/1995	1.5627	-0.0016	0.0027	0.0057	0.0104	0.0062	0.0008
2/13/1995	1.5635	0.0035	0.0065	0.0112	0.0070	0.0008	-0.0060
2/14/1995	1.5575	0.0005	0.0052	0.0010	-0.0052	-0.0060	0.0030
2/15/1995	1.5605	0.0082	0.0040	-0.0022	-0.0030	0.0030	0.0170
2/16/1995	1.5775	0.0210	0.0148	0.0140	0.0200	0.0170	-0.0010
2/17/1995	1.5765	0.0138	0.0130	0.0190	0.0160	-0.0010	0.0050
2/21/1995	1.5815	0.0180	0.0240	0.0210	0.0040	0.0050	0.0045
2/22/1995	1.5860	0.0285	0.0255	0.0085	0.0095	0.0045	0.0070
2/23/1995	1.5930	0.0325	0.0155	0.0165	0.0115	0.0070	-0.0045
2/24/1995	1.5885	0.0110	0.0120	0.0070	0.0025	-0.0045	-0.0050

		Lags					
Date	Pound	5 Day	4 Day	3 Day	2 Day	1 Day	Future
2/27/1995	1.5835	0.0070	0.0020	-0.0025	-0.0095	-0.0050	0.0005
2/28/1995	1.5840	0.0025	-0.0020	-0.0090	-0.0045	0.0005	0.0003
3/1/1995	1.5843	-0.0017	-0.0087	-0.0042	0.0008	0.0003	0.0067
3/2/1995	1.5910	-0.0020	0.0025	0.0075	0.0070	0.0067	0.0300
3/3/1995	1.6210	0.0325	0.0375	0.0370	0.0367	0.0300	0.0120
3/6/1995	1.6330	0.0495	0.0490	0.0487	0.0420	0.0120	0.0110
3/7/1995	1.6440	0.0600	0.0597	0.0530	0.0230	0.0110	-0.0250
3/8/1995	1.6190	0.0347	0.0280	-0.0020	-0.0140	-0.0250	-0.0038
3/9/1995	1.6152	0.0242	-0.0058	-0.0178	-0.0288	-0.0038	-0.0350
3/10/1995	1.5802	-0.0408	-0.0528	-0.0638	-0.0388	-0.0350	0.0166
3/13/1995	1.5968	-0.0362	-0.0472	-0.0222	-0.0184	0.0166	-0.0113
3/14/1995	1.5855	-0.0585	-0.0335	-0.0297	0.0053	-0.0113	0.0175
3/15/1995	1.6030	-0.0160	-0.0122	0.0228	0.0062	0.0175	-0.0170
3/16/1995	1.5860	-0.0292	0.0058	-0.0108	0.0005	-0.0170	-0.0040
3/17/1995	1.5820	0.0018	-0.0148	-0.0035	-0.0210	-0.0040	-0.0015
3/20/1995	1.5805	-0.0163	-0.0050	-0.0225	-0.0055	-0.0015	0.0050
3/21/1995	1.5855	0.0000	-0.0175	-0.0005	0.0035	0.0050	0.0005
3/22/1995	1.5860	-0.0170	0.0000	0.0040	0.0055	0.0005	0.0063
3/23/1995	1.5923	0.0063	0.0103	0.0118	0.0068	0.0063	-0.0043
3/24/1995	1.5880	0.0060	0.0075	0.0025	0.0020	-0.0043	0.0075
3/27/1995	1.5955	0.0150	0.0100	0.0095	0.0032	0.0075	0.0145
3/28/1995	1.6100	0.0245	0.0240	0.0177	0.0220	0.0145	-0.0020
3/29/1995	1.6080	0.0220	0.0157	0.0200	0.0125	-0.0020	-0.0095
3/30/1995	1.5985	0.0062	0.0105	0.0030	-0.0115	-0.0095	0.0205
3/31/1995	1.6190	0.0310	0.0235	0.0090	0.0110	0.0205	-0.0030
4/3/1995	1.6160	0.0205	0.0060	0.0080	0.0175	-0.0030	-0.0145
4/4/1995	1.6015	-0.0085	-0.0065	0.0030	-0.0175	-0.0145	0.0050
4/5/1995	1.6065	-0.0015	0.0080	-0.0125	-0.0095	0.0050	-0.0007
4/6/1995	1.6058	0.0073	-0.0132	-0.0102	0.0043	-0.0007	-0.0043
4/7/1995	1.6015	-0.0175	-0.0145	0.0000	-0.0050	-0.0043	-0.0075
4/10/1995	1.5940	-0.0220	-0.0075	-0.0125	-0.0118	-0.0075	0.0005
4/11/1995	1.5945	-0.0070	-0.0120	-0.0113	-0.0070	0.0005	-0.0045
4/12/1995	1.5900	-0.0165	-0.0158	-0.0115	-0.0040	-0.0045	0.0168
4/13/1995	1.6068	0.0010	0.0053	0.0128	0.0123	0.0168	-0.0048
4/14/1995	1.6020	0.0005	0.0080	0.0075	0.0120	-0.0048	0.0175
4/17/1995	1.6195	0.0255	0.0250	0.0295	0.0127	0.0175	-0.0055
4/18/1995	1.6140	0.0195	0.0240	0.0072	0.0120	-0.0055	0.0020
4/19/1995	1.6160	0.0260	0.0092	0.0140	-0.0035	0.0020	-0.0033
4/20/1995	1.6127	0.0059	0.0107	-0.0068	-0.0013	-0.0033	-0.0027
4/21/1995	1.6100	0.0080	-0.0095	-0.0040	-0.0060	-0.0027	-0.0045
4/24/1995	1.6055	-0.0140	-0.0085	-0.0105	-0.0072	-0.0045	0.0080
4/25/1995	1.6135	-0.0005	-0.0025	0.0008	0.0035	0.0080	-0.0030
4/26/1995	1.6105	-0.0055	-0.0022	0.0005	0.0050	-0.0030	0.0057
4/27/1995	1.6162	0.0035	0.0062	0.0107	0.0027	0.0057	-0.0071
4/28/1995	1.6091	-0.0009	0.0036	-0.0044	-0.0014	-0.0071	0.0089
5/1/1995	1.6180	0.0125	0.0045	0.0075	0.0018	0.0089	-0.0055
5/2/1995	1.6125	-0.0010	0.0020	-0.0037	0.0034	-0.0055	0.0047
5/3/1995	1.6172	0.0067	0.0010	0.0081	-0.0008	0.0047	0.0013
5/4/1995	1.6185	0.0023	0.0094	0.0005	0.0060	0.0013	-0.0195

Date	Pound	Lags 5 Day	4 Day	3 Day	2 Day	1 Day	Future
5/5/1995	1.5990	-0.0101	-0.0190	-0.0135	-0.0182	-0.0195	0.0090
5/8/1995	1.6080	-0.0100	-0.0045	-0.0092	-0.0105	0.0090	-0.0195
5/9/1995	1.5885	-0.0240	-0.0287	-0.0300	-0.0105	-0.0195	-0.0070
5/10/1995	1.5815	-0.0357	-0.0370	-0.0175	-0.0265	-0.0070	-0.0239
5/11/1995	1.5576	-0.0609	-0.0414	-0.0504	-0.0309	-0.0239	0.0134
5/12/1995	1.5710	-0.0280	-0.0370	-0.0175	-0.0105	0.0134	-0.0058
5/15/1995	1.5652	-0.0428	-0.0233	-0.0163	0.0076	-0.0058	0.0038
5/16/1995	1.5690	-0.0195	-0.0125	0.0114	-0.0020	0.0038	-0.0005
5/17/1995	1.5685	-0.0130	0.0109	-0.0025	0.0033	-0.0005	-0.0060
5/18/1995	1.5625	0.0049	-0.0085	-0.0027	-0.0065	-0.0060	0.0110
5/19/1995	1.5735	0.0025	0.0083	0.0045	0.0050	0.0110	0.0015
5/22/1995	1.5750	0.0098	0.0060	0.0065	0.0125	0.0015	-0.0090
5/23/1995	1.5660	-0.0030	-0.0025	0.0035	-0.0075	-0.0090	0.0095
5/24/1995	1.5755	0.0070	0.0130	0.0020	0.0005	0.0095	0.0282
5/25/1995	1.6037	0.0412	0.0302	0.0287	0.0377	0.0282	0.0003
5/26/1995	1.6040	0.0305	0.0290	0.0380	0.0285	0.0003	-0.0030
5/30/1995	1.6010	0.0260	0.0350	0.0255	-0.0027	-0.0030	-0.0145
5/31/1995	1.5865	0.0205	0.0110	-0.0172	-0.0175	-0.0145	0.0080
6/1/1995	1.5945	0.0190	-0.0092	-0.0095	-0.0065	0.0080	-0.0085
6/2/1995	1.5860	-0.0177	-0.0180	-0.0150	-0.0005	-0.0085	0.0095
6/5/1995	1.5955	-0.0085	-0.0055	0.0090	0.0010	0.0095	-0.0055
6/6/1995	1.5900	-0.0110	0.0035	-0.0045	0.0040	-0.0055	0.0042
6/7/1995	1.5942	0.0077	-0.0003	0.0082	-0.0013	0.0042	-0.0022
6/8/1995	1.5920	-0.0025	0.0060	-0.0035	0.0020	-0.0022	0.0025
6/9/1995	1.5945	0.0085	-0.0010	0.0045	0.0003	0.0025	0.0005
6/12/1995	1.5950	-0.0005	0.0050	0.0008	0.0030	0.0005	0.0005
6/13/1995	1.5955	0.0055	0.0013	0.0035	0.0010	0.0005	0.0130
6/14/1995	1.6085	0.0143	0.0165	0.0140	0.0135	0.0130	-0.0130
6/15/1995	1.5955	0.0035	0.0010	0.0005	0.0000	-0.0130	0.0115
6/16/1995	1.6070	0.0125	0.0120	0.0115	-0.0015	0.0115	-0.0075
6/19/1995	1.5995	0.0045	0.0040	-0.0090	0.0040	-0.0075	0.0035
6/20/1995	1.6030	0.0075	-0.0055	0.0075	-0.0040	0.0035	0.0019
6/21/1995	1.6049	-0.0036	0.0094	-0.0021	0.0054	0.0019	-0.0051
6/22/1995	1.5998	0.0043	-0.0072	0.0003	-0.0032	-0.0051	0.0047
6/23/1995	1.6045	-0.0025	0.0050	0.0015	-0.0004	0.0047	-0.0190
6/26/1995	1.5855	-0.0140	-0.0175	-0.0194	-0.0143	-0.0190	-0.0010
6/27/1995	1.5845	-0.0185	-0.0204	-0.0153	-0.0200	-0.0010	-0.0105
6/28/1995	1.5740	-0.0309	-0.0258	-0.0305	-0.0115	-0.0105	0.0175
6/29/1995	1.5915	-0.0083	-0.0130	0.0060	0.0070	0.0175	-0.0010
6/30/1995	1.5905	-0.0140	0.0050	0.0060	0.0165	-0.0010	0.0067

Appendix E

Weekly Deutschemark Data

		Lags					
Date	Mark	5 Weeks	4 Weeks	3 Weeks	2 Weeks	1 Weeks	Future
1/5/1994	1.7410	0.0235	0.0355	0.0247	0.0395	0.0230	-0.0060
1/12/1994	1.7350	0.0295	0.0187	0.0335	0.0170	-0.0060	0.0115
1/19/1994	1.7465	0.0302	0.0450	0.0285	0.0055	0.0115	0.0003
1/26/1994	1.7468	0.0453	0.0288	0.0058	0.0118	0.0003	-0.0133
2/2/1994	1.7335	0.0155	-0.0075	-0.0015	-0.0130	-0.0133	0.0245
2/9/1994	1.7580	0.0170	0.0230	0.0115	0.0112	0.0245	-0.0338
2/16/1994	1.7242	-0.0108	-0.0223	-0.0226	-0.0093	-0.0338	0.0050
2/23/1994	1.7292	-0.0173	-0.0176	-0.0043	-0.0288	0.0050	-0.0262
3/2/1994	1.7030	-0.0438	-0.0305	-0.0550	-0.0212	-0.0262	0.0055
3/9/1994	1.7085	-0.0250	-0.0495	-0.0157	-0.0207	0.0055	-0.0200
3/16/1994	1.6885	-0.0695	-0.0357	-0.0407	-0.0145	-0.0200	-0.0027
3/23/1994	1.6858	-0.0384	-0.0434	-0.0172	-0.0227	-0.0027	-0.0118
3/30/1994	1.6740	-0.0552	-0.0290	-0.0345	-0.0145	-0.0118	0.0412
4/6/1994	1.7152	0.0122	0.0067	0.0267	0.0294	0.0412	-0.0037
4/13/1994	1.7115	0.0030	0.0230	0.0257	0.0375	-0.0037	-0.0165
4/20/1994	1.6950	0.0065	0.0092	0.0210	-0.0202	-0.0165	-0.0245
4/27/1994	1.6705	-0.0153	-0.0035	-0.0447	-0.0410	-0.0245	-0.0115
5/4/1994	1.6590	-0.0150	-0.0562	-0.0525	-0.0360	-0.0115	0.0125
5/11/1994	1.6715	-0.0437	-0.0400	-0.0235	0.0010	0.0125	-0.0145
5/18/1994	1.6570	-0.0545	-0.0380	-0.0135	-0.0020	-0.0145	-0.0120
5/25/1994	1.6450	-0.0500	-0.0255	-0.0140	-0.0265	-0.0120	-0.0005
6/1/1994	1.6445	-0.0260	-0.0145	-0.0270	-0.0125	-0.0005	0.0265
6/8/1994	1.6710	0.0120	-0.0005	0.0140	0.0260	0.0265	-0.0353
6/15/1994	1.6357	-0.0358	-0.0213	-0.0093	-0.0088	-0.0353	-0.0297
6/22/1994	1.6060	-0.0510	-0.0390	-0.0385	-0.0650	-0.0297	-0.0223
6/29/1994	1.5837	-0.0613	-0.0608	-0.0873	-0.0520	-0.0223	-0.0145
7/6/1994	1.5692	-0.0753	-0.1018	-0.0665	-0.0368	-0.0145	-0.0337
7/13/1994	1.5355	-0.1355	-0.1002	-0.0705	-0.0482	-0.0337	0.0265
7/20/1994	1.5620	-0.0737	-0.0440	-0.0217	-0.0072	0.0265	0.0135
7/27/1994	1.5755	-0.0305	-0.0082	0.0063	0.0400	0.0135	0.0055
8/3/1994	1.5810	-0.0027	0.0118	0.0455	0.0190	0.0055	-0.0038
8/10/1994	1.5772	0.0080	0.0417	0.0152	0.0017	-0.0038	-0.0215
8/17/1994	1.5557	0.0202	-0.0063	-0.0198	-0.0253	-0.0215	-0.0095
8/24/1994	1.5462	-0.0158	-0.0293	-0.0348	-0.0310	-0.0095	0.0333
8/31/1994	1.5795	0.0040	-0.0015	0.0023	0.0238	0.0333	-0.0308
9/7/1994	1.5487	-0.0323	-0.0285	-0.0070	0.0025	-0.0308	-0.0092
9/14/1994	1.5395	-0.0377	-0.0162	-0.0067	-0.0400	-0.0092	0.0086
9/21/1994	1.5481	-0.0076	0.0019	-0.0314	-0.0006	0.0086	0.0014
9/28/1994	1.5495	0.0033	-0.0300	0.0008	0.0100	0.0014	-0.0070
10/5/1994	1.5425	-0.0370	-0.0062	0.0030	-0.0056	-0.0070	0.0000
10/12/1994	1.5425	-0.0062	0.0030	-0.0056	-0.0070	0.0000	-0.0397
10/19/1994	1.5028	-0.0367	-0.0453	-0.0467	-0.0397	-0.0397	-0.0073
10/26/1994	1.4955	-0.0526	-0.0540	-0.0470	-0.0470	-0.0073	0.0085
11/2/1994	1.5040	-0.0455	-0.0385	-0.0385	0.0012	0.0085	0.0247

		Lags					
Date	Mark	5 Weeks	4 Weeks	3 Weeks	2 Weeks	1 Weeks	Future
11/9/1994	1.5287	-0.0138	-0.0138	0.0259	0.0332	0.0247	0.0228
11/16/1994	1.5515	0.0090	0.0487	0.0560	0.0475	0.0228	0.0003
11/23/1994	1.5518	0.0490	0.0563	0.0478	0.0231	0.0003	0.0167
11/30/1994	1.5685	0.0730	0.0645	0.0398	0.0170	0.0167	0.0032
12/7/1994	1.5717	0.0677	0.0430	0.0202	0.0199	0.0032	-0.0007
12/14/1994	1.5710	0.0423	0.0195	0.0192	0.0025	-0.0007	-0.0003
12/21/1994	1.5707	0.0192	0.0189	0.0022	-0.0010	-0.0003	0.0007
12/28/1994	1.5714	0.0196	0.0029	-0.0003	0.0004	0.0007	-0.0102
1/4/1995	1.5612	-0.0073	-0.0105	-0.0098	-0.0095	-0.0102	-0.0257
1/11/1995	1.5355	-0.0362	-0.0355	-0.0352	-0.0359	-0.0257	-0.0060
1/18/1995	1.5295	-0.0415	-0.0412	-0.0419	-0.0317	-0.0060	-0.0140
1/25/1995	1.5155	-0.0552	-0.0559	-0.0457	-0.0200	-0.0140	0.0080
2/1/1995	1.5235	-0.0479	-0.0377	-0.0120	-0.0060	0.0080	0.0090
2/8/1995	1.5325	-0.0287	-0.0030	0.0030	0.0170	0.0090	-0.0210
2/15/1995	1.5115	-0.0240	-0.0180	-0.0040	-0.0120	-0.0210	-0.0405
2/22/1995	1.4710	-0.0585	-0.0445	-0.0525	-0.0615	-0.0405	-0.0063
3/1/1995	1.4647	-0.0508	-0.0588	-0.0678	-0.0468	-0.0063	-0.0712
3/8/1995	1.3935	-0.1300	-0.1390	-0.1180	-0.0775	-0.0712	-0.0080
3/15/1995	1.3855	-0.1470	-0.1260	-0.0855	-0.0792	-0.0080	0.0208
3/22/1995	1.4063	-0.1052	-0.0647	-0.0584	0.0128	0.0208	-0.0223
3/29/1995	1.3840	-0.0870	-0.0807	-0.0095	-0.0015	-0.0223	-0.0035
4/5/1995	1.3805	-0.0842	-0.0130	-0.0050	-0.0258	-0.0035	0.0238
4/12/1995	1.4043	0.0108	0.0188	-0.0020	0.0203	0.0238	-0.0478
4/19/1995	1.3565	-0.0290	-0.0498	-0.0275	-0.0240	-0.0478	0.0210
4/26/1995	1.3775	-0.0288	-0.0065	-0.0030	-0.0268	0.0210	-0.0033
5/3/1995	1.3742	-0.0098	-0.0063	-0.0301	0.0177	-0.0033	0.0173
5/10/1995	1.3915	0.0110	-0.0128	0.0350	0.0140	0.0173	0.0455
5/17/1995	1.4370	0.0327	0.0805	0.0595	0.0628	0.0455	0.0015
5/24/1995	1.4385	0.0820	0.0610	0.0643	0.0470	0.0015	-0.0245
5/31/1995	1.4140	0.0365	0.0398	0.0225	-0.0230	-0.0245	-0.0090
6/7/1995	1.4050	0.0308	0.0135	-0.0320	-0.0335	-0.0090	-0.0040
6/14/1995	1.4010	0.0095	-0.0360	-0.0375	-0.0130	-0.0040	-0.0095
6/21/1995	1.3915	-0.0455	-0.0470	-0.0225	-0.0135	-0.0095	0.0100
6/28/1995	1.4015	-0.0370	-0.0125	-0.0035	0.0005	0.0100	-0.0212

Appendix F

Weekly British Pound Data

		Lags					
Date	Pound	5 Weeks	4 Weeks	3 Weeks	2 Weeks	1 Weeks	Future
1/5/1994	1.7410	0.0235	0.0355	0.0247	0.0395	0.0230	-0.0060
1/12/1994	1.7350	0.0295	0.0187	0.0335	0.0170	-0.0060	0.0115
1/19/1994	1.7465	0.0302	0.0450	0.0285	0.0055	0.0115	0.0003
1/26/1994	1.7468	0.0453	0.0288	0.0058	0.0118	0.0003	-0.0133
2/2/1994	1.7335	0.0155	-0.0075	-0.0015	-0.0130	-0.0133	0.0245
2/9/1994	1.7580	0.0170	0.0230	0.0115	0.0112	0.0245	-0.0338
2/16/1994	1.7242	-0.0108	-0.0223	-0.0226	-0.0093	-0.0338	0.0050
2/23/1994	1.7292	-0.0173	-0.0176	-0.0043	-0.0288	0.0050	-0.0262
3/2/1994	1.7030	-0.0438	-0.0305	-0.0550	-0.0212	-0.0262	0.0055
3/9/1994	1.7085	-0.0250	-0.0495	-0.0157	-0.0207	0.0055	-0.0200
3/16/1994	1.6885	-0.0695	-0.0357	-0.0407	-0.0145	-0.0200	-0.0027
3/23/1994	1.6858	-0.0384	-0.0434	-0.0172	-0.0227	-0.0027	-0.0118
3/30/1994	1.6740	-0.0552	-0.0290	-0.0345	-0.0145	-0.0118	0.0412
4/6/1994	1.7152	0.0122	0.0067	0.0267	0.0294	0.0412	-0.0037
4/13/1994	1.7115	0.0030	0.0230	0.0257	0.0375	-0.0037	-0.0165
4/20/1994	1.6950	0.0065	0.0092	0.0210	-0.0202	-0.0165	-0.0245
4/27/1994	1.6705	-0.0153	-0.0035	-0.0447	-0.0410	-0.0245	-0.0115
5/4/1994	1.6590	-0.0150	-0.0562	-0.0525	-0.0360	-0.0115	0.0125
5/11/1994	1.6715	-0.0437	-0.0400	-0.0235	0.0010	0.0125	-0.0145
5/18/1994	1.6570	-0.0545	-0.0380	-0.0135	-0.0020	-0.0145	-0.0120
5/25/1994	1.6450	-0.0500	-0.0255	-0.0140	-0.0265	-0.0120	-0.0005
6/1/1994	1.6445	-0.0260	-0.0145	-0.0270	-0.0125	-0.0005	0.0265
6/8/1994	1.6710	0.0120	-0.0005	0.0140	0.0260	0.0265	-0.0353
6/15/1994	1.6357	-0.0358	-0.0213	-0.0093	-0.0088	-0.0353	-0.0297
6/22/1994	1.6060	-0.0510	-0.0390	-0.0385	-0.0650	-0.0297	-0.0223
6/29/1994	1.5837	-0.0613	-0.0608	-0.0873	-0.0520	-0.0223	-0.0145
7/6/1994	1.5692	-0.0753	-0.1018	-0.0665	-0.0368	-0.0145	-0.0337
7/13/1994	1.5355	-0.1355	-0.1002	-0.0705	-0.0482	-0.0337	0.0265
7/20/1994	1.5620	-0.0737	-0.0440	-0.0217	-0.0072	0.0265	0.0135
7/27/1994	1.5755	-0.0305	-0.0082	0.0063	0.0400	0.0135	0.0055
8/3/1994	1.5810	-0.0027	0.0118	0.0455	0.0190	0.0055	-0.0038
8/10/1994	1.5772	0.0080	0.0417	0.0152	0.0017	-0.0038	-0.0215
8/17/1994	1.5557	0.0202	-0.0063	-0.0198	-0.0253	-0.0215	-0.0095
8/24/1994	1.5462	-0.0158	-0.0293	-0.0348	-0.0310	-0.0095	0.0333
8/31/1994	1.5795	0.0040	-0.0015	0.0023	0.0238	0.0333	-0.0308
9/7/1994	1.5487	-0.0323	-0.0285	-0.0070	0.0025	-0.0308	-0.0092
9/14/1994	1.5395	-0.0377	-0.0162	-0.0067	-0.0400	-0.0092	0.0086
9/21/1994	1.5481	-0.0076	0.0019	-0.0314	-0.0006	0.0086	0.0014
9/28/1994	1.5495	0.0033	-0.0300	0.0008	0.0100	0.0014	-0.0070
10/5/1994	1.5425	-0.0370	-0.0062	0.0030	-0.0056	-0.0070	0.0000
10/12/1994	1.5425	-0.0062	0.0030	-0.0056	-0.0070	0.0000	-0.0397
10/19/1994	1.5028	-0.0367	-0.0453	-0.0467	-0.0397	-0.0397	-0.0073
10/26/1994	1.4955	-0.0526	-0.0540	-0.0470	-0.0470	-0.0073	0.0085
11/2/1994	1.5040	-0.0455	-0.0385	-0.0385	0.0012	0.0085	0.0247

