Study on the effectiveness of the investment strategy based on a classifier with rules adapted by machine learning

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Abstract. *In this paper authors examine two transactional strategies based on the classifier which opens positions using some rules and closes them using different rules. A rule set contains time-varying parameters that when matched allow to make an investment decision. Researches contain the study of variability of these parameters and the relationship between learning period and testing (using the learned parameters). The strategies are evaluated based on the time series of cumulative profit achieved in the test periods. The study was conducted on the most popular currency pair EURUSD sampled with interval of 1 hour.*
Keywords: *machine learning, cross validation, pattern recognition, classification, investment strategy, algotrading, forecasting, time series*

1. Introduction

The aim of this work is to verify the hypothesis of the possibility of extracting patterns from time series, that would be classifiable as those that provide more accurate and better statistic prognosis. Another important objective is to confirm the assumption, that the time series of financial markets have a "memory" about the effectiveness of the learned pattern in a period after the learning one. This approach is consistent with the classic aim of machine learning shown by K.Murphy'ego [1], especially to financial markets described by Satchwell [2]. Authors also intend to follow the principle of reproducibility of studies by other researchers, as well as by themselves, in other data environments, to make sense of the use of computational intelligence in its reasonable reproducibility [3, 4], in extracting of the regularity from chaos [5, 6].

The authors build an investment strategy with a relatively high complexity (measured by the number of factors included in the model), derived from a strategies group called strategy of simple rules (simple rules). In the literature those strategies are considered to be mainly strategies based on moving averages - their intersections and derivatives shown for example by Brock et al. [7], Cai et al. [8] and many other authors [9, 10, 11]. Of course, the world of algorithms as well as prediction methods using a completely different nature, such as regression [12], multiple regression [13, 14], Fourier and wavelet transforms, and many others [15, 16] is plenteous. The authors use these methods as a basis for comparison, however they focus on mentioned simple rules.

Authors propose strategy, that differs by suggesting different behaviors than the ones proposed when using Bollinger's Band, which has its foundation in a band built in an unusual way. According to the strategy based on that band, generally it can be assumed that the trend is horizontal and it is recommended to open position to the center of the band, after its cross by the price from the inside. In proposed strategies, authors use another band that is based on maxima of the maxima and minima of the minima of last several candles.

In considered strategies authors move away from the principle of opening positions to the center of the band. In one modification, hereinafter referred to as sub strategy, position opens into the center of the band, whereas in another one, position opens on the outside. By treating the two considered sub strategies as an entirety and as strategies that are mutually retrieving (although a more appropriate word would be complementary) authors assume, that in the selected trading section, opening positions in opposite directions, of course not at the same time, can be done intentionally and effectively. During the trading, nature of the market (trend, volatility) may change. The market may be in some periods horizontal, in other trended. It is appropriate to seek all opportunities for profit. A similar philosophy is applied by several Krutsinger correspondents [17], who belong to most prominent traders in US, who advocate unfounded reversal of the direction of opening the positions in case of series of failures.

Returning to the issue of the complexity of the strategy, there are often opinions that the growing complexity of the prediction model is not indicated, because in learning section it leads to overfitting [1, 8, 14] resulting in a greater error in the test sections. The problem of selecting the proper ratio between learning and testing phase is still unsolved for the non-stationary time series [5, 18]. In this situation the right approach seems to be the use of the idea of computational intelligence [3, 6] by which the empirical justification hypothesis entitles to use the model.

Therefore authors use two rather complex strategies (described below), achieving results that are in their assessment rewarding. They draw attention to the fact that the satisfaction problem belongs to the other sciences and depends on the trader's individual perception of the relationship between profit and risk, greed and fear [19]. However, the issue of emotions in the trade is not considered here, but only noticed.

The tests were deliberately performed in a fragment of the time series of a heavily diversified course, which contains both rising and downward trends as well as horizontal elements (Fig. 1). It is the time series, consisting of 4734 1-hour candles, of the most important and the most fluent currency pair EURUSD from 22.10.2012.

