Available online at www.sciencedirect.com

ScienceDirect

Procedia Computer Science 36 (2014) 240 – 245

Procedia Computer Science

Complex Adaptive Systems, Publication 4
Cihan H. Dagli, Editor in Chief
Conference Organized by Missouri University of Science and Technology
2014-Philadelphia, PA

TN-RSI: Trend-Normalized RSI indicator for Stock Trading Systems with Evolutionary Computation

Ugur Sahin, A.Murat Ozbayoglu*

TOBB University of Economics and Technology, Department of Computer Engineering, Ankara, 06560, Turkey

Abstract

RSI is a commonly used indicator preferred by stock traders. However, even though it works well when the market is trendless, during bull or bear market conditions (when there is a clear trend) its performance degrades. In this study, we developed a trading model using a modified RSI using trend-removed stock data. The model has several parameters including, the trend detection period, RSI buy-sell trigger levels and periods. These parameters are optimized using genetic algorithms; then the trading performance is compared against B&H and standard RSI indicator usage. 9 different ETFs are selected for evaluating trading performance. The results indicate there is a performance improvement both in profit and success rates using this new model. As future work, other indicators might be modelled in a similar fashion in order to see if it is possible to find one indicator that can work under any market condition.

Peer-review under responsibility of scientific committee of Missouri University of Science and Technology

Keywords: stock market forecasting; RSI; genetic algorithms; stock trading; evolutionary computation; trend detection

1. Introduction

Stock market forecasting and trend detection is among the areas of high interest both to finance professionals and stock market researchers, since almost everybody, one way or another, has a level of interest to be able to select the right stocks, and/or right time to buy/sell stocks [4]. Market professionals and traders use several different technical analysis indicators for either detecting the trend and/or identifying buy/sell points [8,9]. Soft computing methods such as neural networks[9], fuzzy logic[10], genetic algorithms [11] or hybrid models [12] were among different methodologies researchers chose in order to predict the stock price movement, trend detection and/or buy/sell trigger points for stock trading.

* Corresponding author. Tel.: +90-312-292-4073; fax: +90-312-292-4180.
E-mail address: mozbayoglu@etu.edu.tr

Peer-review under responsibility of scientific committee of Missouri University of Science and Technology
doi:10.1016/j.procs.2014.09.086

RSI is perhaps, the most commonly used technical indicator due to its simplicity and performance [5]. However, its performance is not uniformly distributed throughout the selected time horizon. Even though it performs remarkably well during trendless markets, the performance diminishes when there is a clear trend. However, most people still keep using RSI blindly under those circumstances.

In this study, our main motivation was to create an environment where RSI would perform uniformly and stable, hopefully with a consistent success, under any market condition. In order to do that we introduced a new RSI indicator, TN-RSI (trend-normalized RSI), that would take the advantage of RSI's good performance in trendless markets without worrying how the trend will change.

The structure of this paper is as follows. Next section will provide a brief introduction to Genetic Algorithms (GA). GA will be used to optimize the TN-RSI parameters used in the model. Section 3 will give details about the proposed TN-RSI model and how it is paired against traditional RSI and uptrend and downtrend RSI. Results of the optimized TN-RSI model used with several different ETFs can be seen in Section 4. Finally we conclude and provide some discussions and future work in the last section.

2. Genetic Algorithm (GA)

Genetic algorithm is a widely used evolutionary algorithm using the features of the well-known Theory of Evolution [4]. The search space is represented as a population of chromosomes consisted of genes. Each chromosome is a candidate solution to the problem and each gene in these chromosomes is a parameter to the solution. The chromosome qualities are evaluated with a fitness function. The fitness function is problem specific and it reflects the performance of a chromosome. The algorithm creates generations with evolution methods and each generation evolves into another generation. Evolution methods used to create new generations are selection, crossover and mutation. Selection is the process of choosing chromosomes as parents. After the selection process, crossover and mutation operations are performed on the selected parents. Crossover operation takes parent chromosomes and swaps some genes between them to create child chromosomes. The mutation operator is used to change a selected gene in a chromosome.

