ENHANCING TECHNICAL ANALYSIS IN THE FOREX MARKET USING NEURAL NETWORKS

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1. ABSTRACT

Copious test by countless professionals have proven Technical Analysis[1] to be, at best, break-even tools, even with the finest money management techniques. Those who use only Technical Analysis in actual trades find out very painfully what whipsaws, and false breakouts are. The simple mathematical explanation for this is that Technical Analysis, as introduced by Wilder, Lane, etc., are linear, monovariate computation routines. This means that Technical Analysis is not designed to deal with non-uniform periodic, and discontinuous functions. To manage these inadequacies, one employs a neural network. The simple network described in this paper predicts technical indicators, and generates trading signals before regular technical indicators do. This gives one the opportunity to enter, and exit trades before the crowd. Tests, and actual trades, have shown that most of the time, one or two days, is all the advantage one needs.

2. INTRODUCTION

Regular technical indicators, being linear tools lag the market. The moving average, for example, will trail movements of a market, most of the time signalling false breakouts. Oscillators (ie. counter trend tools) such as the RSI, and Stochastics with fixed number of computation periods, have difficulties following non-uniform cycles. Human behavior, and 'real world' events do not follow cycles of simple uniform periodicity. Setting a technical indicator to trace uniform cycles in the markets, would therefore be as chancy as rolling a dice. Being restricted to uniform cyclical patterns, and linear relationships, technical indicators by themselves, would have difficulties signalling profitable trades consistantly.

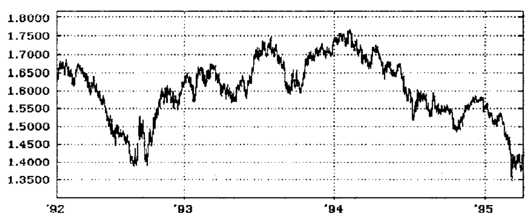
Most academics, on the other hand prefer the Gaussian model, making the bold assumption that variations in prices are random[2], eventhough, historical evidence does not support this assumption. If the markets were, indeed random, Black Monday, the '29 crash, the recent Nikkei plunge, and moves resulting from market manipulations, take-overs (in the case of equity), etc., could not have occurred. Furthermore, it would be impossible for those other than market makers, to make a profit. The fact is that market makers do lose money, and directional traders, as well as market manipulators do make money. Highly successful market makers modify the Black-Scholes differential equation with the help of privileged information. The log normal curve, in the 'real world', has a much fatter tail.

The solution therefore, would be to have a tool which would be able to negotiate irregular cyclical patterns, and impulses (large, sudden amplitudes). This would more closely model the behaviour of successful traders. This paper will show that using a simply Neural Network to enhance (forecast) popular Technical Analysis, not only improve the profitability of popular technical indicators, but also turn otherwise losing systems, into profitable ones.

Comparisons between the Neural Network (NN) forecasted technical indicators, and the orthodox/regular technical indicators, were made using realistic simulated trades -- ie. with transaction costs, stoploss, and slippage. In each case, a popular technical indicator was used as a benchmark, and the NN forecast of that same technical indicator was compared to show the improvements in net profits, and reductions in drawdowns. An equity curve was then plotted for each example, to give a graphical illustration of the improvements.

3. DATA

For all examples, Deutchemark (DEM/USD) daily data from 01 January 1992 to 30 March 1995 was used for test input (see figure 1). Daily (and not intraday) data was chosen, to demonstrate that trading the FOREX market can be profitable not only to banks, and large financial institutions, with expensive real-time quotation services (eg. Reuters, Knight-Ridder, Telerate, etc.), and hyper-speed computers, but also to the average investor, using only end-of-day data, working with an archaic 286 or 386.



For comparison sake, the multivariate attributes of the NN was ignored. No other variables/instruments (eg. T-bonds, S&P500, Crude Oil, etc.) were used for input to the NN. Only inputs used to calculate regular technical indicators (ie. highs, lows, and closes of DEM/USD) were used. The aim of this paper is to focus only on the improvements of NN forecasted technical indicators, over conventional technical indicators. Although the principal advantage of the NN is its facility to accommodate multivariate (many different types of) inputs, here it is shown that even without the benefit of other input variables its predictive qualities remain superior to other univariate systems.

