Automated Trading Based On Uncertain OWA In Financial Markets

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Abstract: During the past decade, the Financial Services industry has been transformed through the applications of computer-based analytics for forecasting, product design, portfolio optimization, risk management and intelligent advisory systems. This paper introduces trading system for financial markets, which is designed for improving trader's decision making process. The paper headed for applying Uncertain Ordered Weighted Averaging (UOWA) operator as a decision making algorithm (DMA) and compare the results with regular trading (Manual) based on technical analysis in Foreign Exchange Market.

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

1 Introduction
Technical analyses derive from the observation of financial markets over hundreds of years. It assumes that certain chart formations can indicate market psychology about either an individual stock or the market as a whole and attempts to understand the emotions in the market by studying the market itself. It involves providing forecasts or trading advice on the basis of largely visual inspection of past prices, without regard to any underlying economic or fundamental analysis [12].
It is suggested by several academic studies that technical analysis may well be an effective means for extracting useful information from market prices [2] and its use is more widespread than is fundamental analysis in the foreign exchange market [5], [12].
Traders, investment firms and fund managers use a trading strategy to help make wiser investment decisions and help eliminate the emotional aspect of trading. A trading strategy is governed by a set of rules that do not deviate. Emotional bias is eliminated because the systems operate within the parameters known by the trader. The parameters can be trusted based on historical analysis (back testing) and real world market studies (forward testing), so that the trader can have confidence in the strategy and its operating characteristics. Advanced computer modeling techniques, combined with electronic access to world market data and information, enable traders using a trading strategy to have a unique market vantage point.
A trading strategy can be executed by a trader (manually) or automated (by computer). Manual trading requires a great deal of skill and discipline. It is tempting for the trader to deviate from the strategy, which usually reduces its performance. Computer trading may be used in any trading strategy. The trading decision and implementation may be augmented at any stage with algorithmic support or may operate completely automatically based on Artificial Intelligence systems. Third of all EU and US stock trades in 2006 were driven by automatic programs, or algorithms, according to Boston-based consulting firm Aite Group LLC. By 2010, that figure will reach 50 percent, according to Aite.
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 Uncertain OWA

After Yager introduced OWA in 1988, some new families of OWA operators emerged. In the short time since their first appearance, the OWA operators have been investigated in many documents and used in an astonishingly wide range of applications.

An OWA operator of dimension \( n \) is a mapping \( f : [0,1]^n \rightarrow [0,1] \), which has an associated weighting vector \( W = (w_1, \ldots, w_n) \), s.t.

\[
\sum_i w_i = 1, \quad w_i \in [0,1]
\]

and where

\[
f(x_1,\ldots,x_n) = \sum_i w_i x_i \tag{2}
\]

The vector \( K = (k_1, \ldots, k_n) \) is such permutation of \((1, 2, \ldots, n)\) that \( x_{k_i} \) is the \( i \)th largest element in \((x_1, \ldots, x_n)\). 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 \( \text{arithmetic mean} \) for the appropriate choice of vector \( W \).

Yager introduced a measure to characterize the type of aggregation performed by OWA operators. He calls it the \( \text{orness measure} \). It is defined as:

\[
\text{Orness}(w) = \frac{1}{n-1} \sum_{i=1}^{n} (n-i)w_i \tag{3}
\]

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.

In Uncertain OWA operator the associated weighting parameters cannot be specified, but value ranges can be obtained and each input argument is given in the form of an interval of numerical values. An Uncertain OWA operator of dimension \( n \) is a mapping \( g : \mathcal{Q} \rightarrow \mathcal{Q} \) that has an associated \( n \) vector \( v = (v_1, v_2, \ldots, v_n) \), such that \( v_i \in [0,1] \) and

\[
\sum_{j=1}^{n} v_j = 1.
\]

Furthermore, \( g(a_1, a_2, \ldots, a_n) = \sum_{j=1}^{n} v_j b_j \),

where \( b_j \) is the \( j \)th largest of the \( a_i \) and all of the \( a_i (i \in N) \) are interval numbers [17]. Now suppose that there are \( n \) input arguments \( a_i (i \in N) \) having the forms of interval numbers which is

\[
[a_i^L,a_i^U],
\]