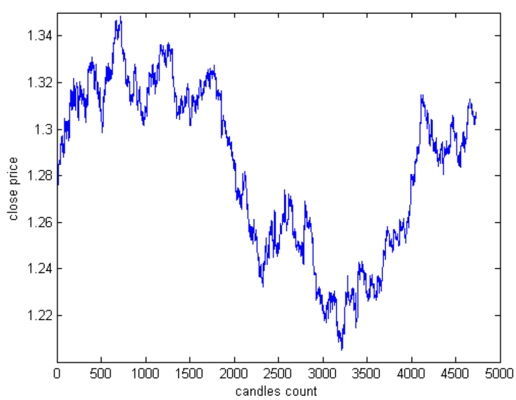


Figure 1: Time series EURUSD 1h

2. Characteristics of investment strategies

The objective of the two considered strategies is to make investment decisions about buying or selling - opening long or short position in the studied market - the currency pair EURUSD. Decision is based on intersection of the current price and one of two barriers of additional indicator, called the ribbon. The band is made of two values calculated at the opening of each candle on the basis of historical data of the market. During the candle values of the band do not change, therefore barriers are creating step functions. In case, when the current price exceeds any of the barrier values (goes out of the band), a decision to buy or sell is made - the type of decision depends on the variant of the considered strategy - decision for sub strategy TewiMiC is different than in case of TewiMiD. Names of the strategies are derived from the name of the project, in which the research was carried out.

2.1. Definition of the band

The value of barriers forming a band is calculated using the maximum and minimum values of the last candle (OHLC). In the case of the upper band, it is the maximum of the maximal values of the n last candles, whereas in the case of the bottom band, it is the minimum of the minimal values of m last candles.

$$topBorder = \max\left(H_{i-n}, ..., H_{i-1}\right) \tag{1}$$

$$bottomBorder = \min\left(L_{i-m}, ..., L_{i-1}\right) \tag{2}$$

As mentioned earlier, strategy comes in two versions that differ in terms of opening the positions when crossing the band. These differences result from different investor assumption about currently prevailing market trend. In the first case it is believed that the trend has just started and positions need to be opened in accordance with it. In the second case, the play is against the trend. The two considered variants, TewiMiC and TewiMiD, are based on excesses of the lower limit of the band. TewiMiD implies existence of a downward trend, for which when crossing (down) the lower limit of the band, a short position (assuming the price drop) is opened. This is known it literature and in trading as Sell Stop model.

TewiMiC assumes the opposite case, therefore it is needed to open a long position (assuming the price increase). This is Buy Limit model.

2.2. Strategy parameters

Considered strategies are based on a objects classification (events that meet the conditions contained in the set of rules which depend on the value of certain parameters). Object - the event - is another candle. Rules are logical sentences like "if the price is greater than the upper barrier of the band", parameter is for example the upper barrier, which is a variable value.

These parameters will determine whether the strategy will earn or lose. Appropriate selection of parameter values is therefore a key optimization issue in the use of the strategy. Considered strategies have 11 parameters, which are subject of optimization.

- p1 — the number of candles, based on which the calculation of the current value of the band barrier is made; for researched time series, value of p1 generally ranges from 10 to 30;

- p2 — number of steps forward, after which the position is closed in case none other close condition was met before; this value belongs to range from 3 to 40;

- p3 — StopLoss condition; usually it remained in range from 0.002 to 0.017 expressed in values of EURUSD, which in researched period stayed in range from 1.2 to 1.4, as can be seen in Fig. 1;

- p4 — TakeProfit condition; generally ranged from 0.0015 to 0.009;

- p5 — band buffer, offset from the barrier of the band defining the actual level of the expected crossing of the price; ranged from -0.002 to 0.003;

- p6 — maximum number of open positions at the same time; ranged from 3 to 20;

- p7 — number of candles that determines average volume value; generally ranged from 2 to 10;

- p8 — maximum value of the difference between the current value of the volume and the average value calculated on the basis of p7 candles back; ranged from 150 to 500;

- p9 — number of candles on the cumulative profit curve, based on which current drawdown is calculated; ranged from 5 to 25;
- p10 — highest acceptable drawdown on the cumulative yield curve; generally ranged from 0.0021 to 0.008;
- p11 — acceptable amount of the cumulative loss for all currently open positions; ranged from 0.0005 to 0.003;

2.3. Conditions of opening

As mentioned before, the signal to open the position is the intersection of the current price of the observed value and some barrier (that results from the calculated band). Special parameter called the buffer (p5) has been added, causing the offset of barrier from its actual value. Thus, the condition for opening TewiMIC strategy is:

$$\begin{aligned} if[(price < bottomBorder(p1) - buffor(p5)) \\ \text{and } (currentp6 < p6) \text{ and } (Vol - meanVol(p7) < p8)] \\ \text{then open position long} \end{aligned} \tag{3}$$

where:
price – current value for EURUSD;
bottomBorder(p1) – value of lower band barrier for parameter p1; here minimum of last p1 minima;
buffor(p5) – value of buffer that moves said barrier;
current p6 – number of currently opened positions;
Vol – current value of volume (in the candle);
meanVol(p7) – mean of volume of last p7 candles;

and the opening condition for TewiMiD is:

$$\begin{aligned} if[(price < bottomBorder(p1) - buffor(p5)) \\ \text{and } (currentp6 < p6) \text{ and } (Vol - meanVol(p7) > p8)] \\ \text{then open position short} \end{aligned} \tag{4}$$

As a result of these conditions, long positions, in sub strategy TewiMIC, are opened when three conditions are met simultaneously: crossing the bottom barrier reduced by buffer by the current price, the number of open positions is lesser than the limit (which is the optimized parameter p6) and the difference between the current volume and the average of the volume of the last p7 candle is less than the parameter p8.

For TewiMiD strategy, similar, with significant differences - short positions will be opened and it is advisable that current volume should be greater than the average. As the result of conducted research, authors concluded that volume (number of price changes in observed time frame – here during one hour) was the most important and most sensitive factor of decision model.

These conditions can be met in two cases during the period of the current considered candle. They can be met immediately at the opening of the candle i.e. the opening value of the current candle is smaller than the barrier bottomBorder reduced by parameter p5. That condition can be met within the candle, when the current value of the price break through the lower barrier.

The result of that is that we have two distinctly different opening conditions.

2.4. Conditions of closing

In both sub strategies there are 7 cases of closing the open positions, which results in their complexity - both in terms of logic and calculation. This complexity, however, exhausts all the possible surprises and does not leave any opportunity for the unexpected market behavior. Of course, depending on the values of the parameters, frequency occurrences of closure cases can be very different.

Firstly the terms for closing the long positions that were opened by conditions for TewiMiC will be presented.

1. Opened long position will be closed, if at the close of the candle (i + p2) the position remained open, where i - number of candle, which was opened;

2. Position will be closed if at the opening of the next (i + k)-th - the candle after i-th candle, in which the position was opened, following condition is met:
$$PriceO(i+k) - Price(i) < -SL \tag{5}$$

where *ProceO(i+k)* is the opening value for (i+k)-th candle;
Then the profit (in this case loss) will be calculated as:

$$Profit = PriceO(i + k) - Price(i); \tag{6}$$

3. Position will be closed if inside the next (i + k)-th - the candle after i-th candle, in which the position was opened, following condition is met:

$$(PriceO(i{+}k){-}Price(i)) > -SL \text{ and } (LowPrice(i{+}k){-}Price(i)) < -SL \tag{7}$$

Then the profit (in this case loss) will be calculated as:

$$Profit = -SL; \tag{8}$$

where LowPrice(i+k) – is a minimum value of (i+k)-th candle;

4. Position will be closed if at the opening of the next (i + k)-th - the candle after i-th candle, in which the position was opened, following condition is met:

$$PriceO(i + k) - Price(i) > TP \tag{9}$$

Then the profit will be calculated as:

$$Profit = PriceO(i + k) - Price(i); \tag{10}$$

5. Position will be closed if inside the next (i + k)-th - the candle after i-th candle, in which the position was opened, following condition is met:

$$(PriceO(i{+}k){-}Price(i)) < TP \text{ and } (HighPrice(i{+}k){-}Price(i)) > TP \tag{11}$$

Then the profit will be calculated as:

$$Profit = TP; \tag{12}$$

where *HighPrice(i+k)* is the maximum value for (i+k) candle;

6. Position will be closed if at the opening of the next (i + k)-th - the candle after i-th candle, in which the position was opened, following condition is met:

$$PriceO(i + k) > topBorder(i + k) \tag{13}$$

Then the profit will be calculated as:

$$Profit = PriceO(i + k) - Price(i); \tag{14}$$

7. Position will be closed if inside the next (i + k)-th - the candle after i-th candle, in which the position was opened, following condition is met:

$$Price(i+k) > topBorder(i+k) \tag{15}$$

Then the profit will be calculated as:

$$Profit = topBorder(i+k) - Price(i); \tag{16}$$

In sub strategy TewiMiD conditions will look slightly different.

1. Opened short position will be closed if at the close of the candle (i + p2)-th the position remained open;

2. Position will be closed if at the opening of the next (i + k)-th - the candle after i-th candle, in which the position was opened, following condition is met:

$$Price(i) - PriceO(i+k) < -SL \tag{17}$$

Then the profit (in this case loss) will be calculated as:

$$Profit = -PriceO(i+k) + Price(i); \tag{18}$$

3. Position will be closed if inside the next (i + k)-th - the candle after i-th candle, in which the position was opened, following condition is met:

$$(-PriceO(i+k) + price(i)) > -SL \text{ and } (-HighPrice(i+k) + Price(i)) < -SL \tag{19}$$

Then the profit (in this case loss) will be calculated as:

$$Profit = -SL; \tag{20}$$

4. Position will be closed if at the opening of the next (i + k)-th - the candle after i-th candle, in which the position was opened, following condition is met:

$$Price(i) - PriceO(i + k > TP \tag{21}$$

Then the profit will be calculated as:

$$Profit = -PriceO(i+k) + Price(i); \tag{22}$$

5. Position will be closed if inside the next (i + k)-th - the candle after i-th candle, in which the position was opened, following condition is met:

$$(-PriceO(i+k) + price(i)) < TP \text{ and } (-LowPrice(i+k) + Price(i)) > TP \tag{23}$$

   Then the profit will be calculated as:

$$Profit = TP; \tag{24}$$

6. Position will be closed if at the opening of the next (i + k)-th - the candle after i-th candle, in which the position was opened, following condition is met:

$$PriceO(i+k) > bottomBorder(i+k) \tag{25}$$

   Then the profit will be calculated as:

$$Profit = -PriceO(i+k) + Price(i); \tag{26}$$

7. Position will be closed when inside the opening of the next (i + k)-th - the candle after i-th candle, in which the position was opened, following condition is met:

$$Price(i+k) > bottomBorder(i+k) \tag{27}$$

   Then the profit (in this case loss) will be calculated as:

$$Profit = -bottomBorder(i+k) + Price(i); \tag{28}$$

Additional conditions that are checked with each closing are the rules containing parameters p9, p10, p11. These parameters are found in the rules limiting the risk of an unacceptable failure. Moreover, the principle stating that in the case when the opening took place at the beginning of the candle, it is permissible to keep it open until following candle is opened was used. Because of that, it was possible to avoid ambiguity involving the unpredictable sequence of the SL and TP.

3. Strategy analysis

In both strategies a fixed period of learning are assumed (in the presented solution - 1000 one hour candles), followed by a testing period. Data from learning period were used to find a class of patterns which allowed to achieve maximum for the selected criterion (in this study Calmar ratio were selected). The same patterns were then searched during the test period and the test results were computed for previously unused data space. Of course, these results do not have to already be positive and acceptable and could negatively surprise investors. During the test as a measure of the effectiveness of the investment was considered the maximum rate of net profit (with transaction costs). The authors believe this two criteria in evaluation the quality of simulation results as legitimate. In the first phase of the validation, the training period is indicated for moderate and prudent risk management. In the test phase (in terms of actual trading) investor is mainly interested in profit.

The main aim of the research was to obtain the most effective investment strategies by dynamic selection of test period duration. Later in this article were used concepts of learning period, a fixed-length 1000 candles but with different start in time. After this were test period, a variable-length immediately following a period of learning. The authors looks for the best (by the criteria described above) length of the test period in their research. This most preferred length of the learning period can be understood in two ways. This length can be changed after each learning period adjusted by additional current information feedback about profits or losses in the test period. It may also be the average length of the test window established on the basis of several recent validation.

The process of finding the optimum parameters for both of the described strategy is divided into two stages. In the first step of the process pseudo-random strategy is used to find the boundaries of the parameter space in which may be the optimal solution. Calmar ratio value was used to assess the adequacy of randomly selected parameter combinations for a given period of learning. In the second stage PSO [20] algorithm was used, searching for solutions within prescribed limits of the first stage. The objective function was the Calmar ratio maximizing as in the first step. The above tactics was used for each stage of the learning period, then checked "sustainability" of designated sets of parameters for test periods of different lengths - the basic rate of 100 candles and the other in the range of 10-400. Figure 2 on page 12 shows how the research was conducted. Knowing the historical data 1000 candles were used and approach described above in order to find optimal parameters for a given period was used for this dataset. After the parameters search, tests were performed on the current data. The strategy for the learned parameters should be used as long as it will bring satisfactory results on new data. When results were no longer good enough, the next parameters search were performed on next piece of historical data. Thus, the authors aim is to determine the point where it should parameters be recalculated. Additionally, the authors set out to test a new standard of quality prediction. Now, extending the period of testing can produce better results, but more slowly or with local drawndown in comparision to first period, when the classifier "remembers" the nature of the market. This new criteria is profit attributable to one candle of the testing period.

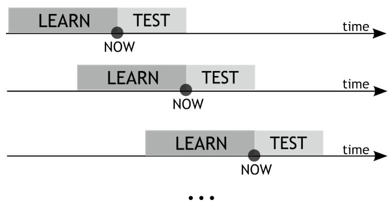
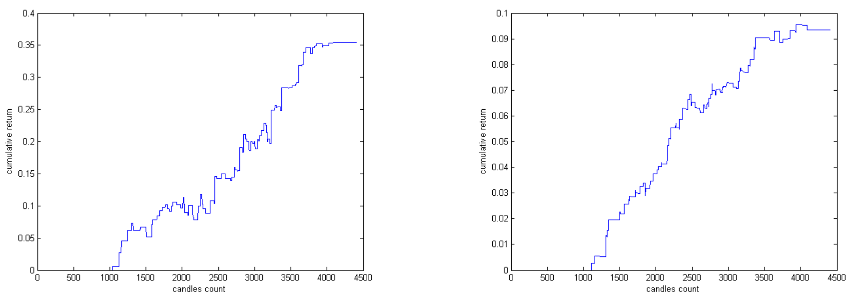


Figure 2: Methods of testing carried out to test the variable size window

Figures 3a and 3b on page 12 shows the cumulative profit for the test period equal to 100 candles (hours) for the two examined strategies.



(a) Sub strategy TewiMiC

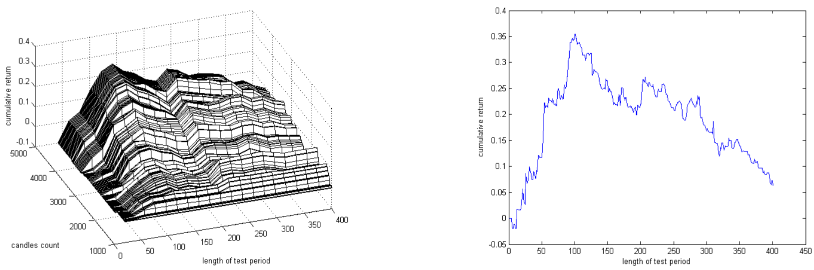
(b) Sub strategy TewiMiD

Figure 3: Chart of the profit for the strategy with fixed test period size - 100 candles

It may be noted that the two policies, for the test period of 100, allow for systematic profit in examined period with only for small drawndowns. Profit for the strategy TewiMiC 0.355, for TewiMiD profit is several times smaller and amounts to 0.094. But second strategy has smaller drawndowns. In addition, it is confirmed with the higher Calmar ratio - 12.79, where the result for first of these strategies is 10.22. According to the authors, results are excellent, achieved on testing sections, not on the learning periods. On learning periods, of course, significantly better results were achieved with classifier matching. It is also clear that asymmetry results for the two strategies arise from different approaches - the first one is focused on horizontal trend, the other on a downward trend. The results depend on the nature of the market, which is automatically founded by learning strategies. Perhaps at another period of time, for other data these results could be different. In addition to the basic performance of the length of the test period equal to 100, a number of studies were conducted on different lengths of the testing period. There may be more favorable length of test window than arbitrarily selected window length of 100 candles.

Results for TewiMiC

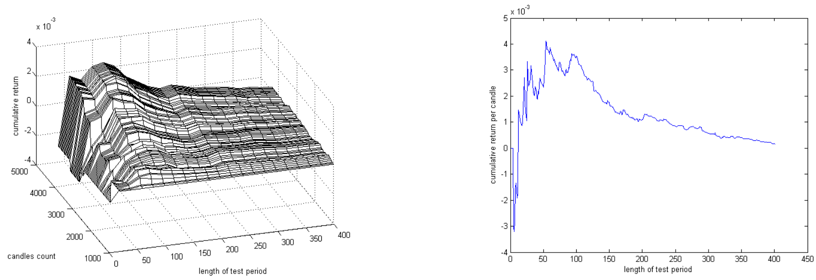
Below, we present four graphs showing the results of the strategy TewiMiC. The first of these (Figure 4a on page 13) shows the effect of test duration on the profit curve in time. To show how long in the test period optimal results are achieved we plotted 2D chart of final profit for each of the examined sizes. Figure 4b on page 13 shows that the number of candles for achieving a high and satisfactory results are attributable to 80-120. The window size 100 reflects quite well expected test section.



(a) Results in 3D (b) Final results

Figure 4: Earnings accumulated over time, depending on the length of the test period for TewiMIC

Due to the different length of the test period studied, more reliable value required in the decision is earnings per candle, what means how much strategy can earn in one hour. This is shown in Figures 5a and 5b. On this basis, and Table 1 it can be concluded that the strategy is most effective for the testing period length beetween 60 and 110 hours. It can therefore be concluded that the average window of 100 candles well "remembers" the learned classifier parameters. Many times in the classification of patterns, it is important whether patterns are frequent. Part of the dilemma is solved by introducing earnings per candle but also in Table. 1 a count of opened market positions in the testing periods are presented.



(a) Results in 3D

(b) Final results

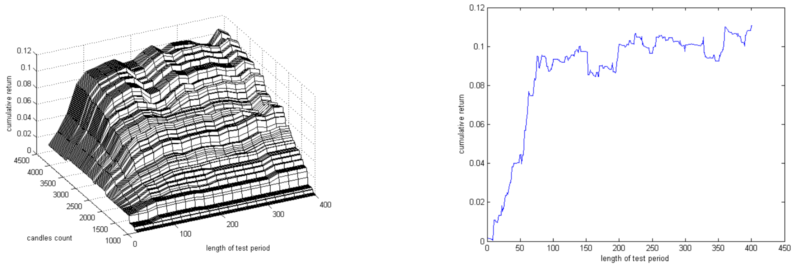
Figure 5: Cumulative profit for one candle in time depending on the length of the testing period for TewiMiC

Table 1: Final profits and Calmar ratio for the selected length of the test period for TewiMiC

size	profit	profit per canlde	Calmar	Open positions	Percentage [%]
30	0.0812	0.0027	2.4182	93	10
40	0.0768	0.0019	1.4048	120	9.68
50	0.1176	0.0024	2.4069	134	8.65
60	0.2318	0.0039	5.3914	153	8.23
70	0.2211	0.0032	4.7859	176	8.11
80	0.2359	0.0029	5.1063	196	7.9
90	0.3005	0.0033	8.6589	221	7.92
100	0.3548	0.0035	10.221	245	7.9
110	0.3294	0.003	9.4905	262	7.68
120	0.3172	0.0026	8.6479	283	7.61
150	0.2648	0.0018	4.6295	345	7.42
200	0.2194	0.0011	2.8244	482	7.77
250	0.2091	0.0008	2.2352	574	7.41
300	0.1684	0.0006	1.5345	720	7.74
350	0.1399	0.0004	1.0402	804	7.41
400	0.073	0.0002	0.5074	914	7.37

Results for TewiMiD

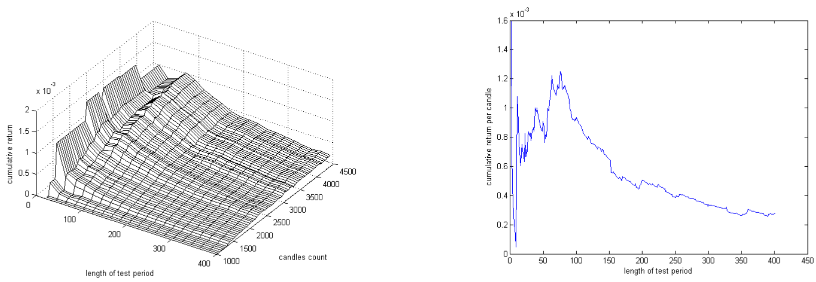
Figures 6a and 6b on page 15 shows the effect of the length of the test period on the profit curve. In case of TewiMiD strategy it is difficult to determine the optimal interval length of the testing period.



(a) Results in 3D (b) Final results

Figure 6: Earnings accumulated over time, depending on the length of the test period for TewiMID

It is possible, however, due to graphs showing earnings per hour (candle) (Figures 7a and 7b), depending on the length of the period and a Table 2 listing the final results of the two studies. Similarly to the first strategy, length of this period is beetween 60 and 90 candles.



(a) Results in 3D (b) Final results

Figure 7: Cumulative profit for one candle in time depending on the length of the testing period for TewiMiD

Of course, the optimal convergence test window length, at least approximately, is a great convenience in design of automatic strategy for algotrading. It should be

Table 2: Final profits and Calmar ratio for the selected length of the test period for TewiMiD

size	profit	profit per canlde	Calmar	Open positions	Percentage [%]
30	0.0249	0.0008	4.2953	47	5.05
40	0.0401	0.001	8.012	60	4.84
50	0.0443	0.0009	8.868	66	4.26
60	0.0636	0.0011	13.25	83	4.46
70	0.0771	0.0011	16.0687	95	4.38
80	0.0914	0.0011	19.0396	118	4.76
90	0.0899	0.001	10.5222	130	4.66
100	0.0935	0.0009	12.7934	141	4.55
110	0.0921	0.0008	12.6559	150	4.4
120	0.0949	0.0008	13.0337	159	4.27
130	0.0955	0.0007	13.1243	178	4.42
200	0.1011	0.0005	9.464	263	4.24
250	0.0965	0.0004	9.0392	328	4.23
300	0.1008	0.0003	9.3983	410	4.41
350	0.0924	0.0003	7.2935	467	4.3
400	0.1105	0.0003	8.1655	558	4.5

noted that the authors assume that it is possible to test each strategy separately and it is not required to synchronize.

4. Conclusion

Following a review of various lengths dependence validation periods shown in Figures 6b and 6b were obtained. It shows a fairly obvious that a good fit of the parameters of the test period will continue for some time after the end of the learning. This is due to the assumption that there are trends in the market in different direction. The nature of trends is well explored during the learning process. The authors have found that the use of optimization methods derived from the area of artificial intelligence, including the PSO [20], given good and quickly reached the optimum values of the rules of the classifier, and good results in the initial stages of the test period. For longer test periods, it can be indeed get good results overall, however, the effectiveness of the strategy per hour decreases significantly. Obtained results allow to conclude that the constant average length of the test window is more efficient and easier to manage than a strategy adaptively changing the length of the period. Strategies properties discovered during the learning period are effective for a short time - for test data period - good lengths for both strategies are about 50 to 120 hours at 1000 hours of learning time.
The real market means that from 2 to 5 days, it can be assumed that the re- learn-

ing the parameters of the strategy should be carried out 1-2 times a week. This frequency is quite practical even for manual search of optimal parameters without fully automatic trading. The options trading strategies (substrategia TewiMiC and TewiMiD) are complementary, since for each variant can develop a set of other parameters. Separate sets of parameters are adapted better to the outdoor during optimization nature of the market, allowing for example, often contain long positions in the market with more frequent by growth trends. It should be noted that a further optimizations discovered trends are short-term and during one cycle of validation can occur several changes in these trends, and they can be of different lengths. Then there is the situation that one of the variants of the strategy takes into account the length of trends for deviating significantly from trends indicated by the second variant. The two variants substrategii are part of an investment strategy that allows you to combine the target until the time the four options trading strategies. It is a fact of this study add to the substrategie associated with opening long positions based on condition (order) Buy Stop and short positions in accordance with the model Sell Limit. Interestingly according to the authors, may also improve the combined strategies through the synthesis of recommendations such as combining four variants, some of which (eg 3) indicates the need for the purchase, and some (such as 1) the need to conclude the sale of stock, it contains a number of transactions indications resulting from the sum of the different options (in the above example - two requests). This implies a lower cost (for example, 2 times smaller). Transaction costs for certain decisions so tests can be omitted, and the reduction significantly affects the efficiency improvement investment strategy. The studies take into account the transaction costs for the pessimistic (above average costs in popular brokers). In practical terms, the strategy is so big possibilities. With traditional software, e-commerce (such as Metatrader) does not have the possibility of converting a simple strategy parameters during operation. This implies the need for a hybrid solution, consisting for example of interprocess communication between the software and e-commerce program developed in universal high-level language (eg Matlab, C#). Algotarding future will very likely be increasingly active domain for experts in algorithmization and programming and less and less economists and econometricians.

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