It is important to note that the spot Deutchemark data here, is in the Indirect Quote -- ie. amount of Deutchemarks required to purchase one U.S. dollar. A long position, therefore refers to a long position in U.S. Dollar, and at the same time, a short position in Deutchemark. In the simulated trade results, gains and losses are reported in terms of Deutchemarks.

4. THE COMPARISONS

Popular technical indicators[1] were chosen for the comparisons -- [1] Donchian's Simple Moving Average (SMA); [2] Lane's Stochastics; and [3] the Momentum. The first is a trend follower, the second is an oscillator used in counter-trend strategies, and the latter possess both trend-following and counter-trend features.

Arguably, many different combinations of computation periods could have been chosen for the technical indicators. However, for the sake of illustration (and simplicity), only one combination of numbers were used for each of the comparisons. Although the combinations of periods were chosen somewhat arbitrarily, they reflect popular selections.

The following were the simulated trade tests performed for comparison :

[1] Orthodox Dual SMA Crossovers, versus NN Predicted Dual SMA Crossovers

Trades were signalled in the direction the 3-day MA crossed over the 12-day MA. In the case of the NN predicted MA's, trades were signalled when the predicted 3-day MA crossed the predicted 12-day MA. The simple moving average of period was calculated as follows :

$$SMA_t = (C_t + C_{(t-1)} + \ldots + C_{(t-n+1)}) / n$$

where

n is the number of averaging days, and

C is the Closing price

[2] Orthodox Stochastic Crossovers, versus NN Predicted Stochastic Crossovers

Periods of both the orthodox and predicted Stochastics were set as follows : %Kfast was calculated over 5 days; %Kslow (or smoothing) was averaged over 5 days; and %D was averaged over 3 days. Trades were signalled when the K-lines crossed the D-lines. Stochastics were calculated as follows :

$$\%Kf = C / (Hh - Ll)$$
$$\%Ks = (\%Kfast_t + \%Kfast_{(t-1)} + \ldots + \%Kfast_{(t-5)}) / 5$$
$$\%D = (\%Kslow_t + \%Kslow_{(t-1)} + \%Kslow_{(t-2)}) / 3$$

where

C is the Closing price,

Hh is the highest High of the last 5 periods, and

Ll is the lowest Low of the last 5 periods.

[3] Orthodox Momentum Crossovers, versus NN Predicted Momentum Crossovers

The computation periods of both the orthodox and ANN predicted momentum were set to 10 trading days, and their respective moving averages were calculated over a period of 5 trading days. Trades were signalled when Momentum lines crossed their respective moving averages. Momentum and its moving average were calculated as follows :

$$Mom_t = C_t - C_{(t-9)}$$
$$Mom's\ MA = (Mom_t + Mom_{(t-1)} + \ldots + Mom_{(t-9)})/10$$

5. THE NEURAL NETWORK

In keeping with the philosophy of simplicity, and functionality, a simple feedforward backpropagation network[3], with one hidden layer was used. Highs, lows, and closes of the last five days, were preprocessed and input to the network to forecast the highs, lows and closes three days into the 'future'. Once these were forecasted, all the above predicted technical indicators can be easily computed.

The network consist of 15 input nodes (5 for highs, 5 for lows, and 5 for closes), 3 output nodes (predicted high, low and close), and 20 hidden nodes. Each input node is connected to all the hidden nodes, and each hidden node is connected to each of the 3 output nodes. Total connections were kept below 400, for the sake of speed, to permit the program to be used on machines slower than the 486. The hyperbolic tangent was used as the activation function in the hidden and output nodes. Weights were initialized with the distribution method suggested by Nguyen and Widrow[4], and NN-momentum was used to increase the network's speed of 'learning'.

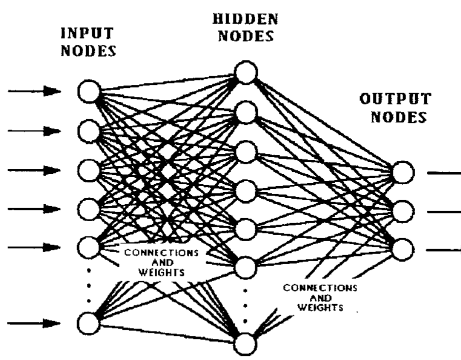


Figure 2. The Simple Backprop Network

6. THE RESULTS

The tables below record the simulated trades made for the three respective comparisons.

Table 1. SMA	Reg	NN
Total net profit	-0.05	0.14
Open position value	-0.00	0.00
Total gain/loss	-4.91%	41.41%
Annual gain/loss	-1.59%	13.41%
Total closed trades	74	83
Commissions paid	0.15	0.17
Total long trades	38	42
Total short trades	36	41
Winning long trades	9	15
Winning short trades	12	23
Total win trades	21	38
Total lose trades	53	45
Amt of win trades	0.66	0.98
Amt of lose trades	-0.70	-0.57
Average win	0.03	0.03
Average loss	-0.01	-0.01
Largest win	0.08	0.11
Largest loss	-0.04	-0.03
Avg length of win	19.76	15.42
Avg length of loss	8.36	6.51
Longest win trade	36	36
Longest lose trade	22	15
Longest cons wins	3	6
Longest cons losses	8	6
Total days out	25	11
System close d/down	-0.11	-0.04
Average length out	5.00	2.75
System open d/down	-0.12	-0.05
Longest out period	13	3
Max open trade d/dn	-0.03	-0.03
Profit/Loss index	-6.97	42.19
Reward/Risk index	-41.53	89.85

Table 2. Stochastics	Reg	NN
Total net profit	-0.20	0.61
Open position value	0.01	0.03
Total gain/loss	-19.7%	61.62%
Annual gain/loss	-6.38%	%19.84%
Total closed trades	190	184
Commissions paid	0.38	0.37
Total long trades	95	92
Total short trades	95	92
Winning long trades	31	37
Winning short trades	40	51
Total win trades	71	88
Total lose trades	119	96
Amt of win trades	0.83	1.51
Amt of lose trades	-1.04	-0.93
Average win	0.01	0.02
Average loss	-0.01	-0.01
Largest win	0.05	0.06
Largest loss	-0.03	-0.03
Avg length of win	6.51	6.14
Avg length of loss	4.36	4.62
Longest win trade	12	12
Longest lose trade	8	10
Longest cons wins	5	7
Longest cons losses	8	6
Total days out	12	2
System close d/down	-0.23	-0.08
Longest out period	12	2
Max open trade d/dn	-0.03	-0.04
Profit/Loss index	-19.15	39.60
Reward/Risk index	-86.13	88.41

Table 3. Momentum	Reg	NN
Total net profit	-0.00	0.58
Open position value	0.02	-0.00
Total gain/loss	-0.02%	57.78%
Annual gain/loss	-0.01%	18.71%
Total closed trades	184	168
Commissions paid	0.37	0.34
Total long trades	92	84
Total short trades	92	84
Winning long trades	32	31
Winning short trades	40	47
Total win trades	72	78
Total lose trades	112	90
Amt of win trades	0.97	1.39
Amt of lose trades	-0.98	-0.81
Average win	0.01	0.02
Average loss	-0.01	-0.01
Largest win	0.06	0.07
Largest loss	-0.03	-0.03
Avg length of win	7.06	7.21
Avg length of loss	4.12	4.52
Longest win trade	17	17
Longest lose trade	12	11
Longest cons wins	6	6
Longest cons losses	12	6
Total days out	16	4
System close d/down	-0.05	-0.06
Average length out	16.00	4.00
System open d/down	-0.06	-0.06
Longest out period	16	4
Max open trade d/dn	-0.03	-0.03
Profit/Loss index	-0.02	41.58
Reward/Risk index	-0.29	90.97

[1] NN Predicted vs. Regular SMA's : The three diagrams below show an excerpt from the 3 years of test data. Note that the Predicted SMA's crossed, and signalled trades, a day or two before the regular SMA's. Equity curves for the 3 years of testing are plotted at the bottom of the page.

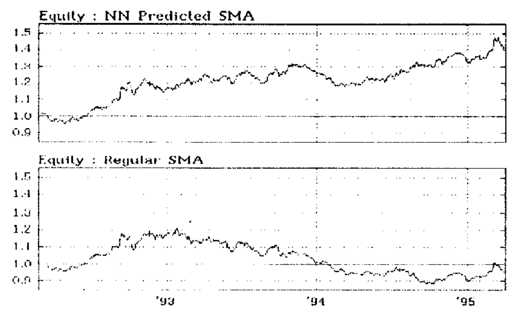


Figure 3. Equity Curves : NN & Reg SMA

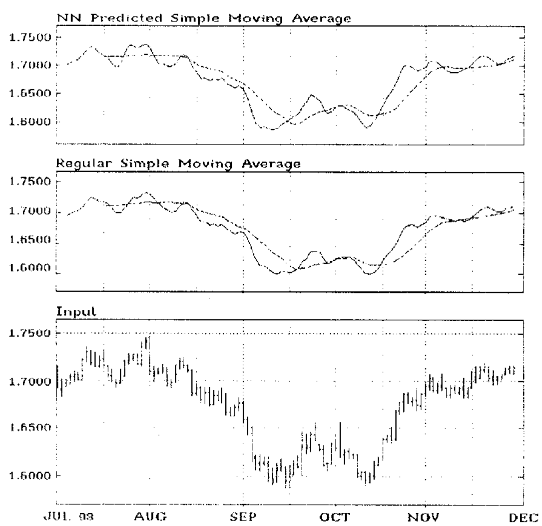


Figure 4. Exerpt of NN & Reg. SMA

[2] NN Predicted vs. Regular Stochastics : Note again that the NN predicted stochastics crossed a day or two before the regular stochastics, as did the SMA's. The advantage of getting in and out of a trade before the crowd seems to be the key to profitable trades, as displayed by the equity curves.

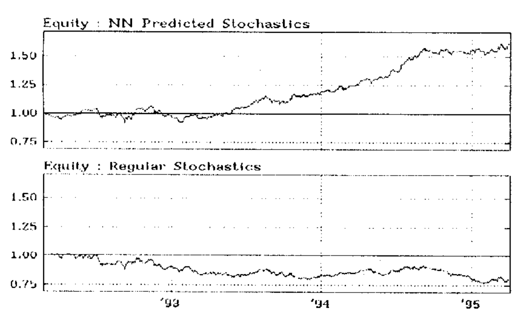


Figure 5. Equity Curves : NN & Reg. Stochastics

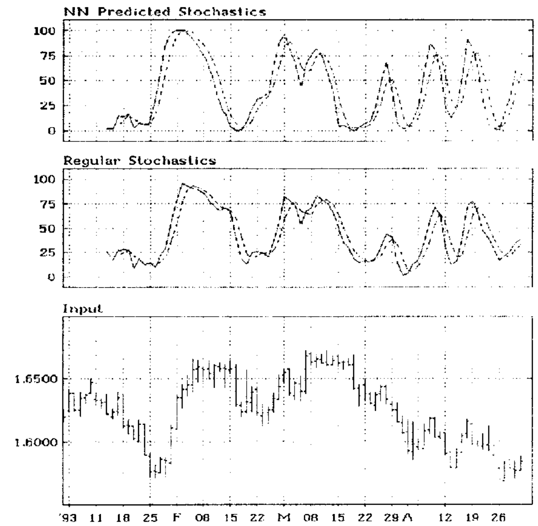


Figure 6. Exerpt of NN & Reg. Stochastics

[3] NN Predicted vs. Regular Momentum : Another example of the advantage of getting ahead of the crowd. The losing system using regular momentum was turned into a profitable one, and drawdowns are again reduced.

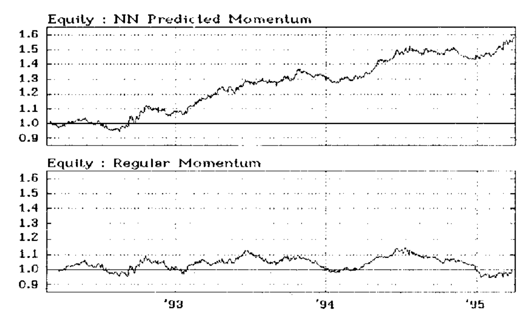


Figure 7. Equity Curves : NN & Reg. Momentum

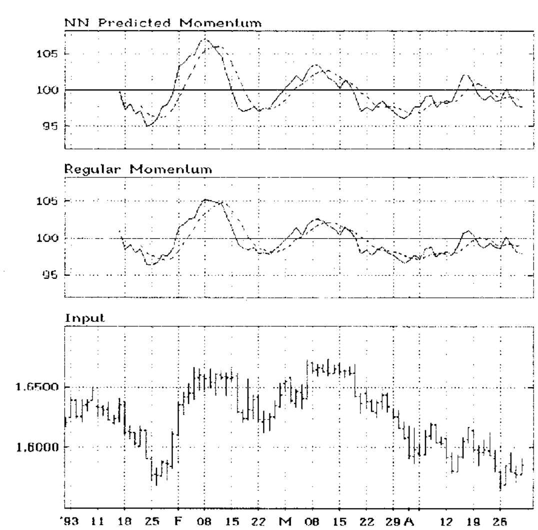


Figure 8. Exerpt of NN & Reg. Momentum

7. CONCLUSION

Many routines using time-series analysis assume linear relationships, either for the ease of calculations, or simply the lack of insight. Human behaviour, and events of the 'real world' have not been known to conform to such simple regularities. Unexpected (ie. irregular time interval) impulses, best characterize human behaviour. Therefore, most of the currently practised linear methods would not be adequate to produce forecast based on historical variations. On the other hand, the non-linear statistical models, which some mathematicians have developed (not described in this paper), make modelling virtually impossible, due to their complexity. To be functional, they have to resort to assumptions, and finally simplifications of overly cumbersome components. As a result, accuracy and reliability, is compromised. To resolve all this, Neural Network is employed.

The neural net's ability to 'anticipate' a non-linear variation (ie. sudden or discontinuous moves) allows one to enter a trade a day or two before it is signalled by a regular (linear) technical indicator. This means, entering a trade before the crowd, and exiting while the liquidity is still in ones favour. Trading this way, as shown by all the tests above, one would be in, and out of a trade with a profit, while others scramble for the narrowing exit -- only after their indicators finally catch up.

Regular technical indicators, will always lag important, large market moves, because of their linear characteristics. Unless the moves signalled continue to become trends, many late entries and exits will be made, resulting in extremely costly whipsaws. Trends are rare, as experienced traders will testify. Therefore, the chances of meeting with false breakouts, and whipsaws, are overwhelmingly high. This explains the results in the all the test for regular indicators above, and also perhaps why most academics conclude that market movements are random.

Another important attribute of a neural net is its ability to adapt itself to new patterns, emerging in the marketplace. The rigid nature of regular technical indicators, will experience large drawdowns, when the market is not moving in synchrony to the computation periods the technical indicator are set to. Since human activities, and global events are not confine to uniform cycles, setting indicators on fixed cycles, to predict future political situations, the weather, and calamities, is not particularly advantageous.

Finally, it should be noted that for the purpose of comparing the NN to regular technical indicators, the network in this paper, was not employed in a way which would have best utilized its potential. It was handicapped by restricting inputs to only monovariate historical data, and further crippled by the fact that it was used to predict technical indicators with unvarying periods. Inspite of these impairments, the net outperformed regular technical indicators, turning hopeless accounts into profitable ones.

8. REFERENCES

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[3] L. Fausett, "Fundamentals of Neural Networks", Prentice Hall, 1994.

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