\( i \in N \). In order to rank the arguments, each \( a_i \) will be compared with all arguments \( a_j, j \in N \) by using equation 4.

\[
p(a_i,a_j) = \max \left\{ 1 - \frac{\max \left( \frac{a_i^U - a_j^L}{1-a_i^L+a_j^L},0 \right)}{0.5}, j \in N \right\} \tag{4}
\]

If we let \( p_{ij} = (a_i \geq a_j) \), complementary matrix will be:

\[
P = \begin{bmatrix}
p_{11} & p_{12} & \cdots & p_{1n} \\
p_{21} & p_{22} & \cdots & p_{2n} \\
p_{n1} & p_{n2} & \cdots & p_{nn}
\end{bmatrix}
\]

where \( p_{ij} \geq 0 \) \( i \neq j \) and \( i, j \in N \).

After summing all elements in each line of the matrix, we have:

\[
p_i = \sum_{j=1}^{n} p_{ij}, \quad i \in N \tag{5}
\]

Now we can rank the arguments \( a_i, i \in N \) in descending order in accordance with the value of \( p_i, i \in N \).

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. In case of using Uncertain OWA, range of values for each indicator must be assigned that listed in Table 3. 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. Next procedure is defining a weighting vector \( W \) that indicating which aggregated object has more priority over the others. The main question would be obtaining the weights associated with Uncertain OWA, because it models process of aggregation used on data set.

Given are a collection of \( m \) samples each comprised of \( n \)-tuple of arguments \( (a_{i1}, a_{i2}, \ldots, a_{in}) \), an associated aggregated value, \( s_k \), where
Where we satisfy the following condition as faithfully as possible:

\[
0 \leq \alpha \leq \beta \leq \sum_{i=1}^{n} \alpha \leq 1, \sum_{j=1}^{n} \beta \leq 1 \]

(6)

Now we need an uncertain OWA operator, a weighting vector \( w \), such that for entire collection data we satisfy the following condition as faithfully as possible:

\[
g(a_{i1}, a_{i2}, ..., a_{im}) = s_k, \quad k = 1, 2, ..., m
\]

We can utilize equation 4 to compare the \( k \)th sample arguments \( a_{ik} \), \( i \in N \), and utilize equation 5 to obtain \( p_{i} \), \( i \in N \). Then we rank the arguments of the \( k \)th sample by \( b_{k1}, b_{k2}, ..., b_{kn} \) in descending order in accordance with the value of \( p_{i} \), \( i \in N \). Using these re-ordered arguments, we need to find a vector of the Uncertain OWA weights \( v = (v_1, v_2, ..., v_n) \) such that:

\[
\sum_{j=1}^{n} v_j b_{kj} = s_k, \quad k = 1, 2, ..., m
\]

that is:

\[
\sum_{j=1}^{n} v_j b_{kj} = s_k, \quad \sum_{j=1}^{n} v_j b_{kj} = s_k, \quad k = 1, 2, ..., m
\]

After relaxing above equation by looking for a vector of the Uncertain OWA weights \( v = (v_1, v_2, ..., v_n) \) that approximates the aggregation operator by minimizing the instantaneous errors \( e_{1k} \) and \( e_{2k} \) where:

\[
e_{1k} = \sum_{j=1}^{n} v_j b_{kj} - s_k, \quad k = 1, 2, ..., m
\]

\[
e_{2k} = \sum_{j=1}^{n} v_j b_{kj} - s_k, \quad k = 1, 2, ..., m
\]

Solution to the above minimization problem is found by solving a linear objective programming model. Following is an algorithm that represents how decision making will be accomplished:

1) Each aggregated value will be calculated by classic Hurwicz’s multi-attribute method and is considered as desired value:

\[
\rho \text{ Max.}a.+(1-\rho)\text{Min.}a. = d
\]

(7)

Where \( \rho \) is Agent’s measure of pessimism.