The population of the algorithm is also important in terms of finding better solutions and time complexity. Increasing the size of the population increases the probability of finding a better solution, however, it also increases the time complexity of the algorithm exponentially. In our study, the size of the population is selected as 1000. To improve the quality of the selection process we used 0.1 elitism rate. The crossover rate is selected as 0.7 and the mutation rate is selected as 0.02. And the profit from the parameters of a chromosome is selected as the fitness function. At each trade, %0.1 of the capital is paid for trade commission.

We used genetic algorithm to optimize the normal RSI indicator and Trend-Normalized RSI indicator. We compared the results against Buy & Hold (B&H) and the generally used 30-70 RSI indicator.

3. The Proposed TN-RSI Model

In this section, the details of the proposed model are provided. First, the trend-normalization process with linear regression is described. Then, the RSI indicator for normal and trend-normalized prices are explained. Downtrend/uptrend analysis are also given.

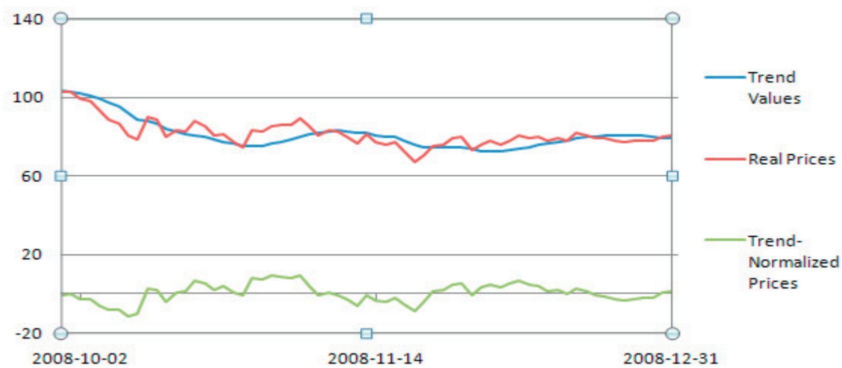

Figure 1 Trend, real prices and trend-normalized prices (for 20-day period) of SPY between 30.09.2008 and 31.12.2008

3.1. Trend-Normalization

A trend is a direction of price moves in a market in a given period. Downtrend is the trend moving downwards, also called bear market, and uptrend is the trend moving upwards, also called bull market. Some indicators including RSI try to find buy and sell signals according to the price moves [2,5]. However, RSI indicator has inferior performance in a downtrend. The problem is generally occurs when a buy signal is created in a bear market. Because of the downtrend, the sell signal couldn't be obtained in the right time and the prices go lower and this ends up with a loss.

Some studies on RSI indicator are conducted on downtrend and uptrend to produce different rules for different trends [1,6]. These studies show that different rules for different trends give better results than one rule. However, how the uptrend and downtrend calculated effects the performance of these rules. Also the calculation to produce different rules increases time complexity.

In this study, we normalized the trend using linear regression. Linear regression is used to find the trend line and function (Equation 3), then the real values (y) are normalized by subtracting the trend value ($\hat{y}$) from the real value of the ETF (Figure 1).

Also, the trend is re-calculated every day to smooth the normalization process. The linear regression formula used in this study is:

$$b_1 = \frac{\sum_{i=1}^{n}(x_i - \overline{x})(y_i - \overline{y})}{\sum_{i=1}^{n}(x_i - \overline{x})^2} \quad (1)$$

$$b_0 = \overline{y} - b_1\overline{x} \quad (2)$$

$$\hat{y}_i = b_0 + b_1 x_i \quad (3)$$

3.2. Downtrend and Uptrend Analysis for RSI Indicator

Working on the RSI parameters without considering the trend moves is a risky behavior as RSI value pattern is not the same for downtrend and uptrend. Widely used 14-day and 30-70 threshold RSI rule works very well in a trendless or a bull market [5]. As the market's expected move is upwards, this simple RSI rule works well. However, when the market enters into a downtrend, the simple RSI rule starts failing. Using any algorithm, if the historical data is not consistent with the current data, the RSI parameters produced from training data will fail because of the different trend pattern. Therefore, the trend should be considered for properly producing the RSI rules. We used genetic algorithm to analyze downtrend and uptrend performances of the RSI indicator on ETFs. And finally, we compare the results of RSI, uptrend / downtrend RSI and Trend-Normalized RSI.

