Big Data Analytics of Financial Strategies

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***Abstract*—this paper first presents an evaluation of profitability of three well-known trading indicators, i.e. the Simple Moving Average (SMA), the Relative Strength Index (RSI) and the Connors Relative Strength Index (CRSI). The evaluation of different trading strategies was based on a financial time-series big data spanning from 2003 to 2013. To overcome the respective weakness and enhance the strength, ensemble approaches combining multiple trading strategies were considered to be more effective. In the literature, the 2-period RSI strategy, commonly known as RSI2, is created by combining SMA and RSI. However, it is known that RSI quite often generates false signals and whipsaws that trigger the unnecessary selling and buying. A whipsaw is when a signal to trade is reversed over a short period of time. False signals increase the probability for losses while whipsaws generate commissions that eat away at profits and test trading stamina. In this paper, an enhanced ensemble trading strategy is proposed. Different from RSI2, the proposed approach uses SMA and CRSI as two base indicators in the ensemble strategy. CRSI helps us identify the trend while simple moving average confirms the trend and indicate the most explosive part, i.e. the highest jump in price. This combination helps minimize acting on sideways movement and instead trading only when the market is showing a profitable movement. Using this in conjunction with a large portfolio set, the experimental results showed that a combination of the Connors RSI and Simple Moving Average resulted in stronger and more appropriate signals and in turn led to generate greater returns. The respective underlying indicators are also tweaked further to create an optimized strategy to maximize profits.**

I. INTRODUCTION

This study is aimed to gain in depth understanding into the performance of three technical indicators widely used in stock trading, including the Simple Moving Average (SMA) [1], the Relative Strength Index (RSI) [2], and the Connors Relative Strength Index (CRSI) [3], and to explore the possibility of developing new trading strategy to enhance the overall performance on different securities.

Simple Moving Average indicator is a widely used “trend-following indicator” that show whether a particular security is displaying an uptrend or a downtrend [2]. This is in turn used to determine whether to buy or sell the security. The biggest drawback of this strategy is that the signals are determined by current market conditions. It is seen that there is always a delay on the action (buying and selling) made using SMA.

The RSI indicator [3] is another widely used trading strategy, which measures the rate of change of a security’s price, and predict whether the price of a security is about to drop or is about to go up. The benefit of a strategy based on such an indicator is the chances of making winning trades are improved when the change of the associate stock is stable. A strategy based on the RSI indicator is, however, a riskier strategy as the trades are based on prediction. This cause the main drawback of this indicator that is it generates false signals and whipsaws.

The Connors RSI is an improved version of the RSI indicator [4]. RSI is likely to present more false signals than the Connors RSI indicator. As Connors RSI is also a predictive indicator, the same drawbacks that apply to the RSI also apply to the Connors RSI although it is at a much lower scale.

It has been proposed to use hybrid/ensemble strategy to make use of the strengths of multiple strategies and minimizes the weaknesses of the respective strategies [3].

Combining the Simple Moving Average (SMA) indicator and the Relative Strength Indicator (RSI) has been proposed in literature, which is known as the 2-Period RSI strategy (RSI2) [3]. The RSI2 strategy is based on the RSI indicator predicting a large price move and the SMA that determines the price trend. This protects the strategy from making unnecessary trades. However, the use of the RSI in conjunction with a SMA involving a relatively short look back period may result in significantly false signals. Certain stocks would require shorter look back periods such as newer stocks that haven’t been trading for a long time.

Connors RSI makes use of multiple variables to generate a value to be used in the decision-making [4]. It is more stable than RSI indicator. Connors RSI is better at generating stronger signals on detecting the direction of the stock than RSI [5]. The proposed ensemble strategy will therefor employs together the Connors RSI and the Simple Moving Average indicators. This combination is to enhance the signal it produces, with aim to reduce the false signals and whipsaws greatly due to the strength of the underlying indicators at work. They also work together to minimize their respective drawbacks.

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Financial historical big data is used to gain great insight into the profitability of those four strategies, i.e. Simple Moving Average, Connors RSI (CRSI), 2-Period Relative Strength Indicator (RSI2) and the Ensemble strategy. In this paper a time series data of 30 Exchange Traded Funds (ETFs) for the time period between 2003 and 2013 is employed for the evaluation of different trading strategies. The time series data is obtained from yahoo in JSON (JavaScript Object Notation and is formatted for analysis by obtaining the close prices of the various types of stocks (details see the methodology section).

II. Methodology

A. Sharpe ratio

The Sharpe Ratio, developed by Nobel laureate William F. Sharpe, is the measure for calculating risk-adjusted return [6]. This ratio has become the industry standard for strategy comparison. The Sharpe ratio is the average return earned in excess of the risk-free rate per unit of volatility or total risk. Subtracting the risk-free rate from the mean return, the performance associated with risk-taking activities can be isolated. One intuition of this calculation is that a portfolio engaging in "zero risk" investment, such as the purchase of U.S. Treasury bills (for which the expected return is the risk-free rate), has a Sharpe ratio of exactly zero. Generally, the greater the value of the Sharpe ratio, the more attractive the risk-adjusted return. The formula used to carry this out is:

$$\textit{Sharpe ratio} = \frac{(\textit{Mean portfolio return} - \textit{Risk free rate})}{\textit{Standard deviation of portfolio return}} \tag{1}$$

A trading strategy reaching a Sharpe ratio equal or over one is considered to be good, a Sharpe ratio of 2 or bigger is considered very good, and a Sharpe ratio of equal or over 3 is considered to be excellent.

B. Net Trading Profit/Loss

The Net Trading Profit/Loss is used to view the profits/losses suffered when implementing a particular strategy over certain period. This enables us to have a general view of the profitability of the strategy when it is applied on a particular security. The higher the profits seen during a back test could indicate that there is a greater chance of making profit when it is implemented in a real market scenario. The net trading profit/loss is determined by the difference between the final value and the initial value, as shown in formula (2).

$$NetProfit/Loss = (Price_{final} \times Shares_{final}) - (Price_{intial} \times Shares_{initial}) \tag{2}$$

C. Data & Backtesting

Data is obtained from yahoo finance using the Quantstrat R library. Further information on the use of R and Quantstrat as financial strategy formulation tools can be found from [7]. The data obtained is OHLC format which include Open, High, Low, Close prices. The Open price is the price at start of trading for a particular security on a particular day. The High price is the highest price that security will trade for on that trading day, the Low price is the lowest price that the security will trade at on that day and the Close price is the final price at the end of the trading day.

III. Strategies

The trading strategies analyzed are the Simple moving average strategy, the Connors RSI based, The RSI2 strategy and the proposed Ensemble strategy:

A. Simple Moving Average based strategy

The strategy involves buying when the stock price is showing an uptrend and selling when the stock suffers a drawdown. A version of the basic trend following strategy was made popular by a hedge fund manager in Switzerland by the name Andreas F. Clenow in his 2013 book Following the Trend [1]. The basic input of this strategy is the number of days that the moving average is calculated on. The moving average in a time-series is the average over "n" number of days. In this variant of the strategy, 2 moving averages are utilized with differing "n" values.

This difference in the look-back period results in having a fast moving average and a slow moving average. When charted, a crossover of the moving average plot results in a signal trigger that would indicate a buy or a sell signal. When the fast moving average is greater than the slow moving average, this triggers a buy signal and the system would respond by buying stocks of the associated security. When the fast moving average is less than the slow moving average this triggers a sell signal. This strategy trades both on the long and the short side of the strategy meaning we will always have a position (either long or short). We are utilizing the closing prices of stocks, where trades will always be carried out the next day [8]. The formula for the simple moving average can be described as below where 'X' is the Close price of a security at time 't' and 'n' is the number of days:

$$SMA(X,n) = \frac{\sum X_t}{n} \tag{2}$$

The strategy can then be described as follows:

To buy:

$$SMA_{fast}(X,n_1)_t > SMA_{slow}(X,n_2)_t \tag{3}$$

Where $n_1 < n_2$

To Sell:

$$SMA_{fast}(X,n_1)_t < SMA_{slow}(X,n_2)_t \tag{4}$$

Where $n_1 < n_2$

B. RSI based strategies

B.1 RSI indicator

An oscillator is a technical analysis tool that is banded between two extreme values and built with the results from a trend indicator for discovering short-term overbought or oversold condition [2]. As the value of the oscillator approaches the upper extreme value the asset is deemed to be overbought, and as it approaches the lower extreme it is deemed to be oversold.

The RSI is a technical momentum indicator that compares the magnitude of recent gains to recent losses in an attempt to determine overbought and oversold conditions of an asset . It is calculated using the following formula [2]:

$$RSI = 100 - 100/(1 + RS^*) \tag{5}$$

*Where RS = Average of x days' up closes / Average of x days' down closes.

B.2 Connors RSI

Pioneered by Laurence Connors of Connors Research LLC, the Connors RSI is an oscillator that makes use of three indicators. Two of the three components utilize the Relative Strength Index (RSI) calculations developed by Welles Wilder in the 1970s, and the third component ranks the most recent price change on a scale of 0 to 100. Taken together, these three factors form a momentum oscillator, i.e. an indicator that fluctuates between 0 and 100 to indicate the level to which a security is overbought (high values) or oversold (low values).

The three components combined in the Connors RSI are:

RSI – Standard RSI developed by Wilder. This is typically a short-term RSI. In this example it is a 3 Period RSI.

UpDown Length – The number of consecutive days that a security price has either closed up (higher than previous day) or closed down (lower than previous days). Closing up values represented in positive numbers and closing down is represented with negative numbers. If a security closes at the same price on back to back days, the UpDown Length is 0. Connors RSI then applies a short-term RSI to the UpDown Streak Value. In this example it is a 2 period RSI.

ROC – The Rate-of-Change. The ROC calculates price change percentage of price within a user-defined look-back period:

$$ROC(l) = \frac{X(t) - X(t-l)}{n} \times 100 \tag{6}$$

The CRSI calculation then is to find the average value of the three components, as defined in the formula (7):

$$CRSI(d,b,l) = \frac{[RSI(d) + RSI(UDL,b) + ROC(l)]}{3} \tag{7}$$

*Where 'd' is the period through which the standard RSI calculation is based on, 'b' is the number of days to consider for calculating the RSI on the UpDown Length and 'l' is the look back period.

The original CRSI proposed by Laurence Connors used 90 and 10 as the bounds. The experiments conducted in this study showed that using 90 and 10 as the bounds generated fewer signals that led to missed opportunities for profitable trading. In this study, 70 and 30 are used to define the upper and lower thresholds to generate signals. Lowering bounds to 70 and 30 led to an increase in the number of trading signals generated without jeopardizing the overall quality of the signals.

The signals are determined whenever the Connors RSI goes above or below a given threshold. In this example, the upper threshold is 75 and the lower threshold is 20. The rules for the CRSI strategy can be summed up as follows [3]:

To buy:

$$(CRSI(d,b,l)_t < 30) \tag{8}$$

To sell:

$$if\ (CRSI(b,d,l)_t > 70) \tag{9}$$

C. RSI2 Strategy

The RSI2 strategy makes use of the RSI and the simple moving average indicators to generate trading signals. It relies on the RSI as initially described in [2] and in the previous section. The original RSI2 strategy described by Laurence Connors and Cesar Alvarez in [3] uses 90 and 10 as the upper and lower bounds respectively. The RSI2 strategy depends on using a look back period of 2 days to generate the RSI value that is then compared with the upper and lower bounds to determine whether a trade should occur. The major trend is identified by using a long term moving average. Connors advocated for a 200 day moving average. When the close price is above its 200 day moving average it is a potential buying opportunity when it is below it is a potential selling opportunity. When coupled with the 2 period RSI, whenever the RSI is above 90 the sell trade is confirmed and a trade is initiated. When it is below 10, a buy trade is confirmed and the trade is initiated.