2) Corresponding weights will be calculated by the algorithm described lately at the beginning of this section. Estimated desired values will be calculated by means of equation 8 Where \( \hat{d}_k \) is Current estimation of \( d_k \).

\[
\hat{d}_k = b_1 w_1 + b_2 w_2 + ... + b_m w_m
\]

(8)

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 \( \rho \) could be interpreted as a measure of the agent’s pessimism. In fact, if \( \rho \to 1 \), 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 \( \rho \) 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>
<thead>
<tr>
<th>Table 1. Indicators List</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>INDICATOR</strong></td>
</tr>
<tr>
<td>Relative Strength Index (RSI)</td>
</tr>
<tr>
<td>Bollinger Bands Width Ratio (BBWR)</td>
</tr>
<tr>
<td>Average Directional Index (ADX)</td>
</tr>
<tr>
<td>EMA Differential</td>
</tr>
</tbody>
</table>
4 Experimental Results

The proposed algorithm was tested over GBPJPY currency pair in 5 minutes timeframe because of its high volatility which provides a better test environment with proper Take Profit and Stop Loss from 9/1/2008 to 11/21/2008. Along with that, the selected strategy was tested without applying the algorithm during the same period of time. The detailed comparison results are shown in Table 4 for both test cases 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, which shows that 78% of all trades done by algorithm ended in profit. Figure 1 is comparison curve of Net Profit in basis points during 12 weeks of trading. Figure 2 compares the actual equity curves of both test scenarios 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. As it can be understood, by using Uncertain OWA as a DMA, trading profitability will be improved.

5 Conclusion and Future Works

This paper is headed for applying Data Fusion techniques, especially Uncertain OWA operator in decision making algorithm in order to extend decision domains to have more trading accuracy and improving trading profitability. The comparison of utilizing Uncertain OWA and regular trading with the same strategy was discussed. Applying other aggregation operators like OWA extensions [13].

Table 2. Indicators Value

<table>
<thead>
<tr>
<th>IND.</th>
<th>SELL Desire Value</th>
<th>Feature Extracted</th>
<th>BUY Desire Value</th>
<th>Feature Extracted</th>
</tr>
</thead>
<tbody>
<tr>
<td>RSI</td>
<td>48.5</td>
<td>48.5</td>
<td>51.5</td>
<td>51.5</td>
</tr>
<tr>
<td>BBWR</td>
<td>25</td>
<td>0.0010</td>
<td>25</td>
<td>0.0010</td>
</tr>
<tr>
<td>ADX</td>
<td>-55</td>
<td>-55</td>
<td>55</td>
<td>55</td>
</tr>
<tr>
<td>EMA</td>
<td>0.0002</td>
<td>0.0002</td>
<td>-0.0002</td>
<td>-0.0002</td>
</tr>
</tbody>
</table>

Table 3. Range of values assigned to each Indicator

<table>
<thead>
<tr>
<th>IND.</th>
<th>SELL Low Range</th>
<th>Up Range</th>
<th>BUY Low Range</th>
<th>Up Range</th>
</tr>
</thead>
<tbody>
<tr>
<td>RSI</td>
<td>48</td>
<td>49.5</td>
<td>50.5</td>
<td>52</td>
</tr>
<tr>
<td>BBWR</td>
<td>0.003</td>
<td>0.0035</td>
<td>0.003</td>
<td>0.0035</td>
</tr>
<tr>
<td>ADX</td>
<td>21</td>
<td>23</td>
<td>21</td>
<td>23</td>
</tr>
<tr>
<td>EMA</td>
<td>0.5</td>
<td>0.8</td>
<td>-0.5</td>
<td>-0.8</td>
</tr>
</tbody>
</table>

Table 4. Detailed Trading Results

<table>
<thead>
<tr>
<th></th>
<th>Net Profit (Points)</th>
<th>Loss (Points)</th>
<th>Profit (Points)</th>
<th>Number of Trades</th>
<th>Profit Trades</th>
<th>Loss Trades</th>
<th>Profit/Loss Ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>With Algorithm</td>
<td>20264</td>
<td>4560</td>
<td>15704</td>
<td>345</td>
<td>269</td>
<td>76</td>
<td>78.0%</td>
</tr>
<tr>
<td>Without Algorithm</td>
<td>11640</td>
<td>10440</td>
<td>1200</td>
<td>383</td>
<td>209</td>
<td>174</td>
<td>54.6%</td>
</tr>
</tbody>
</table>
[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.

References: