commissions added in all this time, the trade will remain a losing trade or the profit will be marginal. Using a tight stop loss will lead for sure to a loss trade in all these cases.

This paper will present a methodology to avoid all these trades and to reduce the risk in capital investment. The main questions this paper will answer to are: when the price is low enough for a low-risk entry, how multiple entries can be done in order to catch better price levels and how long to keep the trades in order to maximize the capital efficiency. This article will present a trading or investment methodology based on price cyclical behavior. The method revealed can be applied and optimized for any stock market, currency and cryptocurrency markets, commodities and raw materials markets and even for the real estate investment market for any timeframe.

The paper will also present a way to optimize the model for any desired capital market. In order to prove the generality of the revealed methodology, this article will include several trading results obtained with the presented algorithms for different types of financial markets. The simplicity of the presented method and the good capital investment efficiency will recommend it for large usage. This methodology can be used with very good results by any investor in order to manage an investment plan with multiple markets.

Literature review

There are multiple trading strategies in the literature for different types of markets. However, few are designed to trade in low-risk conditions. Some relevant techniques are presented in (Connors & Sen, 2004), (Connors & Alvarez, 2009a) and (Connors & Alvarez, 2009b). Other good trading patterns that are still functional in the high price volatility markets are also presented in (Connors, 1999a), (Connors, 1999b) and (Connors, 1999c).

Advanced trading methodologies especially designed for algorithmic trading in the capital markets are presented in (Păuna, 2018a), (Păuna, 2018b) and (Păuna, 2018c). One of the best low-risk trading methods for the stock market is revealed in (Connors & Alvarez, 2009a) and uses the well known 2-period RSI indicator presented as "the trader's holy grail of indicators." The model makes very good trades in the stock market but has significant limitations in the rest of the financial markets, especially in the highest price volatility cases as in the currency and cryptocurrency markets. This model will be considered as reference for this work.

For the cryptocurrency markets, there are no trading patterns or models proved to be generally applicable at this moment. The short price history and the huge price volatility of the cryptocurrencies invalidate any known pattern or strategy until this moment. A profitable arbitrage trading system for cryptocurrencies is presented in (Păuna, 2018d) but a classical trading methodology generally applicable in the cryptocurrency market is still missing. There is no general trading methodology presented in the literature to avoid the high-risk allocation applicable for any markets with good results, to make a significant number of trades and to obtain good capital efficiency. This is the gap in this field of study which is filled by this article. This paper will present a trading methodology that can be applied in any financial market. With the proper functional parameters set, the model can be applied with good results in any market, even in the cryptocurrency market where a general trading methodology is missing at this moment. The generality of the presented model is even higher; the low-risk trading algorithm presented in this paper can be also applied in multiple other particular cases as the real estate investment market.

Methodology

The model presented in this paper is based on a series of fundamental conclusions regarding the trading and investment in capital markets made by different authors during the time. All of these conclusions are set together in order to build the Low-Risk Trading Algorithm.
Starting from the ideas to "buy pullbacks, not breakouts" and to "buy the market after it's dropped; not after it's risen" (Connors & Alvarez, 2009a) in order to reduce the allocated risk, the developed model will use the Price Cyclicality Function presented in (Păuna & Lungu, 2018) in order to integrate the cyclical price behavior. The cyclicality function will indicate the oversold price intervals and the tendency of the price to recover the loss. The purpose is to enter the market when the price was dropped enough and starts to recovers in order to ensure a low-risk trade. Noted with PCY, the Price Cyclicality Function is the proper indicator for the low-risk intervals as it was presented in more details in the author's paper. In figure 1 is presented the graph of the PCY function for the Frankfurt Stock Exchange Deutscher Aktienindex DAX30. As it can be seen the variation of the PCY function is in direct correlation with the price movement and the monotony of the PCY function is a good indicator for the price tendency. In addition, low value for the PCY function will indicate the oversold intervals. Good entry points for buy trades can be found through the ascending intervals with low values of PCY function.

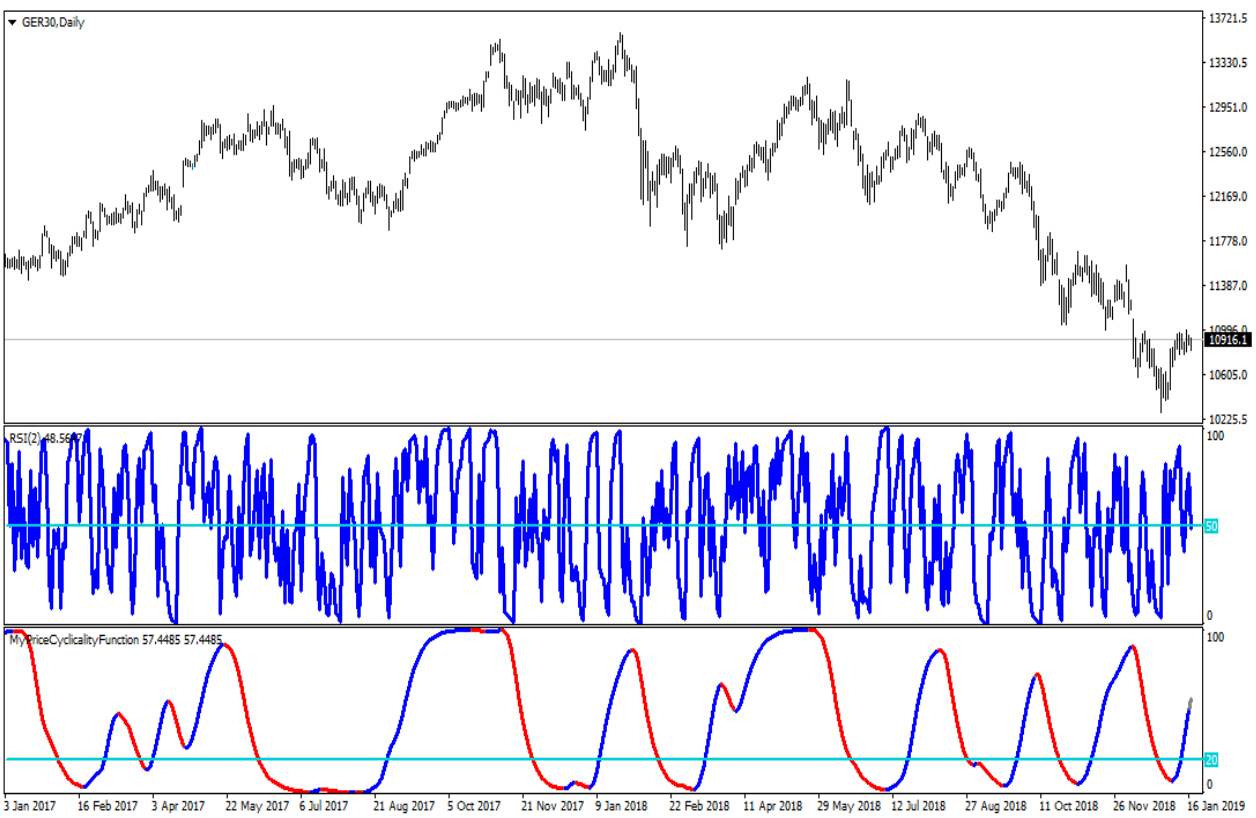

Figure 1. The Price Cyclicality Function for a daily chart of DAX30.
Source: Authors' own research.

A single entry trade has its advantages especially when it is about simple risk management. However, it was found that multiple entries can catch better entry prices and can substantially improve capital efficiency. Consequently, the model presented will use multiple price entries depending on a time price gradient. Once the first trade was initiated, multiple entries will be set each time when the price touches a lower value, with δ lower than the last entry point. The entry step can be fixed or variable in order to optimize the entry process and trading efficiency.

For the exit methodology, two different profit levels will be used. A high-profit target will be set in order to be in the market for a longer period of time and to catch higher profits when the price is trending up. For limited price behavior, a second shorter profit target will be used. It was found that the best indicator to decide which profit level to be used to close the trades is the Relative Strength Index (RSI) developed in (Wilder, 1978).

The Low Risk Trading Algorithm (LRTA) is defined by:

$$\begin{cases} BuySignal_1 = \left(PCY_i < \xi\right) \wedge \left(PCY_i > PCY_{i-1}\right) \\ BuySignal_j = \left(PCY_i < \xi\right) \wedge \left(PCY_i > PCY_{i-1}\right) \wedge \left(p - p_{j-1} < \delta_j\right) \text{ for } j = \overline{2, N} \\ ExitSignal_{High} = \left(\sum_{k=1}^{N}\left(p - p_k\right) > N \cdot \Theta\right) \text{ if } \left(RSI_i < \Omega\right) \\ ExitSignal_{Low} = \left(\sum_{k=1}^{N}\left(p - p_k\right) > N \cdot \theta\right) \text{ if } \left(RSI_i \geq \Omega\right) \end{cases} \tag{1}$$

where *i* represent the index of the time period and *j* is the index of the multiple entry signals. To understand the algorithm (1) we have to say that the $BuySignal_1$ is the first trade initiated by the methodology when the *PCY* function starts to increase and gets lower values than a functional parameter ξ. *p* is the current price level and p_1 is the entry price for the first trade. The next entries will be opened when the price makes lower values than the previous entry price with a δ_j step. For simplicity δ_j can be considered constant $\delta_j = \delta$ but it was proved that a better efficiency can be obtained using a linear variation for $\delta_j = \rho(j-1) + \delta$. The *N* parameter is the maximal number of trades used in order to limit capital exposure.

To catch longer trades the $ExitSignal_{High}$ will be applied only when the *RSI* function will indicate that the price is not yet into an overbought interval. Until the *RSI* function gets *Ω* value, a higher take profit level defined by *Θ* will be applied. If the *RSI* function indicates the price is approaching its local limits, a lower take profit level defined by *θ* will be applied in order to close the opened trades. The exit conditions are set to make *Θ* or *θ* profit value for each k opened trades.

This paper affirms that the Low-Risk Trading Algorithm defined by formula (1) can be applied for any market with a reasonable efficiency. All functional parameters can be optimized with finite computational steps for each market. In addition, the presented algorithm can be applied in any timeframe. It was found that good results are obtained for the daily and weekly timeframes. The number of trades is depending on the price action. The model limits the total maximal number of trades at the *N* value.

Starting from the fact that market behavior is unpredictable, no stop loss levels are used in our model. It is well known and proved that "stops hurt" (Connors & Alvarez, 2009a). For the risk and capital management, the LRTA can be applied together with the "Global Stop Loss Method" presented in (Păuna, 2018e).

The parameters *N, ξ, δ, ρ, Ω, θ,* and *Θ* are functional parameters that will be optimized for each market. The optimization process is a very important step to apply the presented algorithm with good results. Several important steps must be followed in order to find the proper parameter set and to have a stable solution for the next period of time. The optimization process starts with a statistical measure for the higher amplitude value of the price movement in the chosen market for a relevant period of time. By the relevant period of time we understand a time period longer than 12 months in which the price made the highest amplitude movements in the market history. It was found that the period of the last 24 months leads usually to a stable solution for those cases when the price volatility grows continuously. The author uses for the optimization process the historical price movements for the last five years if data are available. The higher price amplitude will give us a fist value for the *N* parameter depending on the capital exposure desired. The optimization procedure will be an iterative process. For each parameter set, the trading efficiency will be computed using the historical price data in the time interval considered. In the next step, a parameter will be changed ant the prices will be repeated until the optimal value for the changed parameter will be found. There are several known iterative methods to find the optimal value for functional parameters presented in (Berbente et. all, 1997). For this case, it was found that the fastest method is the gradient method (Berbente et. all, 1997, p. 170).

In order to start the iterative process, an initial parameter set is needed. For this, we will have the next considerations. A good value for *Ω* to start the optimization process is *Ω*=50. This value will divide the cases to apply the high take profit level *Θ* or the low take profit level *θ* to close the trades. Fist estimation for the *Θ* and *θ* are also provided by the price behavior. A good estimation is $\theta = ATR/2$ and $\Theta = 2 \cdot ATR$, where *ATR* is the Average True Range defined by Wilder in (Wilder, 1978). A good starting approach for the entry price step is given by *δ*=*ATR* and *ρ*=0. With all these starting parameters values the optimal solution for the *ξ* parameter can be computed.

Once we have a first optimal value for the *ξ* parameter we can start to search for the optimal value for each functional parameter. An iterative process will be established using the gradient method which will provide an optimal solution for each functional parameter. The iterative process will be repeated until the optimal solution for all functional parameters will be stable and the optimal valued obtained will remain unchanged. These parameters will depend on the used market and on the capital exposure level used in the beginning. To have a solid confirmation that found the solution is stable, the optimization method can be applied using the cross-validation methodology. The parameters set will be computed for a specified period of time. Once the optimal solution is set, the algorithm will be applied for the next historical period in order to check if the solution is functional and the trading efficiency and the drawdown have desired values. Once the algorithm is functional with optimal parameters set, the iterative optimization process can be organized as a real-time machine learning process in order to incorporate in the parameters set solution the last price movements. If not, it is recommended to run the optimization process at least one time per months.

Regarding the *RSI* function, it was found that the best results are obtained with the 2-period *RSI* or 3-periods *RSI* for all cases studied. The *PCY* function parameters are also important and can be obtained using the same method presented above. There is no general parameter set for the *PCY* function, the cyclical price behavior is depending on the market itself. For each market, the PCY parameters will be also individually optimized.

Results and discussions

In order to prove the efficiency of the presented model, this paper will include the trading results obtained for a wide range of financial markets. The results presented in this paper were obtained using theServer (Păuna, 2010) automated trading software. All the markets were traded as a contract for difference (CFD) for a period of 24 months, between 01.01.2017 and 31.12.2018 using the daily timeframe. The test initial capital was 1.000.000 Euro and the global capital exposure level was set as 1% of the available capital.

Table 1. Optimization process and trading results for different markets

Market	Iterations	Last ξ	Profit	DD	RRR
DAX30	10316	7.88	38552	10181	1:3.79
DJIA30	9622	2.96	37896	5769	1:6.56
FTSE100	11821	3.42	26207	9120	1:2.87
CAC40	9512	18.66	12259	7477	1:1.64
SMI20	9872	9.74	15843	10890	1:1.45
S&P500	10608	14.58	21151	10091	1:2.09
NASDAQ100	7581	3.28	39744	7143	1:5.56
NIKKEI225	12944	10.26	39362	9846	1:3.99
DJUSREI	9814	12.64	18239	9713	1:1.87
Spot Gold	6391	4.98	14549	9881	1:1.47
Brent Crude	7412	3.22	19207	9488	1:2.02
Coffee	9266	4.34	20416	9736	1:2.10
EURUSD	8322	9.28	10728	9380	1:1.14
GBPUSD	9371	4.12	8008	2413	1:3.32
BTCUSD	8722	9.64	9986	9716	1:1.02

Source: Authors' own research.

In the table above is presented the total number of iterations made by theServer system in order to find the latest optimal parameter set. The table includes also the last value for the ξ parameter, the profit, and drawdown obtained for 1% capital exposure and the risk to reward ratio (RRR) for each case in order to compare the results.

The markets included in table 1. are: Frankfurt Stock Exchange Deutscher Aktienindex DAX30, New York Stock Exchange Dow Jones Industrial Average Index DJIA30, Financial Times London Stock Exchange Index FTSE100, Cotation Assistée en Continu Paris Stock Exchange Index CAC40, Swiss Market Index SMI20, Standard & Poor's Index S&P500, National Association of Securities Dealers Automated Quotations NASDAQ100, Tokyo Stock Exchange index NIKKEI225, Dow Jones US Real Estate Index DJUSREI, spot price of gold as XAUUSD, Brent crude oil (WTI), coffee as Dow Jones Commodity Index Coffee, the currency pairs Euro versus US dollar, British Pound versus US Dollar and Bitcoin versus US Dollar. A real-time machine learning process is organized to build the optimal parameter set solution one time per day. The number of iterations reveals the computational cost.

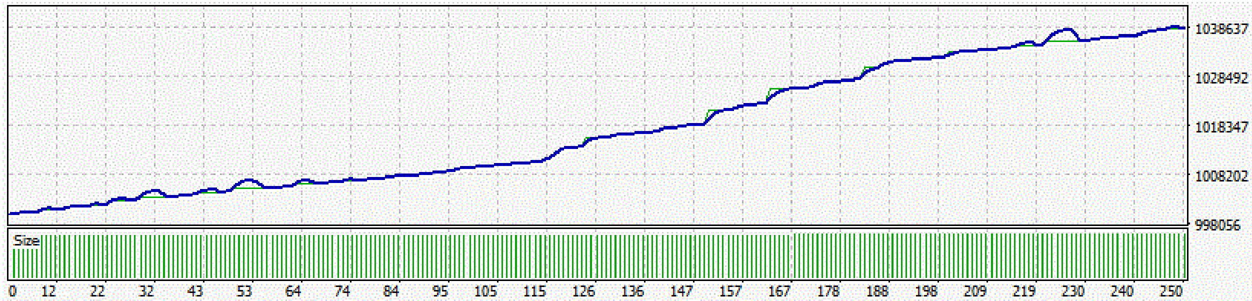

Figure 2. The capital evolution trading DAX30 with LRTA.

Source: Authors' own research.

The application of the LRTA method for the stock markets leads to good results, especially for the high liquidity markets. In the example above the LRTA optimized for DAX30 obtained a risk to reward ratio of 1:3.79 making 255 trades in 4 months. The capital increase is for this case is presented in figure 2. The same algorithm optimized for Dow Jones Industrial Average Index, NASDAQ or Nikkei will produce even better results as it can be seen in table 1. LRTA can be applied with good results for individual stocks. Sometimes, because of the higher volatility of the single stocks that the indexes, LRTA results are positive but with lower profitability that applied for indices. The appliance of the LRTA algorithm for real estate indices can guide for good investment management in the real estate field. In table 1. are included the results for Dow Jones US Real Estate Index. When LRTA is buying, a real estate investor can buy also. The LRTA can be applied for weekly or monthly investments, in this case, the LRTA applied for DJUSREI will guide for good entry points in a long time real estate investments.

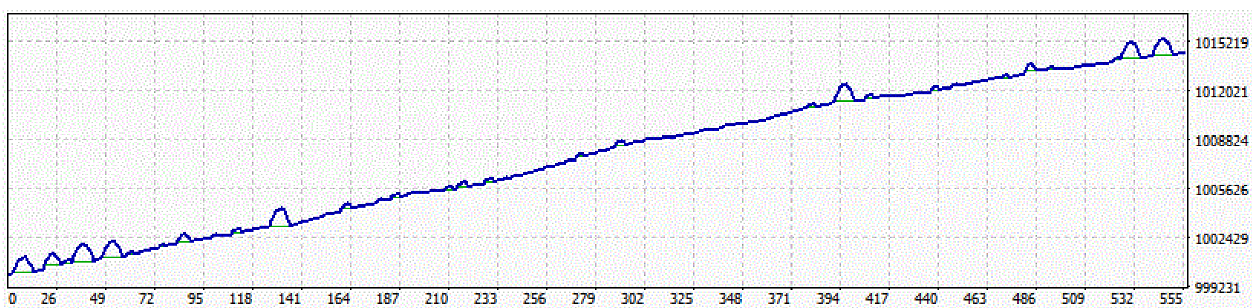

Figure 3. The capital evolution trading XAUUSD with LRTA.

Source: Authors' own research.

The LRTA algorithm can be applied also for all commodities markets. In table 1. are included the results for gold, Brent crude oil, and coffee. As it can be seen the results have a good RRR level in a period of 24 months. In figure 3. is presented the capital evolution for the appliance of LRTA for the spot price of gold on a daily basis. The algorithm made 562 trades in 24 months producing 1:1.47 risk to reward ratio. The results for WTI and coffee are even higher. For the commodity markets, the level of commissions charged by the broker has a very important significance to obtain a good trading efficiency. When the small take profit target θ is comparable with the commission, the LRTA is applicable with substantial limits.

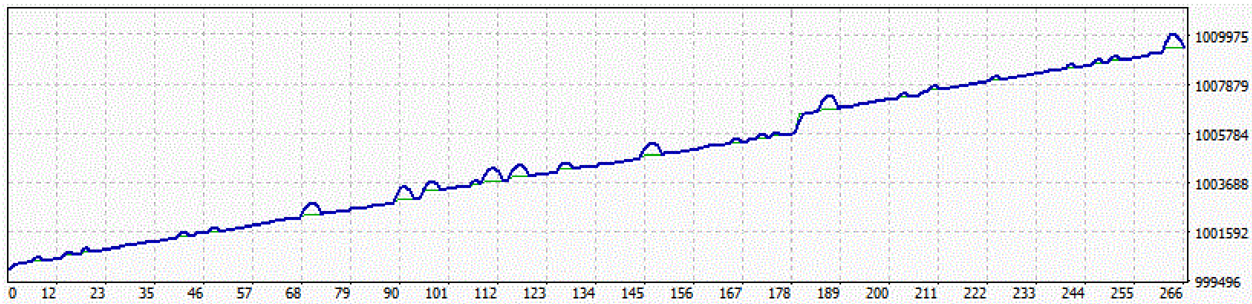

Figure 4. The capital evolution trading Bitcoin versus USD with LRTA.

Source: Authors' own research.

The LRTA can be applied with very good results for the currency markets. In table 1 are presented the results obtained for EURUSD and GBPUSD currency pairs on the daily timeframe. On the currency market, the higher the volatility, the higher the profitability will be obtained by the LRTA. This can be seen comparing the results obtained for the last 24 months for EURUSD and GBPUSD. We have to mention that the LRTA worked for GBPUSD between 01.01.2017 and 31.12.2018 including all the high volatility movements made by the Brexit news and market conditions.

One of the most important aspects working with the LRTA is regarding the cryptocurrency markets. These are still new markets, with short price history and very high volatility. Even so, the LRTA algorithm has obtained a 1:1.02 risk to reward ration in 24 months appliance. At first sight, this is not too much, but thinking there are investors who bought Bitcoin at 18000 USD, and the Bitcoin price is in at 31 December 2018 at 3650 USD, this means those investors risked almost 80% of their capital. The results included in table 1. are obtained with only 1% risk. The profit obtained with 1% risk is about 1% of the capital in 24 months. This means the LRTA applied with higher risk, for example 20% risk would have produced a 20% profit in the investor's account which is totally different than 80% loss in the case of the long term investors who bought at 18000 USD and they are still waiting for a complete recovery. In addition, the LRTA can be used in order to recover any loss investment, using the small profits made by the algorithm on the daily bases to cover the loss made by a wrong entry point.

Conclusion

The Low-Risk Trading Algorithm presented in this paper is a reliable trading and investment algorithm. Applied for timeframes lower or equal with the daily timeframe the algorithm can trade with good results in any market. For longer timeframes as weekly or monthly, the algorithm can be used for investment plans.

The low number of functional parameters and the relatively small computational effort to find the optimal solution for the parameters set make possible the optimization for the LRTA model for any market. The best results are obtained for the high liquidity markets as the main indices as Dow Jones, NASDAQ, DAX or Nikkei. For these cases, the LRTA can produce RRR better than 1:3 in a 24 months period. The algorithm can be also applied for the commodities or currency markets with good results. The appliance of LRTA for the cryptocurrency markets is also possible with positive expectancy as it was presented in the results section.

There are two types of limitations for the LRTA trading methodology. First is about the level of commissions. For lower timeframe when the small take profit level θ is comparable with the commission level, the LRTA results are not good enough. The profit made by LRTA is practically consumed by the broker commissions. An empirical condition for a good profitability level for LRTA is $\theta \geq 2 \cdot \text{commission}$. This condition limits the appliance if the LRTA methodology for some markets. Even so, for those markets with high commission levels, as it is also the cryptocurrency market, the LRTA model can be optimized for positive expectancy using longer timeframes. In this case, the small take profit level will be higher but the longest time period will be also higher, meaning the capital will be allocated for those trades a longer period of time which means higher slippage commissions.

The second negative aspect of the LRTA is the short time capital allocation obtained for trading optimization using timeframes lower or equal with the daily timeframe. In these cases, because the LRTA is trading only in the low-risk price intervals, the time when the capital is allocated to LRTA trades is about 20-25% of the total time. This means there are about 75% of the time when the capital is free and not used in trading. For the longer timeframes as weekly and monthly, the time capital allocation is about 45-50%. This leads to the need to combine the LRTA trading methodology with other strategies in order to have a higher time capital allocation for complete trading and investment plan.

With all of these, the LRTA methodology is a functional strategy that can be optimized for a market with sustainable computational effort in order to obtain a positive expectancy. The LRTA can be used in different modes by any investor in order to trade the capital or to manage a more complex investment plan.

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