The rules for the RSI2 strategy are:

To buy:

$$(Close_t > SMA(Close,n)_t) \ \& \ (RSI(2)_t < 10) \quad (10)$$

To sell:

$$(Close_t < SMA(Close,n)_t) \ \& \ (RSI(2)_t > 90) \quad (11)$$

The RSI2 strategy is well known strategy and the proposed ensemble strategy borrows certain aspects.

D. The proposed Ensemble Strategy

The proposed ensemble strategy makes use of the Connors RSI and the simple moving average

The proposed ensemble strategy combines the two trading signals defined above including Simple moving average strategy and the Connors RSI strategy: whenever the close price is greater than the slow moving average and the Connors RSI is below 30, a buy signal is triggered, and whenever the close price is less than the slow moving average and the Connors RSI is above 70, a sell signal is triggered. The ensemble strategy results in stronger buy and sell signals. The strategy can be described with the diagram below:

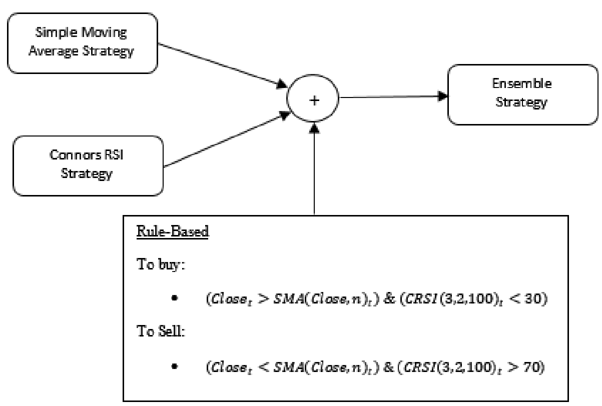

Figure 1 proposed ensemble strategy (CRSI-2)

The rules for this strategy are:

To buy:

$$(Close_t > SMA(Close,n)_t) \ \& \ (CRSI(d,b,l)_t < 30) \quad (12)$$

To sell:

$$(Close_t < SMA(Close,n)_t) \ \& \ (CRSI(d,b,l)_t > 70) \quad (13)$$

IV. EXPERIMENT RESULTS

The portfolio is comprised of Exchange Traded Funds (ETFs). These are funds that own the underlying asset which can vary from stocks, bonds, oil futures, commodities etc. The funds which the strategy is ran against are:

Table 1 : ETFs used and their descriptions

ETF Name	**ETF Description**
'XLB'	(Materials Select Sector SPDR)
'XLE'	(Energy Select Sector SPDR)
'XLF'	(Financial Select Sector SPDR)
'XLP'	(Consumer Staples Select Sector SPDR)
'XLI'	(Industrial Select Sector SPDR)
'XLU'	(Utilities Select Sector SPDR)
'XLV'	(Health Care Select Sector SPDR)
'XLK'	(Technology Select Sector SPDR)
'XLY'	(Consumer Discrete Select Sector SPDR)
RWR'	(SPDR Dow Jones REIT)
'EWJ'	(iShares MSCI Japan)
'EWG'	(iShares MSCI Germany)
'EWU'	(iShares MSCI United Kingdom)
'EWC'	(iShares MSCI Canada)
'EWY'	(iShares MSCI South Korea Capped)
'EWA'	(iShares MSCI Australia)
'EWH'	(iShares MSCI Hong Kong)
'EWS'	(iShares MSCI Singapore)
'IYZ'	(iShares US Telecommunications)
'EZU'	(iShares MSCI Eurozone)
'IYR'	(iShares US Real Estate)
'EWT'	(iShares MSCI Taiwan)
'EWZ'	(iShares MSCI Brazil Capped)
'EFA'	(iShares MSCI EAFE)
'IGE'	(iShares North American Natural Resources)

'EPP'	(iShares MSCI Pacific ex Japan)
'LQD'	(iShares iBoxx $ Invst Grade Crp Bond)
'SHY'	(iShares 1-3 Year Treasury Bond)
'IEF'	(iShares 7-10 Year Treasury Bond)
'TLT'	(iShares 20+ Year Treasury Bond).

The data used to carry out the back test of the strategies is a time series of each security obtained from yahoo finance API. The data runs from 2003 to 2013. The slow moving average look back period (n) is 100 days. The rest of the variable values are as defined in their descriptions in the previous section. The parameters used in the experiment are shown in table 1.

Table 2: Parameters used in the experiments

n	d	b	l	Risk
200	3	2	100	10%

A. Sharpe ratio analysis

They all represent assets in various sectors including T Bills, Finance and Stocks. They will represent our test portfolio. The resulting values of the Sharpe Ratios of the strategies when applied on the whole portfolio are shown in Table 2:

Table 3 The annualized Sharpe ratio of different strategies

	SMA Strategy	***Connors RSI Strategy***	***RSI2 Strategy***	***Ensemble Strategy***
Annualized Sharpe	0.6868341	0.08239905	0.7958094	0.9262463

It is shown that overall the proposed ensemble strategy performs better than all the other strategies in terms of general risk of profitability. A detailed breakdown as it applies to each of 30 securities can be seen in Table 3 and Figure 2. The results showed that the proposed ensemble approach performs best 15 securities, while RSI2 performs best on 12 securities.

Table 4 Annualized Sharp ratio of different strategies on 30 securities

ETF Ticker	SMA	CRSI	RSI2	Ensemble
EFA	1.98	10.83	6.36	8.33
EPP	4.28	4.53	6.84	8.48
EWA	3.2	1.52	6.7	5.53
EWC	2.1	6.34	5.52	11.08
EWG	2.92	3.05	5.11	8.5
EWH	3.3	0.81	7.65	10.13
EWJ	0.25	1.37	0.92	1.17
EWS	3.71	2.23	6.78	5.32
EWT	-1.19	3.96	4.77	4.37
EWU	2.32	1.84	7.34	7.37
EWY	1.98	-0.47	8.21	9.85
EWZ	3.57	6.15	6.74	6.33
EZU	1.71	8.36	6.32	11.34
IEF	3.31	-0.68	6.91	2.13
IGE	2.24	5.86	8.11	6.33
IYR	2.87	1.44	10.83	12.51
IYZ	2.65	0.53	17.06	8.9
LQD	0.84	-0.97	7.9	5.16
RWR	2.68	4.55	10.69	13.52
SHY	5.57	3.79	7.28	7.29
TLT	3.97	0.12	7.1	2.87
XLB	3.19	10.61	9.19	6.37
XLE	3.47	3.57	8.77	5.94
XLF	2.73	3.29	7.3	1.56
XLI	4.31	10.5	20.01	9.99
XLK	0.73	6.53	4	0.81
XLP	4.76	6.02	9.73	13.94
XLU	4.1	2.22	22.45	9.47
XLV	0.1	5.52	0.93	0.68
XLY	-1.04	3.67	9.26	3.96

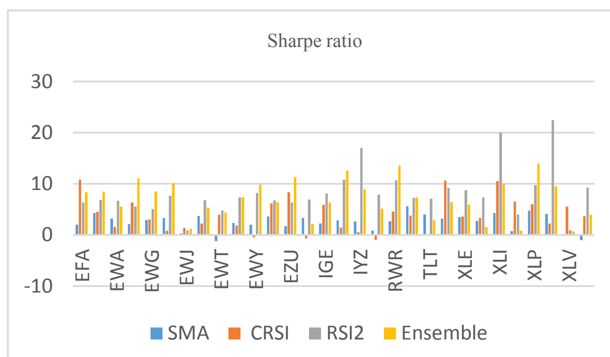

Figure 2 Sharp ratio of different strategies on 30 securities

The proposed Ensemble strategy outperforms the Connors RSI strategy, the simple moving average strategy, as well as the RSI2 strategy in terms of general risk based returns and individually on each security.

B. Net Profit/Loss analysis

The net profit/loss for 30 securities of all four strategies is presented in Table 4 and Figure 3. It shows that the Ensemble strategy, in general, gets better returns than the other strategies after applying a risk of 10%.

Table 4 : Net Profit/Loss of 30 strategies

ETF Ticker	SMA	CRSI	RSI2	Ensemble
EFA	13847.8	6863.78	76645.43	103704.2
EPP	32806.79	5520.78	121543	102030.6
EWA	22386.3	1530.35	96326.84	83944.79
EWC	17813.49	5452.62	82158.67	72100.11
EWG	22394.86	3288.41	79321.2	94098.37
EWH	15088.36	1141.05	82193.11	70198.66
EWJ	7093.68	1226.99	20767.77	48870.32
EWS	10744.85	2468.17	67865.55	82809.09
EWT	-385.24	3508.23	19409.24	55168.01
EWU	11271.8	1196.85	69080.18	69525.65
EWY	12418.71	-667.37	67563.54	70521.66
EWZ	25703.09	4948.02	70376.59	123162.7
EZU	15366.59	5052.42	77731.92	85991.11
IEF	28314.92	-949.62	44108.19	62184.76
IGE	16528.36	6668.35	103578.6	73266.65
IYR	18505.4	1731.57	74130.08	75705.36
IYZ	9938.46	707.74	71364.45	40140.44
LQD	2121.06	-1147.15	68437.06	72384
RWR	21662.27	4353.98	72280.42	76881.39
SHY	45166.07	2687.43	184503.2	206568.9
TLT	15567.32	149.58	27048.04	72191.31
XLB	10454.09	7130.97	60680.83	73917.85
XLE	22004.13	4046.28	112002.8	104079.1
XLF	15845.99	1951.94	50034.04	76662.78
XLI	18206.52	6757.57	76472.83	108011.9
XLK	6016.85	4548.31	24962.01	56796.59
XLP	23438.64	3943.15	117741.8	86651.7
XLU	20018.73	1862.94	71329.5	79365.51
XLV	24191.84	4280.78	60421.74	72368.15
XLY	16349.64	3607.16	65220.89	94373.63

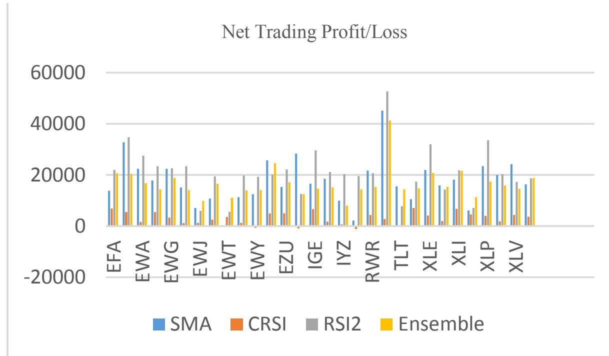

Figure 3 Graph showing Net profit/loss distribution

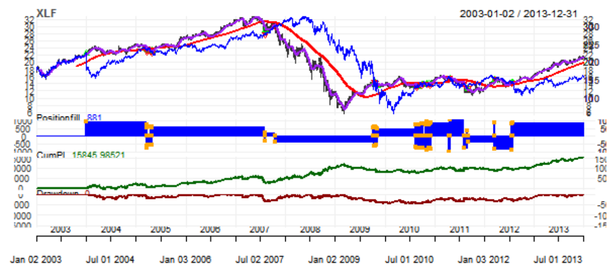

Figure 4 SMA strategy performance on XLF stock

Figure 4 shows the simple moving average based strategy in action. The red plot line shows the 200 day moving average, the black plot is the Close prices. The blue plot is a lag of the close prices. The position fill graph is used to show when a position was entered.

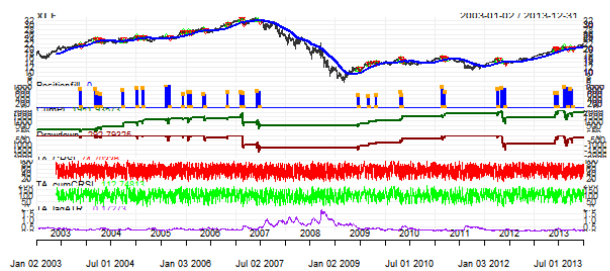

Figure 5 Connors RSI performance on XLF stock

Figure 5 shows the close prices of the XLF stock from 2003 to 2013. The green plots are the Connors RSI values that are used to identify trading opportunities. The red plot is the cumulative Connors RSI plot. i.e a running sum of 4 Connors RSI values. The purple plot is the actual true range (ATR) plot. This can be used to show highly volatile points. During the 2008 financial crisis the ATR value spikes.

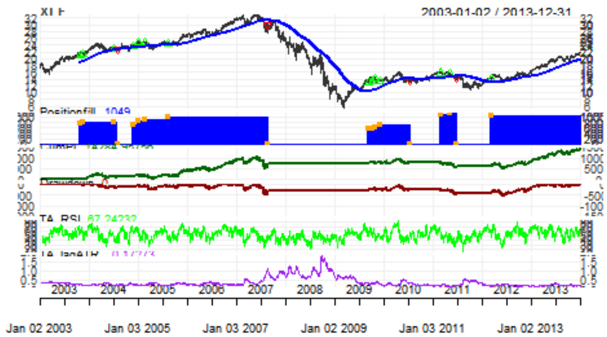

Figure 6 RSI2 performance on XLF stock

Figure 6 shows the close prices of XLF stock from 2003 to 2013. The green plot is the RSI value used to determine entry and exit signals.

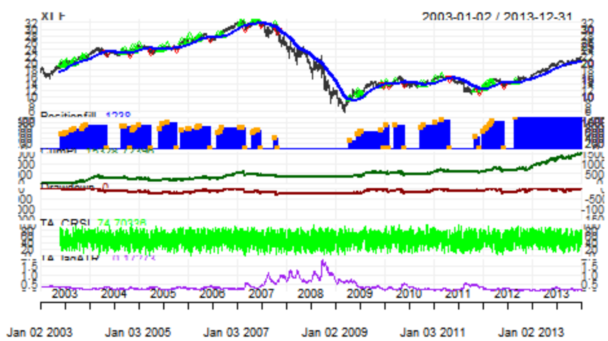

Figure 7 Ensemble performance on XLF stock

Figure 7 shows the close prices of XLF stock from 2003 to 2013. The green plot refers to the Connors RSI values used to generate trading signals.

Figures 4 – 7 present the trading history of XLF stock using the four strategies respectively. In all the graphs, the dark green plot represents the cumulative profit/loss of the strategy on the stock. The dark red plot represents the drawdown the stock suffered during the implementation of the strategy. A drawdown is a decline in value of that particular investment over the period of time i.e. from 2003 to 2013.

It is seen that overall the Ensemble strategy bests both the Connors RSI and the Simple Moving average strategy on the net profits over our test period although the Simple Moving average strategy has potential for profit making. Furthermore, what makes the ensemble strategy more attractive is that it never makes a loss.

C. Conclusion and future work

This paper presents evaluation of three strategies (Simple Moving Average, Relative Strength Indicator and Connors RSI) and proposed an ensemble strategy. Using big data of 30 securities spanning between 2003 and 2013, it shows that the Ensemble strategy generates stronger signals on when to trade thus results in better Sharpe ratio and better profits per trade compared to other strategies. This provides evidence that combining multiple indicators creates stronger strategies than relying on individual indicators. In the future development it is planned to integrate more strategies into the big data analytics framework, and develop optimization approach to real-timely adjust the parameters in order for maximize the probability and reducing the risk of loss.

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