Can Technical Pattern Trading Be Profitably Automated?
2. The Head & Shoulders

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Financial markets, such as the global foreign exchange (FX) market, often exhibit trending and trend-reversing behaviour. During such behaviour, the market level oscillates with changes in market consensus. Continued oscillations of this type result in the formation of patterns, such as the *head & shoulders*, which are used by technical analysts as trade entry signals. A sample space of head & shoulders formations has been constructed from a set of US Dollar/British Pound Spot FX tick data from 1989-97 using pattern recognition algorithms and the profitability of trading using such patterns has been estimated. A number of attributes of the resulting collection of head & shoulders formations has been subjected to statistical analysis with the aim of classifying patterns that can be traded profitably using a number of simple trading rules. Results of this analysis show that such classification can be used to construct filter rules that consistently enhance trading profitability for this pattern.

1 Introduction

Technical analysis is the study of historical price data with the aim of predicting future price levels. Technical analysts who trade markets on the basis of this prediction are known as *technical traders*. Despite the supposed irrationality of such activity under the commonly held assumption (by economists, at least) of efficient markets, technical trading has been found to generate statistically significant profits in a number of markets. Excess profits as a result of technical trading have been found to exist in stock markets by Brock, Lakonishock and LeBaron [3] and in foreign exchange markets by Dooley and Schaffer [5]; Levich and Thomas [8]; and Sweeney [19].

The majority of work published on technical analysis has been based on filters and indicators such as the moving average. This is a result of the ease with which such indicators can be expressed algebraically. More recent work considers the use of genetic algorithms to find technical trading rules (see Neely and Weller [12], [13] and Allen and Karjalainen [1]) and the problems of 'data-snooping' when evaluating rules (Timmermann et al [20]). A large amount of technical analysis[1], however, is applied to technical patterns – visual patterns that can be seen to occur on price-time charts. Good examples of such include the interestingly named *head & shoulders*, *flags*, *pennants* and *wedges* and can be found in Schwager [17] or Pring [16]. Such patterns do not have simple algebraic representations and, despite being easy to identify with the eye, are highly complex to represent in a systematic fashion. There is, however, some work published which contains systematic analysis of technical patterns. Levy [9] tests the profitability of a number of '5-point' chart patterns but finds no evidence of forecasting ability and Neftci [11] considers the problem of hindsight when analysing trading patterns and indicators. Osler and Chang [15], and Osler [14] test the head & shoulders pattern on a number of FX and stock markets and find statistically significant profits in some markets. Other than our companion paper, Dempster and Jones [4], there has been no work that considers pattern trading under the added realism afforded by the use of high frequency. Furthermore, there has been no work on the enhancement of pattern trading.

In this paper, we aim to analyse the head & shoulders pattern. Like Osler and Chang [15], Osler [14] and our companion paper [4] we search for occurrences of the pattern in question using an algorithm based on local maxima and minima. However, unlike most of the existing work, we used high frequency (minute by minute) data. This allows us to be more realistic in our replication of a technical

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[1] Osler [14] has discovered significant increases in the trading volume of US equity markets that coincide with head & shoulders trade entry signals

trader since we can search for occurrences of the pattern on an intra-day basis as well as make use of intra-day cash management strategies – rules used by most technical traders to protect them against extreme loss. Whereas Osler and Chang [15] analyse a wide range of currencies at daily frequency, we choose to analyse by way of illustration just BPUS at multiple frequencies up to minute level.

In this paper, we also present new work on trading rule improvement. Here, as in Dempster and Jones [4], we apply a number of statistical tests and analyses to our set of collected patterns and attempt to create profit enhancing filters based on the market conditions before and during the pattern's formation.

Despite its popularity, we find the head and shoulders pattern to be loss-making. We do, however, find links between the pattern's appearance and profitability and use such links to construct filters that improve on the pattern's profitability (or at least reduce its potential for loss-making).

In Section 2 of this paper we describe the spot FX data on which we base our analysis. Section 3 describes the characteristics of the head & shoulders pattern and the methodology used to analyse it. In Section 4 we present results and conclude and summarise our work in Section 5.

2 The Data

This analysis was carried out on spot foreign exchange (FX) tick[2] data for the British Pound/US Dollar exchange rate (BPUS, or 'spot cable' as it is sometimes called) ranging from 6.89-12.97 inclusive.

This data was supplied by CQG Data Factory and FutureSource, two well known data providers. The CQG data, ranging from 6.89-3.96 inclusive, was gathered from a number of FX brokers whereas the FutureSource data, stored from a live satellite feed via the Omega TradeStation utility, is the amalgamated product of major bank FX quotes and makes up the remaining part of the dataset. The fact that the dataset consists of quotes from two different source providers is not ideal, but such problems are typical with the analysis of high frequency data based on non-exchange traded instruments, since the majority of live tick data providers do not retain historical data.

[2] Here, a new data point, or tick, is recorded with every change in price. As a result, there are often several ticks per minute.

The convention for quoting BPUS is to quote a five digit figure that represents the value of one British pound in US dollars (most other currencies are quoted in a style opposite to this) with an implicit decimal point after the first digit; e.g. a BPUS rate quoted 16104 means £1 = $1.6104.

The CQG data consists of *bid* and *ask* prices – the price that the quoter would buy and sell British pounds for, respectively, if approached in the market. The difference between the bid and the ask (bid – ask) is called the *spread*. The convention, when dealing with such data, is to convert it to *midpoint* data: ½(bid + ask) or, by definition, (bid + ½spread) or (ask - ½spread). In the event that bid and ask quotes are uncoupled (which sometimes occurs), the bid or ask is converted to the midpoint by respectively adding or subtracting one half of the spread calculated from the last coupled bid/ask.

The above data tends to be well checked for errors by the vendor. All the same, the data has been screened for structural breakdown and irregular quotation by sweeping it with simple, proprietary software that checks for conformity to the conventional, fixed width, comma separated ASCII format, for well-ordered temporal structure and for irregularly high or low ticks (which are more than 500 pips[3] from the last quote). The latter has been backed up by inspection of a graphical portrayal of the data.

The data has then been aggregated to various frequencies in the standard open-high-low-close format (OHLC). Consider the set of time stamped tick data $\{(q_i, t_i) \mid 0 < i \leq K ; i, K \in Z^+\}$ where K is the number of ticks in the set, q_i is the price level of the i^{th} midpoint quote and t_i is the time at which the i^{th} tick occurred (converted to be measured in minutes elapsed since the start time – 2200 – and date and so $t_1 = 0$). The ticks are ordered temporally but more than one tick may occur within the same minute and so we have the weak inequality $t_i \leq t_{i+1}$. When such multiple ticks occur, they are listed in order of occurrence.

This set is converted to sets of data aggregated to various frequencies τ, denoted as τmin frequencies; e.g. if $\tau = 1$ then frequency is minutely and denoted 1min (but 1440min is called *daily*).

The aggregation to OHLC τmin frequencies results in the following dataset:

$$\{(o_j, h_j, l_j, c_j, b_j) \mid 0 < j \leq L ; j, L \in Z^+\},$$

where

$$b_j = (b_{j-1} + n\tau) \qquad n := \inf\{s \mid \exists\, i \in [1,K] \text{ s.t. } t_i \in [b_{j-1}, b_{j-1} + s\tau), s \in Z^+\} \quad j > 0$$

[3] A *pip* is the minimum allowable change in price – in this case $0.0001.

$b_0 := 0$

$o_j = q_{io}$ where $io := \inf\{m \mid t_m \in [b_j - \tau, b_j)\}$

$c_j = q_{ic}$ where $ic := \sup\{m \mid t_m \in [b_j - \tau, b_j)\}$

$h_j = \max\{q_{io}, q_{io+1}, \ldots, q_{ic}\}$

$l_j = \min\{q_{io}, q_{io+1}, \ldots, q_{ic}\}$

The index j is known as the bar number and, by convention, b_j is converted from *minutes elapsed* to *time and date* format when quoted. The above, somewhat esoteric, definitions are required since the data is sometimes sparse out of peak trading times.

Finally, the data was split into two groups – the *sample data* and the *test data*. The sample dataset was from 6.89 to 12.95 inclusive and the test dataset was from 1.96 to 12.97 inclusive; these sets are known as the *H-sample* data and the *H-test* data respectively.

3 The Head & Shoulders Pattern

3.1 Description

When analysing the *head & shoulders* (h&s) pattern we consider only the *close* points of the bars. This is in keeping with the considerations of the majority of technical traders.

The pattern (shown in Figure 3.1) consists of three market peaks, formed in succession. The middle peak is significantly higher than the others and is called the *head* (denoted H). The first and third peaks are known as the *shoulders* and denoted S1 and S2 respectively. The minima between S1 and H and between H and S2 are known as the *neckpoints* and denoted N1 and N2 respectively. The line joining the neckpoints is called the *neckline* and the pattern's occurrence is confirmed when the market crosses the neckline within a reasonable time of forming S2. Furthermore, the market must not rise above S2 before crossing the neckline.

Some traders may only consider head & shoulders patterns that occur after a large market rally but we leave this enhancement for later analysis.

We constrain our analysis to the 'upright' h&s pattern, however, reverse head & shoulders patterns are also traded (see Figure 3.2). These are, essentially, head & shoulders patterns rotated through 180°.

Figure 3.3 shows a h&s pattern isolated from BPUS spot FX data.

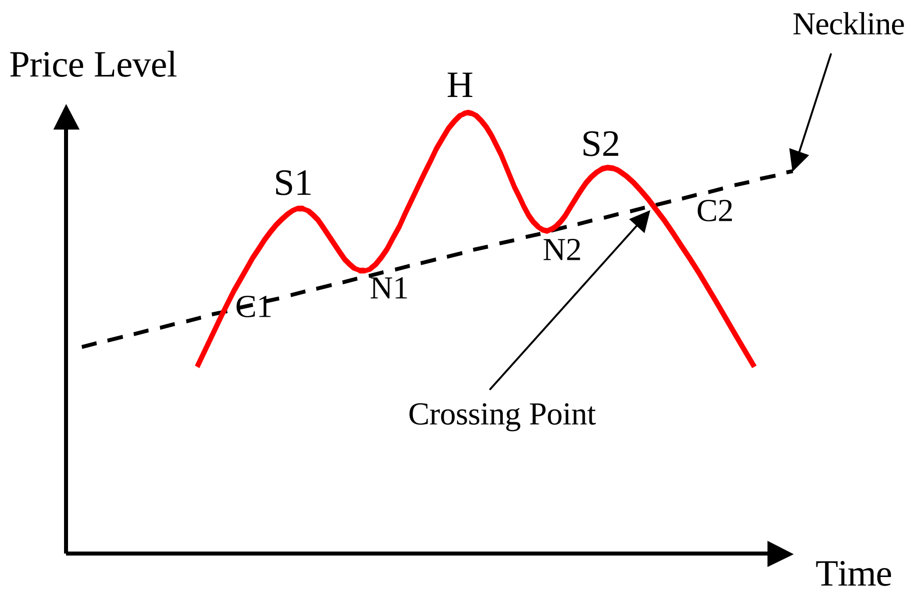

Figure 3.1: The Head & Shoulders Pattern

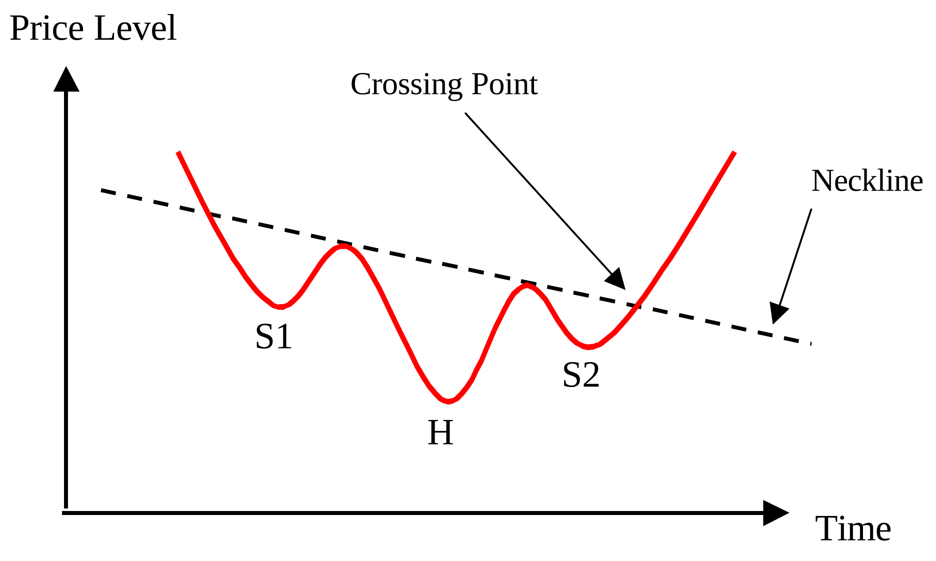

Figure 3.2: The Reverse Head & Shoulders Pattern

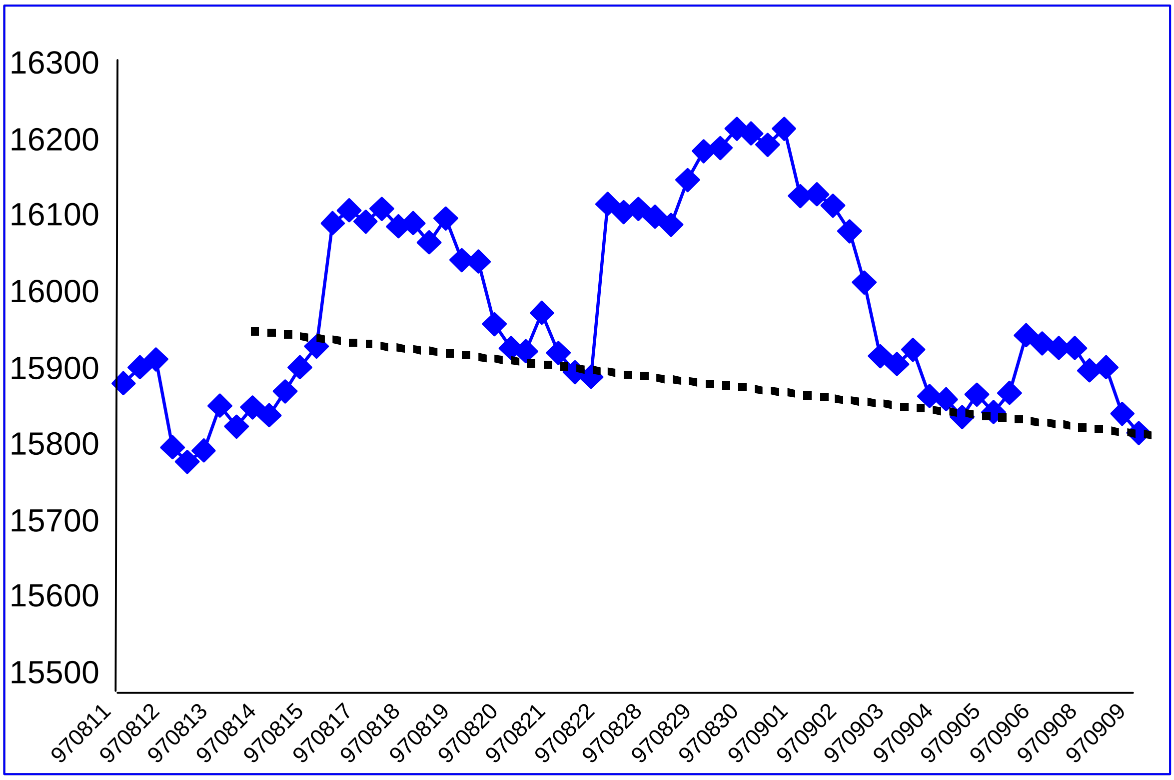

Figure 3.3 Head & Shoulders Pattern Traced by Spot BPUS FX Data

3.2 Trading Head & Shoulders Formations

The aim is to enter the trade as soon as the pattern formation occurs. For the h&s pattern, this is when the market crosses the neckline after having formed the S2 point. This crossing is known as the *downside crossing* and denoted as C2 in Figure 3.1; (when the market crosses the neckline before S1 this is known as the *upside crossing* and marked C1 on Figure 3.1). The market should, therefore, be shorted after C2. The trade is then entered as soon as some confirmatory entry signal, based on the market price action, is registered. The head & shoulders pattern is seen to be a trend reversal pattern and so as soon as the entry signal is received, a short market position is established.

Sometimes a profit objective is set by exiting the market after it has fallen from C2 by an amount equivalent to the difference in price level between the head, H, and the neckline N1N2 at the point H, as in Figure 3.4. However, the short position can also be exited using a fixed profit or time objective, both which can be protected by a trailing stop.

Once the trade is entered, trade exit usually occurs either when a trailing stop[4] level has been hit or when a fixed time period has elapsed since trade entry and this is the form of exit strategy we choose.

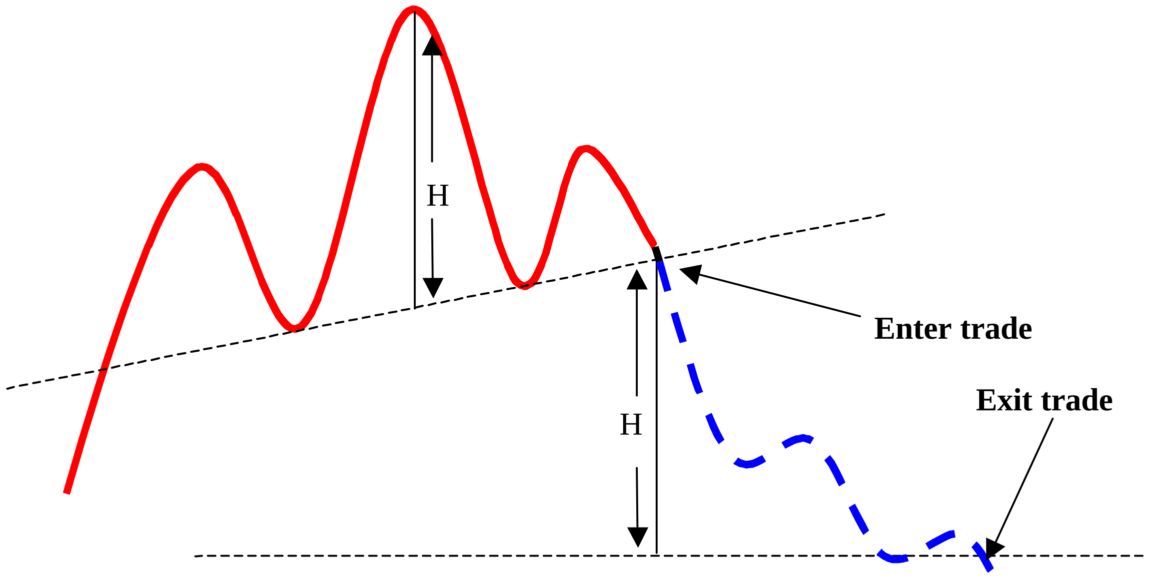

Figure 3.4: Trading the Head & Shoulders

Although we do not consider it here, a reversal trade is also possible with the h&s formation. Should the market make the downside crossing and then re-cross the neckline to make a second upside crossing, then it is possible to place a long trade with the expectation of a further market rally.

3.3 Methodology

An algorithm has been constructed to isolate h&s patterns at a number of different data frequencies and the algorithm has been coded (in Visual Basic on a P200 PC) to allow fast automatic pattern isolation. Using the 60min data frequency as a proxy for all frequencies, a number of different trade entry and exit rules have been tested on the set of h&s pattern specimens isolated on 7 years of BPUS spot FX tick data - the *H-sample* data. The combination of rules that yielded the best slippage-adjusted profits have been applied to the set of isolated h&s pattern specimens on the following data frequencies: daily, 480min, 240min, 60min, 1min.

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[4] Stops and trailing stops are described in detail in Schwager [17] and an analysis of exit strategies is carried out by James & Thomas [6].

The resulting slippage-adjusted profit distributions have been analysed. Pattern attributes that give insights to each pattern's shape and the market price's action prior to and during the pattern's formation have been isolated. Various statistical analyses have been performed on the resulting pattern attributes and slippage-adjusted profits and classification rules constructed which have been tested on a test data set of one year of BPUS spot FX data from 4.96-12.97 inclusive - the *H-test* data. Finally, as a result of the analysis, trading rules and filters have been constructed and tested on the sample and test data and resulting shifts in profit/loss have been analysed statistically.

As with the previous work in this area (Dempster and Jones [4], Osler [14], Osler & Chang [15]), we look for peaks and troughs by searching for local maxima and minima. Furthermore, we check to see that various constraints, needed for the pattern to resemble the idealised pattern, are not broken. Below, in Figure 3.5, we provide a pictorial representation of each step of the algorithm. A complete transcript of the isolation algorithm can be found in Jones [7].

A number of trading rules and combinations of rules were tested on the set of h&s patterns isolated in the 60min frequency sample data and the 'best' rule/collection of rules was identified using the criteria outlined above. The entry rules were applied as soon as the h&s pattern was complete; i.e. when the neckline has been crossed after S2 had been formed.

The best set of rules was deemed to be that which yielded the highest average slippage-adjusted profit, measured in pips per traded British Pound, over all 'entered' trades (since sometimes, due to market behaviour, the entry rule did not emit an entry signal). For example, if I sold British Pounds at $1.6150 and bought at $1.6100 then my pips profit per pound traded before slippage and transaction costs would be $(1.6150 – 1.6100) = $0.0050 = 50 pips.

After consultation with a number of traders, a new slippage model was introduced [5].

A flat 10 pips per round turn are allowed for transaction costs and to compensate for discrepancies between data and actual price. In addition, the following slippage per trade (not round turn) is deducted:

trade time between 0801 and 1700 (London Market) - 2.5 pips

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[5] This slippage model was suggested by Xiaolei Zhu of D.E. Shaw to whom we are grateful.

trade time between 1701 and 2200 (New York Market) - 4 pips

trade time between 2201 and 0800 (Asian Market) - 5 pips.

The flat 10 pip addition to the variable slippage may be an overcompensation but, as we see later, as we are mainly interested in potential large profits and losses, this does not hinder the interpretation of results.

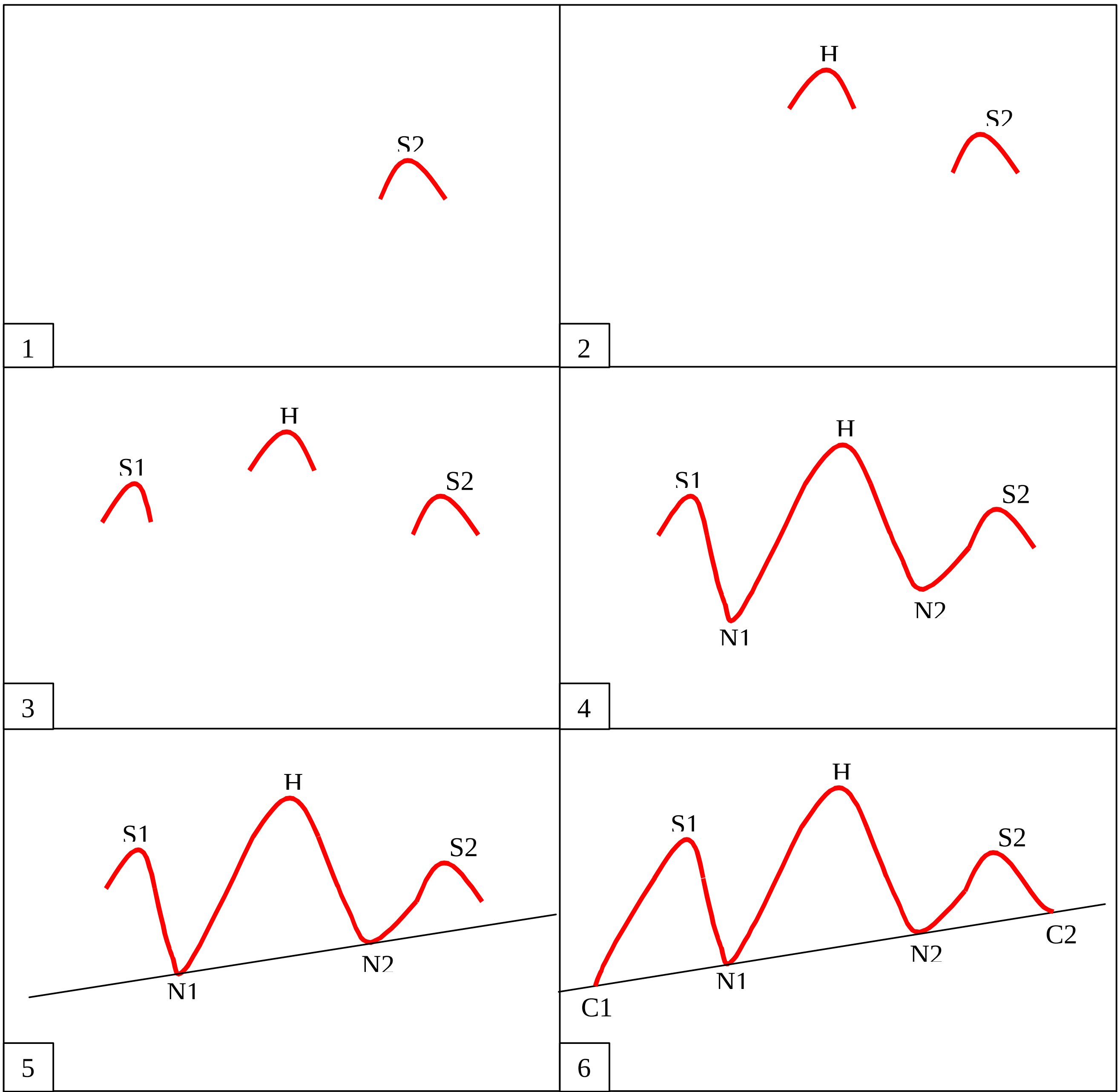

Figure 3.4: Pictorial Representation of Head & Shoulders Isolation Algorithm

As soon as the h&s pattern is formed, entry and exit rules read the 1min frequency data at the corresponding time. This is to replicate the actions of the technical trader who, once he has gained his entry signal from the technical pattern, will look at the higher frequency for entry and exit signals and not 'sit on his hands' while another hourly bar is fully formed.

A description of tested rules and the associated average profit per trade can be found in Section 4.

The 'best' rule that was chosen is as follows:

> *Enter at close point of C2, exit when either 30 pip trailing stop is hit or when the time elapsed when entering the trade is greater than three times the time taken between C1 and C2.*

The best set of rules was identified and applied to the following data frequencies: daily, 480min, 240min, 60min, and 1min and, in each instance, the rules' performance was measured and can be found in Section 4.

Various characteristics of the patterns have been measured for each pattern. The characteristics, or attributes, are listed below:

HA1	S1 – L(N1N2,$s1$)	level of S1 relative to the neckline
HA2	S2 – L(N1N2,$s2$)	level of S2 relative to the neckline
HA3	H – L(N1N2,h)	level of H relative to the neckline
HA4	H – S1	level of H relative to S1
HA5	H – S2	level of H relative to S2
HA6	$(N2 - N1)/(n2 - n1)$	gradient of the neckline
HA7	$s2 - s1$	number of bars between S1 and S2
HA8	$c2 - c1$	number of bars between C1 and C2
HA9	$(s2 - s1)/(c2 - c1)$	ratio of HA& to HA8
HA10	$(h - s1)/(s2 - s1)$	centrality of the head w.r.t shoulders
HA11	C1 – c_i where $i = (c2 - c1)$	momentum measurement
HA12	C1 – c_i where $i = 2 \text{ x } (c2 - c1)$	momentum measurement
HA13	C1 – c_i where $i = 5 \text{ x } (c2 - c1)$	momentum measurement

These attributes can all be measured at or before the pattern's formation and so any predictive power with respect to trading profitability can be exploited in a 'live' trading situation.

Various statistical analyses have been carried out and, as a result, classification rules to classify profitable situations with respect to above attributes have been constructed. Furthermore, trading rules and filters resulting from this analysis have been constructed and tested.

3.4 The Head & Shoulders Pattern – Summary

We have described above work that has been carried out on the head & shoulders pattern – a widely used technical trading pattern. Using BPUS spot FX tick data aggregated to various frequencies, we have developed an algorithm to isolate specimens of such a pattern. Trading rules which use the pattern as an entry signal, have been constructed and their performance tested. Pattern attributes have been analysed for any linkage with trading profit and, as a result, trading rules and filters have been constructed. The results of this programme can be found in Section 4.

4 Results

We here discuss the results of our analysis of the head & shoulders trading pattern. Results tables follow this text and more detailed results can be found in Jones [7]. First we present the results of tests to choose the best set of trading rules. Further, the slippage adjusted profitability of such trading rules applied to BPUS spot FX data is examined for each pattern. Next, the link between various attributes of each pattern and trading profit is explored - firstly by analysing the statistical significance of the difference between mean attribute values of patterns grouped with respect to profitability and then by constructing classification rules with the aim of classifying profitable patterns by consideration of attributes alone. Such classification rules are then tested on a separate set of BPUS data. Finally, trading filters are constructed on the basis of the above analysis and the resulting profit improvement is analysed.

4.1 Profitability Analysis

In Table 1 we present the results of testing a number of different sets of trading rules, at the 60min data frequency, in conjunction with the h&s technical trading pattern, along with a description of each rule. Any occurrence of the pattern was taken to be a primary trade entry signal and a position was taken on the signal of the entry rules that we have tested. Trade exit was on the signal of the tested exit rules. Performance of each set of rules is measured by average profit per trade. Profit is measured in 'pips per traded British Pound' and adjusted for slippage as described in Section 3.3. Trading situations that are abandoned before entry are ignored.

The various trading strategies are outline below:

Strategy 1: Enter when neckline is crossed after S2; exit when trailing stop is hit or a timeout is called after a fixed number of bars at *minute* level; allow multiple pattern setups about the same S2.

Strategy 2: Enter when an error band under the neckline is crossed after S2 at *minute* level; exit when trailing stop is hit or a timeout is called after a fixed number of bars at minute level; allow multiple pattern setups about the same S2.

Strategy 3: Enter when neckline is crossed after S2; exit when trailing stop is hit or a timeout is called after a fixed time period at *minute* level; do not allow multiple pattern setups about the same S2.

Strategy 3 with a trailing stop parameter of 30 pips resulted in the smallest slippage-adjusted loss and so that strategy was chosen. A sensitivity analysis of the trailing stop parameter was carried out at 480min frequency to ensure that the value of the parameter was still near optimal.

Note, from Table 1, that the slippage-adjusted profits are consistently negative and losses are greater than the maximum slippage deduction of twenty pips. Therefore, before slippage is considered this trading strategy is loss-making.

The improvement from worst to best trading rule is over twenty pips.

The best set of trading rules was then applied to the daily, 480min, 240min, 60min and 1min frequency data. Resulting average profits are presented in Table 2.

Slippage-adjusted profit distributions have negative means and skewness is a mix of positive (daily, 240min) and negative. Kurtosis is much smaller for daily patterns than for the rest of the data.

Tables of descriptive statistics and histograms for slippage-adjusted profits can be found in Jones [7] and and example of these results is presented in Figure 4.1, below, and in Table 13.

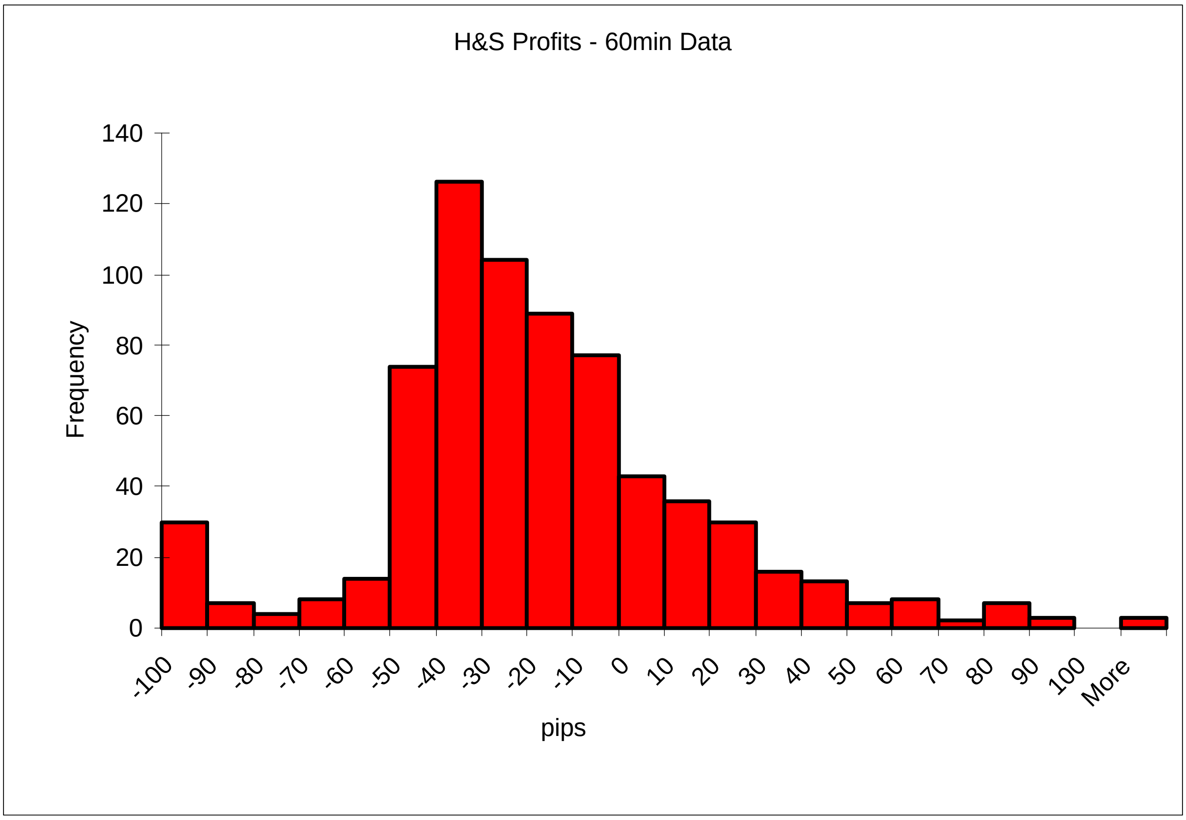

Figure 4.1: Histogram of Trading Profits for the Head & Shoulders Pattern at the 60min Frequency

4.2 Analysis of Pattern Attributes

Table 3 shows the results of a Wilkes lambda test (as in Sharma [18]) on the thirteen different attributes of the 'head & shoulders' patterns isolated in the sample data (1989-96). The samples have been split into 4 groups on the basis of slippage adjusted profits:-

large profit (>35 pips),

small profit (35 pips $\geq p >$ 0 pips),

small loss (0 $\geq l \geq$ -35 pips),

large loss (<-35 pips).

The threshold value of 35 pips has been chosen as -35 pips is close to the average loss made per trade at the most loss-making frequency.

The first section of the table (top of page) displays the results of the test (in terms of statistical significance) when sets of attributes are partitioned into 4 groups as above.

The second section of the table (middle) displays the results of the test (in terms of significance) when sets of attributes are partitioned into 2 groups: *large loss* and *other*.

The third section of the table (bottom) displays the results of the test (in terms of significance) when sets of attributes are partitioned into 2 groups: *large profit* and *other*.

Different attributes are significantly different by group at different data frequencies, with no one attribute acting particularly well throughout. The second 2 group analysis was not executed at daily frequency due to insufficient trading opportunities.

Note also that the significance of the last three attributes is not particularly high when it comes to tests including the *large profit* group. These attributes measure the momentum of the market move before C1. To many traders, a large rally prior to C1 is essential to the profitability of the trade. Our results imply that such a rally is a poor indicator of trade profitability.

A number of discriminant analyses (see Sharma [18]) using all pattern attributes were carried out using the H&S attributes as independent variables with profit group as the dependent variable. Groups were constructed as in the Wilkes lambda tests and the following discriminant analyses were carried out:

large profit or *other* (+2mda)
large loss or *other* (-2mda)
large profit, *small profit*, *small loss*, *large loss* (4mda)

The canonical discriminant functions derived form the analysis show encouraging levels of significance (mainly > 60%) but the associated cc^2 values are low (usually <<1).

Tables 4 –7 show the classification results from the various discriminant analyses described above. The classification techniques are tested on the 1997-98 data.

‘% correct’ is the percentage of group members that have been correctly classified as such.

‘% better than chance’ is the excess of ‘% correct’ over the expected result should classification be left to chance, expressed as a percentage; e.g. in the 4mda, chance would be 25% and so should, under the 4mda classification regime, 50% be correctly classified then this would be 100% greater than chance.

‘% correctly identified as p/l’ lists the percentage of profits (large <u>and</u> small) correctly identified as profits (large <u>or</u> small), and the percentage of losses (large <u>and</u> small) correctly identified as losses (large <u>or</u> small).

The overall number of correctly classified entities, expressed as a percentage, can be found in the extreme left hand column.

Table 4 presents results for the 4mda. There are no large profits in the patterns isolated in the daily data and so here, a 3 group analysis has been carried out. In both test and sample data, classification results worsen as frequency increases. All classification in the sample data is better than if left to chance whereas results are mixed in the test data.

Table 5 presents results for the -2mda. Here, all classification in the sample data is better than if left to chance whereas results are mixed, if not poor, in the test data.

For the +2da (Table 6), there are no large profits in the patterns isolated in the daily data and so here, no analysis has been carried out. All classification in the sample data is better than if left to chance whereas results are mixed in the case of the test data. Furthermore, given the small number of large profits in the test data, it is difficult to draw conclusions from the test results.

A further classification (+/-2da), using the following rule, was also attempted:

> if classified as -2 by the -2da rules and *other* by the +2da rules then classify as –2;
> if classified as -2 by the -2da rules and +2 by the +2da rules then classify as *other*;
> if classified *other* by the -2da rules and +2 by the +2da rules then classify as +2;
> if classified *other* by the -2da rules and *other* by the +2da rules then classify as *other*.

Table 7 presents the results of the +/-2da classification. Although this rule works poorly when comparing numbers of correctly classified entities to those correctly classified in the –2da and +2da, it marginally outperforms when considering classification relative to chance since the above discriminates between three groups whereas the former rules discriminate between two. This rule also performs poorly in comparison to the 4mda.

The above rule seems to remain reasonably consistent when applied to the test set but, given the small number of large profits, is difficult to obtain conclusive results. As the rule has been developed as a response to a characteristic of the data (similarity between +2 and –2 group means for many attributes) and is produced as a result of two 2-group discriminant analyses, it may well prove to be more robust than the (tighter fitted) 4mda classification rule.

4.3 Trading Rule Development

Finally, trading filters, based on the above discriminant analyses and Wilkes lambda tests, have been developed and tested on the sample and test data. These are used as soon as the pattern has been formed to decide whether the situation should be considered for trading. If so, the usual trade entry rules are then applied.

The filters developed from the discriminant analysis use the resulting classification functions, applied to the pattern attributes at the point of the pattern's formation (C2), to classify the patterns with respect to profitability. If the classification filters suggest the pattern is worth considering, we then apply the trade entry and exit rules as before. For the 4mda filter and +2da filter we proceed if a *large profit* is forecast; for the –2mda rule, we proceed if the pattern is classified as NOT *large loss*; for the +/-2mda rule, we proceed if the pattern is classified as a *large profit* <u>and</u> NOT a *large loss*.

The filters developed from the Wilkes lambda tests are simpler. We consider the attributes that have significant (>80%) difference in the 4mda, -2da and 2da groupings. We then inspect such attributes to discern whether there is significant difference between the attribute means for the loss-making groups and those for the profitable groups (as mentioned earlier, there are often similarities between attributes of *large loss*-making and *large profit*-making patterns). Should the inspection test show that reasonable differences occur, then a filter was developed in the style of the following:

Consider the 4mda attribute #n group means:

Large Profit Group Mean	10
Small Profit Group Mean	15
Small Loss Group Mean	20
Large Loss Group Mean	25.

Should the Wilkes Lambda test prove such means to be significantly different, then we construct the following rule:

trade pattern only if attribute #n value < 20 (Small Profit Group Mean).

Furthermore, we consider combinations of the two most profitable rules and the two rules based on attributes with the highest Wilkes lambda test significance value.

We apply such filters as soon as the pattern is formed, at C2, and proceed with the trade – by applying the usual trade entry and exit rules – if a positive outcome is returned.

Tables 8-13 present the results of such trading filters applied to the sample and, in the case of the best rules, the test data. The tables contain the following information:

# Total Trades	total number of trades before the introduction of the filter;
# Accepted Trades	total number of trades after the introduction of the filter;
% Accepted	# Accepted Trades as a percentage of # Total Trades;
Average Profit	average profit per trade before the introduction of filter;
Filtered Profit	average profit per trade after the introduction of filter;
% Improvement	improvement of profit due to filter as a percentage of Average Profit.

Performance is measured on percentage improvement. An outline of the rules used is also displayed.

At the various frequencies, all filters based on the discriminant analysis (Rules 1-5) improve trading profits on the sample data and, at daily, 240min and 1min frequency, these improvements hold on the test data as well. Furthermore, Rule 3, based on the +2da, improves trading profits on the sample and test data at all frequencies.

As for the filters based on the combination of the Wilkes lambda test and inspection techniques, the filters based on the 4-group separation work well, in general, throughout the range of data frequencies of the test and sample data. All filters applied to the 240min and 1min sample data yield consistent improvements.

The filters can sometimes be severe - for example the 60 of the 62 potential trades at the 240min test case are filtered out resulting in a tiny profit.

To summarise, the addition of the filter rules results in an improvement in profitability for approximately 69% of all test cases and improvement is near total at every level but the 60min frequency.

A large number of different rules for trading the head & shoulders pattern have been tested and prove to be generally unprofitable, both before and after slippage considerations. A number of pattern attributes have been analysed for linkage with profitability and, in some cases, the statistical significance of results was high. Discriminant analyses of various kinds have been conducted and resulting classification, in some cases, proved better than chance when applied to out of sample test data. Finally, various filters have been developed from the above analysis which significantly improve trading profitability under test conditions.

5 Summary, Further Work and Concluding Remarks

In the above work, we have developed algorithms (and hence, software) to isolate automatically specimens of a popular technical trading pattern – the head & shoulders. Having isolated specimens of this pattern at several different (mainly intra-day) frequencies using over 8 years of tick FX data, we have simulated the actions of a technical trader who would use the occurrence of such a pattern as an entry signal for a trade and then exit such a trade using an array of cash management exit rules which respond to the intra-day market . Despite the popularity of the head & shoulders as a trading signal, we find that the pattern is loss-making when traded in a systematic and realistic manner with a number of different exit strategies.

Various attributes of the head & shoulders which hold information on the patterns' shape and the market behaviour before and during formation have been isolated with the aim of discovering any potential link between such attributes and the profitability of trading this pattern. Such links have been found to exist to a statistically significant level and have been successfully utilised to construct filters that improve upon trading profitability even when tested on out of sample data. Despite this improvement being significant in magnitude, we have rarely been able to filter to the extent that the loss-making strategy becomes profitable.

As a result of this analysis, we conclude that information released by the market before and during the formation of the head & shoulders pattern can be used to improve upon trading following the completion of this formation – a conclusion that is in disagreement with the standard ‘independent gaussian’ view of market price realisation.

Despite the fact that the pattern is shown to be loss-making, it would be wrong to conclude that those who trade such patterns are irrational. All we have shown is that if every systematic formulation of this pattern were to be traded, a net loss would ensue. Many traders use implicit or explicit filters that aid their selection of ‘winning’ patterns. Furthermore, profitability can be gained from a well-informed or skilful exit policy that may well rely on exogenous information.

By this argument, the filters that we have developed may be of use to one who already profits from trading the head & shoulder and seeks to enhance this profitability.

Few studies in this area mix the analysis of trading rules with the high degree of realism resulting from the use of high frequency data and so there is much work to be done in many related areas. For a start, there exists a litany of trading patterns and it may be the case that others are immediately profitable; our companion paper [4] eliminates one of the possibilities! In addition, it would also be of great use to subject the methods of inter-market technical analysis (as described in Murphy [10]) to rigorous analysis in an attempt to discover the link between trading profitability and the movement of other related markets, e.g. bonds, interest rate futures, stock index futures, etc. Another untapped area that shows promise is the analysis of news and macro-economic indicators on trading profitability[6].

Finally, it would be of use to consider adaptive trading systems. Timmermann et al [20] introduce a bootstrap technique that assesses excess performance with regard to data-snooping and comment that it is only such a methodology that can be used in validation of this kind. However, when considering excess returns, we should not only consider static systems but systems that are allowed to adapt to changes in market conditions, just like technical traders themselves. Consideration of such adaptive systems would result in a closer approximation to the reality of the practice of technical traders and would take the emphasis away from a single data-mined ‘best performing rule’.

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[6] A study of the impact of such macro-level indicators on high frequency data has been published by Almeida et al [2].

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Results Tables

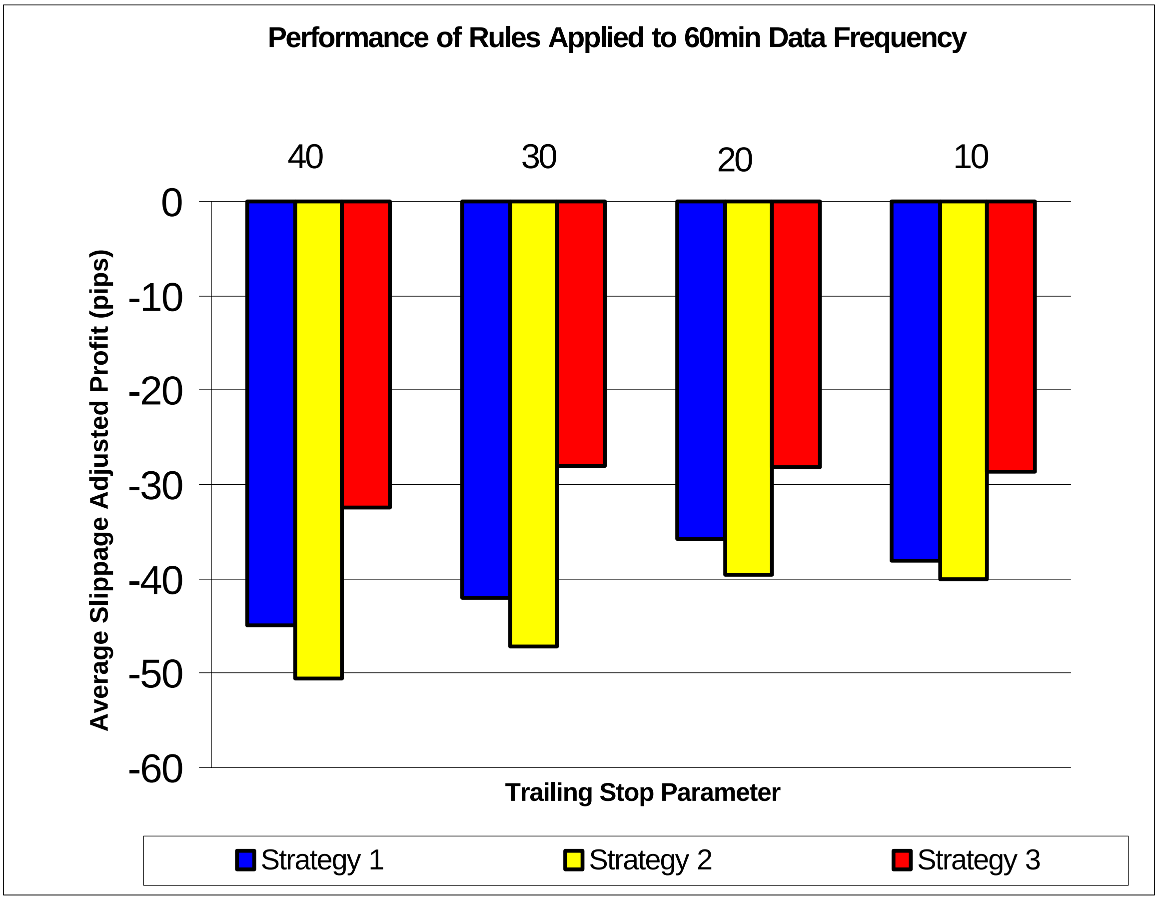

Table 1: Profitability of Various Trading Rules at 60min Frequency

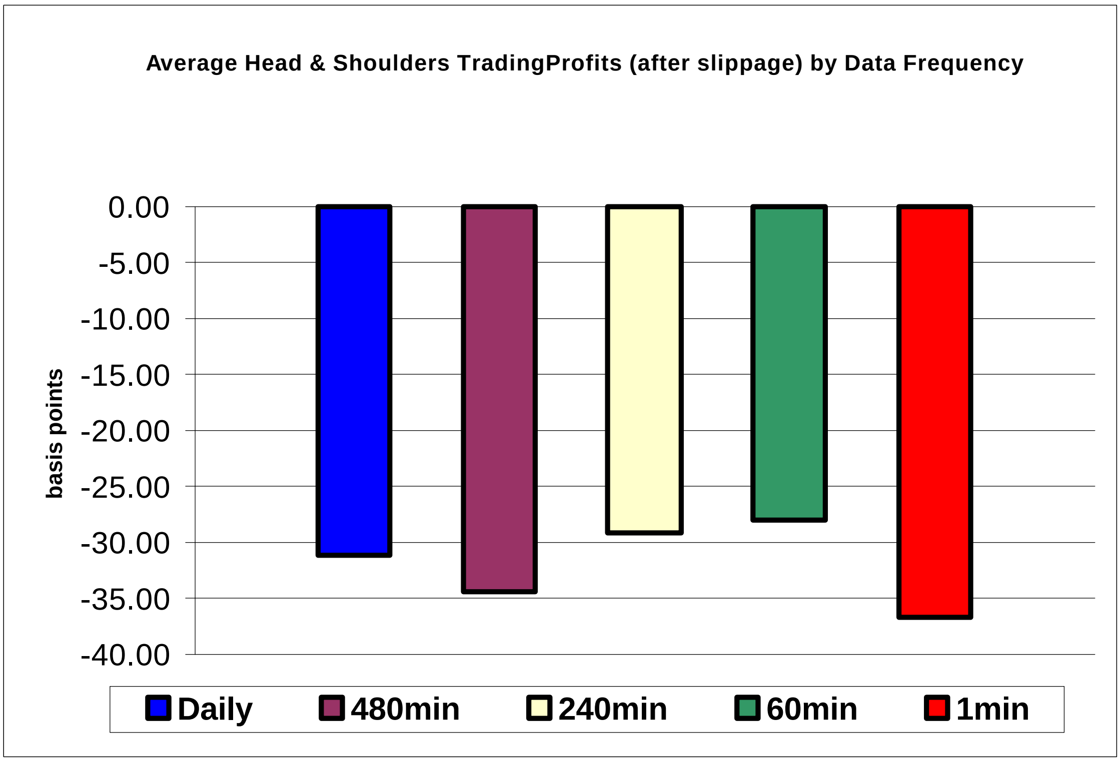

Table 2: Average Slippage Adjusted Profit of Best Set of Trading Rules

	Daily	480min	240min	60min	1min
4-Group Partition					
HA1	86.44%	44.02%	9.56%	93.31%	92.70%
HA2	31.76%	20.64%	90.12%	89.52%	100.00%
HA3	49.90%	20.30%	52.61%	100.00%	45.28%
HA4	49.00%	50.00%	8.83%	98.92%	18.38%
HA5	8.61%	15.01%	89.51%	94.07%	98.73%
HA6	53.15%	58.03%	47.18%	43.51%	54.69%
HA7	35.14%	19.91%	43.82%	88.01%	99.98%
HA8	26.47%	18.48%	37.06%	86.26%	99.96%
HA9	78.04%	64.92%	57.16%	69.97%	27.29%
HA10	33.51%	12.38%	33.49%	85.37%	91.37%
HA11	81.38%	92.76%	65.80%	90.75%	79.74%
HA12	43.74%	46.70%	15.72%	14.69%	88.03%
HA13	66.86%	26.93%	79.89%	51.66%	96.77%
2 Group Partition (*large loss* & *other*)					
HA1	82.85%	83.40%	47.86%	94.71%	65.70%
HA2	61.86%	66.86%	93.35%	31.57%	100.00%
HA3	27.20%	19.86%	46.38%	63.82%	66.82%
HA4	74.70%	85.80%	46.44%	22.91%	61.13%
HA5	18.22%	20.00%	81.72%	89.53%	99.87%
HA6	39.39%	43.88%	46.36%	0.39%	52.84%
HA7	64.93%	59.45%	65.97%	96.51%	99.98%
HA8	53.70%	33.82%	48.38%	96.33%	99.95%
HA9	87.84%	88.62%	87.85%	0.35%	51.30%
HA10	10.55%	13.87%	25.02%	28.14%	93.75%
HA11	37.33%	93.43%	84.54%	11.08%	86.65%
HA12	5.11%	7.48%	2.13%	10.51%	85.38%
HA13	66.37%	55.86%	64.27%	56.54%	98.34%
2 Group Partition (*large profit* & *other*)					
HA1		12.94%	27.94%	25.60%	90.30%
HA2		3.50%	90.30%	97.84%	85.37%
HA3		65.19%	54.30%	100.00%	74.02%
HA4		35.95%	14.09%	99.89%	23.05%
HA5		57.97%	93.90%	88.28%	57.97%
HA6		84.62%	25.09%	81.11%	78.54%
HA7		44.55%	55.74%	41.66%	99.19%
HA8		56.57%	59.44%	7.40%	97.66%
HA9		3.16%	7.32%	93.47%	61.38%
HA10		39.88%	11.35%	69.38%	96.06%
HA11		20.65%	43.98%	93.41%	54.74%
HA12		80.95%	29.27%	38.76%	36.98%
HA13		63.07%	85.80%	77.28%	56.75%

Table 3: Wilkes Lambda Test Results – Significance

		-2	-1	+1	+2	Group Totals	% correct	% better than chance	% correctly identified as p/l
Sample Data									
Daily	-2	11	3	1	xxx	15	73.33%	120.00%	93.33%
% Correctly	-1	2	10	1	xxx	13	76.92%	130.77%	92.31%
Classified:	+1	0	1	2	xxx	3	66.67%	100.00%	66.67%
74.19%	+2	xxx	xxx	xxx	xxx	xxx	xxx	xxx	xxx
480	-2	21	10	10	3	44	47.73%	90.91%	70.45%
% Correctly	-1	10	22	6	2	40	55.00%	120.00%	80.00%
Classified:	+1	2	2	6	0	10	60.00%	140.00%	60.00%
52.08%	+2	1	0	0	1	2	50.00%	100.00%	50.00%
240	-2	40	34	13	19	106	37.74%	50.94%	69.81%
% Correctly	-1	22	39	8	10	79	49.37%	97.47%	77.22%
Classified:	+1	6	4	7	4	21	33.33%	33.33%	52.38%
43.06%	+2	0	2	1	7	10	70.00%	180.00%	80.00%
60	-2	83	97	80	59	319	26.02%	4.08%	56.43%
% Correctly	-1	48	119	51	39	257	46.30%	85.21%	64.98%
Classified:	+1	18	26	32	16	92	34.78%	39.13%	52.17%
36.23%	+2	2	7	4	20	33	60.61%	142.42%	72.73%
1	-2	374	243	251	389	1257	29.75%	19.01%	49.09%
% Correctly	-1	105	175	142	212	634	27.60%	10.41%	44.16%
Classified:	+1	19	30	44	41	134	32.84%	31.34%	63.43%
29.92%	+2	10	16	13	35	74	47.30%	89.19%	64.86%
Test Data									
Daily	-2	2	1	0	xxx	3	66.67%	100.00%	100.00%
% Correctly	-1	1	4	0	xxx	5	80.00%	140.00%	100.00%
Classified:	+1	0	1	0	xxx	1	0.00%	-100.00%	0.00%
66.67%	+2	xxx	xxx	xxx	xxx	xxx	xxx	xxx	xxx
480	-2	6	4	5	0	15	40.00%	60.00%	66.67%
% Correctly	-1	5	5	3	0	13	38.46%	53.85%	76.92%
Classified:	+1	1	1	0	0	2	0.00%	-100.00%	0.00%
38.71%	+2	0	0	0	1	1	100.00%	300.00%	100.00%
240	-2	6	14	7	4	31	19.35%	-22.58%	64.52%
% Correctly	-1	6	11	5	1	23	47.83%	91.30%	73.91%
Classified:	+1	2	2	2	1	7	28.57%	14.29%	42.86%
60	-2	14	41	18	4	77	18.18%	-27.27%	71.43%
% Correctly	-1	13	41	17	6	77	53.25%	112.99%	70.13%
Classified:	+1	6	9	1	0	16	6.25%	-75.00%	6.25%
32.20%	+2	2	2	2	1	7	14.29%	-42.86%	42.86%
1	-2	11	20	20	43	94	11.70%	-53.19%	32.98%
% Correctly	-1	6	15	10	31	62	24.19%	-3.23%	33.87%
Classified:	+1	0	8	3	14	25	12.00%	-52.00%	68.00%
16.67%	+2	0	1	2	2	5	40.00%	60.00%	80.00%

Table 4: MDA Classification Results for Head & Shoulders

		-2	Other	Group Totals	% correct	% better than chance
Sample Data						
Daily	-2	12	3	15	80.00%	60.00%
77.42%	Oth	4	12	16	75.00%	50.00%
480	-2	30	14	44	68.18%	36.36%
65.63%	Oth	19	33	52	63.46%	26.92%
240	-2	59	47	106	55.66%	11.32%
58.33%	Oth	43	67	110	60.91%	21.82%
60	-2	180	139	319	56.43%	12.85%
57.06%	Oth	162	220	382	57.59%	15.18%
1	-2	638	619	1257	50.76%	1.51%
56.12%	Oth	302	540	842	64.13%	28.27%
Test Data						
Daily	-2	2	1	3	66.67%	33.33%
66.67%	Oth	2	4	6	66.67%	33.33%
480	-2	10	5	15	66.67%	33.33%
58.06%	Oth	8	8	16	50.00%	0.00%
240	-2	19	12	31	61.29%	22.58%
53.23%	Oth	17	14	31	45.16%	-9.68%
60	-2	27	50	77	35.06%	-29.87%
47.46%	Oth	43	57	100	57.00%	14.00%
1	-2	27	67	94	28.72%	-42.55%
56.45%	Oth	14	78	92	84.78%	69.57%

Table 5: -2DA Classification Results for Head & Shoulders

		Other	+2	Group Totals	% correct	% better than chance
Sample Data						
480	Oth	89	5	94	94.68%	89.36%
93.75%	+2	1	1	2	50.00%	0.00%
240	Oth	162	44	206	78.64%	57.28%
78.24%	+2	3	7	10	70.00%	40.00%
60	Oth	509	159	668	76.20%	52.40%
75.75%	+2	11	22	33	66.67%	33.33%
1	Oth	1147	878	2025	56.64%	13.28%
56.79%	+2	29	45	74	60.81%	21.62%
Test Data						
480	Oth	30	0	30	100.00%	100.00%
100.00%	+2	0	1	1	100.00%	100.00%
240	Oth	46	15	61	75.41%	50.82%
75.81%	+2	0	1	1	100.00%	100.00%
60	Oth	152	18	170	89.41%	78.82%
86.44%	+2	6	1	7	14.29%	-71.43%
1	Oth	65	116	181	35.91%	-28.18%
36.02%	+2	3	2	5	40.00%	-20.00%

Table 6: +2DA Classification Results for Head & Shoulders

		-2	Other	+2	Group Totals	% correct	% better than chance
Sample Data							
480	-2	27	17	0	44	61.36%	84.09%
60.42%	Other	18	30	2	50	60.00%	80.00%
	+2	1	0	1	2	50.00%	50.00%
240	-2	35	58	13	106	33.02%	-0.94%
41.20%	Other	40	49	11	100	49.00%	47.00%
	+2	2	3	5	10	50.00%	50.00%
60	-2	139	140	40	319	43.57%	30.72%
48.50%	Other	114	190	45	349	54.44%	63.32%
	+2	4	18	11	33	33.33%	0.00%
1	-2	505	358	394	1257	40.18%	20.53%
38.11%	Other	218	258	292	768	33.59%	0.78%
	+2	17	20	37	74	50.00%	50.00%
Test Data							
480	-2	10	5	0	15	66.67%	100.00%
56.67%	Other	8	7	0	15	46.67%	40.00%
	+2	0	0	1	1	100.00%	200.00%
240	-2	17	9	5	31	54.84%	64.52%
53.23%	Other	11	16	3	30	53.33%	60.00%
	+2	0	1	0	1	0.00%	-100.00%
60	-2	26	45	6	77	33.77%	1.30%
41.24%	Other	37	47	9	93	50.54%	51.61%
	+2	3	4	0	7	0.00%	-100.00%
1	-2	17	31	46	94	18.09%	-45.74%
20.97%	Other	10	20	57	87	22.99%	-31.03%
	+2	1	2	2	5	40.00%	20.00%

Table 7: +/-2DA Classification Results for Head & Shoulders

Daily	# Total Trades	# Accepted Trades	% Accepted	Average Profit	Filtered Profit	% Improvement
Sample Data						
Rule 1	xxx	xxx	xxx	xxx	xxx	xxx
Rule 2	31	4	12.90%	-31.2	-5.5	82.37%
Rule 3	xxx	xxx	xxx	xxx	xxx	xxx
Rule 4	31	15	48.39%	-31.2	-22.1	29.17%
Rule 5	xxx	xxx	xxx	xxx	xxx	xxx
Rule 6	31	5	16.13%	-31.2	-6.8	78.21%
Rule 7	31	3	9.68%	-31.2	-22.0	29.49%
Rule 8	31	2	6.45%	-31.2	-20.0	35.90%
Rule 9	31	10	32.26%	-31.2	-27.0	13.46%
Rule 10	31	10	32.26%	-31.2	-24.5	21.47%
Rule 11	31	2	6.45%	-31.2	-38.0	-21.79%
Test Data						
Rule 1	xxx	xxx	xxx	xxx	xxx	xxx
Rule 2	xxx	xxx	xxx	xxx	xxx	xxx
Rule 3	xxx	xxx	xxx	xxx	xxx	xxx
Rule 4	9	5	55.56%	-24.4	-22.0	9.84%
Rule 5	xxx	xxx	xxx	xxx	xxx	xxx
Rule 6	xxx	xxx	xxx	xxx	xxx	xxx
Rule 8	xxx	xxx	xxx	xxx	xxx	xxx
Rule 10	9	5	55.56%	-24.4	-22	9.84%
Rule 11	9	1	11.11%	-24.3	-33.0	-35.80%

Rule 1	Trade if	4mda classifies pattern as *Large Profit*
Rule 2	Trade if	4mda classifies pattern as *Large Profit* or *Small Profit*
Rule 3	Trade if	+2mda classifies pattern as *Large Profit*
Rule 4	Trade if	-2mda classifies pattern as *Other*
Rule 5	Trade if	Rule 3 is TRUE and Rule 4 is TRUE
Rule 6	Trade if	Attribute 1 > Attribute 1 *Small Profit* group mean
Rule 7	Trade if	Attribute 11 < Attribute 11 *Small Profit* group mean
Rule 8	Trade if	Rule 6 is TRUE **and** Rule 7 is TRUE
Rule 9	Trade if	Attribute 1 > Attribute 1 -2mda *Other* group mean
Rule 10	Trade if	Attribute 9 < Attribute 9 -2mda *Other* group mean
Rule 11	Trade if	Rule 9 is TRUE **and** Rule 10 is TRUE

Table 8: Results of Trading Rules Developed on the Daily Data

480min	# Total Trades	# Accepted Trades	% Accepted	Average Profit	Filtered Profit	% Improvement
Sample Data						
Rule 1	96	6	6.25%	-34.4	-21.7	36.92%
Rule 2	96	28	29.17%	-34.4	-27.9	18.90%
Rule 3	96	6	6.25%	-34.4	-21.7	36.92%
Rule 4	96	47	48.96%	-34.4	-32.1	6.69%
Rule 5	96	3	3.13%	-34.4	-0.7	97.97%
Rule 6	96	34	35.42%	-34.4	-32.8	4.65%
Rule 7	96	51	53.13%	-34.4	-29.8	13.37%
Rule 8	96	28	29.17%	-34.4	-23.9	30.52%
Rule 9	96	31	32.29%	-34.4	-27.9	18.90%
Rule 10	96	13	13.54%	-34.4	-15.7	54.36%
Rule 11	96	9	9.38%	-34.4	-23.1	32.85%
Rule 12	96	11	11.46%	-34.4	-27.5	20.06%
Rule 13	96	2	2.08%	-34.4	13.5	139.24%
Test Data						
Rule 1	xxx	xxx	xxx	xxx	xxx	xxx
Rule 2	30	8	26.67%	-29.1	-33.5	-15.12%
Rule 3	xxx	xxx	xxx	xxx	xxx	xxx
Rule 4	30	12	40.00%	-29.1	-27.7	4.81%
Rule 5	xxx	xxx	xxx	xxx	xxx	xxx
Rule 10	30	4	13.33%	-29.0	-21.8	24.83%
Rule 13	xxx	xxx	xxx	xxx	xxx	xxx

Rule 1	Trade if	4mda classifies pattern as *Large Profit*
Rule 2	Trade if	4mda classifies pattern as *Large Profit* or *Small Profit*
Rule 3	Trade if	+2da classifies pattern as *Large Profit*
Rule 4	Trade if	-2da classifies pattern as *Other*
Rule 5	Trade if	Rule 3 is TRUE **and** Rule 4 is TRUE
Rule 6	Trade if	Attribute 1 > Attribute 1 -2da *Other* group mean
Rule 7	Trade if	Attribute 4 < Attribute 4 -2da *Other* group mean
Rule 8	Trade if	Attribute 9 < Attribute 9 -2da *Other* group mean
Rule 9	Trade if	Attribute 11 < Attribute 11 -2da *Other* group mean
Rule 10	Trade if	Rule 8 is TRUE **and** Rule 9 is TRUE
Rule 11	Trade if	Attribute 6 < Attribute 6 *Large Profit* group mean
Rule 12	Trade if	Attribute 12 < Attribute 12 *Large Profit* group mean
Rule 13	Trade if	Rule 11 is TRUE **and** Rule 12 is TRUE

Table 9: Results of Trading Rules Developed on the 480min Data

240min	# Total Trades	# Accepted Trades	% Accepted	Average Profit	Filtered Profit	% Improvement
Sample Data						
Rule 1	216	40	18.52%	-29.2	-16.0	45.21%
Rule 2	216	69	31.94%	-29.2	-19.4	33.56%
Rule 3	216	51	23.61%	-29.2	-20.7	29.11%
Rule 4	216	117	54.17%	-29.2	-25.6	12.33%
Rule 5	216	29	13.43%	-29.2	-10.6	63.70%
Rule 6	216	130	60.19%	-29.2	-26.9	7.88%
Rule 7	216	69	31.94%	-29.2	-21.1	27.74%
Rule 8	216	110	50.93%	-29.2	-28.0	4.11%
Rule 9	216	92	42.59%	-29.2	-28.5	2.40%
Rule 10	216	70	32.41%	-29.2	-24.8	15.07%
Rule 11	216	43	19.91%	-29.2	-10.2	65.07%
Rule 12	216	45	20.83%	-29.2	-27.5	5.82%
Rule 13	216	57	26.39%	-29.2	-20.4	30.14%
Rule 14	216	15	6.94%	-29.2	-43.1	-47.60%
Rule 15	216	10	4.63%	-29.2	-3.5	88.01%
Test Data						
Rule 1	62	7	11.29%	-28.2	-16.4	41.84%
Rule 2	62	21	33.87%	-28.2	-25.4	9.93%
Rule 3	62	16	25.81%	-28.2	-22.1	21.63%
Rule 4	62	26	41.94%	-28.2	-25.5	9.57%
Rule 5	62	8	12.90%	-28.2	-28.0	0.71%
Rule 10	62	26	41.94%	-28.3	-24.3	14.13%
Rule 11	62	25	40.32%	-28.2	-21.2	24.82%
Rule 15	62	2	3.23%	-28.2	0.5	101.77%

Rule 1	Trade if	4mda classifies pattern as *Large Profit*
Rule 2	Trade if	4mda classifies pattern as *Large Profit* or *Small Profit*
Rule 3	Trade if	+2da classifies pattern as *Large Profit*
Rule 4	Trade if	-2da classifies pattern as *Other*
Rule 5	Trade if	Rule 3 is TRUE **and** Rule 4 is TRUE
Rule 6	Trade if	Attribute 2 < Attribute 2 -2da *Other* group mean
Rule 7	Trade if	Attribute 5 > Attribute 5 -2da *Other* group mean
Rule 8	Trade if	Attribute 9 > Attribute 9 -2da *Other* group mean
Rule 9	Trade if	Attribute 11 < Attribute 11 -2da *Other* group mean
Rule 10	Trade if	Rule 6 is TRUE **and** Rule 8 is TRUE
Rule 11	Trade if	Rule 6 is TRUE **and** Rule 7 is TRUE
Rule 12	Trade if	Attribute 2 < Attribute 2 *Large Profit* group mean
Rule 13	Trade if	Attribute 5 > Attribute 5 *Large Profit* group mean
Rule 14	Trade if	Attribute 13 > Attribute 13 *Large Profit* group mean
Rule 15	Trade if	Rule 12 is TRUE **and** Rule 13 is TRUE

Table 10: Results of Trading Rules Developed on the 240min Data

60min	# Total Trades	# Accepted Trades	% Accepted	Average Profit	Filtered Profit	% Improvement
Sample Data						
Rule 1	701	134	19.12%	-28.0	-19.1	31.79%
Rule 2	701	301	42.94%	-28.0	-25.8	7.86%
Rule 3	701	181	25.82%	-28.0	-21.6	22.86%
Rule 4	701	359	51.21%	-28.0	-24.6	12.14%
Rule 5	701	96	13.69%	-28.0	-17.8	36.43%
Rule 6	701	295	42.08%	-28.0	-28.6	-2.14%
Rule 7	701	298	42.51%	-28.0	-25.8	7.86%
Rule 8	701	127	18.12%	-28.0	-28.2	-0.71%
Rule 9	701	434	61.91%	-28.0	-25.8	7.86%
Rule 10	701	427	60.91%	-28.0	-28.9	-3.21%
Rule 11	701	321	45.79%	-28.0	-27.8	0.71%
Rule 12	701	331	47.22%	-28.0	-25.8	7.86%
Rule 13	701	287	40.94%	-28.0	-26.9	3.93%
Rule 14	701	15	2.14%	-28.0	-24.0	14.29%
Rule 15	701	193	27.53%	-28.0	-26.1	6.79%
Rule 16	701	107	15.26%	-28.0	-22.9	18.21%
Rule 17	701	144	20.54%	-28.0	-21.5	23.21%
Rule 18	701	202	28.82%	-28.0	-26.1	6.79%
Rule 19	701	231	32.95%	-28.0	-29.7	-6.07%
Rule 20	701	308	43.94%	-28.0	-26.9	3.93%
Rule 21	701	222	31.67%	-28.0	-25.1	10.36%
Rule 22	701	59	8.42%	-28.0	-24.8	11.43%
Test Data						
Rule 1	177	10	5.65%	-25.6	-31.9	-24.61%
Rule 2	177	49	27.68%	-25.6	-24.3	5.08%
Rule 3	177	19	10.73%	-25.6	-21.5	16.02%
Rule 4	177	107	60.45%	-25.6	-29.8	-16.41%
Rule 5	177	15	8.47%	-25.6	-32.3	-26.17%
Rule 7	177	66	37.29%	-25.6	-22.0	14.06%
Rule 8	177	42	23.73%	-25.6	-24.5	4.30%
Rule 13	177	72	40.68%	-25.6	-28.9	-12.89%
Rule 14	177	74	41.81%	-25.6	-30.4	-18.75%
Rule 17	177	9	5.08%	-25.6	-30.7	-19.92%
Rule 22	xxx	xxx	xxx	xxx	xxx	xxx

Table 11a: Results of Trading Rules Developed on the 60min Data

Rule 1	Trade if	4mda classifies pattern as *Large Profit*
Rule 2	Trade if	4mda classifies pattern as *Large Profit* or *Small Profit*
Rule 3	Trade if	+2da classifies pattern as *Large Profit*
Rule 4	Trade if	-2da classifies pattern as *Other*
Rule 5	Trade if	Rule 3 is TRUE **and** Rule 4 is TRUE
Rule 6	Trade if	Attribute 10 > Attribute 10 *Small Profit* group mean
Rule 7	Trade if	Attribute 11 < Attribute 11 *Small Profit* group mean
Rule 8	Trade if	Rule 6 is TRUE **and** Rule 7 is TRUE
Rule 9	Trade if	Attribute 1 < Attribute 1 -2da *Other* group mean
Rule 10	Trade if	Attribute 5 < Attribute 5 -2da *Other* group mean
Rule 11	Trade if	Attribute 7 < Attribute 7 -2da *Other* group mean
Rule 12	Trade if	Attribute 8 < Attribute 8 -2da *Other* group mean
Rule 13	Trade if	Rule 11 is TRUE **and** Rule 12 is TRUE
Rule 14	Trade if	Rule 9 is TRUE **and** Rule 12 is TRUE
Rule 15	Trade if	Attribute 2 > Attribute 2 *Large Profit* group mean
Rule 16	Trade if	Attribute 3 > Attribute 3 *Large Profit* group mean
Rule 17	Trade if	Attribute 4 > Attribute 4 *Large Profit* group mean
Rule 18	Trade if	Attribute 5 > Attribute 5 *Large Profit* group mean
Rule 19	Trade if	Attribute 6 > Attribute 6 *Large Profit* group mean
Rule 20	Trade if	Attribute 9 > Attribute 9 *Large Profit* group mean
Rule 21	Trade if	Attribute 11 < Attribute 11 *Large Profit* group mean
Rule 22	Trade if	Rule 16 is TRUE **and** Rule 17 is TRUE

Table 11b: Summary of Trading Rules Developed on the 60min Data

1min	# Total Trades	# Accepted Trades	% Accepted	Average Profit	Filtered Profit	% Improvement
Sample Data						
Rule 1	2099	677	32.25%	-36.7	-34.3	6.54%
Rule 2	2099	1127	53.69%	-36.7	-34.0	7.36%
Rule 3	2099	923	43.97%	-36.7	-33.8	7.90%
Rule 4	2099	1159	55.22%	-36.7	-31.6	13.90%
Rule 5	2099	723	34.44%	-36.7	-31.4	14.44%
Rule 6	2099	1090	51.93%	-36.7	-34.3	6.54%
Rule 7	2099	1122	53.45%	-36.7	-32.5	11.44%
Rule 8	2099	713	33.97%	-36.7	-35.6	3.00%
Rule 9	2099	1102	52.50%	-36.7	-35.4	3.54%
Rule 10	2099	1056	50.31%	-36.7	-34.6	5.72%
Rule 11	2099	1092	52.02%	-36.7	-35.7	2.72%
Rule 12	2099	1178	56.12%	-36.7	-35.6	3.00%
Rule 13	2099	1107	52.74%	-36.7	-36.0	1.91%
Rule 14	2099	1107	52.74%	-36.7	-35.7	2.72%
Rule 15	2099	606	28.87%	-36.7	-31.0	15.53%
Rule 16	2099	552	26.30%	-36.7	-30.6	16.62%
Rule 17	2099	1090	51.93%	-36.7	-34.3	6.54%
Rule 18	2099	1075	51.21%	-36.7	-32.3	11.99%
Rule 19	2099	972	46.31%	-36.7	-35.0	4.63%
Rule 20	2099	913	43.50%	-36.7	-34.2	6.81%
Rule 21	2099	939	44.74%	-36.7	-36.3	1.09%
Rule 22	2099	766	36.49%	-36.7	-34.7	5.45%
Rule 23	2099	444	21.15%	-36.7	-30.4	17.17%
Test Data						
Rule 1	186	90	48.39%	-26.2	-24.1	8.02%
Rule 2	186	125	67.20%	-26.2	-24.9	4.96%
Rule 3	186	118	63.44%	-26.2	-24.3	7.25%
Rule 4	186	145	77.96%	-26.2	-24.2	7.63%
Rule 5	186	105	56.45%	-26.2	-23.1	11.83%
Rule 6	186	137	73.66%	-26.2	-24.2	7.63%
Rule 15	186	98	52.69%	-26.2	-24.1	8.02%
Rule 16	186	88	47.31%	-26.2	-22.6	13.74%
Rule 22	186	98	52.69%	-26.2	-25.2	3.82%
Rule 23	186	74	39.78%	-26.2	-21.3	18.70%

Table 12a: Results of Trading Rules Developed on the 1min Data

Rule 1	Trade if	4mda classifies pattern as *Large Profit*
Rule 2	Trade if	4mda classifies pattern as *Large Profit* or *Small Profit*
Rule 3	Trade if	+2da classifies pattern as *Large Profit*
Rule 4	Trade if	-2da classifies pattern as *Other*
Rule 5	Trade if	Rule 3 is TRUE **and** Rule 4 is TRUE
Rule 6	Trade if	Attribute 1 < Attribute 1 *Small Profit* group mean
Rule 7	Trade if	Attribute 2 < Attribute 2 Other group mean (-2da)
Rule 8	Trade if	Attribute 5 > Attribute 5 Other group mean (-2da)
Rule 9	Trade if	Attribute 7 > Attribute 7 Other group mean (-2da)
Rule 10	Trade if	Attribute 8 > Attribute 8 Other group mean (-2da)
Rule 11	Trade if	Attribute 10 < Attribute 10 Other group mean (-2da)
Rule 12	Trade if	Attribute 11 > Attribute 11 Other group mean (-2da)
Rule 13	Trade if	Attribute 12 > Attribute 12 Other group mean (-2da)
Rule 14	Trade if	Attribute 13 > Attribute 13 Other group mean (-2da)
Rule 15	Trade if	Rule 7 is TRUE **and** Rule 9 is TRUE
Rule 16	Trade if	Rule 7 is TRUE **and** Rule 10 is TRUE
Rule 17	Trade if	Attribute 1 < Attribute 1 *Large Profit* group mean
Rule 18	Trade if	Attribute 2 < Attribute 2 *Large Profit* group mean
Rule 19	Trade if	Attribute 7 > Attribute 7 *Large Profit* group mean
Rule 20	Trade if	Attribute 8 > Attribute 8 *Large Profit* group mean
Rule 21	Trade if	Attribute 10 < Attribute 10 *Large Profit* group mean
Rule 22	Trade if	Rule 19 is TRUE **and** Rule 20 is TRUE
Rule 23	Trade if	Rule 18 is TRUE **and** Rule 20 is TRUE

Table 12b: Summary of Trading Rules Developed on the 1min Data

Data Frequency	Mean	Standard Error	Median
Daily	-31.16	4.66	-34
480min	-34.42	4.80	-34
240min	-29.21	2.90	-35
60min	-27.98	1.56	-32
1min	-36.68	0.87	-41
Data Frequency	**Standard Deviation**	**Sample Variance**	**Kurtosis**
Daily	25.93	672.37	0.02
480min	47.07	2215.50	18.20
240min	42.68	1821.51	11.99
60min	41.41	1714.88	15.39
1min	39.91	1593.14	16.04
Data Frequency	**Skewness**	**Range**	**Minimum**
Daily	0.69	101	-70
480min	-2.98	426	-325
240min	1.12	482	-232
60min	-0.96	644	-394
1min	-0.98	621	-422
Data Frequency	**Maximum**	**Sum**	**Count**
Daily	31	-966	31
480min	101	-3304	96
240min	250	-6308.5	216
60min	250	-19610.5	701
1min	199	-76987.5	2099

Table 13: Head & Shoulders Profit Descriptive Statistics