Designing Financial Market Intelligent Monitoring System Based On OWA

BENJAMIN FONOONI, SEIED JAVAD MOUSAVI MOGHADAM
Artificial Intelligence Alternative Solutions Lab, Tehran
IRAN

Abstract: The need for intelligent monitoring systems for financial markets especially Foreign Exchange has become a necessity to keep track of this market. Financial markets conform to some mathematical concepts and cause it to be analyzed with different Artificial Intelligence (AI) algorithms. Data Fusion has been applied in different fields and the corresponding applications utilize numerous mathematical tools. This paper headed for applying Ordered Weighted Averaging (OWA) operator in order to support trading decisions based on technical analysis in Foreign Exchange Market.

Key-Words: Decision Making, Data Fusion, OWA, Computational Finance, Financial Markets Analysis, Foreign Exchange

1 Introduction

Technical analysis has been a part of financial practice for many decades. It attempts to understand the emotions in the market by studying the market itself, as opposed to its components and assumes that certain chart formations can indicate market psychology about either an individual stock or the market as a whole at key points. It is suggested by several academic studies that technical analysis may well be an effective means for extracting useful information from market prices [2].

Technical analysis is widely used among traders and financial professionals, and some studies say its use is more widespread than is fundamental analysis in the foreign exchange market [5], [12].

Technical analysts identify non-random price patterns and trends in financial markets and attempt to exploit those patterns [11] by using various methods and tools. Technicians especially search for archetypal patterns, such as head and shoulders, and also study such indicators as price, volume, and moving averages of the price.

They use judgment gained from experience to decide which pattern a particular instrument reflects at a given time, and what the interpretation of that pattern should be.

A trader has in mind the task of developing a trading system that optimizes some profit criterion, the simplest being the total return. A trading system is governed by a set of rules that do not deviate based on anything other than market action. The system operate within the parameters known by the trader comes from tools and indicators. The parameters can be trusted based on historical analysis and real world market studies, so that the trader who is familiar with the trading strategy and its operating characteristics can have confidence in a pre-determined trading strategy.

A trading strategy can automate all or part of investment portfolio. Computer trading models can be adjusted for either conservative or aggressive trading styles.

The proposed algorithm formed based on the fact that all technical analysts fuse information to determine next market trend.

Data fusion is the process of combining data or information to estimate or predict entity states and involves combining data in the broadest sense to estimate or predict the state of some aspect of the universe. Often the objective is to estimate or predict the physical state of entities including their identity, attributes, activity, location, and motion over some past, current, or future time period [10]. This project utilizes data fusion concepts in order to help technical analysts make better trading decisions by integrating information perceived from current market state involving some indicators values and price patterns.

The use of data fusion in Forex Market would be integrating data and knowledge from different indicators and price patterns with the aim of maximizing the useful information. It improves reliability or discriminant capability while offering the opportunity to minimize the data retained.

2 Overview on OWA

Data Fusion is the process of combining data and

knowledge from different sources with the aim of maximizing the useful information content [1]. Data Fusion algorithms has been categorized into several categories [10]. Among all these approaches, OWA chose which discussed in the following paragraph.
Ordered weighted averaging (OWA) operators were introduced by Yager [16].
An OWA operator of dimension n is a mapping $f:[0,1]^n \rightarrow [0,1]$, which has an associated weighting vector

$\boldsymbol{W} = (w_1, \ldots, w_n)^t$, s.t.

$$\sum_i w_i = 1,\ w_i \in [0,1] \quad (1)$$

and where

$$f(x_1,\ldots,x_n) = \sum_i w_i x_{k_i} \quad (2)$$

The vector $\boldsymbol{K} = (k_1, \ldots, k_n)^t$ is such permutation of $(1, 2, \ldots, n)^t$ that x_{k_i} is the ith largest element in $(x_1, \ldots, x_n)^t$. The fundamental aspect of the OWA operator is that a particular weight w_i is associated with a particular ordered position i of the arguments. OWA operators include min, max, and arithmetic mean for the appropriate choice of vector $\boldsymbol{W}$.
Yager introduced a measure to characterize the type of aggregation performed by OWA operators. He calls it the *orness measure*. It is defined as:

$$\text{Orness(w)} = \frac{1}{n-1}\sum_{i=1}^{n}(n-i)w_i \quad (3)$$

It can be shown that orness of max operator is 1, orness of min operator is 0, and orness of the arithmetic mean is 0.5. Orness of other OWA operators lies in the unit interval. The measure of orness is used frequently as an additional constraint when determining weights of the operator.
One of the main concerns in using OWA operator is how to obtain weights vector. There are several approaches introduced by Yager and other people [6], [7], [8], [9]. In the next section this issue is discussed in details.

3 Decision Making Algorithm

Suggested algorithm needs to specify a set of attributes for each goal which has to be assigned by a user. Set of attributes includes values from different indicators which have to be chosen depending on trading strategy. The cause of choosing each indicator is discussed in Table 1 and their desired values are listed in Table 2. According to data fusion rules, some of these values can not be used directly and need to be feature extracted in order to have optimized fusion results. These values are considered as collection of aggregated objects in the unit interval, a_i, which has to be ordered and stored in decision table. In case of using OWA operator in decision making algorithm, a weighting vector $\boldsymbol{W}$ should be defined and initialized. The vector $\boldsymbol{W}$ is indicating which aggregated object has more priority over the others and must be in more attention. The main question would be obtaining the weights associated with OWA, because it models process of aggregation used on data set.
Back propagation method is used to learn from agent's observations [3], [6]. Suggested algorithm is described below:
1) Each aggregated value will be calculated by classic Hurwicz's multi-attribute method and is considered as desired value:

$$\rho\,\text{Max}_i\, a_i + (1-\rho)\,\text{Min}_i\, a_i = d \quad (4)$$

Where ρ is Agent's measure of pessimism.

2) Following learning algorithm should be applied to estimate the corresponding weights:

$$\lambda_i(l+1) = \lambda_i(l) - \beta w_i (b_{k_i} - \hat{d}_k)(\hat{d}_k - d_k) \quad (5)$$

$$w_i = \frac{e^{\lambda_i(l)}}{\sum_{j=1}^{n} e^{\lambda_j(l)}} \quad (6)$$

$$\hat{d}_k = b_{k_1}w_1 + b_{k_2}w_2 + \cdots + b_{k_n}w_n \quad (7)$$

Where β is Learning rate and $\hat{d}_k$ is Current estimation of d_k. Parameters λ_i determine the OWA weights and are updated with back propagation of the error ($\hat{d}_k - d_k$).

Finally, after 20000 iterations, the best $\hat{d}_k$ with the nearest value to buy or sell desired values will be chosen and delegated to the output system in order to be considered as an entry point. The next step is to determine the exit point which can be handled with same or different strategy. In our study we did not determine the exit points based on our system, therefore by choosing proper *Take Profit* and *Stop Loss* we cut losses short and let our winners run longer to increase overall trading profitability. The value of ρ could be interpreted as a measure of the agent's *pessimism*. In fact, if $\rho \rightarrow 1$, the agent should tend to pay greater attention to the minimum value of the attributes, whereas if $\rho \to 0$, agent should consider mainly the maximum value of the attributes [4]. Author has to set a proper value for ρ according to the agent's risk tolerance. In general, values less than 0.5 is used for an agent with more risk tolerance and values greater than 0.5 for the opposite. Because the suggested algorithm relies on chosen trading strategy, selecting one which has applied indicators values and bounded to be used only in a specific timeframe is important. As a typical day trading strategy this system based on the combination of output parameters of four different indicators which monitors different aspects of price move. The occurrence of Sell or Buy desired value signals the potential Sell or Buy position.

Table 1. Indicators List

INDICATOR	USAGE
Relative Strength Index (RSI)	Compares the magnitude of recent gains to recent losses in an attempt to determine overvalued and undervalued conditions.
Bollinger Bands Width Ratio (BBWR)	Checking if price action of an issue becomes volatile (expansion) or becomes bound into a tight trading pattern (contraction).
Average Directional Index (ADX)	Indicates the strength of a prevailing trend and gauge its strength.
EMA Differential	Differential of two moving averages which emphasize the direction of a trend and to smooth out price and volume fluctuations that can confuse interpretation.

Table 2. Indicators Value

IND.	SELL		BUY	
	Desire Value	Feature Extracted	Desire Value	Feature Extracted
RSI	48.5	48.5	51.5	51.5
BBWR	25	0.0010	25	0.0010
ADX	-55	-55	55	55
EMA	0.0002	0.0002	-0.0002	-0.0002

4 Experimental Results

In order to understand the whole mechanism, an example of decision making is discussed.

According to Table 2 and equation (4), if ρ=0.75 and β=0.35, desire values are calculated and shown in Table 3. By using equations (5) and (6), λ_i and w_i are calculated. Table 5 and 6 indicates their values.

Table 3. Desired values

d_1 (Sell)	d_2 (Buy)
0.746	0.377

Table 4. Initial values of weights

w_1	w_2	w_3	w_4
0.25	0.25	0.25	0.25

Table 5. Calculated λ_i values

λ_1	λ_2	λ_3	λ_4
1.667	-1.261	-0.241	-0.136

Table 6. Calculated w_i values

w_1	w_2	w_3	w_4
0.7318	0.0391	0.1084	0.1205

As it can be understood, $\sum_i w_i = 1$, $w_i \in [0,1]$.

Finally, according to equation (7), value of each $\hat{d}_k$ after 20000 iterations are calculated and shown in Table 7.

Table 7. Estimated desired values

$\hat{d}_1$ (Sell)	$\hat{d}_2$ (Buy)
0.750	0.369

Figure 1 depicts learning curve of w_i.

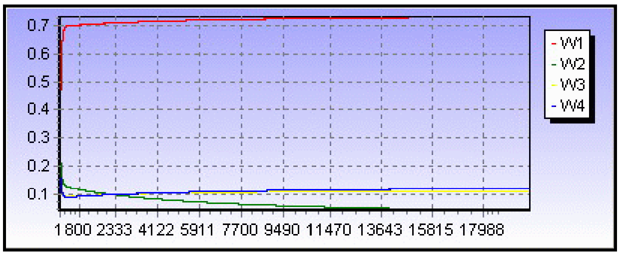

Fig. 1. Weights Learning Curve

According to equation (2), the output of decision making algorithm is:

$$f(x_1,\ldots,x_n) = \sum_i w_i x_{k_i} = 0.7505$$

The selected goal (Sell or By order) regarding to threshold of 0.05 is *Sell* with value of 0.746.

The proposed algorithm was tested over GBPUSD currency pair in 5 minutes timeframe with proper *Take Profit* and *Stop Loss* from 9/3/2007 to 11/23/2007 and detailed results are shown in Table 8 for each trading week including profit and loss in basis points (The smallest price change that a given exchange rate can make) and number of win or lose trades with overall and weekly average results, which shows that ¾ (74 %) of all trades ended in profit. Figure 2 is curve of Net Profit in basis points during 12 weeks of trading. Figure 3 is the actual equity curve of the system based on entering each signaled position with one standard Lot (100,000 of base currency units) and exit on meeting the preset take profit or stop loss.

Table 8. Detailed Trading Results

Week	Profit (Points)	Loss (Points)	Net Profit (Points)	Number of Trades	Winners	Losers
1	290	60	230	7	5	2
2	149	30	119	6	5	1
3	120	30	90	4	3	1
4	224	60	164	8	6	2
5	180	30	150	6	5	1
6	275	60	215	5	3	2
7	346	60	286	7	5	2
8	196	90	106	6	3	3
9	156	30	126	6	5	1
10	115	30	85	5	4	1
11	265	30	235	5	4	1
12	286	60	226	8	6	2
Overall	**2602**	**570**	**2032**	**73**	**54**	**19**
Average	**216.8**	**47.5**	**169.3**	**6**	**4.5**	**1.5**

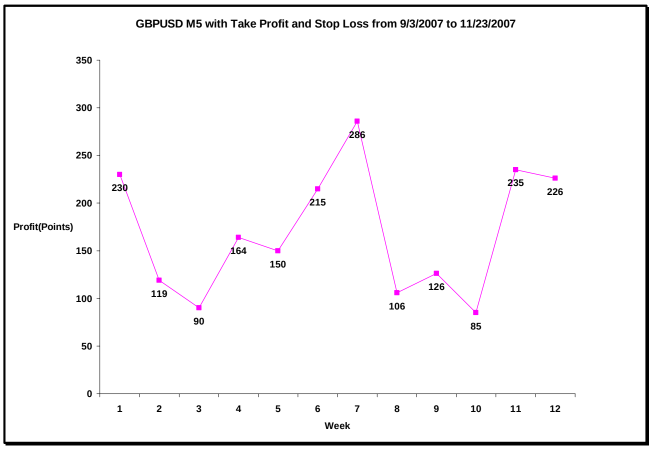

Fig. 2. Net Profit Curve

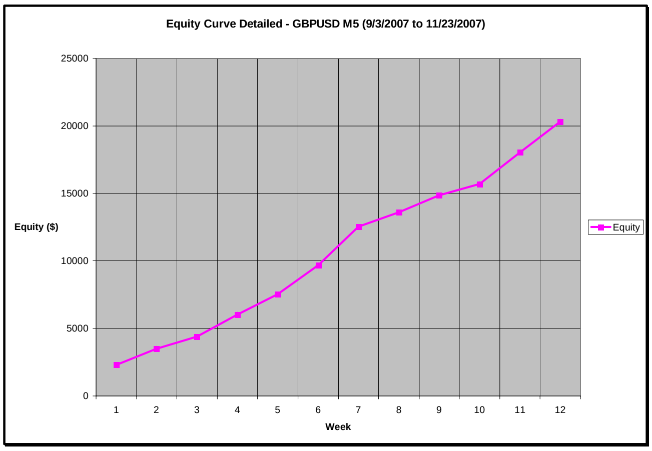

Fig. 3. Equity Curve

5 Conclusion and Future Works

This paper is headed for applying Data Fusion techniques, especially OWA operator in decision making algorithm in order to extend decision domains to have more trading accuracy. Applying other aggregation operators like OWA extensions [13], [14], [15] can increase the performance and profitability of trading decisions.

Along with the use of technical analysis in financial markets, many analysts and traders use fundamental analysis in their overall market analyzing. Fundamental indicators show underlying forces that affect the well being of the economy, industry groups, and companies. Fusion Analysis or intersection of technical and fundamental analysis, which overlays fundamental with technical analysis, in an attempt to improve portfolio manager performance. Therefore fuse of fundamental and technical parameters in the proper circumstances would lead to more winning trades. This will be happened by using another data fusion level which is decision fusion.

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