Date	Pound	Lags: 5 Weeks	4 Weeks	3 Weeks	2 Weeks	1 Weeks	Future
11/9/1994	1.5287	-0.0138	-0.0138	0.0259	0.0332	0.0247	0.0228
11/16/1994	1.5515	0.0090	0.0487	0.0560	0.0475	0.0228	0.0003
11/23/1994	1.5518	0.0490	0.0563	0.0478	0.0231	0.0003	0.0167
11/30/1994	1.5685	0.0730	0.0645	0.0398	0.0170	0.0167	0.0032
12/7/1994	1.5717	0.0677	0.0430	0.0202	0.0199	0.0032	-0.0007
12/14/1994	1.5710	0.0423	0.0195	0.0192	0.0025	-0.0007	-0.0003
12/21/1994	1.5707	0.0192	0.0189	0.0022	-0.0010	-0.0003	0.0007
12/28/1994	1.5714	0.0196	0.0029	-0.0003	0.0004	0.0007	-0.0102
1/4/1995	1.5612	-0.0073	-0.0105	-0.0098	-0.0095	-0.0102	-0.0257
1/11/1995	1.5355	-0.0362	-0.0355	-0.0352	-0.0359	-0.0257	-0.0060
1/18/1995	1.5295	-0.0415	-0.0412	-0.0419	-0.0317	-0.0060	-0.0140
1/25/1995	1.5155	-0.0552	-0.0559	-0.0457	-0.0200	-0.0140	0.0080
2/1/1995	1.5235	-0.0479	-0.0377	-0.0120	-0.0060	0.0080	0.0090
2/8/1995	1.5325	-0.0287	-0.0030	0.0030	0.0170	0.0090	-0.0210
2/15/1995	1.5115	-0.0240	-0.0180	-0.0040	-0.0120	-0.0210	-0.0405
2/22/1995	1.4710	-0.0585	-0.0445	-0.0525	-0.0615	-0.0405	-0.0063
3/1/1995	1.4647	-0.0508	-0.0588	-0.0678	-0.0468	-0.0063	-0.0712
3/8/1995	1.3935	-0.1300	-0.1390	-0.1180	-0.0775	-0.0712	-0.0080
3/15/1995	1.3855	-0.1470	-0.1260	-0.0855	-0.0792	-0.0080	0.0208
3/22/1995	1.4063	-0.1052	-0.0647	-0.0584	0.0128	0.0208	-0.0223
3/29/1995	1.3840	-0.0870	-0.0807	-0.0095	-0.0015	-0.0223	-0.0035
4/5/1995	1.3805	-0.0842	-0.0130	-0.0050	-0.0258	-0.0035	0.0238
4/12/1995	1.4043	0.0108	0.0188	-0.0020	0.0203	0.0238	-0.0478
4/19/1995	1.3565	-0.0290	-0.0498	-0.0275	-0.0240	-0.0478	0.0210
4/26/1995	1.3775	-0.0288	-0.0065	-0.0030	-0.0268	0.0210	-0.0033
5/3/1995	1.3742	-0.0098	-0.0063	-0.0301	0.0177	-0.0033	0.0173
5/10/1995	1.3915	0.0110	-0.0128	0.0350	0.0140	0.0173	0.0455
5/17/1995	1.4370	0.0327	0.0805	0.0595	0.0628	0.0455	0.0015
5/24/1995	1.4385	0.0820	0.0610	0.0643	0.0470	0.0015	-0.0245
5/31/1995	1.4140	0.0365	0.0398	0.0225	-0.0230	-0.0245	-0.0090
6/7/1995	1.4050	0.0308	0.0135	-0.0320	-0.0335	-0.0090	-0.0040
6/14/1995	1.4010	0.0095	-0.0360	-0.0375	-0.0130	-0.0040	-0.0095
6/21/1995	1.3915	-0.0455	-0.0470	-0.0225	-0.0135	-0.0095	0.0100
6/28/1995	1.4015	-0.0370	-0.0125	-0.0035	0.0005	0.0100	-0.0212

Appendix G

Input File Layout for Neural Network Calculations

Variable	Type	Values/Use
intNumPts	Short Integer	Total number of data points
intNumSamp	Short Integer	Total number of training points
strSetID	String	Prefix for output sets
intNumSets	Short Integer	Number of sets to process
intNumInput	Short Integer	Number of nodes in input layer
intNumOutput	Short Integer	Number of points in output nodes
dblLearnParm	Double Precision	Learning parameter
dblMomentum	Double Precision	Momentum value – not used in this application
dblErrorTol	Double Precision	Error tolerance which will stop processing for the set
lngMaxCycles	Long Integer	Maximum number of cycles
lngOutFreq	Long Integer	Frequency for displaying intermediate results
strConvert	String	"Y" or "N" Determines post processing conversion of calculated points
bolWtChoice	Boolean	"Y" [Random] or "N" [Fixed – read from file]
bolSavInWts	Boolean	"Y" [true] or "N" [false]) Save input weights
dblBias	Double Precision	Bias factor – not used in this application
intNumHideLayers	Short Integer	Number of hidden layers, maximum 4
intNodesLayer1 ... 4	Short Integer	Nodes in respective hidden layer

Appendix H

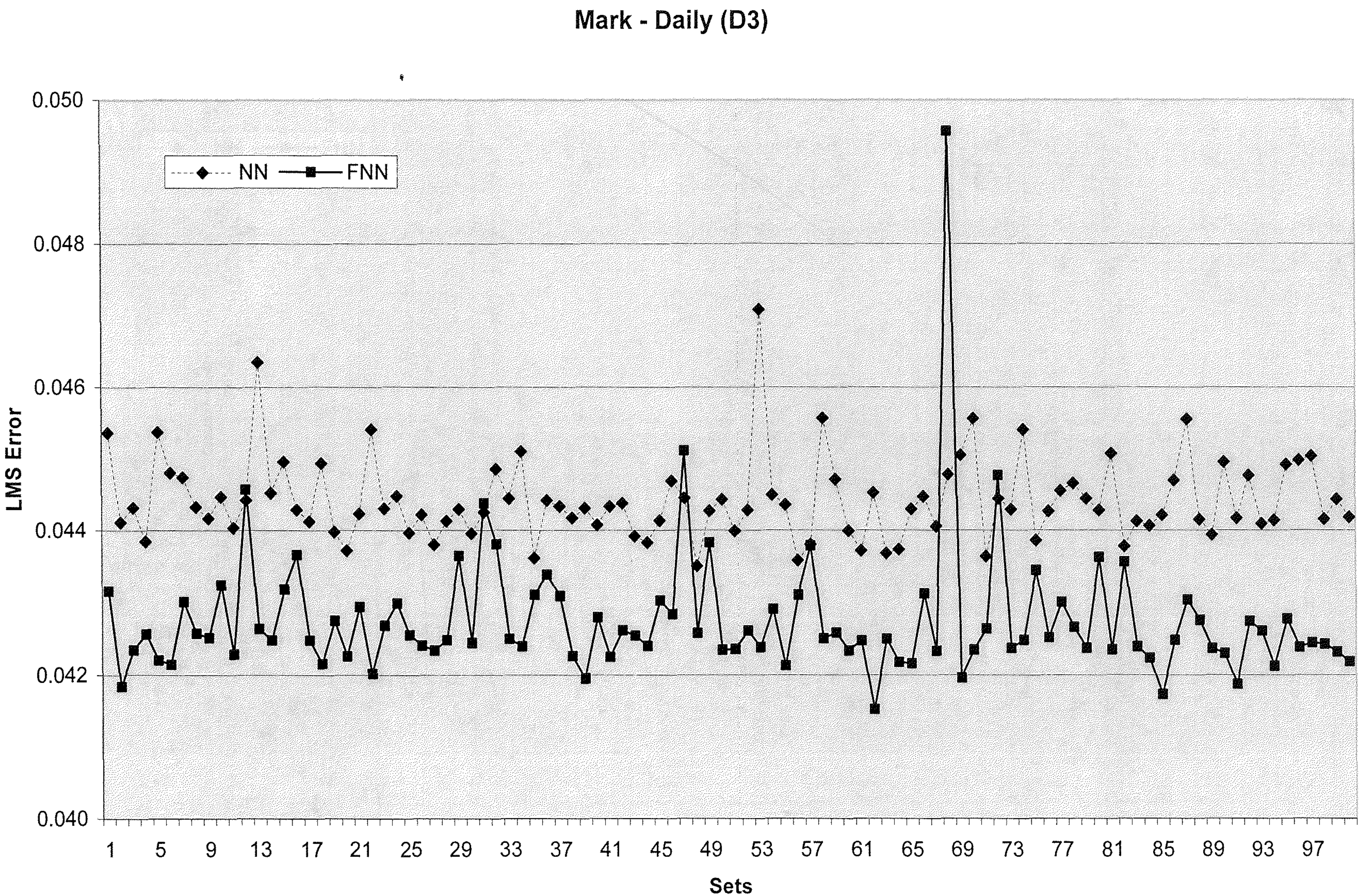
Data Input File Layout for Fractal Neural Network Calculations

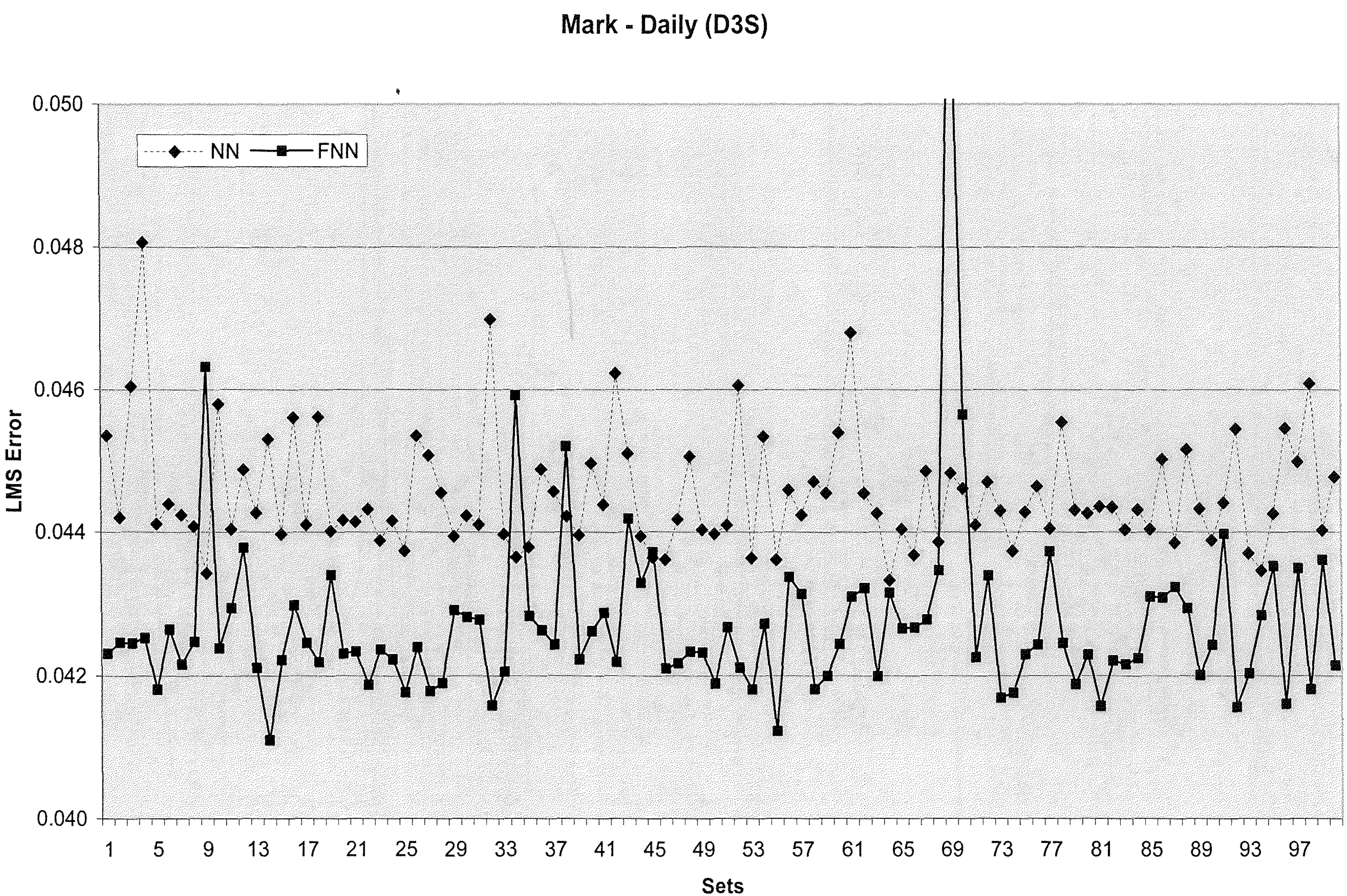
Variable	Type	Values/Use
intNumPts	Short Integer	Total number of data points
intNumSamp	Short Integer	Total number of training points
strSetID	String	Prefix for output sets
intNumSets	Short Integer	Number of sets to process
intNumInput	Short Integer	Number of nodes in input layer
intNumOutput	Short Integer	Number of points in output nodes
dblLearnParm	Double Precision	Learning parameter
dblFLearnParm	Double Precision	Fractal learning parameter
dblBias	Double Precision	Bias factor – not used in this application
dblFBias	Double Precision	Fractal bias factor – not used in this application
dblMomentum	Double Precision	Momentum value – not used in this application
dblFMomentum	Double Precision	Fractal momentum value – not used in this application
dblErrorTol	Double Precision	Error tolerance which will stop processing for the set
dblErrDif	Double Precision	Test for no further convergence – not used in this application
lngMaxCycles	Long Integer	Maximum number of cycles
lngOutFreq	Long Integer	Frequency for saving intermediate results
lngDispFreq	Long Integer	Frequency for displaying intermediate results

Variable	Type	Values/Use
strConvert	String	"Y" or "N" Determines post processing conversion of calculated points
intWtChoice	Short Integer	1 = Random 2 = Fixed – read all weights from file 3 = Input layer – read input layer weights from file
intNumHideLayers	Short Integer	Number of hidden layers, maximum 4
intNodesLayer1 ... 4	Short Integer	Nodes in respective hidden layer

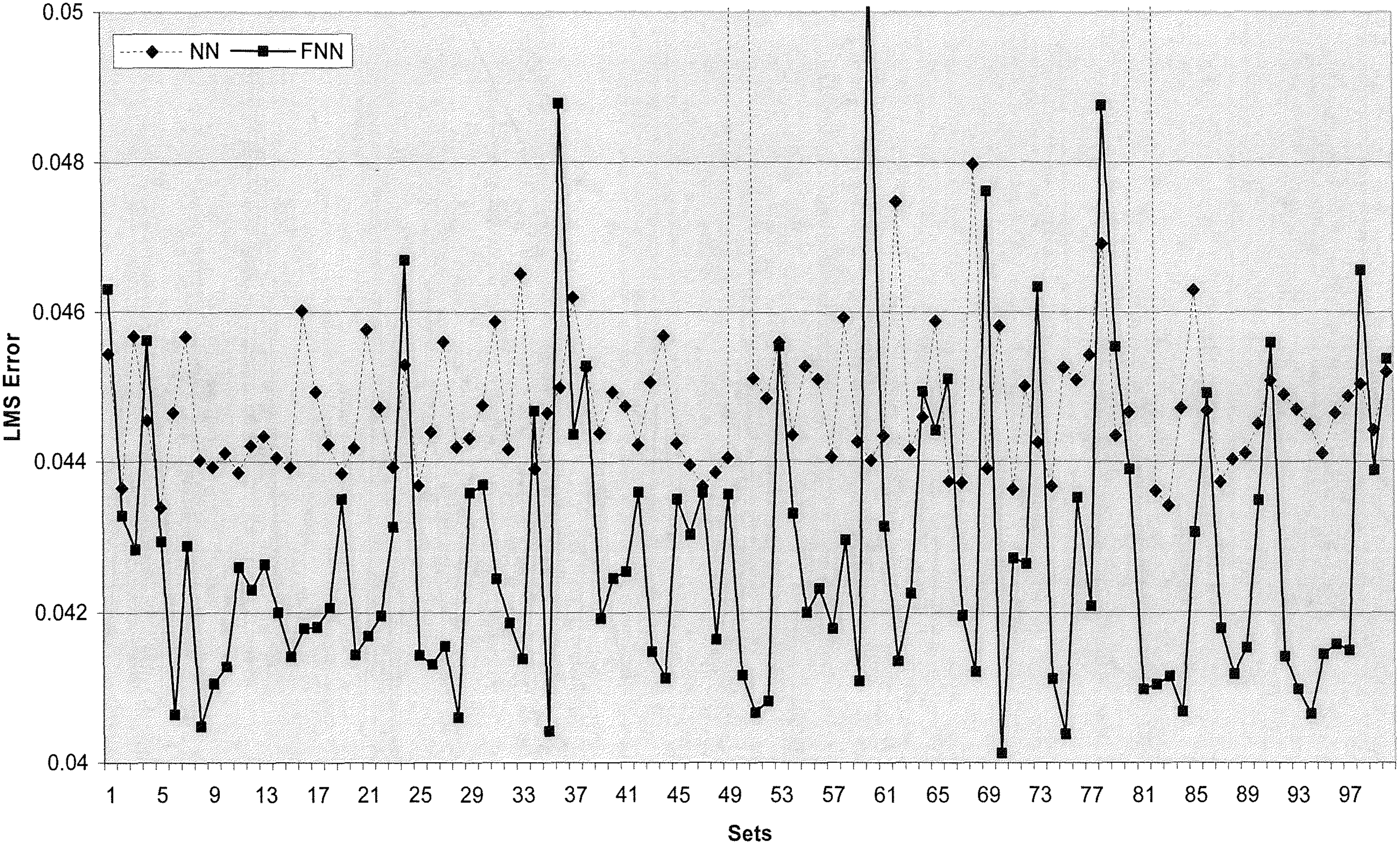
Appendix I

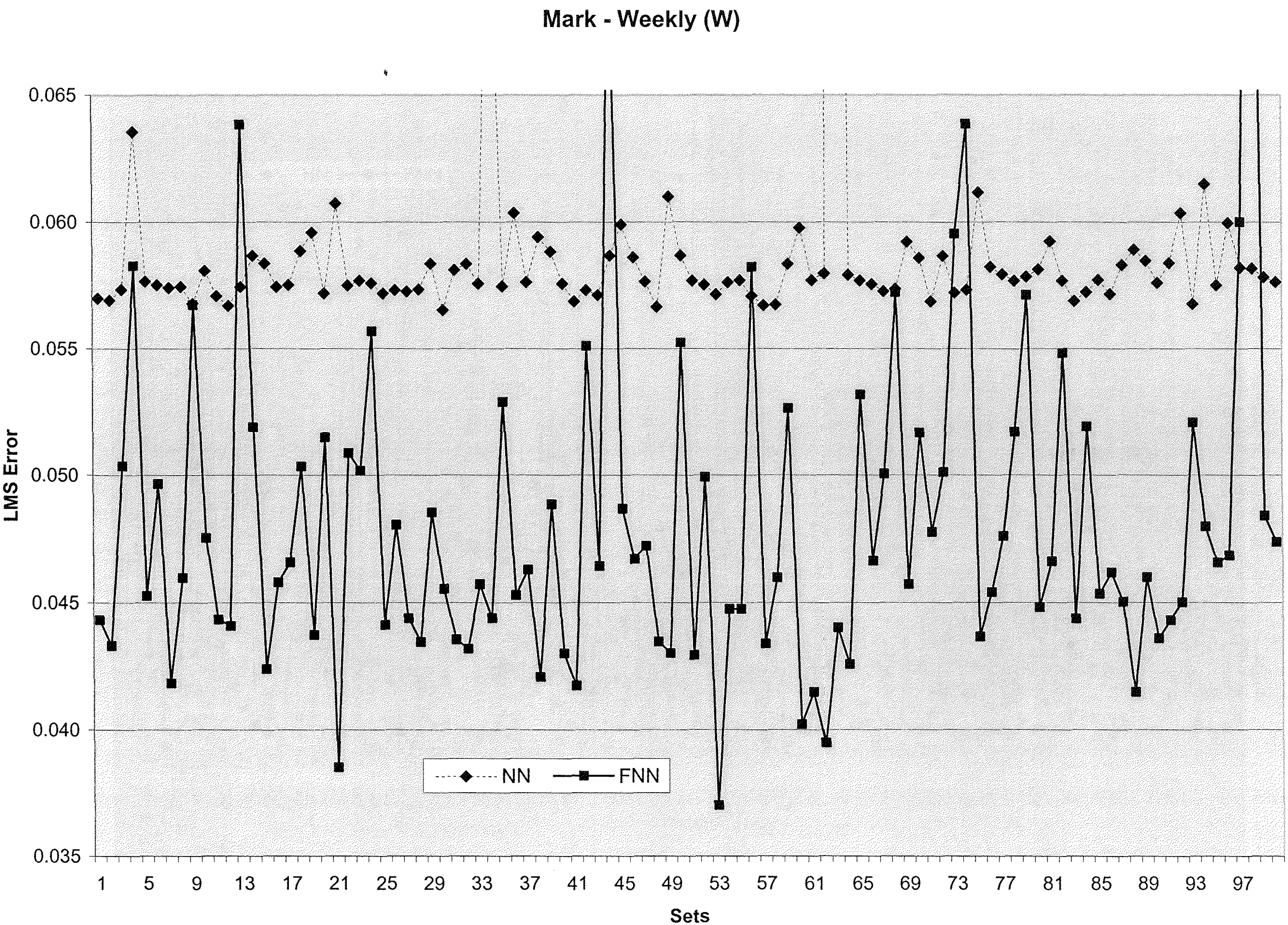
Least Mean Square Errors


Mark - Daily (D3)
NN
FNN
LMS Error
0.050
0.048
0.046
0.044
0.042
0.040
1
5
9
13
17
21
25
29
33
37
41
45
49
53
57
61
65
69
73
77
81
85
89
93
97
Sets

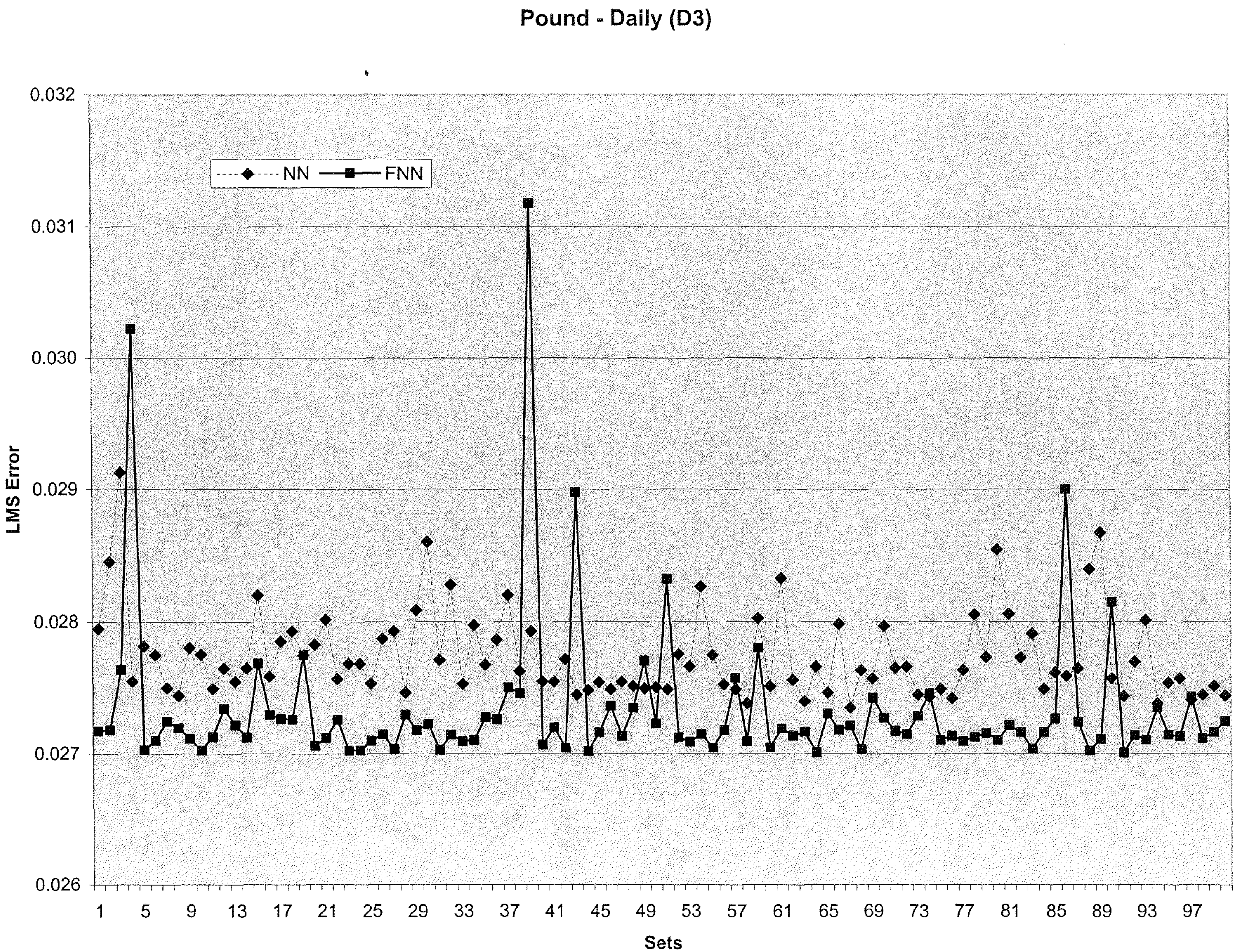

Mark - Daily (D3S)
NN
FNN
LMS Error
0.050
0.048
0.046
0.044
0.042
0.040
1
5
9
13
17
21
25
29
33
37
41
45
49
53
57
61
65
69
73
77
81
85
89
93
97
Sets

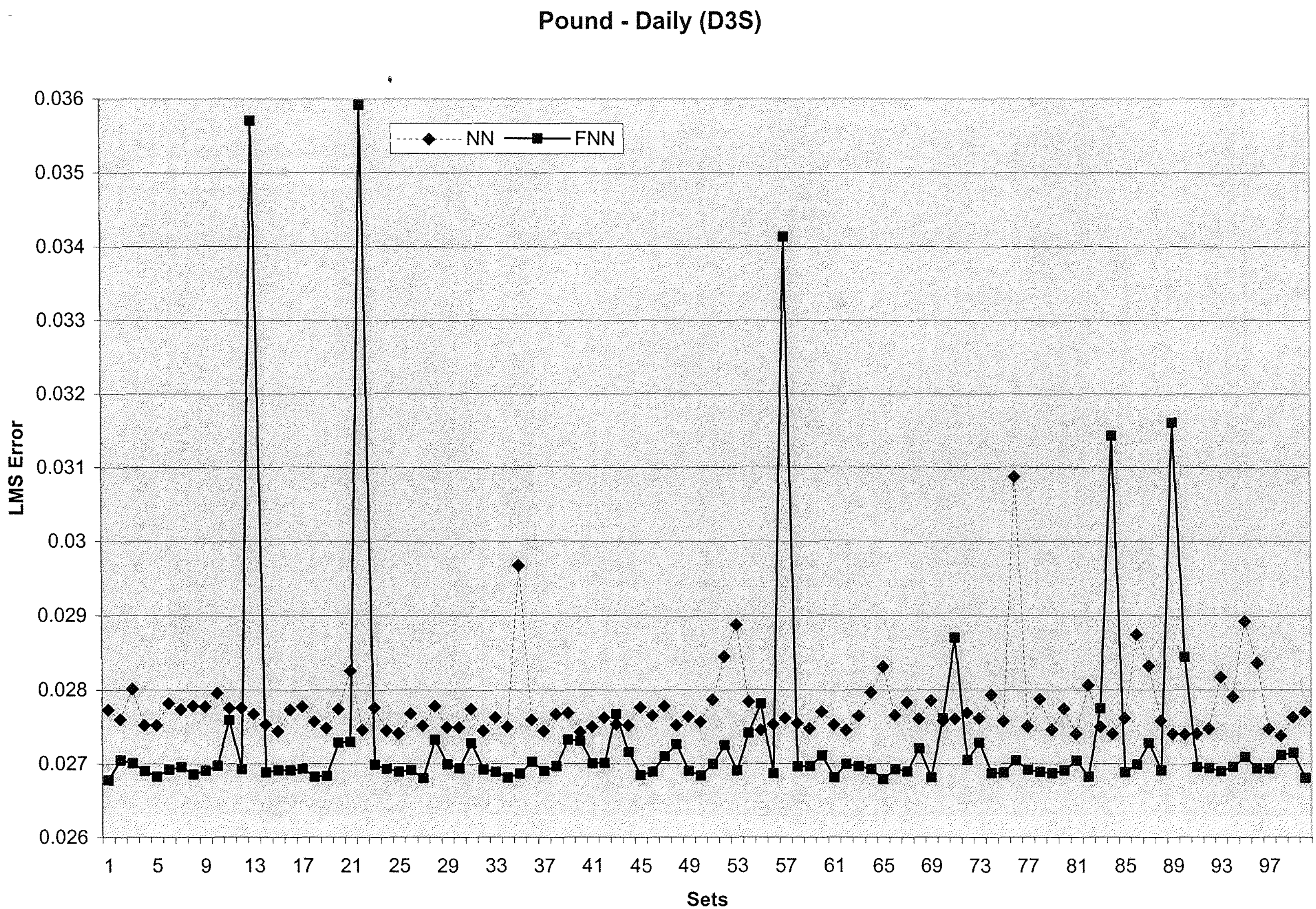
Mark - Daily (D5)

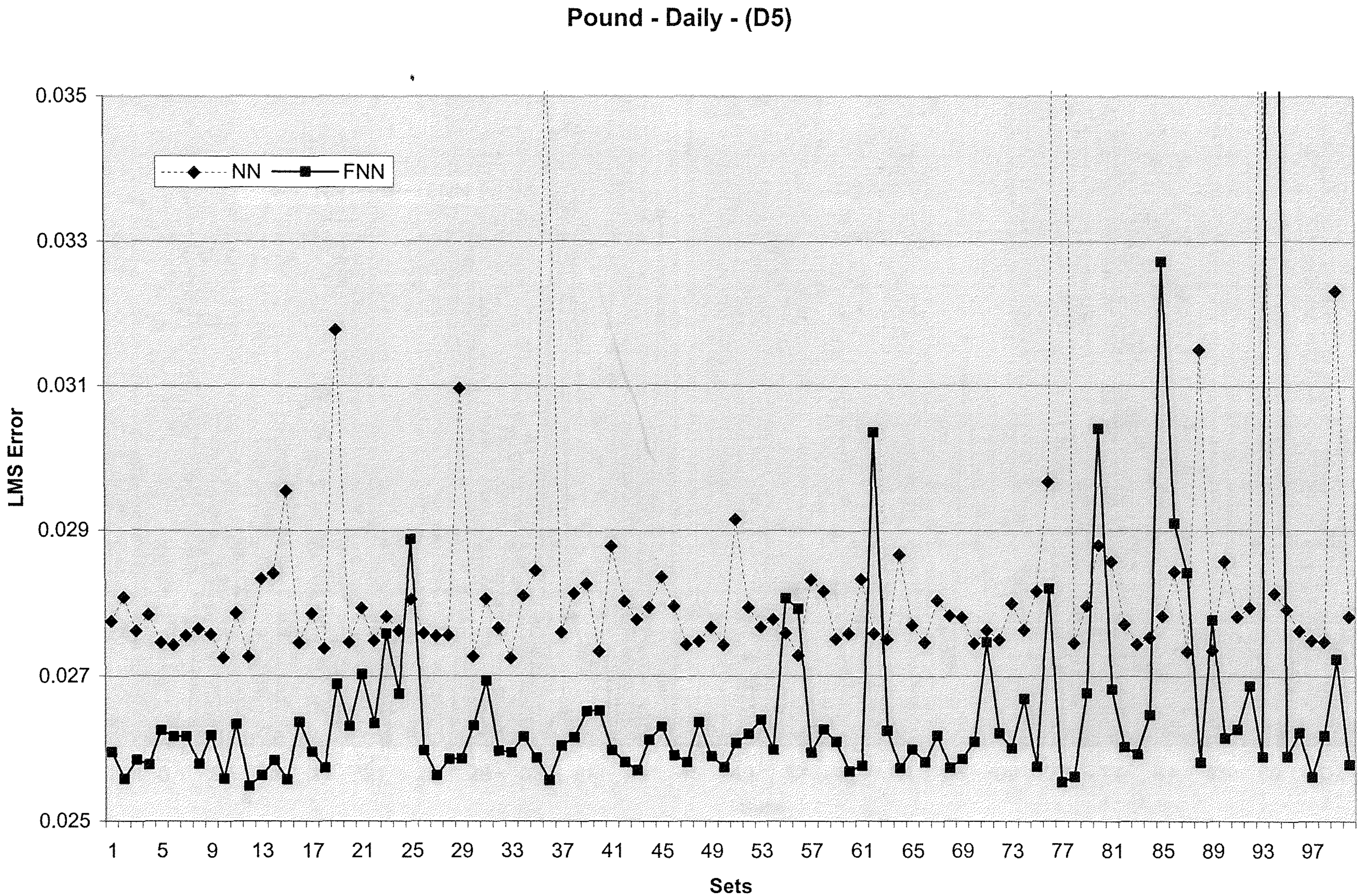


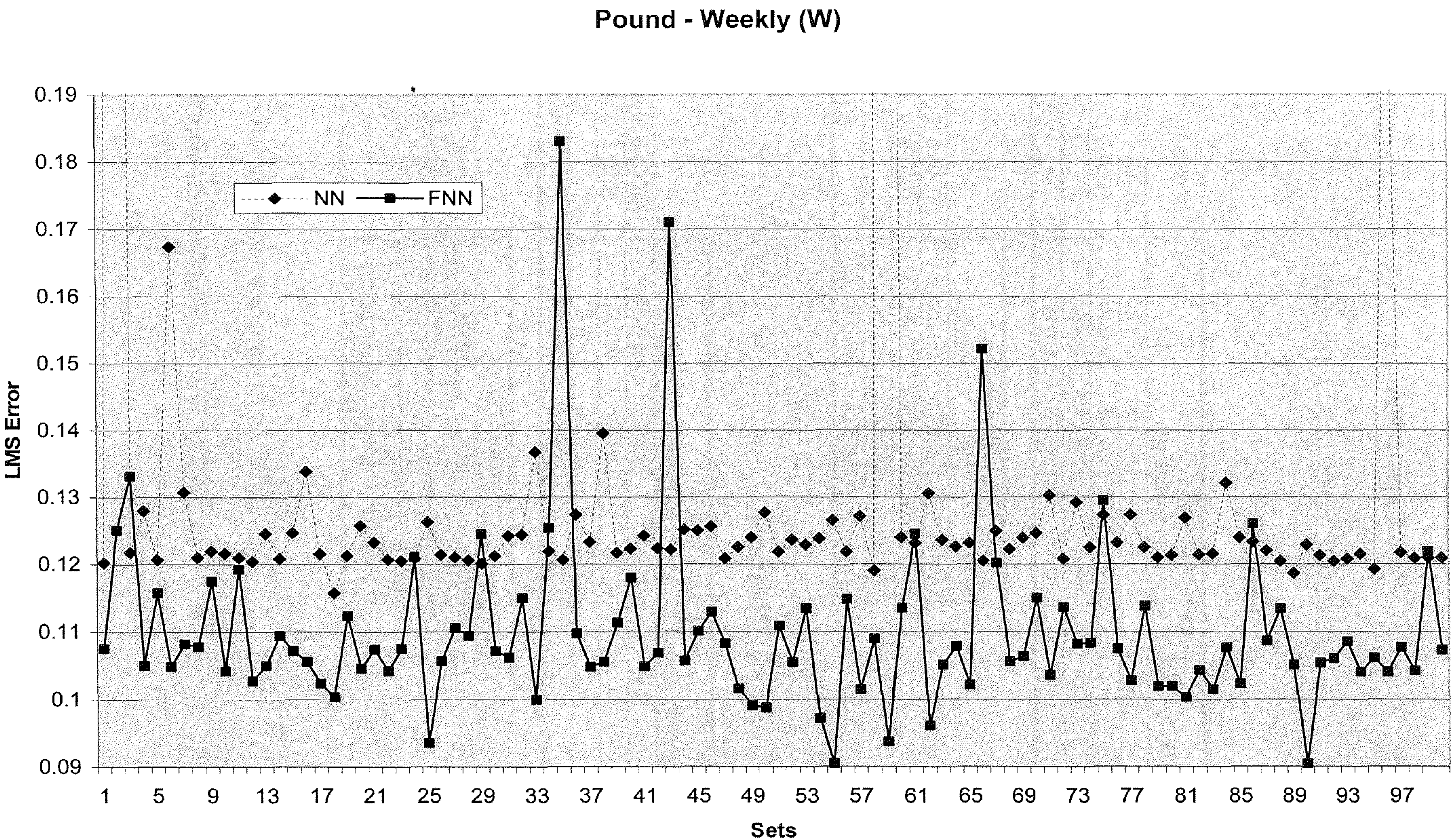


Mark - Weekly (W)
0.065
0.060
0.055
0.050
0.045
0.040
0.035
LMS Error
1
5
9
13
17
21
25
29
33
37
41
45
49
53
57
61
65
69
73
77
81
85
89
93
97
Sets
NN
FNN


Pound - Daily (D3)
NN
FNN
LMS Error
0.032
0.031
0.030
0.029
0.028
0.027
0.026
1
5
9
13
17
21
25
29
33
37
41
45
49
53
57
61
65
69
73
77
81
85
89
93
97
Sets


Pound - Daily (D3S)
NN
FNN
LMS Error
0.036
0.035
0.034
0.033
0.032
0.031
0.03
0.029
0.028
0.027
0.026
1 5 9 13 17 21 25 29 33 37 41 45 49 53 57 61 65 69 73 77 81 85 89 93 97
Sets


Pound - Daily - (D5)
NN
FNN
0.035
0.033
0.031
0.029
0.027
0.025
LMS Error
1
5
9
13
17
21
25
29
33
37
41
45
49
53
57
61
65
69
73
77
81
85
89
93
97
Sets


Pound - Weekly (W)
NN
FNN
LMS Error
0.19
0.18
0.17
0.16
0.15
0.14
0.13
0.12
0.11
0.1
0.09
1 5 9 13 17 21 25 29 33 37 41 45 49 53 57 61 65 69 73 77 81 85 89 93 97
Sets

Appendix J

Network Calculation Summary

Mark*

	Directional Test					
	NN	FNN	Difference	# Better	# Worse	# Same
3 Day - 1, 2, 5 (D3S)	48.5%	46.7%	-1.8%	28	65	7
3 Day - 1, 2, 3 (D3)	48.6%	46.7%	-1.9%	28	66	6
5 Day (D5)	49.6%	49.6%	0.0%	49	42	9
Weekly (W)	50.0%	57.3%	7.3%	71	29	0

	Profit / Loss		
	Actual	NN	FNN
3 Day - 1, 2, 5 (D3S)	75,725.00	-128.63	2,746.37
3 Day - 1, 2, 3 (D3)	75,725.00	1,231.50	5,332.75
5 Day (D5)	75,725.00	763.00	5,891.37
Weekly (W)	29,523.75	623.88	3,524.37

Pound**

	Directional Test					
	NN	FNN	Difference	# Better	# Worse	# Same
3 Day - 1, 2, 5 (D3S)	50.9%	55.0%	4.1%	71	27	2
3 Day - 1, 2, 3 (D3)	50.7%	56.4%	5.7%	70	29	1
5 Day (D5)	49.4%	54.8%	5.4%	75	24	1
Weekly (W)	48.5%	52.5%	4.0%	51	49	0

	Profit / Loss		
	Actual	NN	FNN
3 Day - 1, 2, 5 (D3S)	29,134.38	720.31	1,946.63
3 Day - 1, 2, 3 (D3)	29,134.38	865.12	2,191.06
5 Day (D5)	29,134.38	-113.88	1,931.75
Weekly (W)	11,896.88	-654.58	131.44

* Mark/Dollar transactions in units of 62,500

** Dollar/Pound transactions in units of 31,250

Mark*

	LMS Errors			
	Average Values			Average %
	NN	FNN	Difference	Difference
3 Day - 1, 2, 5 (D3S)	0.044771	0.042732	0.002039	13.0%
3 Day - 1, 2, 3 (D3)	0.044421	0.042757	0.001664	3.9%
5 Day (D5)	0.045288	0.042826	0.002462	4.9%
Weekly (W)	0.063010	0.048283	0.014727	17.6%

	Cycles		
	Average Values		Cycle
	NN	FNN	Increase
3 Day - 1, 2, 5 (D3S)	3,035	18,524	6.1
3 Day - 1, 2, 3 (D3)	3,417	15,600	4.6
5 Day (D5)	2,312	13,359	5.8
Weekly (W)	1,684	4,295	2.6

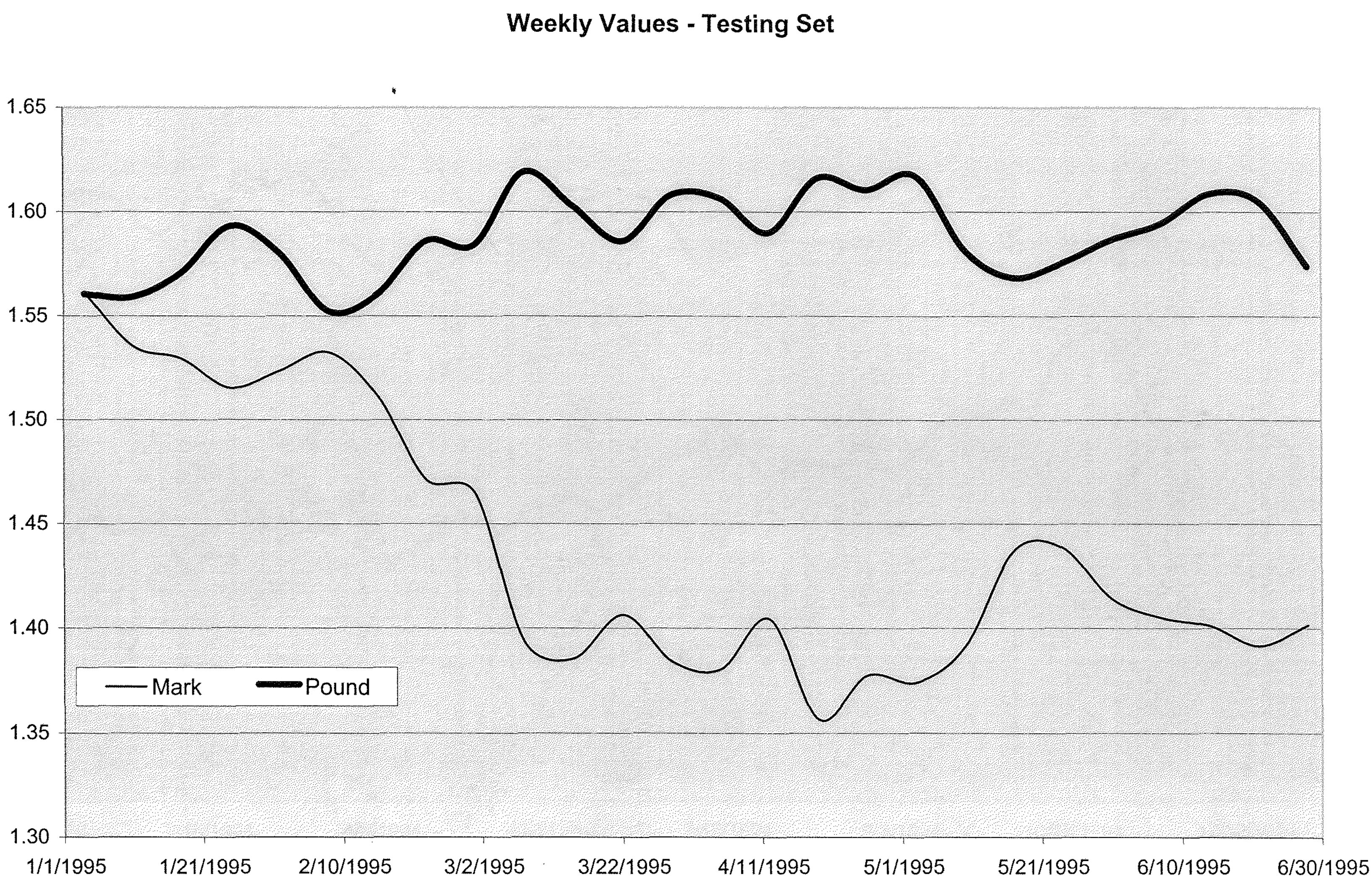
Pound**

	LMS Errors			
	Average Values			Average %
	NN	FNN	Difference	Difference
3 Day - 1, 2, 5 (D3S)	0.027757	0.027388	0.000369	1.3%
3 Day - 1, 2, 3 (D3)	0.027737	0.027331	0.000406	1.4%
5 Day (D5)	0.028325	0.026629	0.001696	5.6%
Weekly (W)	0.141709	0.110004	0.031705	4.0%

	Cycles		
	Average Values		Cycle
	NN	FNN	Increase
3 Day - 1, 2, 5 (D3S)	3,340	21,976	6.6
3 Day - 1, 2, 3 (D3)	4,467	24,733	5.5
5 Day (D5)	1,963	21,128	10.8
Weekly (W)	1,572	1,849	1.2