Also we chose to use ETFs instead of single stocks in order to be more resilient to unpredictable company-specific events that might effect the trading performance. As a result we assume to have smoother (less volatile) prices with ETFs compared to stocks.

In this study, we used Simple Moving Average (SMA) to determine the trend direction. We calculated SMA(50) and SMA(200) of the data points and if SMA(50) surpasses SMA(200), we marked the data in an uptrend and if SMA(200) surpasses SMA(50) the data point is marked in a downtrend. After analyzing the RSI data, we also propose a general RSI indicator for Trend-Normalized RSI as 14-day RSI period and 25-65 thresholds. We provide results for this general rule in the results section.

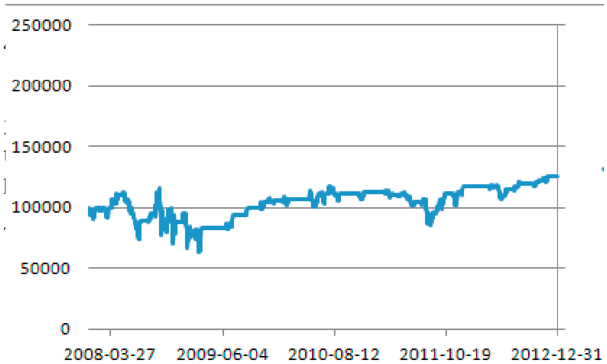

Figure 2 RSI test performance of XLF

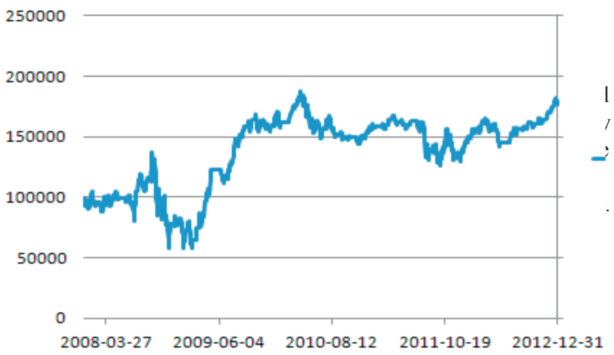

Figure 3 TN RSI test performance of XLF

Table 1Parameters resulted from GA for XLF.

Parameter	*Value*
RSI buy period	*6*
RSI buy signal threshold	*26*
RSI sell period	*8*
RSI sell signal threshold	*59*
TN RSI buy period	*5*
TN RSI buy signal threshold	*29*
TN RSI sell period	*5*
TN RSI sell signal threshold	*82*
TN RSI trend period	*22*

Table 2 Performance of the XLF (U = Uptrend, D = Downtrend, TN = Trend-Normalized)

XLF PERFORMANCE						
			Total Profit (%)		Annual Profit (%)	
			Training	Test	Training	Test
RSI			111.67	24.88	15.95	4.98
RSI downtrend			76.47	5.52	10.92	1.10
RSI uptrend			42.20	9.33	6.02	1.87
RSI U + D	150.96	15.36	21.57	3.07		
TN RSI	120.54	79.38	17.22	15.88		
RSI 30-70	15.67	-13.53	2.24	-2.71		
TN 25-65	33.46	11.59	4.78	2.32		
Buy & Hold	17.33	-35.59	2.47	-7.12		

Trade profit performances of RSI, uptrend and downtrend RSI, Trend-Normalized RSI and Buy&Hold method on 9 different ETFs are shown in Table 3. The table illustrates the total profit and the annual profit of training and test.

Table 3 Profit comparison of RSI, RSI D&U (Downtrend & Uptrend), Trend-Normalized RSI and Buy & Hold (Tot. P. = Total Profit (%), Ann. P. = Annual Profit (%), Trn. = Training)

	RSI				RSI Downtrend&Uptrend				Trend-Normalized RSI				Buy&Hold			
	Tot. P. (%)		Ann. P. (%)		Tot. P. (%)		Ann. P. (%)		Tot. P. (%)		Ann. P. (%)		Tot. P. (%)		Ann. P. (%)	
	Trn.	Test	Trn.	Test	Trn.	Test	Trn.	Test	Trn.	Test	Trn.	Test	Trn.	Test	Trn.	Test
SPY	106.6	7.1	15.2	1.4	186.6	-14	26.6	-2.8	87.7	65.5	12.5	13.1	27.7	9.6	4	1.9
QQQ	61.1	9.9	8.7	1.9	133.1	20.5	19	4.1	121.6	33.7	17.4	6.7	-2.3	34.5	-0.3	6.9
XLF	116.8	2.0	23.4	0.4	150.9	15.3	21.5	3.1	96.5	17.3	13.8	3.5	17.3	-36	2.5	-7.1
IWM	156.7	2.3	22.4	0.5	226.6	32.7	32.3	6.5	251.8	79	36	15.8	77.9	20.9	11.1	4.2
EWH	193.7	-0.4	27.7	-0.1	384.8	-0.4	55	-0.1	281.4	-7.2	40.2	-1.4	128.7	4.3	18.4	0.9
MDY	148.4	44.1	21.2	8.8	167.1	40.2	23.9	8	227.5	49	32.5	9.8	83.3	28.2	11.9	5.6
XLE	217.8	31.3	31.1	6.3	390.4	38.9	55.8	7.8	365.8	-24	52.9	-4.8	165.9	-2.2	23.7	-0.4
EWT	128.1	-28	18.3	-5.6	287.2	13.1	41	2.6	324.1	6.2	46.3	1.2	51.3	12.3	7.3	2.5
EWZ	538.4	-11	76.9	-2.2	1083	-20	154.8	-4	1029	-4.4	147	-0.9	466.7	-17	66.7	-3.4

Trade profit performances of 14-Day RSI 30-70 rule, proposed 14-Day TN RSI 25-65 rule, Trend-Normalized RSI of GA and Buy&Hold method on 9 different ETFs are illustrated in Table 4.

Table 4 Profit comparison of 14-Day RSI 30-70 rule, proposed 14-Day TN RSI 25-65 rule, TN RSI of GA and Buy&Hold (TN = Trend-Normalized, Tot. P. = Total Profit (%), Ann. P. = Annual Profit (%), Trn. = Training)

	14-Day RSI 30-70				14-Day TN RSI 25-65				Trend-Normalized RSI				Buy&Hold			
	Tot. P. (%)		Ann. P. (%)		Tot. P. (%)		Ann. P. (%)		Tot. P. (%)		Ann. P. (%)		Tot. P. (%)		Ann. P. (%)	
	Trn.	Test	Trn.	Test	Trn.	Test	Trn.	Test	Trn.	Test	Trn.	Test	Trn.	Test	Trn.	Test
SPY	4.1	-2.7	0.6	-0.5	7.4	31	1.1	6.2	87.7	65.5	12.5	13.1	27.7	9.6	4	1.9
QQQ	-20.1	8.7	-2.9	1.7	50.4	30.8	7.2	6.2	121.6	33.7	17.4	6.7	-2.3	34.5	-0.3	6.9
XLF	15.7	-13	2.2	-2.6	33.5	11.6	4.8	2.3	96.5	17.3	13.8	3.5	17.3	-36	2.5	-7.1
IWM	10.5	73.5	1.5	14.7	45	26.3	6.4	5.3	251.8	79	36	15.8	77.9	20.9	11.1	4.2
EWH	5.4	-8.6	0.8	-1.7	19.9	-3.7	2.8	-0.7	281.4	-7.2	40.2	-1.4	128.7	4.3	18.4	0.9
MDY	22.4	-1.5	3.2	-0.3	27.2	24.1	3.9	4.8	227.5	49	32.5	9.8	83.3	28.2	11.9	5.6
XLE	55.9	2.9	8	0.6	-1.9	28.1	-0.3	5.6	365.8	-24	52.9	-4.8	165.9	-2.2	23.7	-0.4
EWT	44.6	-35	6.4	-7	1.7	17.3	0.2	3.5	324.1	6.2	46.3	1.2	51.3	12.3	7.3	2.5
EWZ	-11.9	-14	-1.7	-2.8	28,4	76.9	4.1	15.4	1029	-4.4	147	-0.9	466.7	-17	66.7	-3.4

Tables 5 and 6 provide further detailed statistics about the trading performances of RSI, uptrend and downtrend RSI, Trend-Normalized RSI and Buy&Hold method (Table 5), 14-Day RSI 30-70 rule, proposed 14-Day TN RSI 25-65 rule, Trend-Normalized RSI of GA and Buy&Hold performances (Table 6) on 9 different ETFs.

Table 5 Performance comparison of RSI, RSI D&U (Downtrend & Uptrend), Trend-Normalized RSI and Buy & Hold (TDD = trade drawdown, TP = trade profit, PDD = investment drawdown, PV = Investment value)

	RSI					RSI Downtrend & Uptrend					Trend-Normalized RSI				
	Max TDD	Avg TP	Max TP	Max PDD	Max PV	Max TDD	Avg TP	Max TP	Max PDD	Max PV	Max TDD	Avg TP	Max TP	Max PDD	Max PV
SPY	-26.3	9.6	45.5	73.6	107.1	-32.5	-0.4	9.1	67.5	100.0	0.0	65.7	65.7	100.0	165.7
QQQ	-34.7	0.6	9.5	62.1	116.4	-30.1	0.7	8.0	71.8	122.0	-21.4	1.1	20.0	78.7	143.5
XLF	-21.6	0.3	10.1	73.4	108.9	-19.5	0.5	13.0	75.3	121.7	-39.8	1.6	48.9	41.5	117.3
IWM	-31.4	0.5	17.4	58.9	105.0	-20.9	1.2	13.8	68.7	139.5	-20.4	1.3	18.3	86.6	179.0
EWH	-32.8	0.8	43.3	50.8	100.0	-21.7	0.3	8.7	82.1	114.6	-21.5	0.1	12.5	64.5	100.0
MDY	-27.3	1.2	20.5	66.5	145.1	-29.1	0.8	21.5	73.9	140.2	-28.1	1.4	21.6	58.2	149.0
XLE	-13.9	0.6	7.8	75.9	132.2	-13.9	0.8	13.8	78.9	141.4	-23.1	-0.1	22.9	59.0	106.8
EWT	-33.3	-0.6	11.5	63.2	107.1	-39.5	0.8	26.1	63.2	129.6	-15.6	0.5	26.5	98.6	137.0
EWZ	-59.9	2.4	29.6	48.8	121.8	-48.4	0.5	20.4	44.7	121.7	-48.3	2.5	59.7	53.8	126.6

Table 6. Performance comparison of 14-Day RSI 30-70 rule, proposed 14-Day TN RSI 25-65 rule, TN RSI of GA and Buy&Hold (TDD = trade drawdown, TP = trade profit, PDD = investment drawdown, PV = Investment value)

	14-Day RSI 30-70						14-Day TN RSI 25-65					
	Max TDD	Avg TP	Max TP	Max PDD	Max PV	Std. D. TP	Max TDD	Avg TP	Max TP	Max PDD	Max PV	Std. D. TP
SPY	-37.0	0.8	10.4	60.7	107.1	13.1	-6.8	2.9	8.6	93.1	131.0	4.4
QQQ	-30.1	2.3	12.3	71.8	116.4	11.4	-3.5	2.2	7.3	98.2	135.9	3.1
XLF	-36.1	-0.2	15.4	57.3	108.9	12.8	-4.9	1.6	10.2	97.0	111.5	4.6
IWM	-10.8	4.0	13.5	95.8	105.0	6.6	-16.6	2.1	33.9	100.0	137.1	11.0
EWH	-38.1	0.3	14.7	59.1	100.0	12.3	-7.6	0.0	5.0	94.8	109.1	4.7
MDY	-33.4	0.8	10.8	66.3	145.1	12.6	-15.0	2.1	11.3	100.0	130.1	6.6
XLE	-41.0	1.4	11.2	63.7	132.2	13.3	-5.1	3.5	14.5	96.0	134.3	7.8
EWT	-45.0	-2.6	12.8	54.9	107.1	16.1	-8.0	2.2	9.4	96.4	117.3	5.1
EWZ	-49.2	0.6	15.2	54.1	121.8	15.1	-11.2	8.2	33.0	100.0	177.8	13.4

From these results, it can be observed that normalizing the trend and finding the technical parameters accordingly helps in achieving better performance when compared to traditional RSI methods and Buy & Hold.

5. Conclusions

Trend-Normalized RSI optimization and a general RSI rule to use with this new indicator is proposed and the results are shown. The RSI indicator alone is vulnerable against trend direction, especially in downtrend. We also analyzed the downtrend and uptrend RSI and the results are slightly better than normal RSI. However, deciding the trend direction and analyzing two different trend data bring extra complexity. To exclude the effects of trend we proposed a trendless way to perform the RSI. The results show that under good market conditions (trendless or bull market) classic RSI performs well, however, it is vulnerable to trend changes. The training period (2001 January to 2007 December) and the test period (2008 January to 2012 December) has different trend patterns for ETFs and the results show that the profit from normal RSI and downtrend & uptrend RSI are very volatile against trend changes. Our proposed model shows that the profit from Trend-Normalized RSI is not very volatile and the profits are achievable. Also our proposed general Trend-Normalized rule performs better than general RSI rule and the profits are consistent with different trend patterns.

In future work, the additional parameters to be optimized (trend slope, period, etc) can be included to the study. Also the deciding rule for trend directions can be examined. At the same time indicators similar to RSI can be tested with this trend-normalization approach to see if these results can be generalized for other indicators.

Nomenclature

RSI: Relative Strength Index
SMA: Simple Moving Average
ETF: Exchange-Traded Fund
SPY: SPDR (Standard & Poor's Depositary Receipts) S&P 500 Trust
QQQ: PowerShares QQQ Trust
XLF: Financial Select Sector SPDR ETF
IWM: iShares Russell 2000
EWH: iShares MSCI Hong Kong
MDY: SPDR S&P MidCap 400
XLE: Energy Select Sector SPDR ETF
EWT: iShares MSCI Taiwan
EWZ: iShares MSCI Brazil Capped

References

1. Mustafa Ucar, Ilknur Bayram, A. Murat Ozbayoglu, A Two-level Cascade Evolutionary Computation based Covered Call Trading Model, Procedia Computer Science, Volume 20, 2013, Pages 472-477
2. J. Welles Wilder, New Concepts in Technical Trading Systems, 1978
3. Atsalakis, George. S., Valavanis, Kimon, P., “Surveying stock market forecasting techniques – Part II: Soft computing methods”, Expert Systems with Applications, vo 36, pp. 5932-5941, 2009.
4. Goldberg, David (1989). Genetic Algorithms in Search, Optimization and Machine Learning. Reading, MA: Addison-Wesley Professional. ISBN 978-0201157673.
5. Darrell R. Jobman, Handbook of Technical Analysis: A Comprehensive Guide to Analytical Methods, Trading Systems and Technical Indicators, McGraw-Hill, Nov 1994.
6. A.M. Ozbayoglu, U. Erkut, Stock Market Technical Indicator Optimization by Genetic Algorithms, Intelligent Engineering Systems through Artificial Neural Networks vol 20, pp. 589-596 pp., St. Louis, MO, Nov 2010.
7. Alejandro Rodríguez-González, Ángel García-Crespo, Ricardo Colomo-Palacios, Fernando Guldrís Iglesias, Juan Miguel Gómez-Berbís, CAST: Using neural networks to improve trading systems based on technical analysis by means of the RSI financial indicator, Expert Systems with Applications 38 (2011) 11489–11500.
8. Depei Bao, Zehong Yang, Intelligent stock trading system by turning point confirming and probabilistic reasoning, Expert Systems with Applications 34 (2008) 620–627.
9. Thira Chavarnakul, David Enke, Intelligent technical analysis based equivolume charting for stock trading using neural networks, Expert Systems with Applications 34 (2008) 1004–1017.
10. Pei-Chann Chang, Chen-Hao Liu, A TSK type fuzzy rule based system for stock price prediction, Expert Systems with Applications 34 (2008) 135–144.
11. Stephanos Papadamou, George Stephanides, Improving technical trading systems by using a new MATLAB-based genetic algorithm procedure, Mathematical and Computer Modelling 46 (2007) 189–197.
12. Yung-Keun Kwon, Byung-Ro Moon, A Hybrid Neurogenetic Approach for Stock Forecasting, IEEE Transactions on Neural Networks, Vol 18, No 3, May 2007, 851-864.