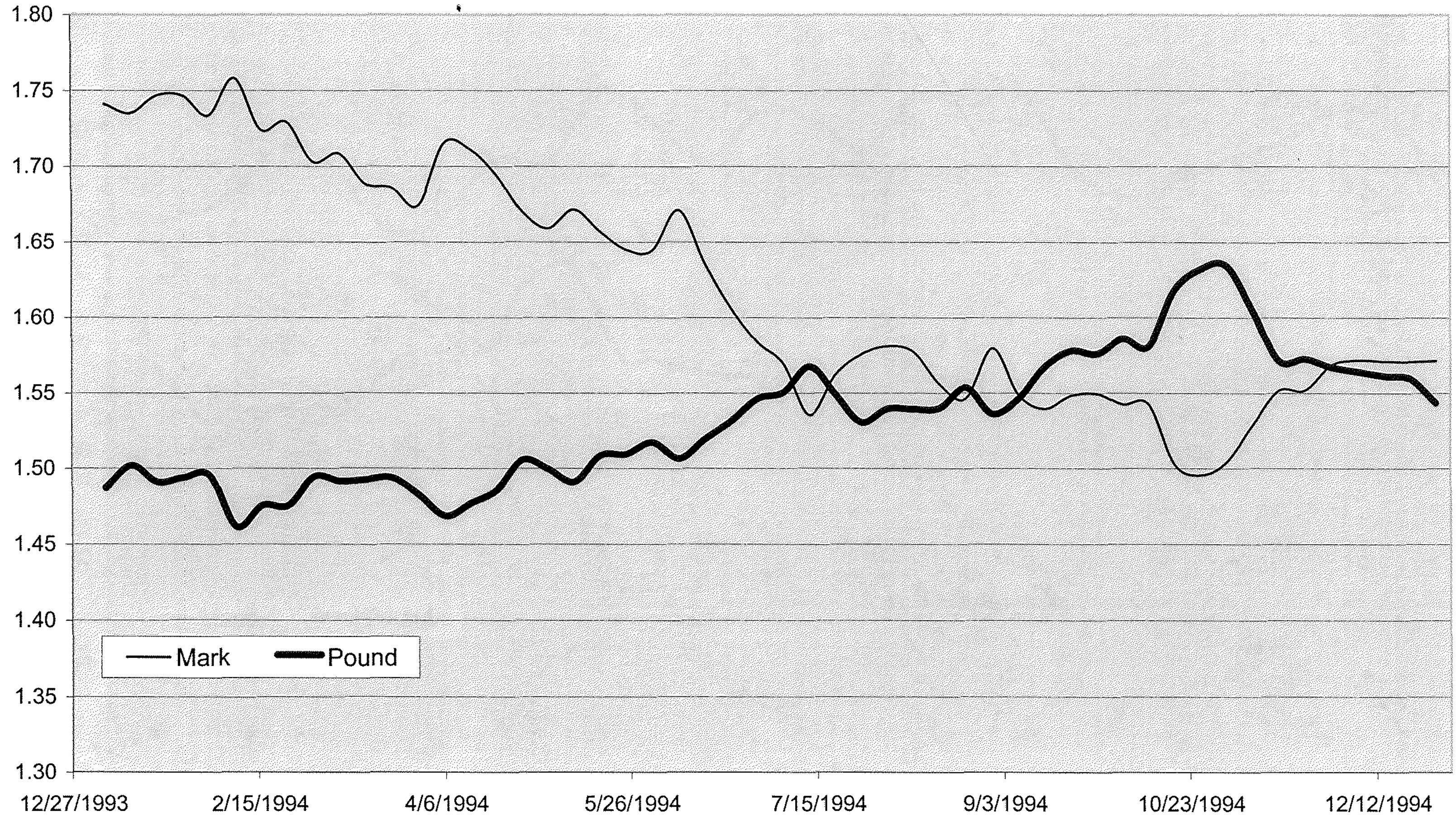
Appendix K

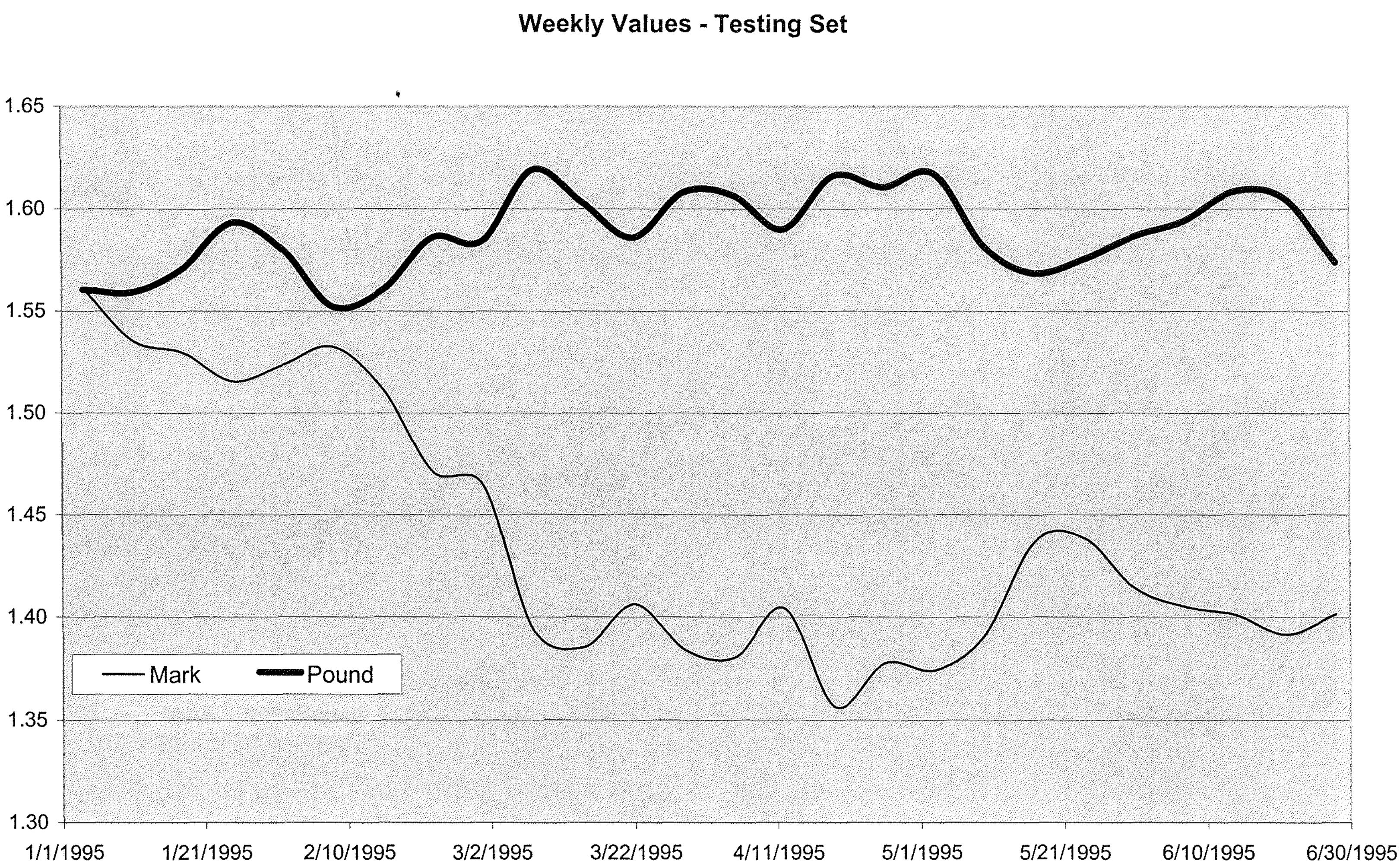
Data Point Charts



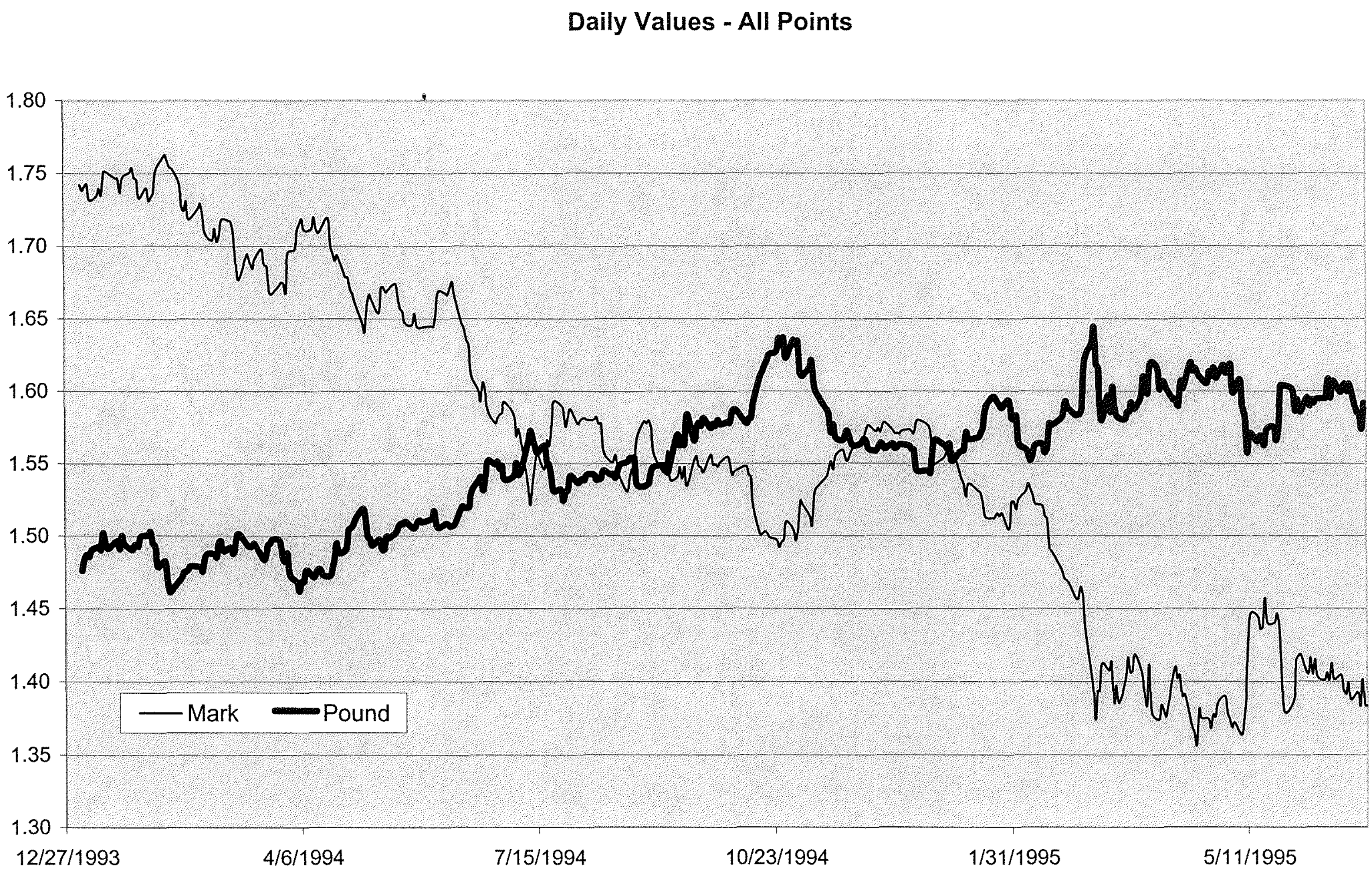
Weekly Values - Testing Set
1.65
1.60
1.55
1.50
1.45
1.40
1.35
1.30
1/1/1995
1/21/1995
2/10/1995
3/2/1995
3/22/1995
4/11/1995
5/1/1995
5/21/1995
6/10/1995
6/30/1995
Mark
Pound

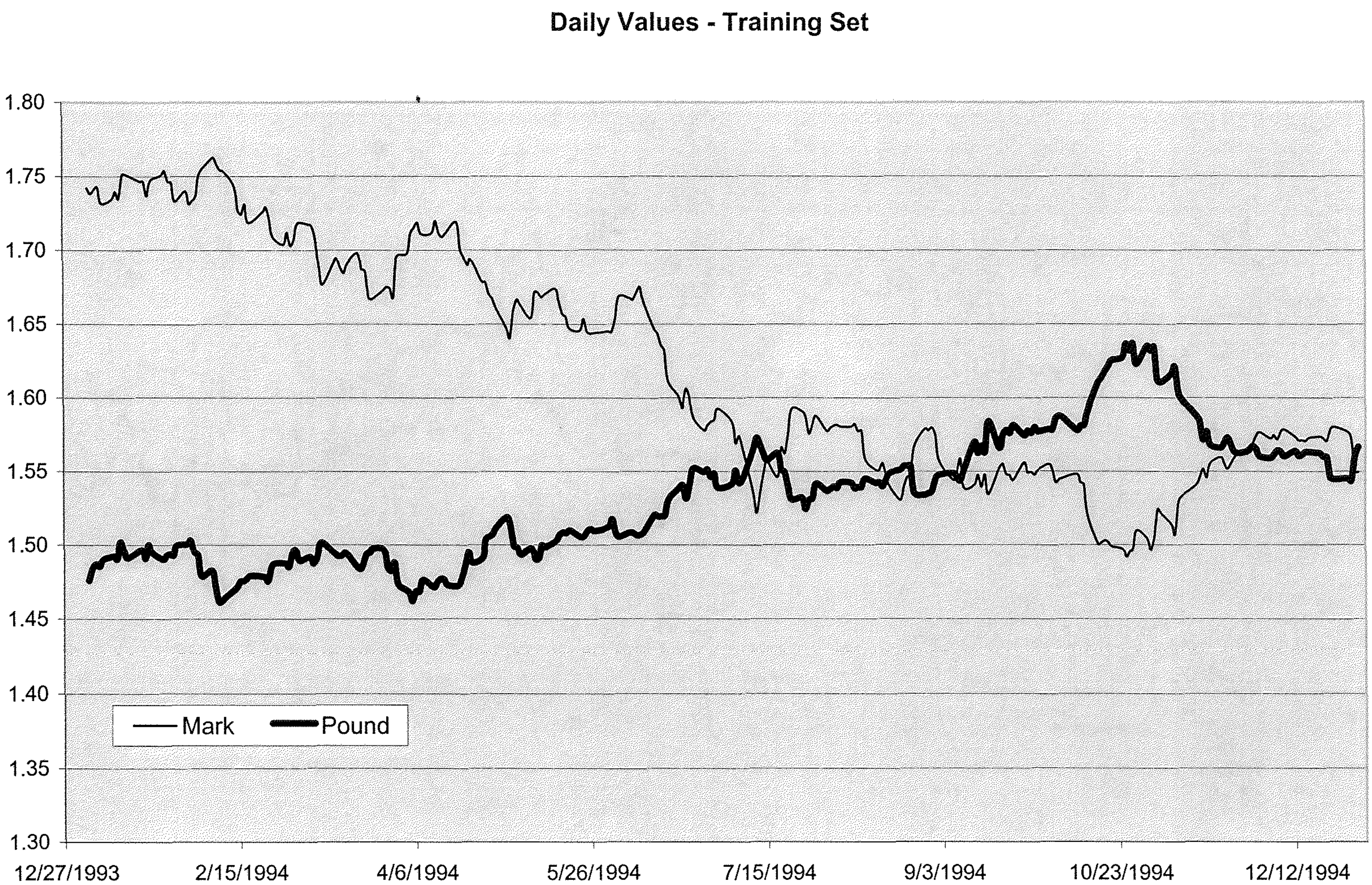
Weekly Values - Training Set





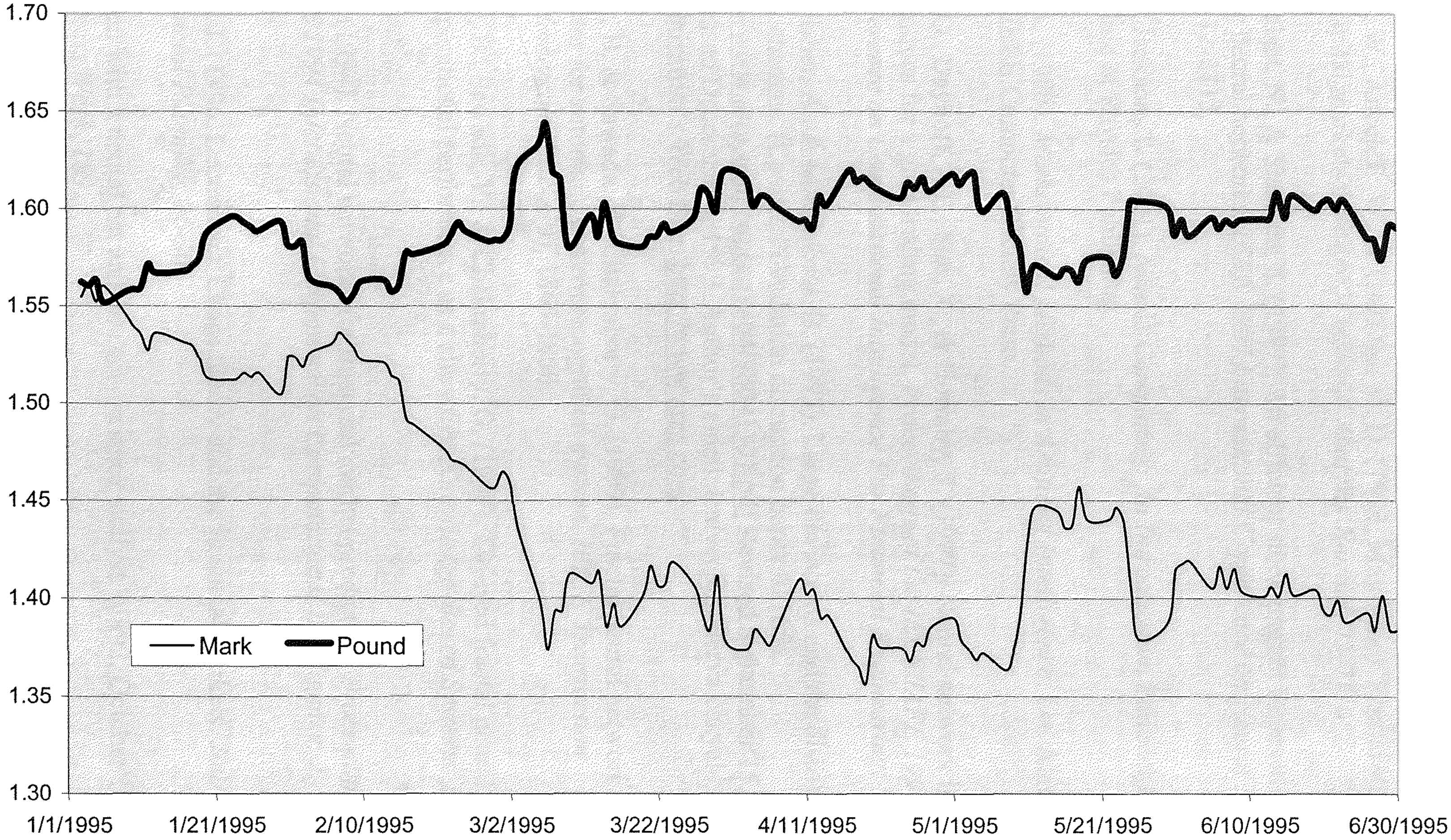
Weekly Values - Testing Set
1.65
1.60
1.55
1.50
1.45
1.40
1.35
1.30
Mark
Pound
1/1/1995
1/21/1995
2/10/1995
3/2/1995
3/22/1995
4/11/1995
5/1/1995
5/21/1995
6/10/1995
6/30/1995


Daily Values - All Points
1.80
1.75
1.70
1.65
1.60
1.55
1.50
1.45
1.40
1.35
1.30
Mark
Pound
12/27/1993
4/6/1994
7/15/1994
10/23/1994
1/31/1995
5/11/1995



Daily Values - Training Set
1.80
1.75
1.70
1.65
1.60
1.55
1.50
1.45
1.40
1.35
1.30
12/27/1993
2/15/1994
4/6/1994
5/26/1994
7/15/1994
9/3/1994
10/23/1994
12/12/1994
Mark
Pound

Daily Values - Testing Set



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